Analysis, Modeling, and Simulation (AMS) Testbed Development and Evaluation to Support Dynamic Mobility Applications (DMA) and Active Transportation and Demand Management (ATDM) Programs

Evaluation Report for ATDM Program

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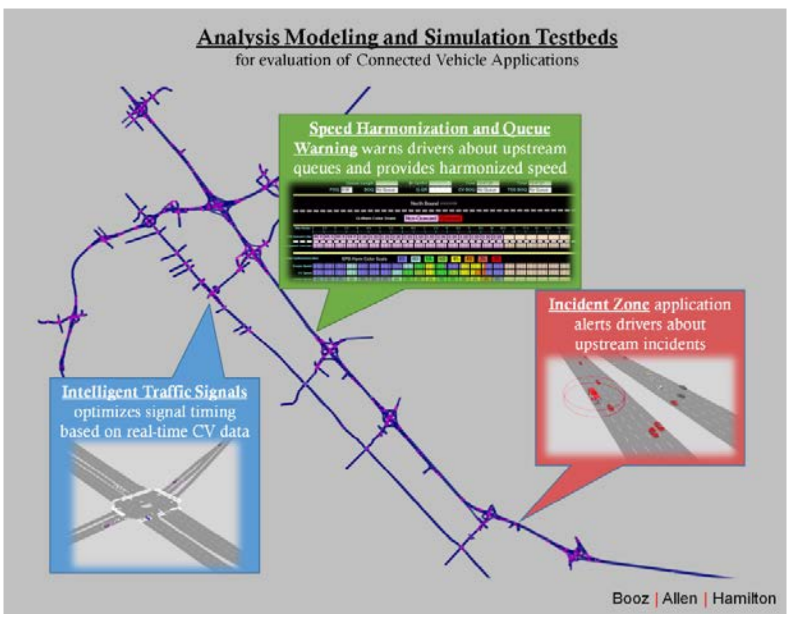

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16. Abstract

The primary objective of this project is to develop multiple simulation testbeds/transportation models to evaluate the impacts of Dynamic Mobility Applications (DMA) and the Active Transportation and Demand Management (ATDM) strategies. Specifically, the evaluations will involve analyzing the system-wide impacts of individual DMA applications/ATDM strategies, individual DMA bundles, and logical combinations of bundles, strategies and applications, and identifying conflicts and synergies for maximum benefits.

While the project aims at evaluating both DMA applications and ATDM strategies, the primary purpose of this report is to document the evaluation done in terms of ATDM strategies using the AMS Testbeds. DMA evaluation will be documented in a separate report. Primarily, Dallas and Phoenix were used as ATDM-centric testbeds and were used to assess the ATDM strategies under various scenarios of combinations of strategies, prediction attributes and evaluation attributes to answer a set of research questions set forth by the USDOT.

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Executive Summary

The United States Department of Transportation (USDOT) initiated the Active Transportation and Demand Management (ATDM) and the Dynamic Mobility Applications (DMA) programs to achieve transformative mobility, safety, and environmental benefits through enhanced, performance-driven operational practices in the management of surface transportation systems. In order to explore a potential transformation in the transportation system's performance, both programs require an Analysis, Modeling, and Simulation (AMS) capability. As part of this project, the team developed six AMS Testbeds to evaluate these DMA applications and ATDM strategies using real-world operational conditions. They are San Mateo (CA), Pasadena (CA), Dallas (TX), Phoenix (AZ), Chicago (IL) and San Diego (CA) Testbeds.

While the project aims at evaluating both DMA applications and ATDM strategies, the primary purpose of this report is to document the evaluation done in terms of ATDM strategies using the AMS Testbeds. DMA evaluation will be documented in a separate report. ATDM analysis was performed under various scenarios of combinations of strategies, prediction attributes and evaluation attributes to answer a set of research questions set forth by the USDOT using the following testbeds: Dallas, Phoenix, Chicago, San Diego and Pasadena. Through these research questions, the report is expected to provide additional insights to readers on the different ATDM strategies with respect to how they can be implemented and evaluated in a model-based simulation environment, synergies and conflicts between the strategies, favorable operational conditions, modes and facility types for the strategies as well as an evaluation of their sensitivity to different prediction attributes.

ATDM Strategies

ATDM is the dynamic management, control, and influence of travel demand, traffic demand, and traffic flow of transportation facilities. Through the use of available tools and assets, traffic flow is managed and traveler behavior is influenced in real-time to achieve operational objectives, such as preventing or delaying breakdown conditions, improving safety, promoting sustainable travel modes, reducing emissions, or maximizing system efficiency. Several ATDM strategies have been evaluated under the AMS testbed using different testbeds. This following table provides a listing of the different ATDM strategies that are evaluated and a mapping to the AMS testbeds that were used for each.

Three types of ATDM strategies exist, in addition to weather-related strategies. Active Traffic Management (ATM) is the ability to dynamically manage recurrent and non-recurrent congestion based on prevailing and predicted traffic conditions. Active Demand Management (ADM) uses information and technology to dynamically manage demand, which could include redistributing travel to less congested times of day or routes, or reducing overall vehicle trips by influencing a mode choice. Active Parking Management (APM) is the dynamic management of parking facilities in a region to optimize performance and utilization of those facilities while influencing travel behavior at various stages along the trip making process: i.e., from origin to destination.

Table ES-1: ATDM Strategies and Corresponding Testbeds

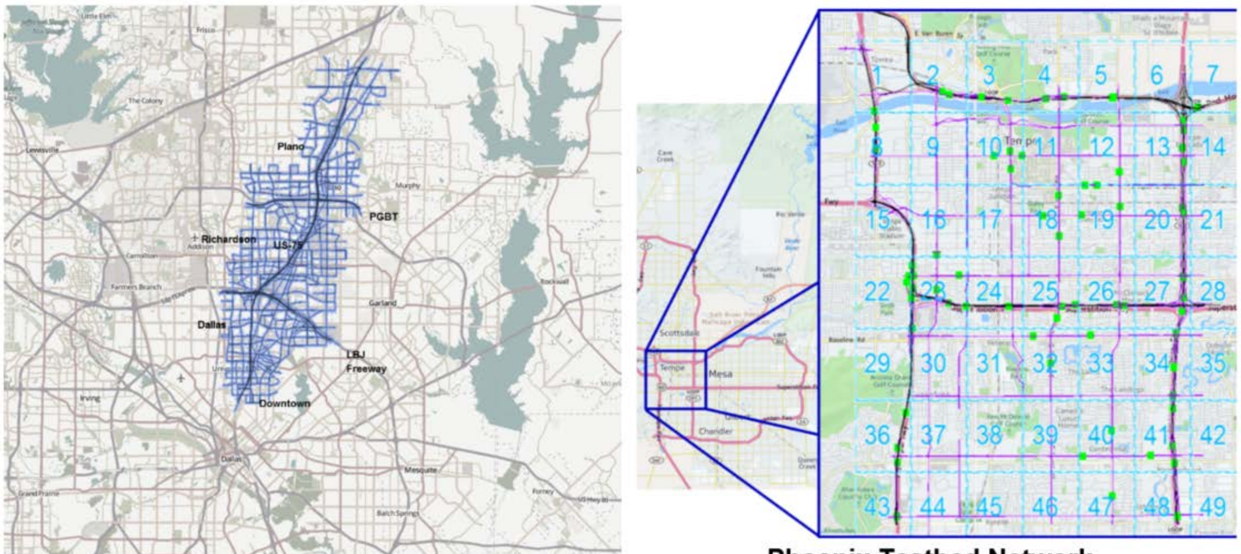
Bundle	ATDM Strategies	Pasadena	Dallas	Phoenix	Chicago	San Diego
Active Traffic Management	Dynamic Shoulder Lanes	●	●		●	
	Dynamic Lane Use Control	●			●	●
	Dynamic Speed Limits	●			●	●
	Adaptive Ramp Metering	●	●	●		
	Dynamic Junction Control	●				
	Dynamic Merge Control					●
	Adaptive Traffic Signal Control	●	●	●	●	
Active Demand Management	Predictive Traveler Information		●	●	●	●
	Dynamic HOV/Managed Lanes					●
	Dynamic Routing	●	●	●	●	●
Active Parking Management	Dynamically Priced Parking		●			
Weather Related Strategies	Snow Emergency Parking				●	
	Preemption for Winter Maintenance				●	
	Snowplow Routing				●	
	Anti-Icing and Deicing Operations				●	

AMS Testbed Summary

The AMS Testbed project spans over six testbeds, namely – San Mateo, Phoenix, Dallas, Pasadena, Chicago and San Diego. However, ATDM-specific evaluation is being performed using Phoenix, Dallas, Pasadena, Chicago and San Diego testbeds.

The Dallas Testbed consists of the US-75 freeway and all associated arterial roadways. The US-75 Corridor is a major north-south radial corridor connecting downtown Dallas with many of the suburbs and cities north of Dallas. It contains a primary freeway, an HOV facility in the northern section, continuous frontage roads, a light-rail line, park-and-ride lots, major regional arterial streets, and significant intelligent transportation system (ITS) infrastructure. The length of the corridor is about 21 miles and its width is in the range of 4 miles. The corridor is equipped with 13 Dynamic Message Signs (DMSs) and numerous cameras that cover all critical sections of the US-75 freeway. The US-75 corridor is a multimodal corridor where travelers can use the following mode options: a) private car; b) transit; c) park-and-ride; and d) carpooling. Transit and park-and-ride travelers are estimated to represent less than 2% of the traveler population. The freeway consists of four lanes per direction for most of its sections with the exception of the section at the interchange with I-635 freeway which consists of three lanes only. This lane reduction creates a major bottleneck during the morning and afternoon peak periods.

The Phoenix Testbed covers the entire Maricopa Association of Governments (MAG) which is home to more than 1.5 million households and 4.2 million inhabitants. This multi-resolution simulation model takes multiple modes into account such as single/high occupancy vehicles, transit buses and light-rail and freight vehicles. The region covers an area of 9,200 square miles and is characterized by a low density development pattern with population density of 253 people per square mile. The region has one city with more than 1 million people (Phoenix) and eight cities/towns with more than 100,000 people each. The region has experienced dramatic population growth in the past two decades, with the pace of growth slowing rather significantly in 2008-2012 period in the wake of the economic downturn. The region is home to the nation’s largest university (Arizona State University with more than 73,000 students), several special events centers and sports arenas, recreational opportunities, a 20-mile light rail line, and a large seasonal resident population. The focus of the Testbed is Tempe area which covers an area of 40 square miles. This testbed considers PM peak traffic between 3PM and 7PM.



Dallas Testbed Network **Phoenix Testbed Network**

Figure ES-1: Dallas and Phoenix Testbeds Used for ATDM Evaluation [Source: SMU, ASU, BAH]

The Pasadena Testbed models the roadway network of the City of Pasadena in Los Angeles County, California. This testbed network was derived from the regional travel model shown in Figure ES-2 that had been developed under US DOT contract DTFH6111C00038, which is publicly accessible through the Research Data Exchange portal (https://www.its-rde.net/). Primarily covering the City of Pasadena, the network also includes unincorporated area of Altadena to the north, part of the Cities of Arcadia to the east, Alhambra to the south and Glendale and Northeast Los Angles to the west. The total area is 44.36 square miles.

The Chicago Testbed network includes Chicago downtown area located in the central part of the network, Kennedy Expressway of I-90, Edens Expressway of I-94, Dwight D. Eisenhower Expressway of I-290, and Lakeshore Drive. The Testbed network is bounded on east by Michigan Lake and on west by Cicero Avenue and Harlem Avenue. Roosevelt Road and Lake Avenue bound the Testbed network from south and north, respectively. This network was extracted from the entire Chicago Metropolitan Area Network to enhance the estimation and prediction performance during the implementation procedure. The testbed, modeled in DYNASMART, a (meso) simulation-based intelligent transportation network planning tool, consist of over 4800 links and 1500 nodes, with over 500 signalized intersections, nearly 250 metered and non-metered ramps. The network demand is coded for 24 hours at 5-minute intervals with over a million vehicles simulated.

The San Diego Testbed facility comprises of a 22-mile stretch of interstate I-15 and associated parallel arterials and extends from the interchange with SR 78 in the north to the interchange with SR-163 in the south. The current I-15 corridor operates with both general-purpose (GP) lanes and four express lanes from the Beethoven Drive DAR to the southern extent of the model. These lanes currently run with two northbound lanes and two southbound lanes and are free to vehicles travelling with two or more passengers in the car (High-Occupancy Vehicles, or HOVs); they also allow Single Occupancy Vehicles (SOV) to use the lanes for a fee, using a variable toll price scheme making them High Occupancy Tolled (HOT) lanes. In addition, it is possible to change the lane configuration of the express lanes with the use of barrier transfer (zipper) vehicles and the Reversible Lane Changing System (RLCS). The network was coded in Aimsun microsimulation software and was calibrated to four different operational conditions.

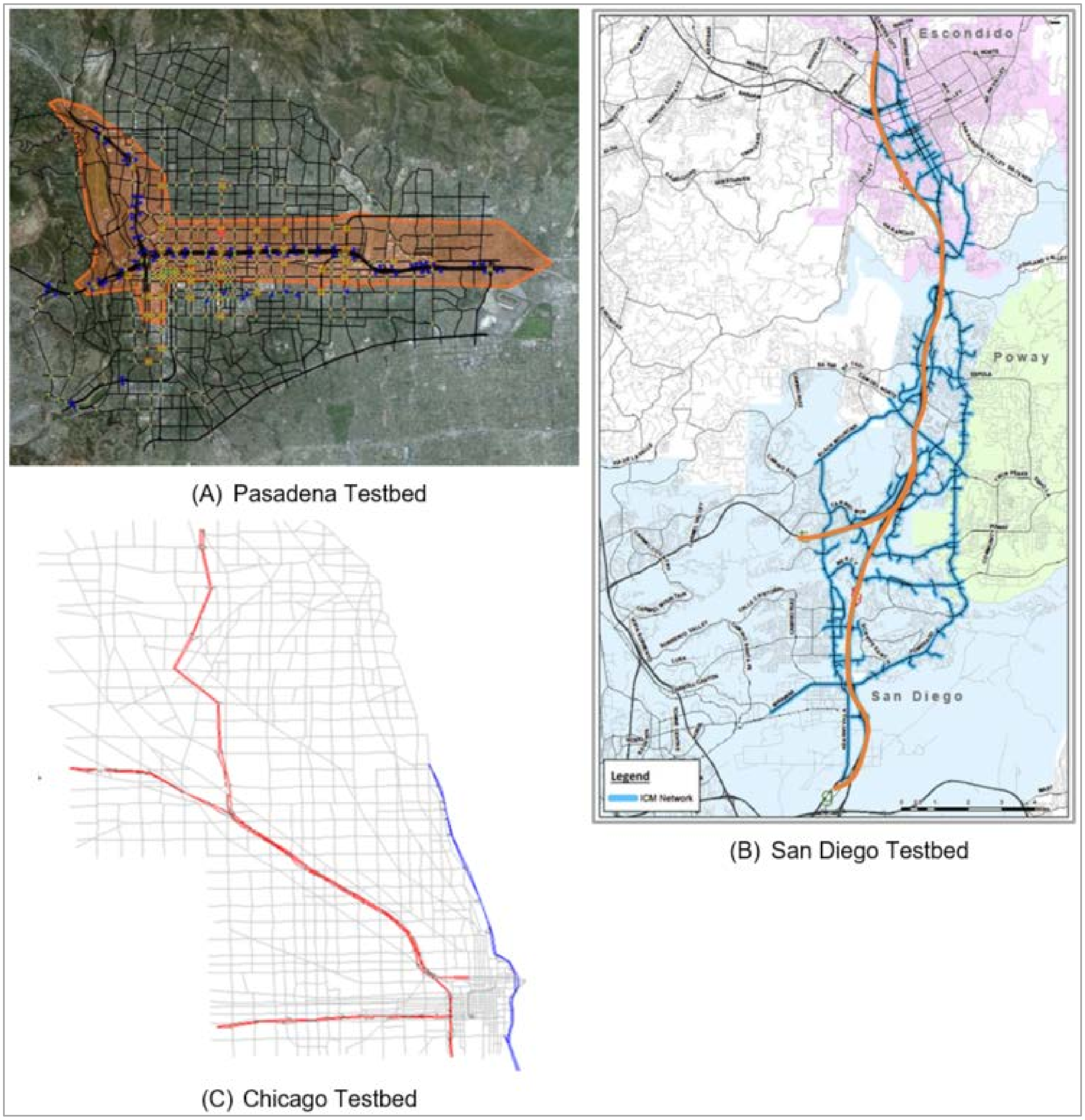


Figure ES-2: Pasadena, San Diego and Chicago Testbeds Used for ATDM Evaluation [Source: BAH, HBA, NWU]

Research Questions and Hypotheses

The AMS Preliminary Evaluation Plan put forth by the USDOT[1] lists several research questions that can be addressed using the AMS Testbeds. The AMS project's analysis plans for individual testbeds were developed based on these research questions. The ATDM-specific research questions and their hypotheses are shown in Table ES-2. It has to be noted that not all research questions could be answered in the existing AMS scope. This include the research questions that assesses the impacts of ATDM on short-term and long-term travel behavior.

Table ES-2: ATDM Research Question Analysis Hypothesis

ID	ATDM Research Question	Analysis Hypotheses
Synergies and Conflicts		
1	Are ATDM strategies more beneficial when implemented in isolation or in combination (e.g., combinations of ATM, ADM, or APM strategies)?	ATDM strategies that are synergistic (e.g., ADM, APM, ATM) will be more beneficial when implemented in combination than in isolation.
2	Which ATDM strategy or combinations of strategies yield the most benefits for specific operational conditions?	An ATDM strategy will yield higher benefits only under certain operational conditions. Certain combinations of ATDM strategies will yield the highest benefits for specific operational conditions.
3	What ATDM strategies or combinations of strategies conflict with each other?	Certain ATDM strategies will be in conflict with each other, resulting in no benefits or reduced benefits.
Prediction Accuracy		
4	Which ATDM strategy or combination of strategies will benefit the most through increased prediction accuracy and under what operational conditions?	Improvements in prediction accuracy will yield higher benefits for certain ATDM strategies and combinations of strategies than for others. An ATDM strategy or combinations of strategies will yield the most benefits with improvements in prediction accuracy only under certain operational conditions.
5	Are all forms of prediction equally valuable, i.e., which attributes of prediction quality are critical (e.g., length of prediction horizon, prediction accuracy, prediction speed, and geographic area covered by prediction) for each ATDM strategy?	Increased prediction accuracy is more critical for certain ATDM strategies over others, with certain attributes (e.g., length of prediction horizon, prediction accuracy, prediction speed, and geographic area covered by prediction) of prediction quality being most critical.
Active Management or Latency		

[1] Vasudevan and Wunderlich, Analysis, Modeling, and Simulation (AMS) Testbed Preliminary Evaluation Plan for Dynamic Mobility Applications (DMA) Program, FHWA-JPO-13-097

ID	ATDM Research Question	Analysis Hypotheses
6	Are the investments made to enable more active control cost-effective?	Incremental improvements in latency will result in higher benefit-cost ratio for certain ATDM strategy or combinations of strategies up to a certain latency threshold, after which benefit-cost ratio will be reduced.
7	Which ATDM strategy or combinations of strategies will be most benefited through reduced latency and under what operational conditions?	Reductions in latency will yield higher benefits for certain ATDM strategies and combinations of strategies than for others. An ATDM strategy or combinations of strategies will yield the most benefits with reduced latency only under certain operational conditions.
Operational Conditions, Modes, Facility Types with most benefit.		
8	Which ATDM strategy or combinations of strategies will be most beneficial for certain modes and under what operational conditions?	Certain ATDM strategies and combinations of strategies will yield the highest benefits for specific modes and under certain operational conditions.
9	Which ATDM strategy or combinations of strategies will be most beneficial for certain facility types (freeway, transit, arterial) and under what operational conditions?	Certain ATDM strategies and combinations of strategies will yield the highest benefits for specific facility types and under certain operational conditions.
10	Which ATDM strategy or combinations of strategies will have the most benefits for individual facilities versus system-wide deployment versus region-wide deployment and under what operational conditions?	Certain synergistic ATDM strategies will yield most benefits when deployed together on individual facilities rather than as system-wide or region-wide deployments and under certain operational conditions and vice-versa
Prediction Latency and Coverage Tradeoffs		
11	What is the tradeoff between improved prediction accuracy and reduced latency with existing communications for maximum benefits?	Incremental improvements in prediction accuracy will result in higher benefits, when latency is fixed up to a certain threshold, after which marginal benefits will be reduced and vice-versa. Maximum system benefit will be obtained at an intermediate point balancing prediction accuracy and latency.
12	What is the tradeoff between prediction accuracy and geographic coverage of ATDM deployment for maximum benefits?	Incremental improvements in prediction accuracy will result in higher benefits when geographic coverage is fixed up to a certain threshold, after which marginal benefits will be reduced and vice-versa. Maximum system benefit will be obtained at an

ID	ATDM Research Question	Analysis Hypotheses
		intermediate point balancing prediction accuracy and geographic coverage.
13	What is the tradeoff between reduced latency (with existing communications) and geographic coverage for maximum benefits?	Incremental improvements in latency will result in higher benefits when geographic coverage is fixed up to a certain threshold, after which marginal benefits will be reduced and vice-versa. Maximum system benefit will be obtained at an intermediate point balancing latency and geographic coverage.
14	What will be the impact of increased prediction accuracy, more active management, and improved robust behavioral predictions on mobility, safety, and environmental benefits?	Increases in prediction accuracy, more active management, and improvements in robust behavioral predictions will result in significant mobility, safety, and environmental benefits. ATDM strategies will reduce the impact of congestion by delaying its onset, and reducing its duration and geographic extent. ATDM strategies will impact all three characteristics of congestion (onset, duration, and extent) but different strategies will impact specific congestion characteristics differently. Traveler and system mobility measures will vary inversely with respect to congestion characteristics, but not uniformly by characteristic.
15	What is the tradeoff between coverage costs and benefits?	Incremental increase in geographic coverage will result in higher benefit-cost ratio up to a certain coverage cost threshold, after which benefit-cost ratio will be reduced.
Connected Vehicle Technology and Prediction		
16	Are there forms of prediction that can only be effective when coupled with new forms of data, such as connected vehicle data?	Prediction will be most effective only when coupled with connected vehicle data capture and communications technologies that can systematically capture motion and state of mobile entities, and enable active exchange of data between vehicles, travelers, roadside infrastructure, and system operators.
Short-term and Long-term Behaviors		
17	Which ATDM strategy or combinations of strategies will have the most impact in influencing short-term behaviors versus long term behaviors and under what operational conditions?	Certain ATDM strategies and combinations of strategies will influence short-term behaviors more than long-term behaviors under certain operational conditions, while others will influence long-term

ID	ATDM Research Question	Analysis Hypotheses
		behaviors more than short-term behaviors under certain operational conditions.
18	Which ATDM strategy or combinations of strategies will yield most benefits through changes in short-term behaviors versus long-term behaviors and under what operational conditions?	Certain ATDM strategies and combinations of strategies will have the most impact through changes in short-term behaviors under certain operational conditions, while others will have the most impact through changes in long-term behaviors under certain operational conditions.

Research Findings

Using simulation scenarios that were structured to answer the different research questions, the team was able to conduct hypotheses testing for the different hypotheses summarized in the previous page. Our findings and supporting figures are provided below.

Synergies and Conflicts

The project team analyzed the impact of combining different strategies and implementing them together in an Active Traffic Management context and to find out synergistic and conflicting strategies. In order to assess the impact of combination of different ATDM strategies, the proposed strategies were assessed in isolation and in combination. It was found that these strategies are synergistic in nature, with combination of strategies showing better performance measures than isolation.

The results from the Dallas Testbed shows that all of the ATDM strategies improve the overall network performance during non-recurrent congestion scenario. Integrated ATDM strategies such as Dynamic Signal Timing, Dynamic Routing, Adaptive Ramp Metering and Dynamic Shoulder Lane could have significant benefits in terms of congestion reduction. All the applications are synergistic with each other with the exception of Dynamic Shoulder Lanes and Dynamic Routing, where we have seen a reduction in benefits provided by Dynamic Shoulder Lanes when implemented with Dynamic Routing. According to Table ES-3, Dynamic Shoulder Lanes strategy contributed to the highest benefits, in isolation and in combination. Most of the strategies were synergistic.

Table ES-3: Deploying Different ATDM Strategies on Dallas Testbed under Medium Demand and Low Incident Severity

Dynamic Signal Timing	***Dynamic Shoulder Lanes***	***Dynamic Ramp Metering***	***Dynamic Routing***	***Total Network Travel Time Savings (minutes) per peak-hour simulation***
✓				223
	✓			48,630
		✓		10,923
	✓		✓	44,210
✓			✓	15,125
✓	✓		✓	53,871
✓		✓	✓	22,926
✓	✓	✓	✓	75,304

Based on the Phoenix Testbed analysis, it was seen that Adaptive Ramp Metering and Adaptive Signal Control was synergistic in the sense that together, they were able to reduce travel time on freeways as well as arterials. Dynamic Routing/Predictive Traveler Information System was shown to help travelers avoid bottlenecks and therefore considerably reduce their overall travel delays. Table ES-4 demonstrates the combined travel time savings when compared to individual strategies. Please note that an average of all operational conditions were used in this table for comparison.

Table ES-4: Deploying Different ATDM Strategies on the Phoenix Testbed

Oper. Cond	***Adaptive Signal Control***	***Predictive Traveler Information***	***Adaptive Ramp Metering***	***Dynamic Route Guidance***	***Total Network Travel Time Savings (%)***
Average of	✓				15 %
all			✓		14 %
operational	✓		✓		17 %
conditions		✓		✓	45 %

Results from the Pasadena testbed indicates that Dynamic Speed Limit (DSL) and Queue Warn (QW) causes negative operational impact. These operational results are also reflected in the combination scenarios that include the DSL + QW strategy. In the later sections of this report, DSL + QW demonstrates significant safety improvement along the freeway where the strategy is used to distribute the isolated congestions and reducing any abrupt speed changes. Other strategy combinations without DSL + QW demonstrate synergy performance. Although the summary results shown in Table ES-5 below shows the isolated Hard Shoulder Running (HSR) and Dynamic Junction Control (DJC) operates with the best travel time savings when deployed in isolation, a more detailed analysis in the later sections show that under combination, the ATDM performances can yield almost similar travel time savings with only a fraction of the HSR + DJC activation time. Most travel time savings are shown from the freeway focused strategies compared to the arterial focused strategies.

Table ES-5: Deploying Different ATDM Strategies on the Pasadena Testbed

ARM	DSC	HSR + DJC	DSL + QW	DRG	Network Travel Time Savings (Seconds)	Network Travel Time Savings (Percent)
✓					64,663	2.45
	✓				20,322	0.77
		✓			205,075	7.77
			✓		-187,920	-7.12
				✓	55,425	2.10
	✓			✓	55,689	2.11
✓		✓			175,251	6.64
✓	✓	✓		✓	176,370	6.68
✓		✓	✓		-118,769	-4.50
✓	✓	✓	✓	✓	-105,573	-4.00

From the Chicago Testbed results, we can conclude that the low-medium penetration rate yields the most benefits for system performance, while the high penetration rate requires coordination in vehicle routing to achieve benefits. Therefore, for the ADM involved scenarios, we recommend the net penetration level could be set with the low-medium penetration rate. In terms of synergies and conflicts, it is observed that (1) the ATM, ADM and the Weather-related strategies are synergistic for clear day and rain-to snow day scenarios; (2) the ATM, ADM and the Weather-related strategies are synergistic for high demand snow day scenarios and (3) the ATM and the Weather-related strategy may not be effective when applied jointly for the low demand, snow day scenario considered. The analyses showed the most beneficial strategy or combination of strategies.

In the San Diego Testbed, Dynamic Lane Use, Dynamic HOV/Managed Lanes and Dynamic Speed Limits show neither a significant conflict nor a significant synergy. The increase of congestion at the entrances and exits of the HOV lanes due to the increase of demand triggered by Dynamic Lane Use, Dynamic HOV/Managed Lanes is sensed by Dynamic Speed Limits, which extends the congestion over a larger space and longer time in order to avoid abrupt speed changes. This increase of safety is obtained at the expense of throughput and travel time. Dynamic Lane Use and Dynamic HOV/Managed Lanes alone would produce better traffic performance, at the expense of safety. Dynamic Speed Limits alone would produce an increase of safety, but with a more pronounced reduction of throughput. The combined effect of having an increase of safety with less reduction of throughput can be interpreted as a good compromise, which can be considered a synergy. Dynamic Merge Control and Dynamic HOV/Managed Lanes show a synergy: Dynamic HOV/Managed Lanes compensate the slightly negative effect in terms of traffic performance caused by Dynamic Merge Control, which facilitates the entrance from SR-78, at the expense of penalizing traffic coming from the northern boundary of the I-15 corridor in the southbound direction. In other words, the decision to activate Dynamic Merge Control or not should be dictated purely by the need to reduce queueing on the ramp coming from SR-78 rather than by overall traffic performance benefits, and if Dynamic Merge Control is activated, Dynamic HOV/Managed Lanes would compensate its slightly negative impact on throughput. Dynamic Merge Control, Dynamic HOV/Managed Lanes and Dynamic Routing show also a synergy: Dynamic HOV/Managed Lanes and Dynamic Routing compensate the slightly negative effect in terms of traffic performance caused by Dynamic Merge Control, which facilitates the entrance from SR-78, at the expense of penalizing traffic coming from the northern boundary of the I-15 corridor in the southbound direction. Again, the decision to activate Dynamic Merge Control or not should be dictated purely by the need to reduce queueing on the ramp coming from SR-78 rather than by overall traffic performance benefits, and if Dynamic Merge Control is activated, Dynamic HOV/Managed Lanes and Dynamic Routing would compensate its slightly negative impact on throughput.

Prediction and Active Management

The team also analyzed the impacts of prediction attributes such as accuracy and length of prediction horizon in the effectiveness of ATDM strategies. Prediction accuracy represents the degree to which the traffic state prediction is accurate, whereas, prediction horizon represents the time-horizon in future to which the traffic state prediction is made. Intuitively, it was seen that greater prediction accuracy and a longer prediction horizon resulted in better results in the Dallas, Phoenix, and Pasadena Testbeds (Figure ES-3).

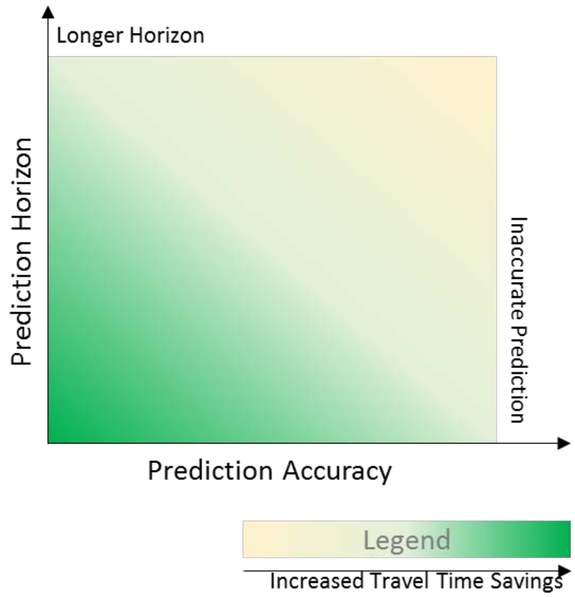


Figure ES-3: Impact of Prediction Horizon and Accuracy on Travel Time Savings due to ATDM Implementation [Source: Booz Allen]

Prediction Accuracy

For the Dallas Testbed, a superior network performance is obtained when perfect demand prediction is assumed. The network performance gradually worsens with the increase in the level of demand prediction error. For example, savings of 7,806 and 12,341 minutes are recorded for the scenarios with 5% demand prediction error in the underestimation and overestimation cases, respectively. As the error increases to 10%, the savings are reduced to 2,252 and 3,298 minutes, respectively. For the Phoenix Testbed, it is found that the performance of adaptive ramp metering is very sensitive to the prediction accuracy. After certain system errors are superimposed to the prediction accuracy, the adaptive ramp metering will be under or overestimated in different scenarios. For the Pasadena testbed, prediction accuracy has the most significant effect on arterial focused strategies when selecting the appropriate plans. The operational results for scenarios where the prediction accuracy falls to 50% demonstrates noticeable operational deteriorations for DSC and DRG strategies. DSC strategy even shows negative operational benefits when the prediction accuracy falls to 50%. The freeway focused strategies, ARM and HSR + DJC, shows small operational changes between 100%, 90%, and 50% prediction accuracy.

Prediction Horizon

The network performance generally improves as the length of the prediction horizon increases. In other words, positive correlation is observed between increasing the length of prediction horizon, and total travel time savings in the network. For example, Dallas testbed was evaluated using different prediction horizons. Using 15-minute prediction horizon resulted in less travel time savings compared to that obtained for the scenario in which 60-minute prediction horizon is considered. For the 15-minute prediction horizon, a saving of 9,114 minutes is recorded. This saving increased to 21,586 minutes when the prediction horizon increased to 60 minutes. For the Phoenix Testbed, freeway travel time was assessed with Adaptive Ramp Metering under different configurations. A longer prediction horizon resulted in a slight reduction in the average travel times and the impact of communication latency on the traffic mobility was also marginal (less than 1%). For the Pasadena testbed, longer prediction horizon yields better operational performance for all strategies. The impacts of prediction horizon is most noticeable for freeway focused strategies, ARM and HSR + DJC, when the prediction horizon is increased from 30-minutes to 60-minutes. Prediction horizon is more noticeable for arterial focused strategies when prediction horizon is increased from 15-minutes to 30-minutes. For the Chicago Testbed, clear weather scenarios prefer prediction accuracy with a shorter prediction horizon and roll period for the peak hours when travel demand is high, while the snow-affected scenarios prefer a longer prediction horizon, and are sensitive to accuracy and latency. More frequent updates with shorter roll periods of the predictive strategies may lead to instabilities in system performance. As with the hypothetical scenario, i.e. the combined incident-snow scenario reaches a trade-off state between accuracy and prediction horizon, and is not particularly sensitive to latency due to incident-related delay.

Operational Conditions, Modes and Facility Types

The different ATDM strategies were also evaluated under the different operational conditions identified for the Dallas, Phoenix, and Pasadena Testbeds (Figure ES-4). The operational conditions were a combination of demand levels, incident severity as well as weather conditions. In general, it was seen that the highest benefits are sought when the demand levels and the incident severity are lower. Under high demand and high incident severity, Dallas testbed showed an increase in travel time, while the Phoenix testbed showed lower benefits for ATDM strategies.

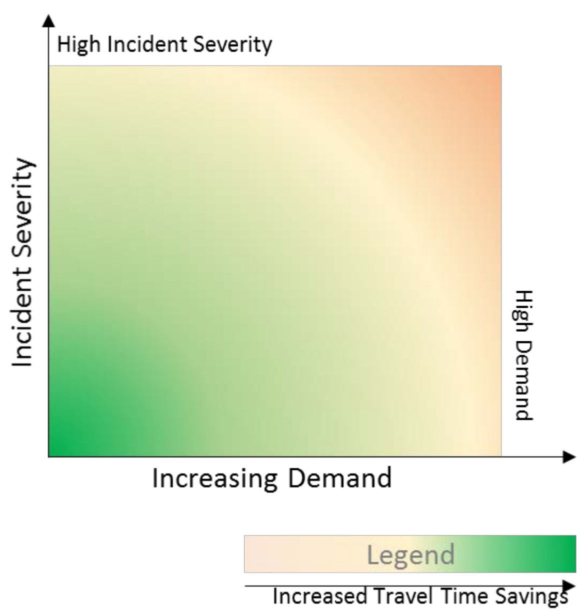


Figure ES-4: Impact of Demand Levels and Incident Severity on ATDM Implementation [Source: Booz Allen]

The four operational conditions that were assessed for Dallas testbed were: 1) medium to high demand level with low severity incident; 2) high demand level with low severity incident; 3) high demand level with medium severity incident; and 4) medium demand level with high severity incident. In all these cases, a dry weather condition is assumed. The four operational conditions that were assessed for Phoenix tested were: 1) high demand with low incident severity; 2) high demand with high incident severity; 3) low demand with low incident severity; and 4) high demand with medium incident severity and wet weather. The three operational conditions that were assessed for the Pasadena testbed were: 1) High demand, low to medium incident frequency/severity, medium freeway travel times; 2) Medium to high demand, high incident frequency/severity, medium to low freeway travel times; 3) High demand, medium incident frequency/severity, high corridor travel times. The six operational conditions that were assessed for Chicago Testbed were: 1) High AM High PM Demand, No Incidents, 2) High AM, High PM Demand, No Incidents, Moderate Rain AM, Moderate Rain to Snow, 3) Medium AM, High PM Demand, No Incidents, Moderate Snow, 4) Low AM Medium PM Demand, No Incidents, Moderate Snow, 5) Medium AM High PM Demand, No Incidents, Moderate to Heavy Snow, and 6) Medium AM to High PM Demand, AM Incidents, Moderate Snow. The four operational conditions that were assessed for San Diego Testbed were: 1) Southbound (AM) +Medium Demand + Medium Incident, 2) Southbound (AM) +Medium Demand + High Incident, 3) Northbound (PM) +Medium Demand + High Incident, and 4) Northbound (PM) +Medium Demand + Medium Incident

Given that all the Dallas operational conditions represented dry weather conditions, the effectiveness of the ATDM strategies in reducing the network congestion associated with adverse weather conditions is also examined using a hypothetical scenario. ATDM strategies that combine the dynamic routing strategy and the dynamic signal timing strategy are considered in the analysis. Based on the obtained simulation results, ATDM strategies helps in alleviating the network congestion due to the adverse weather. Travel time savings of 163,480 minutes and 84,913 minutes were recorded for two different scenarios of weather impacts on the traffic flow, namely, reduced free-flow speed and a combination of reduced free-flow speed and jam density. The performance of ATDM strategies is examined considering a hypothetical evacuation scenario for Dallas testbed. A demand scenario is created in which evacuees are traveling from their work places to a pre-defined set of safe destinations in the northern section of the corridor. Different combinations of ATDM strategies are implemented to evaluate their effectiveness in reducing the congestion associated with the evacuation scenario. These strategies include demand management, dynamic signal timing, traveler information provision, dynamic shoulder lane, and tidal flow operation. The results indicate that effective demand management and the dynamic shoulder lane could significantly reduce the congestion associated with the evacuation process.

Predication Latency, Accuracy and Coverage Trade-Offs

The impact of prediction latency and extent of prediction coverage on the effectiveness of ATDM Strategies was assessed using both Dallas and Phoenix Testbed.

For the Dallas Testbed, promptly responding to the incident (zero latency) helped in alleviating the congestion, and achieving considerable saving in total network travel time. On the other hand, as the latency increases, the system does not respond to the congestion for longer period. By the time the plan is generated, its effectiveness in alleviating the congestion reduces. For example, a saving of 15,125 minutes is recorded for the scenario with zero latency. As the latency extends to 20-minutes, an increase in the travel time, compared to the baseline scenario, is observed implying that the scheme is no longer effective because of the change in the network conditions. For limited area coverage, the recommended ATDM strategies fail to significantly achieve significant travel time savings. On the other hand, as the coverage expands, more information on the congestion pattern in the area is obtained and also more traffic control devices could be included (traffic signals and DMSs) to developing the generated ATDM recommendations. Thus, more significant improvement in the network performance can be achieved. Based on the obtained simulation results, extending the covered area provides more total network travel time saving. For example, travel time saving of 9,930 minutes is obtained for the spatial coverage of two miles. The saving is increased to 16,460 minutes as the coverage is extended to four miles.

Similar analysis with Phoenix Testbed with variable prediction latencies showed that as latencies go up, effectiveness of ATDM Strategies go down. Specifically, two traffic conditions were evaluated and the latencies were set as 5 minutes and 10 minutes for adaptive ramp metering strategies. The evaluation results show up 4% reduction of freeway travel times along the segment if the prediction latency was reduced from 10 min to 5 min.

The Pasadena testbed has demonstrated that prediction latency has a significant effect on arterial strategies compared to freeway strategies. Though ARM is typically considered a freeway focused strategy, it is also the transition from aterial collector roads to and from the freeway. The ARM does show degradation with increase in prediction latency from 5-minutes to 10-minutes. This degradation is likely due to vehicles metered at a rate that was recommended for a traffic state 10-minutes before. HSR + DJC strategy shows negligeble changes between 5-minute to 10-minute prediction latency.

As far as the Chicago Testbed was concerned, the sensitivity of system performance to the specific operational settings implemented depends on the particular operational conditions experienced on a given day. In other words, the best settings are one operational condition are not necessarily best under all operational conditions. Different from OC1, OC3 prefers longer prediction horizon and roll period, and is only sensitive to latency for the evening peak hours. Though the predictive information is updated more frequently with a short roll period, it may still lead to an unstable system as vehicles may change routes very often. OC6 reaches a trade-off state between short roll period and long prediction horizon., and it is not sensitive to latency due to incident-related delay. By and large, the use of the predictive approach ensures that the deployed strategies result in improved overall network performance. The improvements resulting from application of a particular strategy, or bundle of strategies, depend on selecting appropriate operational settings. The operational settings include net penetration rate and prediction/latency features, and the combination of strategies.

Chapter 1. Introduction

The United States Department of Transportation (USDOT) initiated the Active Transportation and Demand Management (ATDM) and the Dynamic Mobility Applications (DMA) programs to achieve transformative mobility, safety, and environmental benefits through enhanced, performance-driven operational practices in the management of surface transportation systems. In order to explore a potential transformation in the transportation system's performance, both programs require an Analysis, Modeling, and Simulation (AMS) capability. Capable and reliable AMS Testbeds provide valuable mechanisms to address this shared need by providing a laboratory to refine and integrate research concepts in virtual computer-based simulation environments prior to field deployments. Developing and using AMS Testbeds to evaluate these DMA applications and ATDM strategies using real-world operational conditions is the primary goal of the AMS Testbed Project featured in this report.

The foundational work conducted for the DMA and ATDM programs revealed a number of technical risks associated with developing an AMS Testbed which can facilitate detailed evaluation of the DMA and ATDM concepts. Therefore, instead of selecting a single Testbed, a portfolio of AMS Testbeds was identified to mitigate the risks posed by a single Testbed approach. At the conclusion of the AMS Testbed selection process, six (6) AMS Testbeds were selected to form a diversified portfolio to achieve rigorous DMA bundle and ATDM strategy evaluation. They are San Mateo (CA), Pasadena (CA), Dallas (TX), Phoenix (AZ), Chicago (IL) and San Diego (CA) Testbeds. While the project aims at evaluating both DMA applications and ATDM strategies, the primary purpose of this report is to document the evaluation done in terms of ATDM strategies using the AMS Testbeds. DMA evaluation is documented in a separate report. Primarily, Dallas and Phoenix were used as ATDM-centric Testbeds and were used to assess the ATDM strategies under various scenarios of combinations of strategies, prediction attributes and evaluation attributes to answer a set of research questions set forth by the USDOT.

1.1 Project Overview

The AMS Project consists of using six virtual simulation based testbeds to evaluate transformative mobility and environmental benefits of DMA applications and ATDM strategies. As a result, the team identified several research questions in these two programs that could be potentially be answered by the testbeds. The project consists of the several tasks and aims at documenting the efforts through a series of deliverables. Please note that these tasks roughly summarize the project and may not be in line with the actual project management plan due to additions of testbeds and simultaneous tasks. A list of all the publications from the AMS Project is provided in the Appendix I.

Table 1-1: AMS Project Deliverables at a Glance

No.	Milestone	Description	Deliverables
1.	Identification of Stakeholders	The team identified a number of stakeholders for different aspects to this project including DMA applications, ATDM strategies, state and local DOT personnel and road-weather experts.	Stakeholder List

2.	AMS Requirements	The team identified a set of requirements for the project based on the DMA-ATDM AMS Requirements, ATDM AMS Requirements and DMA Bundle System Requirements Documents.	Detailed AMS Requirements Document
3.	Testbed Selection	The team selected six priority testbeds which will, in combination, cover the different aspects of the AMS evaluation objective.	Testbed Selection Report
4.	Development of Analysis Plans	The team developed test-bed specific analysis plan which details each testbed's geographic, traffic and data characteristics, the cluster analysis and calibration procedure to down-select operational conditions, scenarios, applications and strategies to be tested as well as mapping of which research questions will be addressed by the testbed.	Testbed-specific Analysis Plans
5.	Development of Evaluation Plan	Evaluation plan summarizes the individual testbed's analysis plan from a DMA and ATDM standpoint. Specifically, it addresses how the overall evaluation will address the research questions and why hypotheses will be used.	AMS Project Evaluation Plan
6.	Calibration of Testbeds	Individual testbeds are calibrated for the operational conditions identified during the cluster analysis. The task also documents the cluster analysis procedure, calibration procedure and targets and a comparison on the target performance measures before and after calibration.	Testbed-specific Calibration Report
7.	Application/ Strategy Modeling	The team acquired DMA applications working with prototype developers and in some cases, even developed the applications based on the System Design Document. ATDM strategies were developed based on the priority functional features requested by stakeholders.	Testbed-specific Briefing
8.	DMA Evaluation	DMA Evaluation includes specific simulation-based quantitative research as well as qualitative research to answer the several research questions related to DMA applications and bundles across the different testbeds.	DMA Evaluation Report
9.	ATDM Evaluation	ATDM Evaluation includes specific simulation-based quantitative research as well as qualitative research to answer the several research questions related to ATDM strategies and bundles across the different testbeds.	ATDM Evaluation Report (this report)

10.	AMS Gaps, Challenges and Future Research	The team will develop a white paper documenting the gaps and challenges faced during the course of the project as well as some focus for future research.	White Paper
11	Chicago Evaluation	Chicago will have its own full evaluation report, owing to the fact that it was added as a modification to the project. However, this ATDM evaluation report will include excerpts from those reports to support full ATDM program objectives.	Chicago Evaluation Report
12	San Diego Evaluation	San Diego will have its own full evaluation report, owing to the fact that it was added as a modification to the project. However, this ATDM evaluation report will include excerpts from those reports to support full ATDM program objectives.	San Diego Evaluation Report

This report (#9 in the above table) is a part of the ATDM Evaluation task and summarizes the qualitative and quantitative evaluation done for the different ATDM strategies.

1.2 Report Overview

As far as the layout of the report is concerned, it is organized into numerous chapters in the following order:

1. Chapter 1 is the introduction chapter and describes the AMS project in brief and provides a narrative of the report overview.
2. Chapter 2, named ATDM Strategies Summary, describes the different ATDM strategies evaluated in the AMS project along with details on how they are modeled within the AMS eco-system so that combinations and special cases can be evaluated.
3. Chapter 3, named Testbeds and Research Hypotheses, specifically describe the testbeds and research questions that they answer, along with the different operational conditions and characteristics of these testbeds. In addition, this chapter also describes the key performance measures assessed in this report.
4. Chapter 4, named ATDM Modeling Approach, describes the modeling details regarding how each individual and combination strategy is modeled within each of the testbeds.
5. Chapters 5 through 8 describe the specific categories of research questions along with their assessment methodology and research findings. These are mapped towards the research hypothesis so that findings can be reported on the different research questions. The research questions are stated as defined by the USDOT and the analysis was assembled around them.
6. Chapter 9 provides an overall summary of the report along with results, answers to research questions and lesson learned in the analysis.

Chapter 2. ATDM Strategies Summary

This chapter summarizes the ATDM strategies that are evaluated in the AMS project. Specifically, six bundles of strategies are included in this evaluation of which some of the strategies are prototyped together. Table 2-1 shows a mapping of different ATDM strategies to the different testbeds.

Table 2-1: ATDM Strategies Implemented in Different Testbeds

Bundle	ATDM Strategies	Pasadena	Dallas	Phoenix	Chicago	San Diego
Active Traffic Management	Dynamic Shoulder Lanes	●	●		●	
	Dynamic Lane Use Control	●			●	●
	Dynamic Speed Limits	●			●	●
	Adaptive Ramp Metering	●	●	●		
	Dynamic Junction Control	●				
	Dynamic Merge Control					●
	Adaptive Traffic Signal Control	●	●	●	●	
Active Demand Management	Predictive Traveler Information		●	●	●	●
	Dynamic HOV/Managed Lanes					●
	Dynamic Routing	●	●	●	●	●
Active Parking Management	Dynamically Priced Parking		●			
Weather Related Strategies	Snow Emergency Parking				●	
	Preemption for Winter Maintenance				●	
	Snowplow Routing				●	
	Anti-Icing and Deicing Operations				●	

2.1 Active Traffic Management

Active Traffic Management (ATM) is the ability to dynamically manage recurrent and non-recurrent congestion based on prevailing and predicted traffic conditions[2]. Focusing on trip reliability, it maximizes the effectiveness and efficiency of the facility. It increases throughput and safety through the use of integrated systems with new technology, including the automation of dynamic deployment to optimize performance quickly and without delay that occurs when operators must deploy operational strategies manually. ATM approaches focus on influencing travel behavior with respect to lane/facility choices and operations. ATM strategies can be deployed singularly to address a specific need such as the utilizing

[2] FHWA Active Traffic Management Website at http://www.ops.fhwa.dot.gov/atdm/approaches/atm.htm

adaptive ramp metering to control traffic flow or can be combined to meet system-wide needs of congestion management, traveler information, and safety resulting in synergistic performance gains.

Some of the examples of Active Traffic Management strategies are listed below:

1. **Dynamic Shoulder Lanes:** This strategy enables the use of the shoulder as a travel lane(s), known as Hard Shoulder Running (HSR) or temporary shoulder use, based on congestion levels during peak periods and in response to incidents or other conditions as warranted during non-peak periods. In contrast to a static time-of-day schedule for using a shoulder lane, an ATDM approach continuously monitors conditions and uses real-time and anticipated congestion levels to determine the need for using a shoulder lane as a regular or special purpose travel lane (e.g., transit only).
2. **Dynamic Lane Use Control:** This strategy involves dynamically closing or opening of individual traffic lanes as warranted and providing advanced warning of the closure(s) (typically through dynamic lane control signs), in order to safely merge traffic into adjoining lanes. In an ATDM approach, as the network is continuously monitored, real-time incident and congestion data is used to control the lane use ahead of the lane closure(s) and dynamically manage the location to reduce rear-end and other secondary crashes.
3. **Dynamic Speed Limits[3]:** This strategy adjusts speed limits based on real-time traffic, roadway, and/or weather conditions. Dynamic speed limits can either be enforceable (regulatory) speed limits or recommended speed advisories, and they can be applied to an entire roadway segment or individual lanes. In an ATDM approach, real-time and anticipated traffic conditions are used to adjust the speed limits dynamically to meet an agency's goals/objectives for safety, mobility, or environmental impacts.
4. **Adaptive Ramp Metering[4]:** This strategy consists of deploying traffic signal(s) on ramps to dynamically control the rate vehicles enter a freeway facility. This, in essence, smoothens the flow of traffic onto the mainline, allowing efficient use of existing freeway capacity. Adaptive ramp metering utilizes traffic responsive or adaptive algorithms (as opposed to pre-timed or fixed time rates) that can optimize either local or system-wide conditions. Adaptive ramp metering can also utilize advanced metering technologies such as dynamic bottleneck identification, automated incident detection, and integration with adjacent arterial traffic signal operations. In an ATDM approach, real-time and anticipated traffic volumes on the freeway facility will be used to control the rate of vehicles entering the freeway facility. Based on the conditions, the ramp meter rates will be adjusted dynamically.
5. **Dynamic Junction Control:** This strategy consists of dynamically allocating lane access on mainline and ramp lanes in interchange areas where high traffic volumes are present and the relative demand on the mainline and ramps change throughout the day. For off-ramp locations, this may consist of assigning lanes dynamically either for through movements, shared through-exit movements, or exit-only. For on-ramp locations, this may involve a dynamic lane reduction on the mainline upstream of a high-volume entrance ramp, or might involve extended use of a shoulder lane as an acceleration lane for a two-lane entrance ramp which culminates in a lane drop. In an ATDM approach, the volumes on the mainline lanes and ramps are continuously monitored and lane access will be dynamically changed based on the real-time and anticipated conditions.
6. **Dynamic Merge Control:** This strategy (also known as dynamic late merge or dynamic early merge) consists of dynamically managing the entry of vehicles into merge areas with a series of advisory messages (e.g., displayed on a dynamic message sign [DMS] or lane control sign) approaching the merge point that prepare motorists for an upcoming merge and encouraging or directing a consistent merging behavior. Applied conditionally during congested (or near

[3] FHWA Variable Speed Limit website at http://safety.fhwa.dot.gov/speedmgt/vslimits/
[4] FHWA Ramp Metering website at http://www.ops.fhwa.dot.gov/freewaymgmt/ramp_metering/index.htm

congested) conditions, dynamic merge control can help create or maintain safe merging gaps and reduce shockwaves upstream of merge points. In an ATDM approach, conditions on the mainline lanes and ramps approaching merge areas are continuously monitored and the dynamic merge system will be activated dynamically based on real-time and anticipated congestion conditions.

7. **Adaptive Traffic Signal Control[5]:** This strategy continuously monitors arterial traffic conditions and the queuing at intersections and dynamically adjusts the signal timing to optimize one or more operational objectives (such as minimize overall delays). Adaptive Traffic Signal Control approaches typically monitor traffic flows upstream of signalized locations or segments with traffic signals, anticipating volumes and flow rates in advance of reaching the first signal, then continuously adjusting timing parameters (e.g., phase length, offset, cycle length) during each cycle to optimize operational objectives.

2.2 Active Demand Management

Active Demand Management (ADM) uses information and technology to dynamically manage demand, which could include redistributing travel to less congested times of day or routes, or reducing overall vehicle trips by influencing a mode choice[6]. ADM seeks to influence more fluid, daily travel choices to support more traditional, regular mode choice changes. ADM is very supportive of other active measures by redistributing or reducing overall traffic levels during congested conditions, thus becoming an integral part of an overall management philosophy to actively manage a facility or system.

1. **Predictive Traveler Information:** This strategy involves using a combination of real-time and historical transportation data to predict upcoming travel conditions and convey that information to traveler's pre-trip and en-route (such as in advance of strategic route choice locations) in an effort to influence travel behavior. In an ATDM approach, predictive traveler information is incorporated into a variety of traveler information mechanisms (e.g., multi-modal trip planning systems, 511 systems, dynamic message signs) to allow travelers to make better informed choices.
2. **Dynamic HOV/Managed Lanes[7]:** This strategy involves dynamically changing the qualifications for driving in a high-occupancy vehicle (HOV) lane(s). HOV lanes (also known as carpool lanes or diamond lanes) are restricted traffic lanes reserved at peak travel times or longer for exclusive use of vehicles with a driver and one or more passengers, including carpools, vanpools and transit buses. The normal minimum occupancy level is 2 or 3 occupants. Many agencies exempt other vehicles, including motorcycles, charter buses, emergency and law enforcement vehicles, low emission vehicles, and/or single-occupancy vehicles paying a toll. In an ATDM approach, the HOV lane qualifications are dynamically changed based on real-time or anticipated conditions on both the HOV and general purpose lanes. Qualifications that can potentially be dynamically adjusted include the number of occupants (e.g., from 2 to 3 occupants), the hours of operation, and the exemptions (e.g., change from typical HOV operation to buses only). Alternatively, the HOV restrictions could be dynamically removed allowing general use of the previously managed lane.
3. **Dynamic Routing:** This strategy uses variable destination messaging to disseminate information to make better use of roadway capacity by directing motorists to less congested facilities. These messages could be posted on dynamic message signs in advance of major routing decisions. In an ATDM approach, real-time and anticipated conditions can be used to provide route guidance and distribute the traffic spatially to improve overall system performance.

[5] FHWA EDC-1 Adaptive Traffic Signal Control website at https://www.fhwa.dot.gov/innovation/everydaycounts/edc-1/asct.cfm
[6] FHWA Active Demand Management website at http://www.ops.fhwa.dot.gov/atdm/approaches/adm.htm
[7] http://ops.fhwa.dot.gov/freewaymgmt/hov.htm

2.3 Active Parking Management

Active Parking Management (APM) is the dynamic management of parking facilities in a region to optimize performance and utilization of those facilities while influencing travel behavior at various stages along the trip making process: i.e., from origin to destination[8]. Dynamically managing parking can affect travel demand by influencing trip timing choices, mode choice, as well as parking facility choice at the end of the trip. This ATDM approach can also have a positive impact on localized traffic flow by providing real-time parking information to users and ensuring the availability of spaces to reduce circling around parking facilities. The overall goal is to help maximize the nation's transportation infrastructure investments, reduce congestion, and improve safety.

1. **Dynamically Priced Parking[9]:** This strategy involves parking fees that are dynamically varied based on demand and availability to influence trip timing choice and parking facility or location choice in an effort to more efficiently balance parking supply and demand, reduce the negative impacts of travelers searching for parking, or to reduce traffic impacts associated with peak period trip making. In an ATDM approach, the parking availability is continuously monitored and parking pricing is used as a means to influence travel and parking choices and dynamically manage the traffic demand

[8] FHWA Active Parking Management website at http://www.ops.fhwa.dot.gov/atdm/approaches/apm.htm
[9] http://www.ops.fhwa.dot.gov/congestionpricing/strategies/not_involving_tolls/parking_pricing.htm

Chapter 3. Testbeds and Research Hypotheses

This chapter summarizes the five testbeds that are used for evaluating ATDM strategies – (a) Dallas Testbed, (b) Phoenix Testbed, (c) Pasadena Testbed, (d) Chicago Testbed and (e) San Diego Testbed. In addition, it highlights the different operational conditions that will be used for the evaluation as well as the key research questions that would be answered by this project.

3.1 Evaluation Testbeds

The AMS Testbed project spans over six testbeds, namely – San Mateo, Phoenix, Dallas, Pasadena, Chicago and San Diego. Since San Mateo testbed was exclusive to DMA applications and was not used for evaluating ATDM concepts, it has been excluded from this report. Given below is a description of the five testbeds used for ATDM evaluation.

3.1.1 Dallas Testbed

The US-75 Corridor in Dallas, Texas is used as one of the AMS Testbeds. As illustrated in Figure 3-1, the US-75 Corridor is a major north-south radial corridor connecting downtown Dallas with many of the suburbs and cities north of Dallas. It contains a primary freeway, an HOV facility in the northern section, continuous frontage roads, a light-rail line, park-and-ride lots, major regional arterial streets, and significant intelligent transportation system (ITS) infrastructure. The length of the corridor is about 21 miles and its width is in the range of 4 miles. The corridor is equipped with 13 Dynamic Message Signs (DMSs) and numerous cameras that cover all critical sections of the US-75 freeway.

The US-75 corridor is a multimodal corridor where travelers can use the following mode options: a) private car; b) transit; c) park-and-ride; and d) carpooling. Transit and park-and-ride travelers are estimated to represent less than 2% of the traveler population. The freeway consists of four lanes per direction for most of its sections with the exception of the section at the interchange with I-635 freeway which consists of three lanes only. This lane reduction creates a major bottleneck during the morning and afternoon peak periods.

Traffic incidents are also frequently observed nearby this bottleneck. Freeway incidents occur at an average frequency of about two incidents per day; resulting in severe congestion especially during the peak periods. In general, the travel time for about 50% of the peak periods is greater than the average travel time recorded during the peak period for the US-75 freeway. This pattern is observed for the northbound and southbound directions. Congestion related to adverse weather conditions has also been observed along the corridor. While such conditions are not frequently encountered, their impact on the overall operational performance of the corridor is significant as drivers are generally not used to driving in such conditions. Based on data collected in 2013, the highest level of congestion is observed along the NB direction in the afternoon peak period with an average speed of about 25 miles per hour. In the morning peak period, congestion is typically observed along the SB direction with an average speed of about 32 miles per hour. The measured daily Vehicle-Mile Traveled (VMT) varies by no more than ±10% from the average value of all days observed. Another important observation is that the morning peak period is generally subjected to more variability in the demand level than the afternoon peak period. The VMT ratio - which is defined as the ratio between the VMT recorded for a peak period and the average VMT for all peak periods in the analysis horizon - ranges from 0.2 to 1.4 in the morning peak period, and it ranges from 0.3 to 1.2 in the afternoon peak periods.

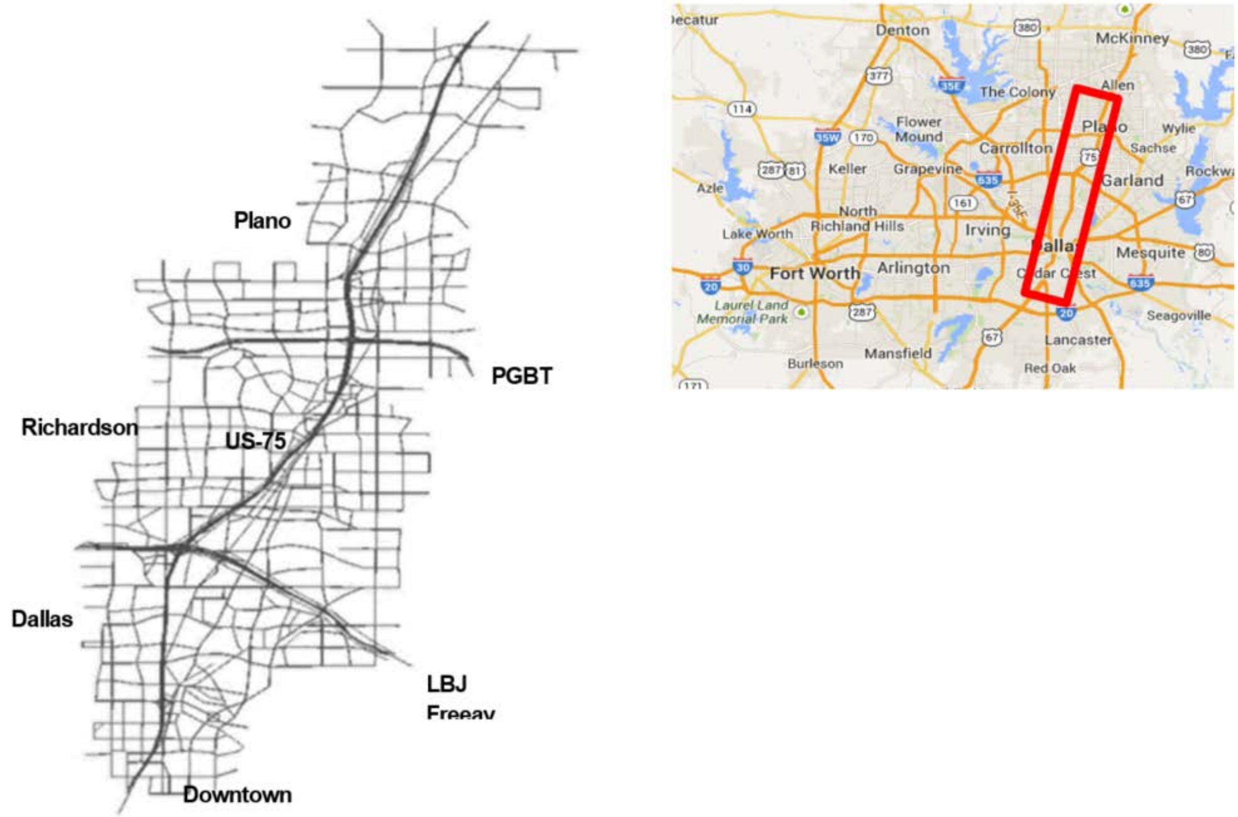


Figure 3-1: The Dallas Testbed Showing US-75 Freeway [Source: SMU]

Several operation management strategies have been developed for the US-75 corridor as part of the ongoing ICM (Integrated Corridor Management) project[10]. These strategies focus primarily on a) providing real-time multimodal traveler information that allows travelers to better plan their trips using a newly-developed regional 511 systems; and b) implementing efficient ATDM response plans to mitigate non-recurrent congestion. These response plans are designed such that they alert travelers of any downstream congestion and provide route diversion instructions using DMSs along the freeway, while increasing the capacity of the diversion routes through modifying the timing plans at signalized intersections along these routes. Depending on the severity of the incident, the traffic could be diverted to the frontage roads only or to the frontage roads and other parallel arterials. In the case of severe incidents (e.g., full closure of the freeway), drivers could be guided to use the light rail system, if parking capacity at the stations permits. A rule-based decision support system is developed to map the observed operational conditions associated with the incident to the most suitable response plan. The real-time simulation-based prediction subsystem, DIRECT, is used to quantify the potential benefits associated with deploying a response plan as recommended by the decision support system.

[10] http://www.its.dot.gov/icms/docs/icm_demo_sites.pdf

Evaluation Baseline and Operational Conditions

For the purposes of conducting the analysis for this study, the Dallas Testbed leads identified up to four operational conditions or baselines. Table 3-1 provides a summary of the main four operational conditions obtained based on the cluster analysis. The table gives the number of peak periods and the average value for each variable used in the analysis and gives the date for the representative day used to model each cluster. As shown in the table, the descriptive variables used to construct these cluster includes: a) the vehicle miles traveled (VMT); b) incident severity described in terms of total lane closure-minutes (i.e., number of closed lanes multiplied by their closure period); c) the freeway travel time; and d) level of precipitation. Comparing the vehicle miles traveled (VMT) level of these four conditions with the average VMT value, they were named in terms of Demand, Incident and Weather conditions. No precipitation is recorded for these operational conditions (except one condition with average precipitation of 1.0 mm) suggesting that they represent dry operational conditions. Based on this analysis, the following four operational scenarios are proposed to represent the main operational conditions in the evening peak period.

- MD-LI: Medium-High Demand + Minor Severity Incident + Dry Conditions
- HD-LI: High Demand + Minor Incident + Dry Conditions
- HD-MI: High Demand + Medium Severity Incident + Dry Conditions
- MD-HI: Medium-High Demand + High Severity Incident + Dry Conditions

Table 3-1: Dallas Operational Conditions

Descriptive Label	***MD-LI***	***HD-LI***	***HD-MI***	***MD-HI***
Representative Day	08/31/2013	07/26/2013	10/22/2013	11/13/2013
Operational Condition	Medium-High Demand + Minor Incident	High Demand + Minor Incident	High Demand + Medium Severity Incident	Medium to High Demand + High Severity Incident
VMT	324,504	362,694	349,158	332,891
Weather Condition	Dry	Dry	Dry	Dry
Incident Severity (min.)	12.6	10.2	32.2	141.6
Travel Time (min.)	23	32	40	45

Figure 3-2 provides a summary of the incidents reported for the representative peak period representing each cluster. The figure illustrates the location of each incident along the US-75 freeway. In addition, the start time, duration and number of closed lanes of each incident are provided. To further illustrate the different between these operational conditions, the average time-varying travel time for the US 75 Freeway in the NB direction is obtained for each representative day. The time-varying travel time pattern for these four operational conditions is shown in Figure 3-3. As shown in this Figure, all four OCs are shown to have distinct time-varying travel time implying that they represent distinct operational conditions.

An intensive calibration effort was performed to ensure that the model was realistically able to replicate the traffic pattern of each representative peak period. Thus, the model is calibrated to represent four different baseline scenarios. Dallas Testbed is simulated under each baseline scenario without adopting any ATDM strategies representing the baseline scenarios. The simulation is performed for the peak period (3:00 pm to 7:00 pm) with a one-hour warm-up period with 50% of the demand of the first hour. The simulation horizon is extended one hour after the end of the peak period to allow the network to clear up the demand loaded during the peak period.

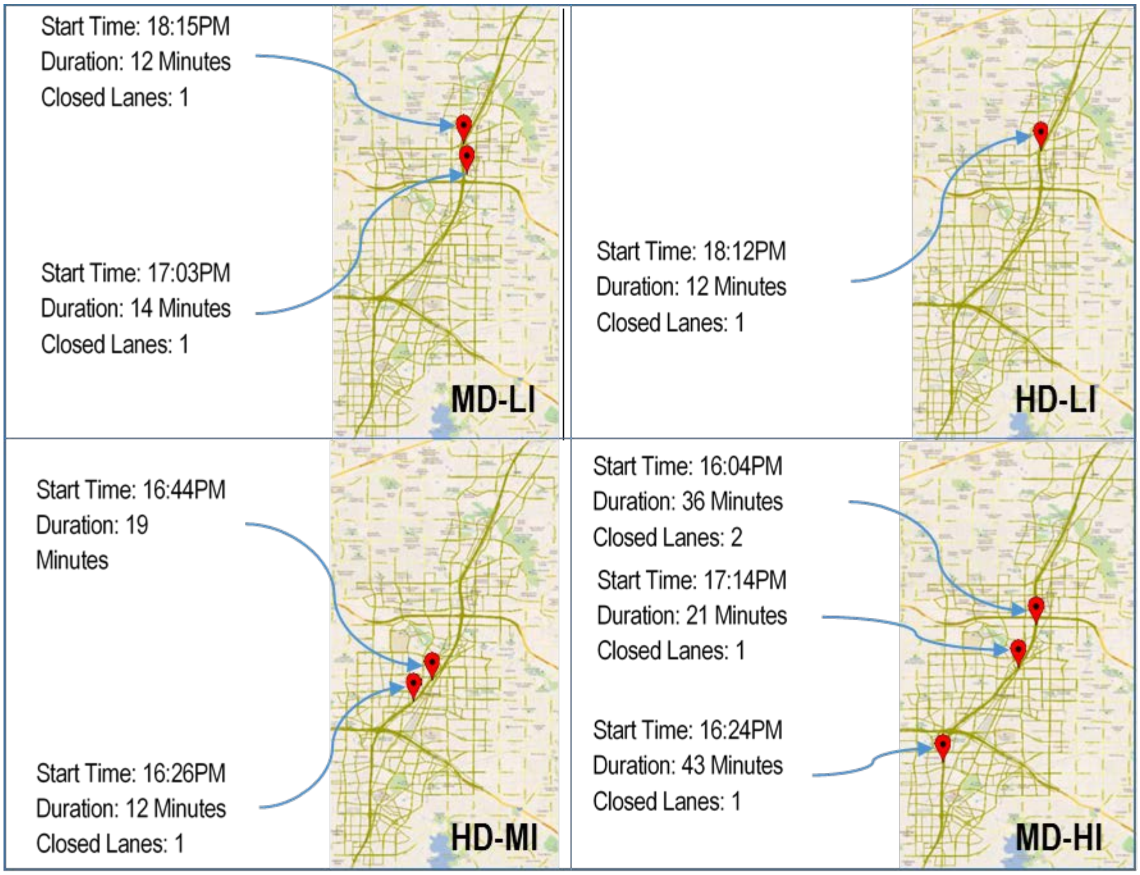


Figure 3-2: Incident Locations for Different Operational Conditions [Source: SMU]

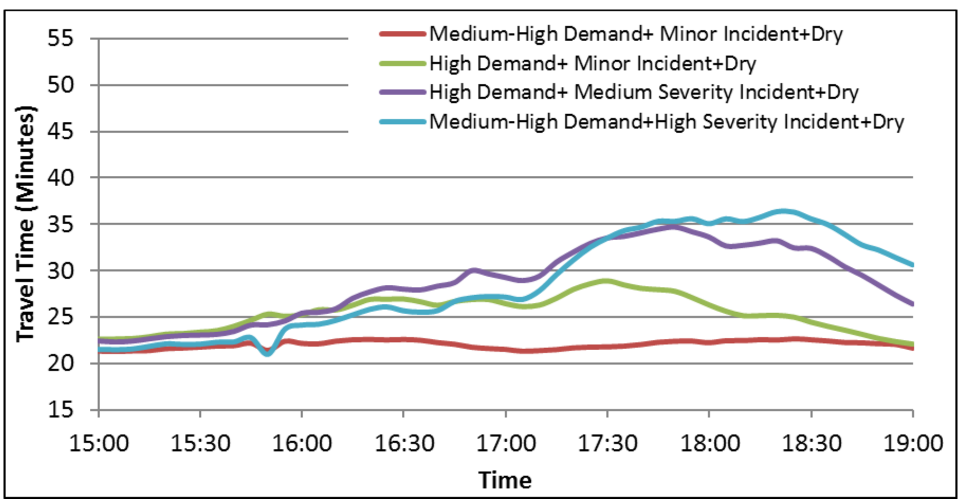


Figure 3-3: Time-Varying Travel Time for the Main Four Operational Conditions Obtained for the PM Peak Period [Source: SMU]

In addition to the four operational conditions representing dry conditions, the project team also developed two hypothetical operational conditions: (1) Adverse Weather and (2) Evacuation Conditions. These two conditions are explained in Sections 7.2.2 and 7.2.3 of this report, respectively. In addition, the team also modeled a typical AM peak operational condition to support evaluation of Dynamically Priced Parking strategy.

3.1.2 Phoenix Testbed

The Phoenix Testbed covers the entire Maricopa Association of Governments (MAG) which is home to more than 1.5 million households and 4.2 million inhabitants. This multi-resolution simulation model takes multiple modes into account such as single/high occupancy vehicles, transit buses and light-rail and freight vehicles. The region covers an area of 9,200 square miles and is characterized by a low density development pattern with population density of 253 people per square mile. The region has one city with more than 1 million people (Phoenix) and eight cities/towns with more than 100,000 people each. The region has experienced dramatic population growth in the past two decades, with the pace of growth slowing rather significantly in 2008-2012 period in the wake of the economic downturn. The region is home to the nation's largest university (Arizona State University with more than 73,000 students), several special events centers and sports arenas, recreational opportunities, a 20-mile light rail line, and a large seasonal resident population. The focus of the Testbed is Tempe area which covers an area of 40 square miles. This testbed considers PM peak traffic between 3PM and 7PM and Figure 3-4 shows the geographic overlay map of the Testbed along with the traffic analysis zones in DTALite (Dynamic Traffic Assignment Tool).

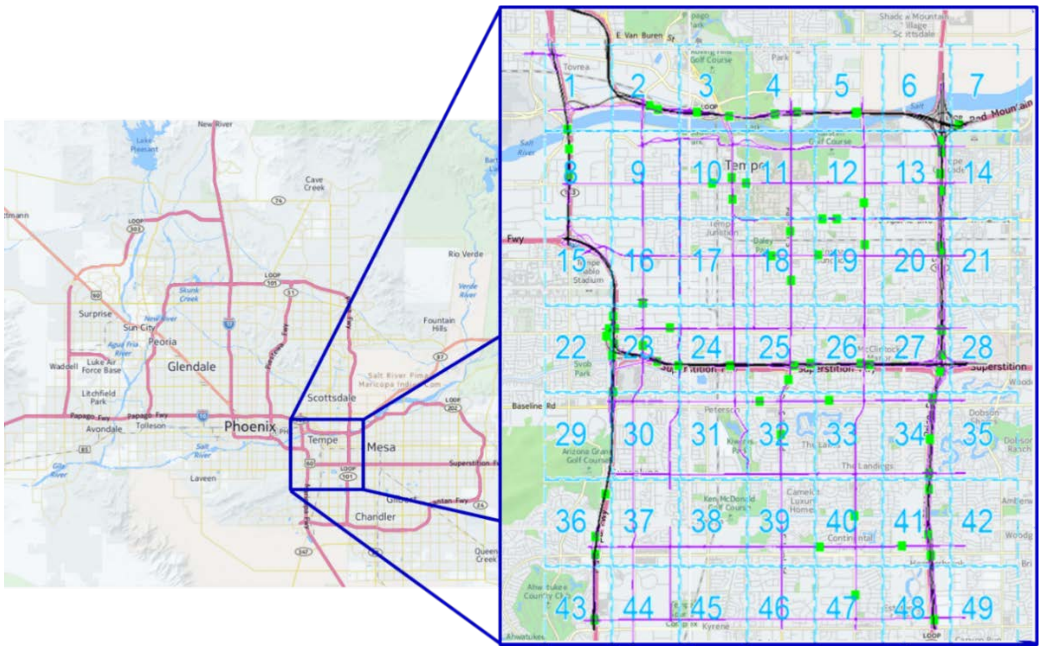


Figure 3-4: Phoenix Testbed [Source: Booz Allen]

Evaluation Baseline and Operational Conditions

For the Phoenix Testbed as well, baseline scenarios are defined over four different operational conditions on to represent the whole spectrum of traffic conditions for the evaluation of ATDM strategies. Each operational condition (cluster) represents a bin of multiple days in the analysis year and one representative day was selected for each cluster that is closest to the cluster centroid. The four different scenarios are defined over the PM peak hours of 3:00 PM - 7:00 PM as is shown in Table 3-2. The clusters are named based on the representative values of traffic demand, travel speeds, incident severity and weather conditions. The traffic demand is represented by the average hourly volume in the network. The travel-speed is represented by the average speed of vehicles on the freeways in miles per hour and incident severity is represented by the product of number of incidents and the number of lane closures resulted from it. For example, cluster 1 consists of higher traffic volumes, higher vehicle speeds and low number of incidents and is therefore abbreviated as HD-LI (for High Demand and Low Incident Severity). The location of incidents is of extreme importance in modeling and is computed using the data patterns (loop-detector data) from freeways. Clusters 1 through 3 represent dry weather conditions, while Cluster 4 is associated with wet pavement (or rain at 0.01 in/hour).

Table 3-2: Phoenix Operational Conditions

Descriptive Label	HD-LI	HD-HI	LD-LI	HD-MI-WW
Representative Day	7/17/2014	5/21/2014	6/29/1014	11/22/2013
Operational Condition	High Traffic + High Speed + Low Incidents	High Traffic + High Speed + High Incidents	Low Traffic + High Speed + Low Incidents	High Traffic + Low Speed + Medium Incidents + Wet
Avg. Volume (veh/hr)	8383	8782	6004	7708
Avg. Speed (mph)	65	65.4	65.4	38.4
Weather Condition	Dry	Dry	Dry	Rainy (0.01 in/hour)
Incident Severity[11]	9	22	3	23

The four representative days are chosen according to the Euclidean distances of samples away from the centroid values with each clusters. Only the PM attributes were used to calculate the Euclidean distances. For further details on the clusters and operational conditions, please refer to the Testbed-specific Calibration Report. Figure 3-5 shows a comparison of the baseline travel-time across the network for different operational conditions between 3:00 PM and 7:00 PM averaged at 15-minutes interval.

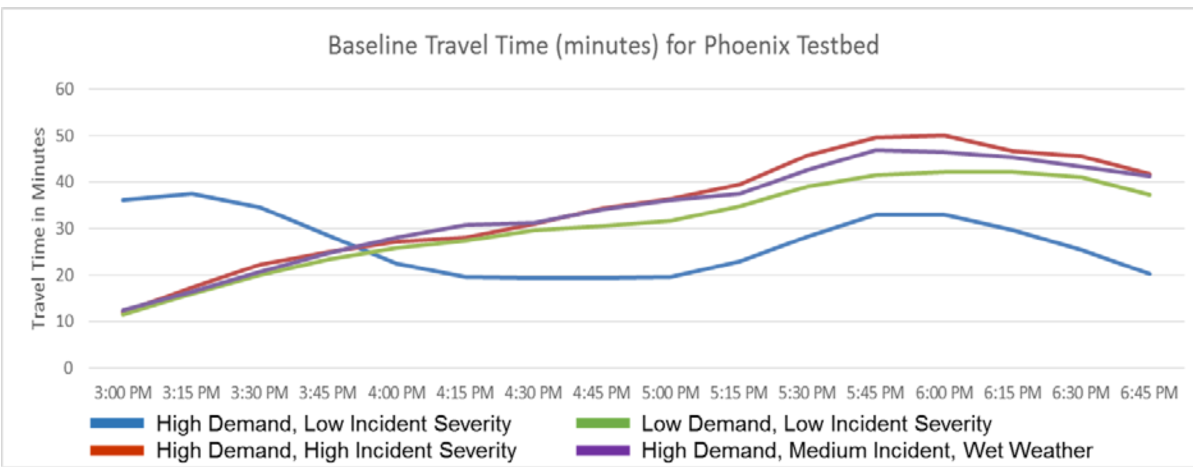


Figure 3-5: Comparison of Baseline Travel Time for Different Operational Conditions [Source: BAH]

3.1.3 Pasadena Testbed

The Pasadena Testbed models the roadway network of the City of Pasadena in Los Angeles County, California. This testbed network was derived from the regional travel model shown in Figure 3-6 that had been developed under US DOT contract DTFH6111C00038, which is publicly accessible through the Research Data Exchange portal (https://www.its-rde.net/). Primarily covering the City of Pasadena, the network also includes unincorporated area of Altadena to the north, part of the Cities of Arcadia to the east, Alhambra to the south and Glendale and Northeast Los Angles to the west. The total area is 44.36 square miles.

[11] This is calculated by the number of lanes closed during each incident, or as a product of number of incidents and number of lanes closed.

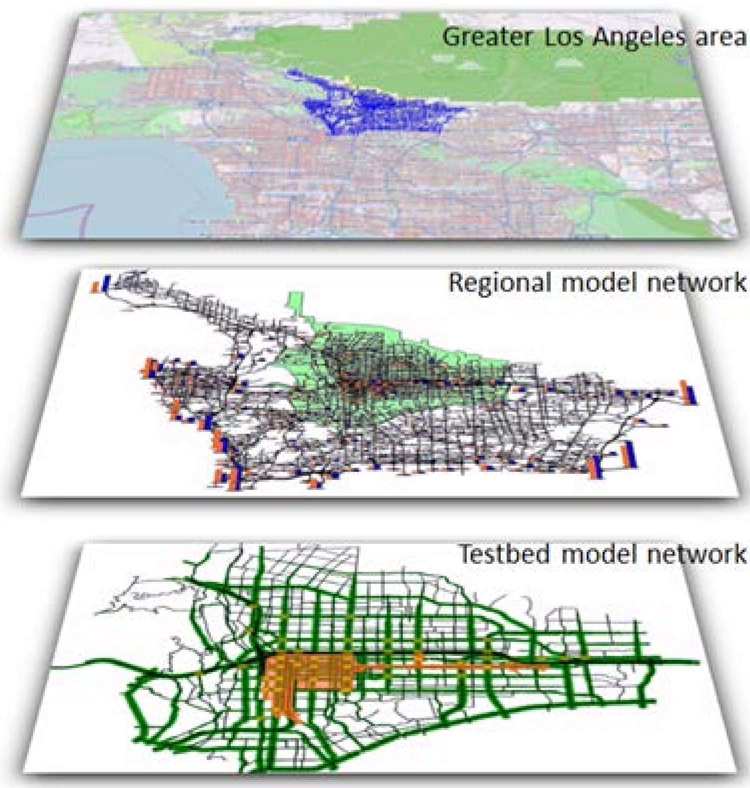


Figure 3-6: Pasadena Testbed Network Derived from past USDOT Project in the Greater Los Angeles Area [Source: HBA]

The modes of transportation included in the Pasadena testbed includes single occupancy vehicle (SOV), high occupancy vehicles (HOV), and heavy vehicles. Field ITS infrastructure includes:

- Traffic detection: extensive freeway vehicle detection stations (VDS) known as Freeway Performance Measurement System (PeMS)
- Freeway on-ramp and freeway to freeway connector meters
- Variable message signs (VMS)
- CCTV cameras
- 31 ramp meter locations

The final network derived from the regional travel model is a VISSIM microscopic simulation network used to quantify and compare the potential benefits associated with each strategy. A separate TRANSIMS mesoscopic simulation network of the same geographic boundary constraint was developed to assess the impacts of each tested strategy plans and recommend the best plan for implementation.

Evaluation Baseline and Operational Condition

The Pasadena Testbed team identified three operational conditions based on the cluster analysis. Table 3-3 provides a summary of the operational conditions selected from the cluster analysis and Figure 3-7 shows the representative days for each of the operational condition.

- OC 1: High demand, low to medium incident frequency/severity, medium corridor travel times
- OC 2: Medium to high demand, high incident frequency/severity, medium or low corridor travel times

- OC 3: High demand, medium incident frequency/severity, high corridor travel times

Table 3-3: Pasadena Operational Conditions

Description Label	Operational Condition 1	Operational Condition 2	Operational Condition 3
Representative Day	12/18/2013	01/06/2014	11/14/2013
Operational Condition	High Demand + Low to Medium Incident	Medium to High Demand + High Incident	High Demand + Medium Incident
VMT	934,711	953,332	953,332
Incident Frequency (Incident / Day)	2.26	2.80	2.56
Weather Condition	Dry	Dry	Dry
Network Travel Time (Vehicle Seconds)	2,639,326	2,308,780	2,723,258

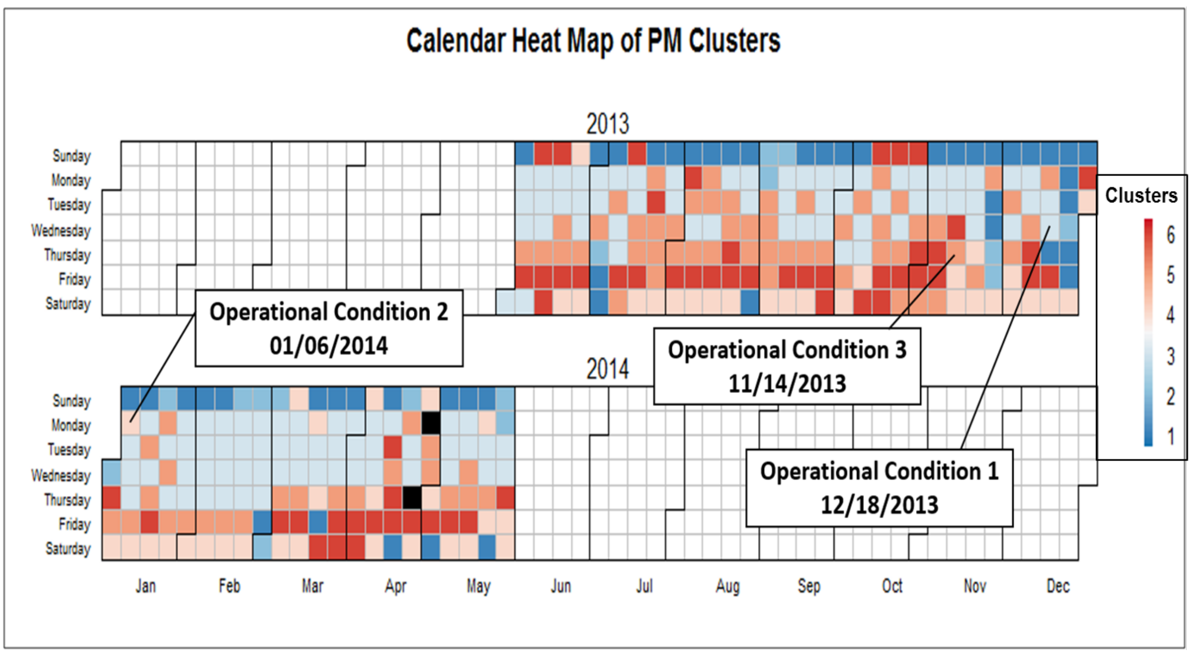


Figure 3-7: Pasadena Operational Conditions Representative Days [Source: HBA]

Intensive calibration efforts were performed for both the VISSIM microscopic and TRANSIMS mesoscopic simulation model to ensure that the models were able replicate the traffic pattern of each representative operational conditions. Thus, the model is calibrated to represent three different baseline scenarios. The simulation was performed for the PM peak period (3:00 pm to 7:00 pm). Figure 3-8 shows a comparison of each baseline operational condition for network travel time.

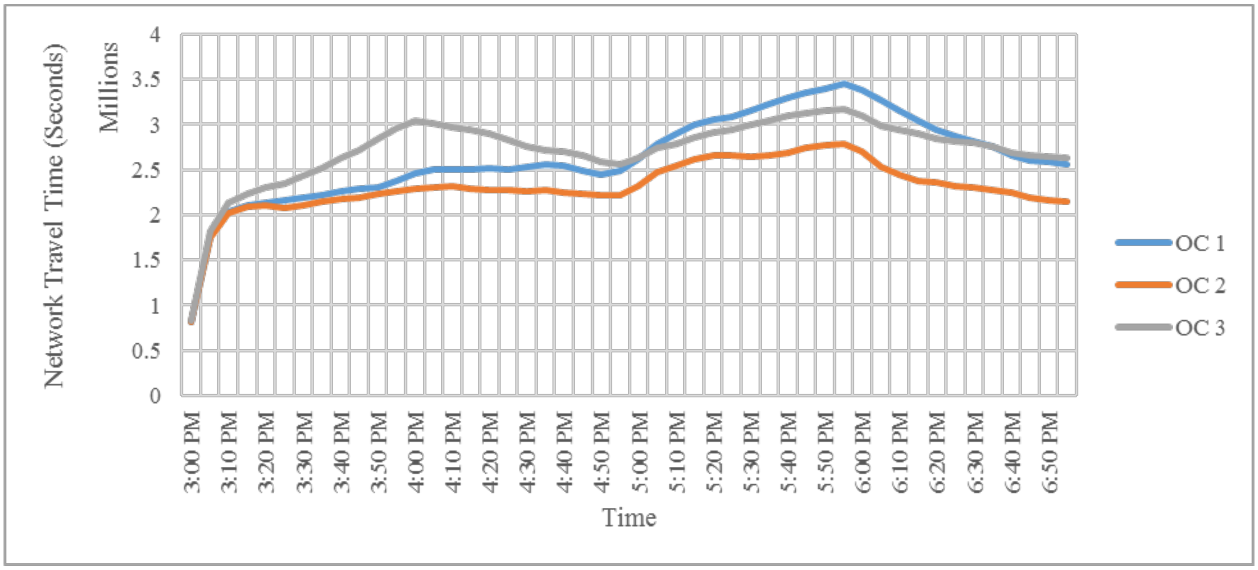


Figure 3-8: Comparison of Baseline Travel Time for Different Operational Conditions [Source: Booz Allen]

3.1.4 Chicago Testbed

The Chicago Testbed network includes Chicago downtown area located in the central part of the network, Kennedy Expressway of I-90, Edens Expressway of I-94, Dwight D. Eisenhower Expressway of I-290, and Lakeshore Drive. The Testbed network is bounded on east by Michigan Lake and on west by Cicero Avenue and Harlem Avenue. Roosevelt Road and Lake Avenue bound the Testbed network from south and north, respectively. This network was extracted from the entire Chicago Metropolitan Area Network to enhance the estimation and prediction performance during the implementation procedure Figure 3-9.

Figure 3-9. Extend of the Chicago Network [Source: NWU]

The testbed, modeled in DYNASMART, a (meso) simulation-based intelligent transportation network planning tool, consist of over 4800 links and 1500 nodes, with over 500 signalized intersections, nearly 250 metered and non-metered ramps. The network demand is coded for 24 hours at 5-minute intervals with over a million vehicles simulated.

Evaluation Baseline and Operational Conditions

The Chicago Testbed simulated six operational conditions including a hypothetical operational condition. Unlike other testbeds, the Chicago consisted of weather-specific events on most of the selected operational conditions as moderate to heavy rain or snow. The hypothetical incident events were determined per historical car crash records. Four hypothetical incident events were selected that are located around the center of these areas, two are on the interstate highway (5 AM and 6 AM) and the rest are on arterial roads (8 AM and 4 PM). The details on these operational conditions are shown in Table 3-4.

For details on the operational conditions, readers are encouraged to refer the AMS Chicago Evaluation Report (FHWA-JPO-16-)

Table 3-4: Chicago Testbed Operational Conditions

Description Label	OC1	OC2	OC3	OC4	OC5	HO1
Representative Day	4/22/2009	2/18/2009	12/22/2009	12/19/2009	1/9/2009	N/A
Operational Condition	High AM High PM Demand, No Incidents	High AM, High PM Demand, No Incidents, Moderate Rain AM, Moderate Rain to Snow	Medium AM, High PM Demand, No Incidents, Moderate Snow	Low AM Medium PM Demand, No Incidents, Moderate Snow	Medium AM High PM Demand, No Incidents, Moderate to Heavy Snow	Medium AM to High PM Demand, AM Incidents, Moderate Snow
Number of Vehicles	1,191,575	1,065,901	986,978	902,225	1,076,431	986,978
Average Travel Time (Minutes)	16.26	16.53	18.63	14.09	19.71	20.34

Figure 3-10 shows the comparison of different operational conditions as a time-dependent function of demand for the 24 hours for each of the selected representative days. As shown the selected representative days demonstrate great variability in their 24-hour demand patterns.

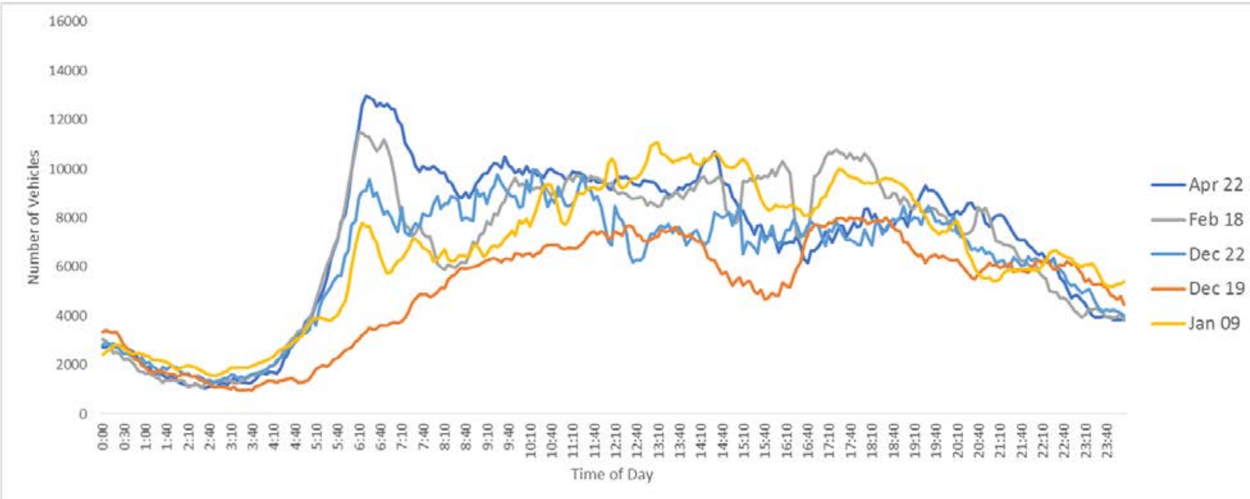


Figure 3-10. Comparison of the Operational Conditions of Chicago Testbed as a Function of Demand [Source: NWU]

3.1.5 San Diego Testbed

The San Diego Testbed facility comprises of a 22-mile stretch of interstate I-15 and associated parallel arterials and extends from the interchange with SR 78 in the north to the interchange with SR-163 in the south as shown in Figure 3-11.

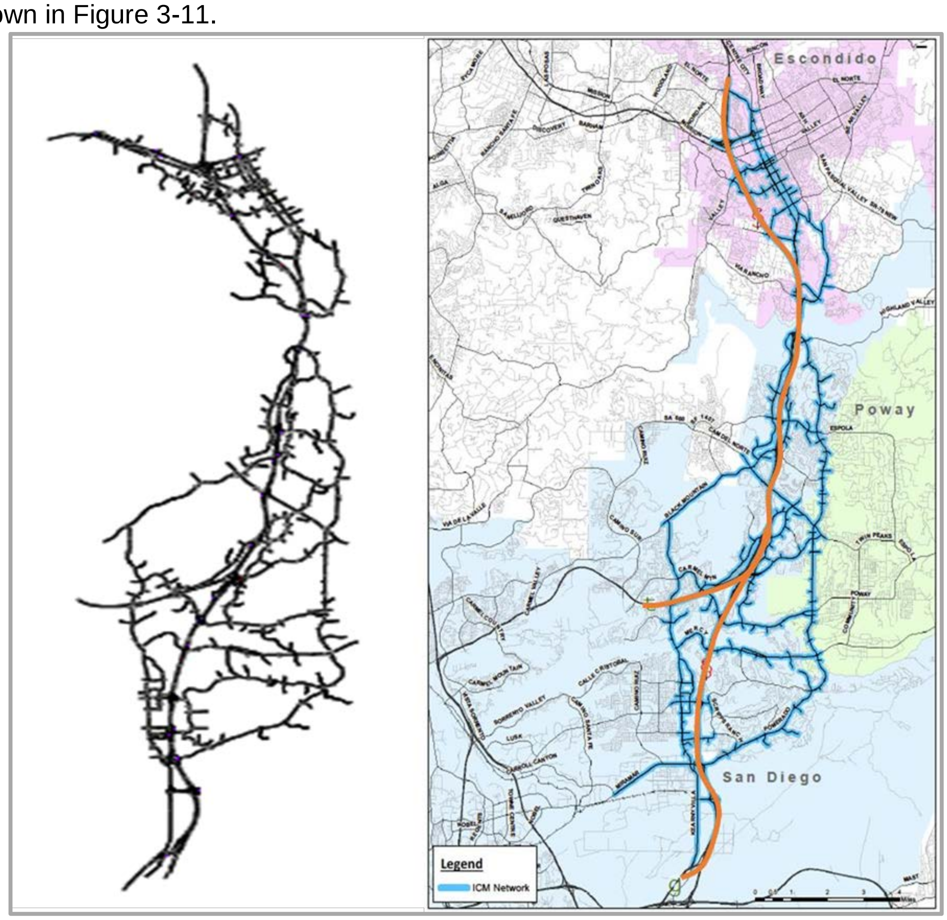


Figure 3-11: Map of the Extracted Network of San Diego [Source: TSS]

The current I-15 corridor operates with both general-purpose (GP) lanes and four express lanes from the Beethoven Drive DAR to the southern extent of the model. These lanes currently run with two northbound lanes and two southbound lanes and are free to vehicles travelling with two or more passengers in the car (High-Occupancy Vehicles, or HOVs); they also allow Single Occupancy Vehicles (SOV) to use the lanes for a fee, using a variable toll price scheme making them High Occupancy Tolled (HOT) lanes. In addition, it is possible to change the lane configuration of the express lanes with the use of barrier transfer (zipper) vehicles and the Reversible Lane Changing System (RLCS).

The entry to the GP lanes is managed during the morning and evening peak hours throughout the corridor by the Ramp Metering Information System (RMIS) that has localized ramp meters running the San Diego Ramp Metering System (SDRMS) algorithm. Along the arterials there are two corridors, which are running a Traffic Light Synchronization Program (TLSP) that allows for the use of a more responsive coordinated directional approach to manage the traffic in the peak directions. The TLSP corridors use an algorithm to step through the available timing plans to apply the appropriate plan for the corridor to handle the level of flow.

Evaluation Baseline and Operational Conditions

Four operational conditions were identified from the results of a cluster analysis that was performed as part of the ICM Demonstration Evaluation project. The detailed approach of the cluster analysis and the selection of operational conditions are presented in the “San Diego Testbed Analysis Plan” document (FHWA-JPO-16-375)[12]. The analysis was primarily focused on analyzing incidents within the corridor occurring during the AM peak hours (from 5 AM to 10 AM) or the PM peak hours (from 2 PM to 7 PM) where the ICM system developed and deployed a response plan. As the I-15 corridor is a North/South corridor serving daily commuters to and from downtown San Diego, the analysis focused on the AM Southbound and the PM Northbound datasets. Table 3-5 provides a description of these clusters and Figure 3-12 shows the time-based distribution of travel demand for the different clusters used. In the figure, the x-axis represents 6AM to 10AM for AM clusters at 15-minute intervals and 4PM to 8PM for PM clusters.

Table 3-5: Selected Operational Scenarios for the San Diego Testbed

	AM1	AM2	PM3	PM4
Representative day	05/27/15	02/09/15	06/30/15	07/07/14
Operational Condition	Southbound (AM) +Medium Demand + Medium Incident	Southbound (AM) +Medium Demand + High Incident	Northbound (PM) +Medium Demand + High Incident	Northbound (PM) +Medium Demand + Medium Incident
VPH	6201	6348	9034	8870
Total Cluster Delay (min)	49.88	108.03	99.72	63.25
Number of Incidents/Period	1.9	3.7	5.5	2.1

[12] https://ntl.bts.gov/lib/61000/61100/61113/FHWA-JPO-16-375.pdf

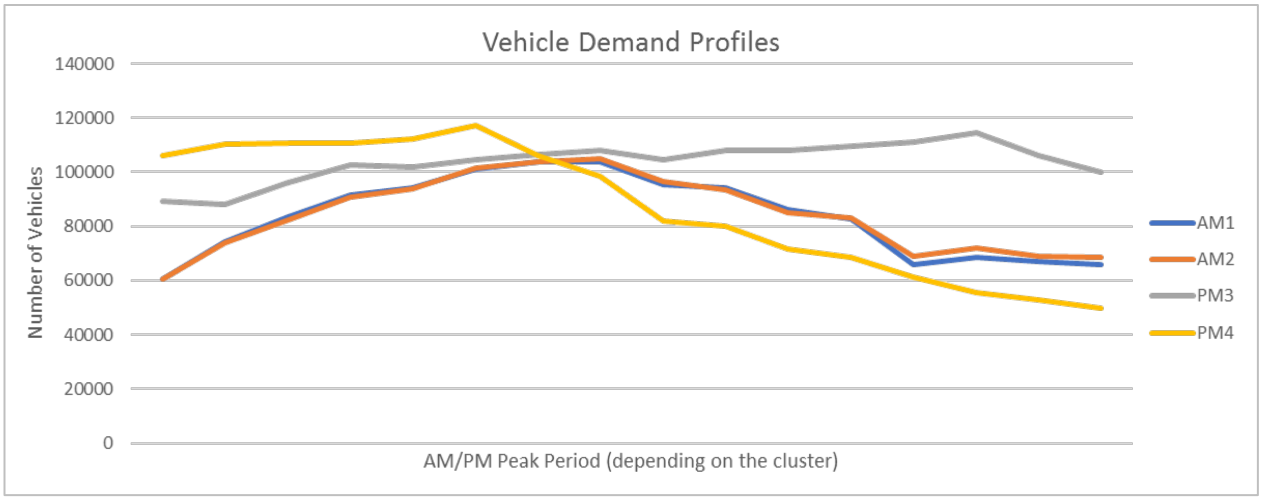


Figure 3-12. Time-based Distribution of Demand for AM and PM clusters [Source: Booz Allen]

3.2 ATDM Research Questions

This section summarizes ATDM research questions and their mapping to the Testbeds that were used to test each of those. The research questions are broadly divided into 7 categories and the major findings for each of these categories are given in later chapters. As shown in Table 3-6, a majority of research questions are answered by at least one of the testbeds.

Table 3-6: ATDM Research Questions Mapped to the Testbeds

ID	ATDM Research Question	Pasadena	Dallas	Phoenix	Chicago	San Diego
	Synergies and Conflicts					
1	Are ATDM strategies more beneficial when implemented in isolation or in combination (e.g., combinations of ATM, ADM, or APM strategies)?	●	●	●	●	●
2	Which ATDM strategy or combinations of strategies yield the most benefits for specific operational conditions?	●	●		●	●
3	What ATDM strategies or combinations of strategies conflict with each other?	●	●		●	●
	Prediction Accuracy					
4	Which ATDM strategy or combination of strategies will benefit the most through increased prediction accuracy and under what operational conditions?	●		●	●	●

ID	ATDM Research Question	Pasadena	Dallas	Phoenix	Chicago	San Diego
5	Are all forms of prediction equally valuable, i.e., which attributes of prediction quality are critical (e.g., length of prediction horizon, prediction accuracy, prediction speed, and geographic area covered by prediction) for each ATDM strategy?	●	●	●	●	●
	Active Management or Latency					
6	Are the investments made to enable more active control cost-effective?	●			●	
7	Which ATDM strategy or combinations of strategies will be most benefited through reduced latency and under what operational conditions?	●		●	●	●
	Operational Conditions, Modes and Facility Types					
8	Which ATDM strategy or combinations of strategies will be most beneficial for certain modes and under what operational conditions?	●	●		●	●
9	Which ATDM strategy or combinations of strategies will be most beneficial for certain facility types (freeway, transit, arterial) and under what operational conditions?	●	●		●	●
10	Which ATDM strategy or combinations of strategies will have the most benefits for individual facilities versus system-wide deployment versus region-wide deployment and under what operational conditions?		●		●	
	Prediction, Latency and Coverage Tradeoffs					
11	What is the tradeoff between improved prediction accuracy and reduced latency with existing communications for maximum benefits?	●		●	●	●
12	What is the tradeoff between prediction accuracy and geographic coverage of ATDM deployment for maximum benefits?	●		●	●	
13	What is the tradeoff between reduced latency (with existing communications) and geographic coverage for maximum benefits?	●			●	
14	What will be the impact of increased prediction accuracy, more active management, and improved robust	●		●	●	

ID	ATDM Research Question	Pasadena	Dallas	Phoenix	Chicago	San Diego
	behavioral predictions on mobility, safety, and environmental benefits?					
15	What is the tradeoff between coverage costs and benefits?	●			●	
	Connected Vehicle Technology and Prediction					
16	Are there forms of prediction that can only be effective when coupled with new forms of data, such as connected vehicle data?				●	●
	Short-Term and Long-Term Behaviors					
17	Which ATDM strategy or combinations of strategies will have the most impact in influencing short-term behaviors versus long term behaviors and under what operational conditions?				●	●
18	Which ATDM strategy or combinations of strategies will yield most benefits through changes in short-term behaviors versus long-term behaviors and under what operational conditions?				●	●

3.3 ATDM Hypotheses

This section outlines the preliminary hypothesis used to assess different research questions identified for the AMS Project[13]. These are shown in Table 3-7.

Table 3-7: ATDM Research Question Analysis Hypothesis

ID	ATDM Research Question	Analysis Hypotheses
Synergies and Conflicts		
1	Are ATDM strategies more beneficial when implemented in isolation or in combination (e.g., combinations of ATM, ADM, or APM strategies)?	ATDM strategies that are synergistic (e.g., ADM, APM, ATM) will be more beneficial when implemented in combination than in isolation.

[13] Vasudevan and Wunderlich, Analysis, Modeling, and Simulation (AMS) Testbed Preliminary Evaluation Plan for Dynamic Mobility Applications (DMA) Program, FHWA-JPO-13-097

ID	ATDM Research Question	Analysis Hypotheses
2	Which ATDM strategy or combinations of strategies yield the most benefits for specific operational conditions?	An ATDM strategy will yield higher benefits only under certain operational conditions. Certain combinations of ATDM strategies will yield the highest benefits for specific operational conditions.
3	What ATDM strategies or combinations of strategies conflict with each other?	Certain ATDM strategies will be in conflict with each other, resulting in no benefits or reduced benefits.
Prediction Accuracy		
4	Which ATDM strategy or combination of strategies will benefit the most through increased prediction accuracy and under what operational conditions?	Improvements in prediction accuracy will yield higher benefits for certain ATDM strategies and combinations of strategies than for others. An ATDM strategy or combinations of strategies will yield the most benefits with improvements in prediction accuracy only under certain operational conditions.
5	Are all forms of prediction equally valuable, i.e., which attributes of prediction quality are critical (e.g., length of prediction horizon, prediction accuracy, prediction speed, and geographic area covered by prediction) for each ATDM strategy?	Increased prediction accuracy is more critical for certain ATDM strategies over others, with certain attributes (e.g., length of prediction horizon, prediction accuracy, prediction speed, and geographic area covered by prediction) of prediction quality being most critical.
Active Management or Latency		
6	Are the investments made to enable more active control cost-effective?	Incremental improvements in latency will result in higher benefit-cost ratio for certain ATDM strategy or combinations of strategies up to a certain latency threshold, after which benefit-cost ratio will be reduced.
7	Which ATDM strategy or combinations of strategies will be most benefited through reduced latency and under what operational conditions?	Reductions in latency will yield higher benefits for certain ATDM strategies and combinations of strategies than for others. An ATDM strategy or combinations of strategies will yield the most benefits with reduced latency only under certain operational conditions.
Operational Conditions, Modes, Facility Types with most benefit.		
8	Which ATDM strategy or combinations of strategies will be most beneficial for certain modes and under what operational conditions?	Certain ATDM strategies and combinations of strategies will yield the highest benefits for specific modes and under certain operational conditions.

ID	ATDM Research Question	Analysis Hypotheses
9	Which ATDM strategy or combinations of strategies will be most beneficial for certain facility types (freeway, transit, arterial) and under what operational conditions?	Certain ATDM strategies and combinations of strategies will yield the highest benefits for specific facility types and under certain operational conditions.
10	Which ATDM strategy or combinations of strategies will have the most benefits for individual facilities versus system-wide deployment versus region-wide deployment and under what operational conditions?	Certain synergistic ATDM strategies will yield most benefits when deployed together on individual facilities rather than as system-wide or region-wide deployments and under certain operational conditions and vice-versa
Prediction, Latency and Coverage Tradeoffs		
11	What is the tradeoff between improved prediction accuracy and reduced latency with existing communications for maximum benefits?	Incremental improvements in prediction accuracy will result in higher benefits, when latency is fixed up to a certain threshold, after which marginal benefits will be reduced and vice-versa. Maximum system benefit will be obtained at an intermediate point balancing prediction accuracy and latency.
12	What is the tradeoff between prediction accuracy and geographic coverage of ATDM deployment for maximum benefits?	Incremental improvements in prediction accuracy will result in higher benefits when geographic coverage is fixed up to a certain threshold, after which marginal benefits will be reduced and vice-versa. Maximum system benefit will be obtained at an intermediate point balancing prediction accuracy and geographic coverage.
13	What is the tradeoff between reduced latency (with existing communications) and geographic coverage for maximum benefits?	Incremental improvements in latency will result in higher benefits when geographic coverage is fixed up to a certain threshold, after which marginal benefits will be reduced and vice-versa. Maximum system benefit will be obtained at an intermediate point balancing latency and geographic coverage.
14	What will be the impact of increased prediction accuracy, more active management, and improved robust behavioral predictions on mobility, safety, and environmental benefits?	Increases in prediction accuracy, more active management, and improvements in robust behavioral predictions will result in significant mobility, safety, and environmental benefits. ATDM strategies will reduce the impact of congestion by delaying its onset, and reducing its duration and geographic extent. ATDM strategies will impact all three characteristics of congestion (onset, duration, and extent) but different strategies will impact specific congestion characteristics differently.

ID	ATDM Research Question	Analysis Hypotheses
		Traveler and system mobility measures will vary inversely with respect to congestion characteristics, but not uniformly by characteristic.
15	What is the tradeoff between coverage costs and benefits?	Incremental increase in geographic coverage will result in higher benefit-cost ratio up to a certain coverage cost threshold, after which benefit-cost ratio will be reduced.
Connected Vehicle Technology and Prediction		
16	Are there forms of prediction that can only be effective when coupled with new forms of data, such as connected vehicle data?	Prediction will be most effective only when coupled with connected vehicle data capture and communications technologies that can systematically capture motion and state of mobile entities, and enable active exchange of data between vehicles, travelers, roadside infrastructure, and system operators.
Short-term and Long-term Behaviors		
17	Which ATDM strategy or combinations of strategies will have the most impact in influencing short-term behaviors versus long term behaviors and under what operational conditions?	Certain ATDM strategies and combinations of strategies will influence short-term behaviors more than long-term behaviors under certain operational conditions, while others will influence long-term behaviors more than short-term behaviors under certain operational conditions.
18	Which ATDM strategy or combinations of strategies will yield most benefits through changes in short-term behaviors versus long-term behaviors and under what operational conditions?	Certain ATDM strategies and combinations of strategies will have the most impact through changes in short-term behaviors under certain operational conditions, while others will have the most impact through changes in long-term behaviors under certain operational conditions.

3.4 Key Performance Measures

The performance measures should provide an understanding of travel conditions in the study area; and demonstrate the ability of ATDM strategies to improve corridor mobility and reliability. Below is the list of performance measures for each tested ATDM scenario:

- Mobility – travel time;
- Emissions – carbon dioxide (CO_2), and Nitrogen Oxides (NO_x);
- Fuel Consumption– The consumed gallons

The modeling framework for the Dallas testbed adopts mesoscopic simulation logic, which is not suitable to directly evaluate safety. As the simulation Testbed is used to emulate real-time traffic network management decisions, the total network travel time is recorded every five minutes to capture the time-varying effect of the ATDM strategies deployed in the network. The travel time associated with activating the ATDM strategies could be compared to the travel time in the baseline scenario. The percentage saving in the travel time is a good measure for the effectiveness of the ATDM strategies deployed in the network.

The total travel time for all travelers existing in the network for any part of their trips during a pre-defined past horizon is used as a measure to evaluate the effectiveness of the generated ATDM response plans. Define τ_{at}^{i} as the travel time of vehicle i on link a in simulation interval t. Also, define T as the number of simulation intervals in the pre-defined past horizon T. The total travel time at each roll (5 minutes) is computed as follows:

$$\boldsymbol{Total\,Travel\,Time} = \sum_{t\in T}\sum_{i}\sum_{a}\boldsymbol{\tau_{at}^{i}} \qquad (3\text{-}1)$$

The fuel consumption is determined for vehicle as a function of its running speeds, and the vehicle's type (e.g., car, bus, and truck). Figure 3-13 gives the fuel consumption rate for the private car vehicle class. Considering the running speed v_i^t of vehicle i in the time interval t, the function $F(v_i^t)$ gives the vehicle fuel consumption in grams per unit of time time. Thus, the total fuel consumption for all vehicles I observed in the past horizon T is computed as follows:

$$\boldsymbol{Total\,Fuel\,Consiption\,(grams)} = \sum_{t\in T}\sum_{i\in I}\Delta\times\boldsymbol{F(v_i^t)} \qquad (3\text{-}2)$$

where v_i^t is the running speed of vehicle i at simulation interval t, Δ is the length of simulation interval, and function $F(.)$ is depicted as Figure 3-13.

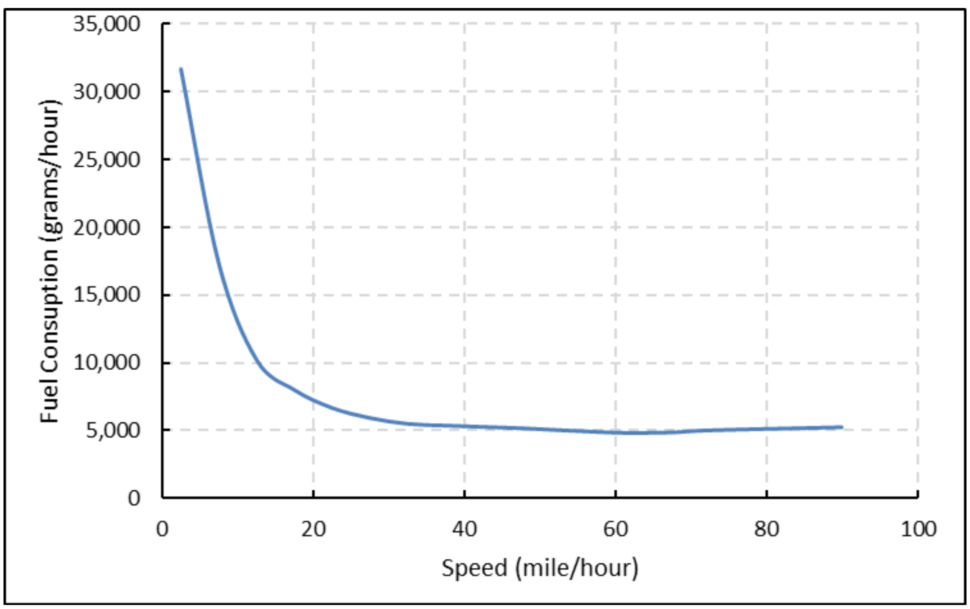


Figure 3-13: Fuel Consumption Rate for the Private Car Vehicle Class [Source: SMU]

Similar to the fuel consumption, the rates of carbon dioxide $G(.)$ and nitrogen oxide $H(.)$ emissions are depicted in Figure 3-14 and Figure 3-15, respectively. Similar to the fuel consumption rate, the CO and

NOX emission rates are functions of vehicle's running speed. Thus, the amount of CO and NOX emissions can be calculated as illustrated in Equations (33) and (34), respectively.

$$\boldsymbol{Total\ Carbon\ Dioxide\ Emission}\ (\boldsymbol{grams}) = \sum_{t \in T} \sum_{i \in I} \Delta \times \boldsymbol{G}(\boldsymbol{v}_i^t) \tag{3-3}$$

$$\boldsymbol{Total\ Nitrogen\ Oxide\ Emission}\ (\boldsymbol{grams}) = \sum_{t \in T} \sum_{i \in I} \Delta \times \boldsymbol{H}(\boldsymbol{v}_i^t) \tag{3-4}$$

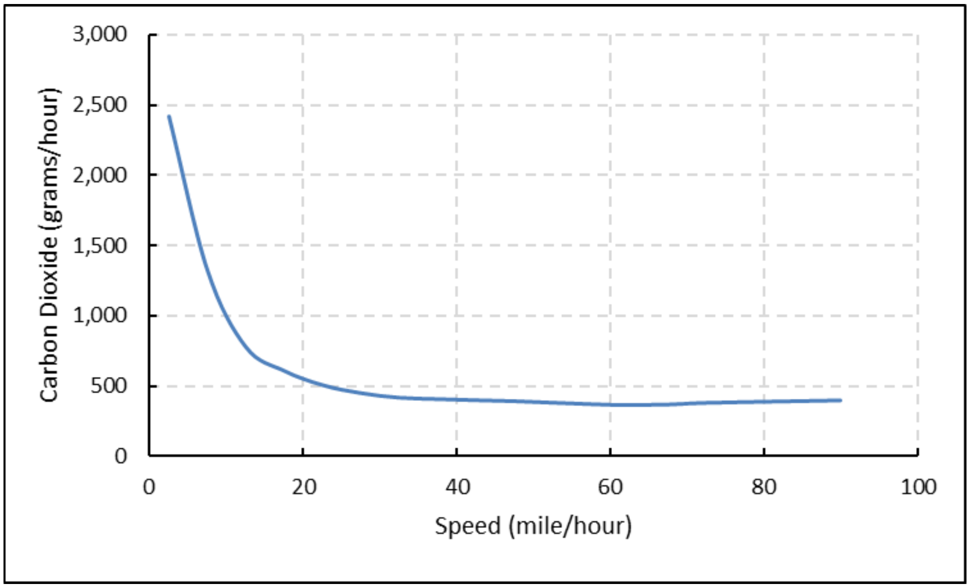


Figure 3-14: Carbon Dioxide Emission Rate for the Private Car Vehicle Class [Source: SMU]

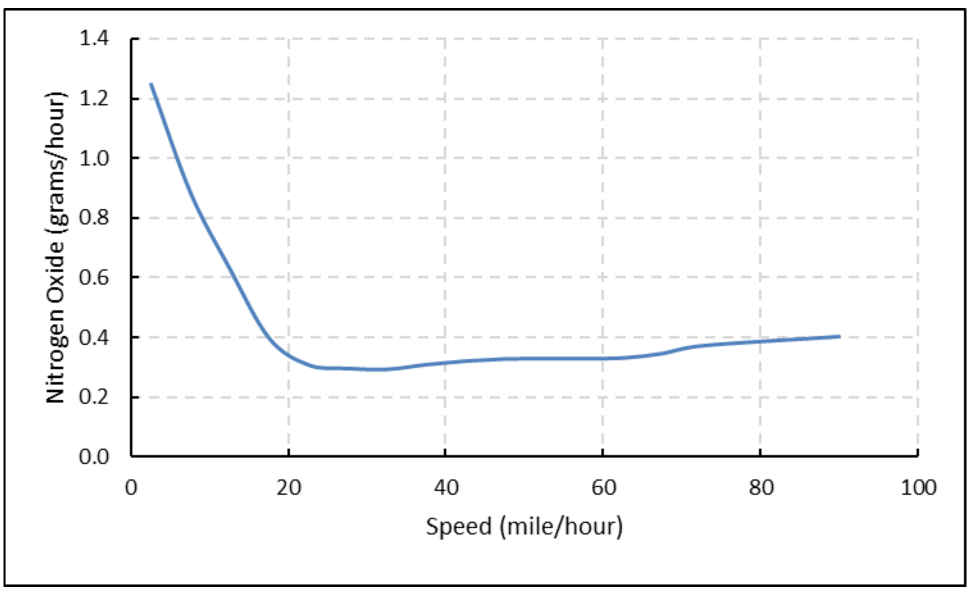


Figure 3-15: Nitrogen Oxide Emission Rate for the Private Car Vehicle Class [Source: SMU]

Chapter 4. ATDM Modeling Approach

This chapter presents the modeling approach utilized by each testbed to implement and evaluate the different ATDM strategies. The chapter describes the modeling approach for the overall testbed as well as for individual strategies that were testbed using the testbeds.

4.1 Dallas Testbed Modeling Approach

Figure 4-1 and Figure 4-2 illustrate the overall framework of the implemented ATDM analysis framework that was utilized in the Dallas Testbed. The framework is designed to virtually emulate the decision-making process in a typical traffic network management center. The framework describes main processes detection, communications, and control/advisory information dissemination technologies; and system management decisions.

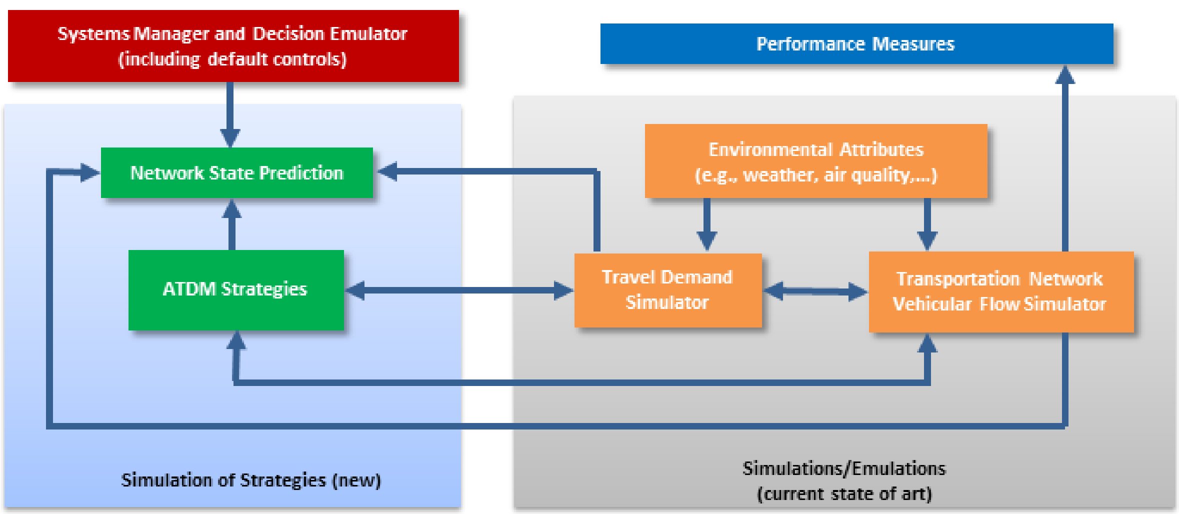


Figure 4-1: Preliminary Analysis Framework for Dallas Testbed [Source: SMU]

The dynamic traffic assignment simulation-based modeling framework, DIRECT (Dynamic Intermodal Routing Environment for Control and Telematics) which is developed by researchers at Southern Methodist University (DIRECT), is used to emulate the decision-making process for active traffic network management. As illustrated in Figure 4-2, the DIRECT simulation testbed adopts a rolling horizon framework, which integrates 1) network state estimation module; 2) a network state prediction module; 3) demand estimation and prediction module; 4) consistency checking module; and 5) decision support subsystem (scheme generator). The network state estimation module is synchronized with the real clock and provides an estimate of the current network conditions at any point in time. It consists of a real-time simulation-based DTA model capable of capturing the network congestion dynamics resulting from the network's demand-supply interaction. The DTA simulation-based model, DIRECT is used as the basis for the estimation and the prediction modules. DIRECT consists of several interconnected components including: (a) demand generation; (b) travel behavior; (c) shortest path algorithm; (d) vehicle simulation; and (e) statistics collection.

The network prediction module is periodically activated (e.g., every 5 to 10 minutes) to predict the network conditions over a predefined horizon (30 minutes to 1 hour). The prediction module consists of another instance of the network simulation model running faster than real-time. The initial conditions for each prediction horizon are obtained from the estimation module which provides a snapshot of the network conditions at the start time of each prediction horizon. This snapshot defines the current location, speed, and assigned route for all travelers in the network. The new vehicles to be loaded during the prediction horizon are obtained through activating the online dynamic demand estimation and prediction module for the prediction horizon, which is described in more details in the next section. The system also allows the use of demand data that are estimated offline. For example, several OD demand tables representing different congestion levels could be estimated offline to reflect the demand levels for the different operational conditions identified based on the cluster analysis. Vehicles already in the network at the start of the prediction horizon and newly generated vehicles are simulated for the pre-specified horizon. In case the prediction module is used to evaluate an ATDM response scheme, the parameters of the simulated control devices are updated to replicate this scheme. For example, if a scheme requires a modification to the timing plan of one or more intersections, these plans are fed to the prediction module to simulate their effect.

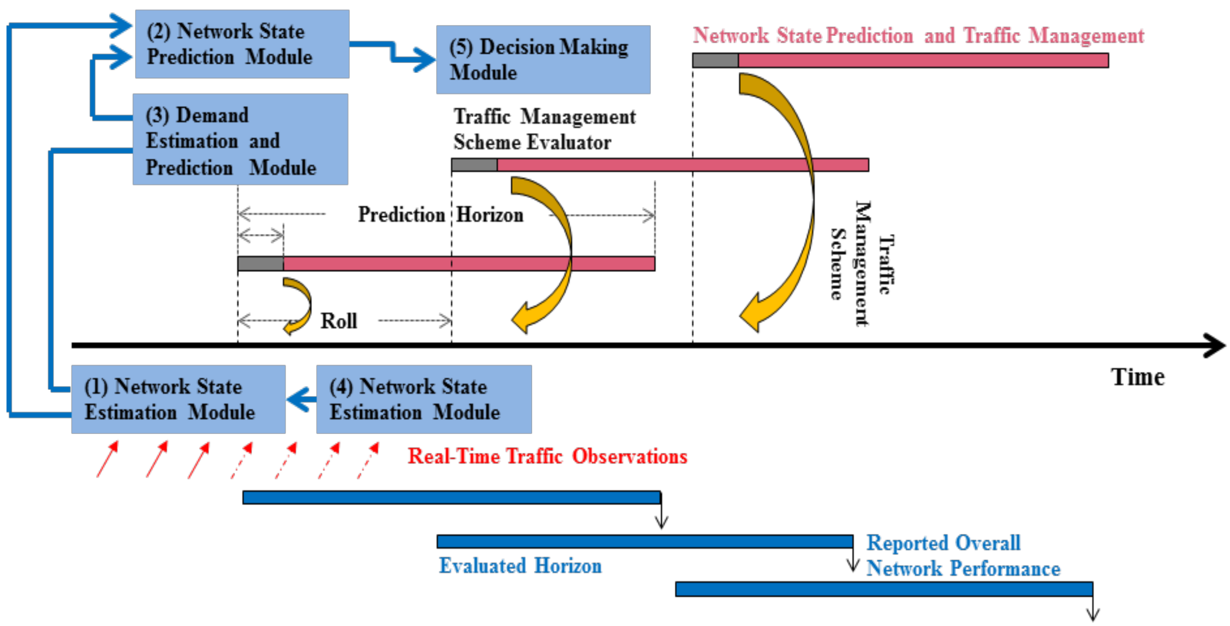


Figure 4-2: Real-Time Network State Estimation and Prediction System Utilized in Dallas Testbed [Source: SMU]

To ensure consistency between the simulation and the real network, the simulation model receives continuous data feeds in the form of speed and flow rate observations for roadway links equipped with surveillance devices. These observations can be used to adjust the model parameters in real-time to achieve better estimation results. The DIRECT framework is ready to integrate correction algorithms to any of its parameters. In the current implementation, as the model is fully calibrated off-line, no online model adjustment modules are activated to adjust any of the model parameters.

As illustrated in the figure, the estimation module implements a moving horizon approach to report the estimated measures of performance. Following this approach, statistics that covers a pre-defined horizon (e.g., 30 minutes) are continuously collected and reported at each roll (e.g., 5 minutes). Such approach is more suitable for real-time applications as it continuously monitors the time-varying network performance associated with any emerging congestion and the implemented response plans. Several measures of performances are reported at each roll. In the analysis conducted in this report, the total travel time for all travelers existing in the network for any part of their trips during the pre-defined past horizon is used as a measure to evaluate the effectiveness of the generated response schemes. In addition, the corresponding fuel consumption and emissions (e.g., Carbon Dioxide and Nitrogen Oxide) are reported.

4.1.1 Traffic Network Management Module

As mentioned above, the Dallas Testbed provides decision support capabilities by developing efficient ATDM response plans that are consistent with the predicted network conditions. The ATDM response plan determines the optimal settings for available traffic control devices in the network.

In the current implementation, we adopt a Genetic Algorithm (GA) approach to generate efficient ATDM response plans. GA is a machine-learning model, which adopts its behavior from the processes of evolution in nature. The process starts with the creation of a population of individuals represented by chromosomes. Chromosomes in this population continuously pass through a process of evolution to increase their fitness and adaption to their environments. The evolution occurs by exchanging characteristics with other chromosomes of the population (crossover) or through self-changes in the chromosome (mutation). New generations appear from clones of the current population, in proportion to their fitness. The fitness is a single objective function of the chromosome that returns a numerical value to differentiate between good and bad chromosomes.

A ATDM response plan is modeled in the form of a chromosome. As illustrated in Figure 4-3, a gene in a chromosome defines a control action implemented as part of the scheme. A timing plan at a signalized intersection, a route diversion message on a dynamic message sign, a speed limit advisory, and a ramp meter flow rate are examples of possible control actions.

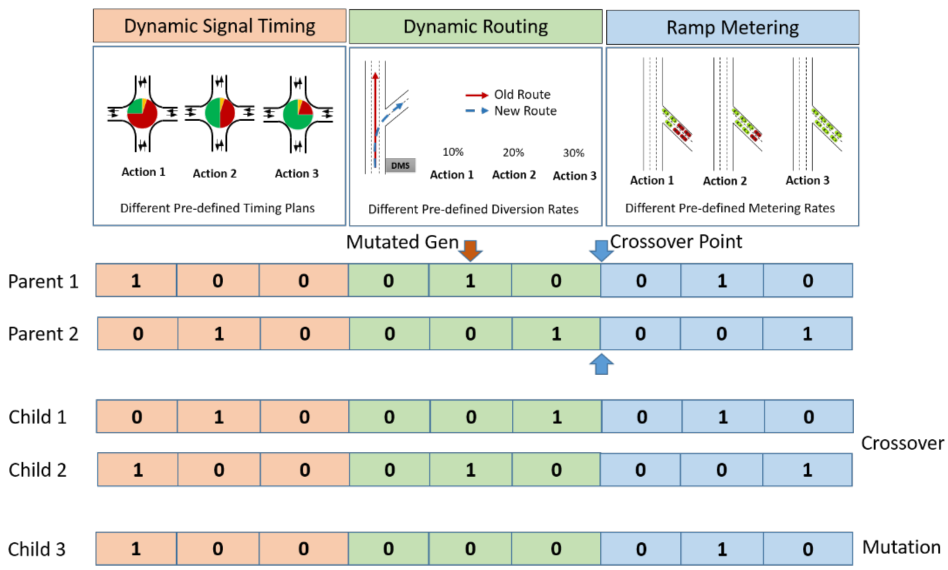


Figure 4-3: Representation of the Integrated Traffic Management Schemes using Genetic Algorithm [Source: SMU]

Figure 4-3 gives examples of multiple schemes with different combinations of actions. The figure illustrates the structure of two parent schemes (1 and 2) in a generation. These two schemes are used to produce three new schemes as part of a subsequent generation. Children 1 and 2 are two new schemes formed by the crossover of Parents 1 and 2. A crossover point is randomly selected to execute the action exchange. Child 3 is obtained by the mutation of Parent 1 by randomly changing one or more of its actions. In the presented example, the DMS action is mutated.

Each scheme is evaluated by its fitness, measured as the average travel time over the prediction horizon when the scheme represented by this chromosome is implemented. The prediction module is activated to estimate the average traveler travel time for each considered scheme. The traffic network is simulated after modifying the settings of the control devices to represent their corresponding values in the generated scheme. The use of the DTA simulation model to evaluate the fitness of each scheme not only ensures accurate performance evaluation of the generated schemes but also ensures that the scheme is consistent with the drivers' route choice behavior.

The steps of the used GA are as follows. First, an initial population and the fitness values of all its schemes are obtained. Schemes in the population are sorted based on their fitness value and top elements are used to produce the next generation using crossover and mutation strategies. Schemes in the new population are again evaluated and ranked. The process continues until the improvement in the fitness of the best scheme in two successive generations is smaller than a pre-defined threshold. In the current implementation, for each activation of the traffic management module at each roll, an initial population of 20 management traffic schemes is used. In addition, the GA is set to evolve for five generations with a population of five schemes in each generation. Thus, a total of 45 schemes are evaluated for each horizon. The DIRECT simulation model is used to evaluate the traffic network considering the deployment of each of these schemes. The simulation model provides accurate estimation of the fitness of each scheme which is measured in terms of the network total travel time for the prediction horizon. The scheme with the best overall network performance in terms of total travel time is recommended for deployment.

Steps of the GA

Step 1: Set iteration number itr = 0.

Step 2: Generate initial feasible population of ATDM response plans P(itr).

Step 3: Using the prediction module, identify the fitness of each scheme in the population.

Step 4: While convergence is not obtained:

Step 4a: Update the counter.

Step 4b: Select a sub-population with the highest fitness from the population P(itr-1).

Step 4c: Elements of the sub-population are then used to generate a new population P(itr) using crossover and mutation strategies.

Step 4d: Each ATDM response plan in the population is evaluated using the simulation model.

Step 5: Output the ATDM response plan with the best fitness.

Figure 4-4 illustrates an example of a developed ATDM strategy for the occurred incident in the network. As shown in the figure an impacted region is selected around the incident location which mainly includes dynamic message signs (DMSs), and traffic control signals. With provision of the information on the DMSs, the travelers might find new routes to avoid the delay due to the incident in the network. In this example, the two major diverted routes that are mostly used by the travelers are drawn in the figure (orange and green routes). In addition, it requires adjusting the settings of traffic signal control which reduces the delay at the intersections due to increased traffic flow in these diverted routes compared with the ordinary traffic. These signal controls are enlarged in the figure.

The traffic management module develops an efficient ATDM response plan that identifies the appropriate settings for DMSs and traffic signal controls in the impacted region. The effectiveness of developed ATDM response plan is evaluated in terms of total network travel time. The next sections provide more details for other traffic control devices that could be developed as a part of ATDM response plan.

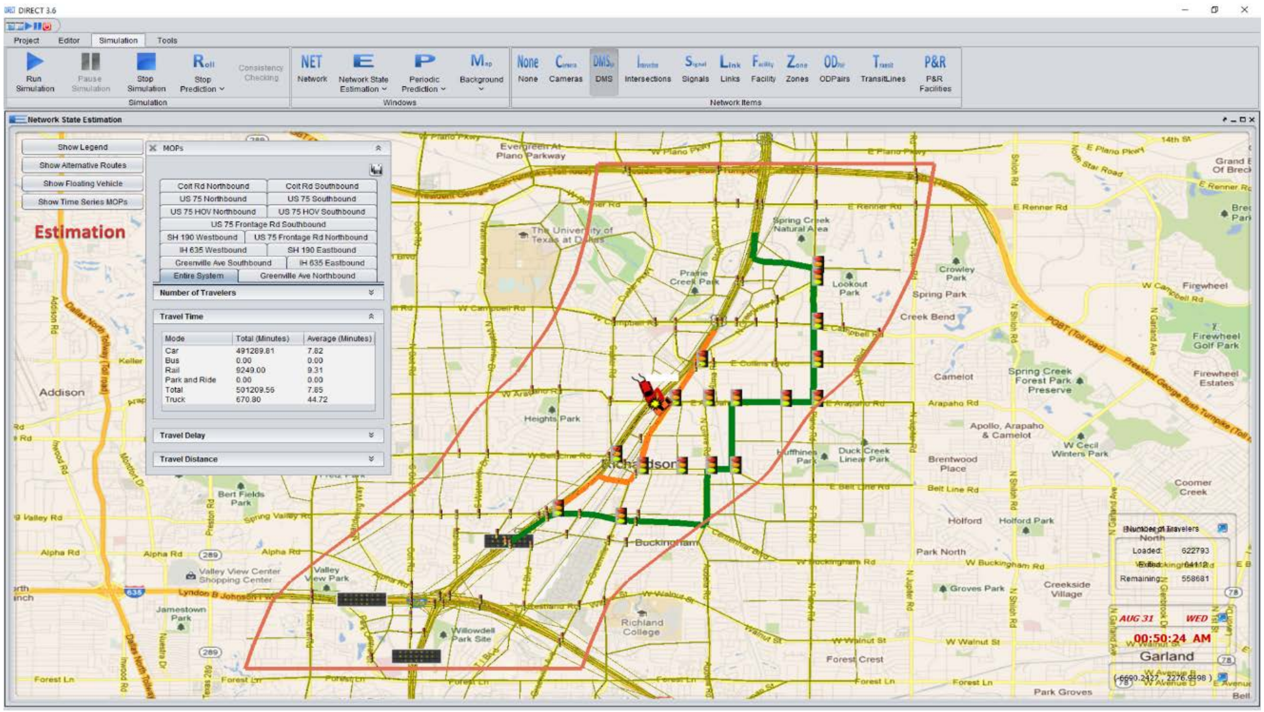


Figure 4-4: An Example of an Integrated Traffic Management Scheme Developed by the Traffic Network Management Module [Source: SMU]

4.1.2 Active Traffic Management in DIRECT

This section describes the different active traffic management strategies that are considered for the Dallas Testbed. These strategies include: a) Dynamic Routing; b) Adaptive Traffic Signal Control; c) Adaptive Ramp Metering and d) Dynamic Shoulder Lane. Please note that Dallas testbed uses Dynamic Signal Timing strategy as Adaptive Traffic Signal Control. An overview of the modeling logic of these strategies integrated as part of the DIRECT simulation platform is described. Table 4-1 presents an overview of the logic used to model these strategies. The table provides a description of each strategy as well as a pseudo-code of how these strategies is modeled using the DIRECT simulation platform.

Table 4-1: Active Traffic Management Strategies Modeled Using the Dallas Testbed

ATDM Strategy	Description	Logic

Dynamic Lane Shoulder	DIRECT represents highway links at the lane level. To model the dynamic lane shoulder strategy, a shoulder lane, with pre-defined characteristics, could be added to the link. This shoulder lane would be configured to serve the traffic as long as the strategy is active (e.g., peak period, incident, evacuation).	if (shoulder lane strategy starts) {
		for (selected freeway links) {
		- Define a new Lane Object
		(speed limit, capacity, jam density)
		- Mark Lane as a shoulder lane
		- Add Lane to Link
		}
		}
		if (shoulder lane strategy terminates) {
		for (selected freeway links) {
		- Shift traffic from shoulder lane to adjacent lanes
		- Remove Lane from Link
		}
		}

Adaptive Ramp Metering	The outflow capacity is reduced to represent the recommended ramp metering rate. Based on the adjusted capacity, the number of vehicles that can enter the freeway through the ramp in each simulation interval is determined. If the number of vehicles that need to enter the freeway exceeds this maximum number of vehicles allowed in a simulation interval, a queue is formed and the vehicles join this queue. Vehicles are discharged from the queue based on the first-in-first-out queue order.	Assumption: the optimal inflow rate for each ramp is determined exogenously to the simulation model
		if (Adaptive Ramp Metering Scheme is activated) {
		for (Ramps in this schemes) {
		outflowRate = newOutflowRate
		}
		}

Dynamic Routing	DIRECT is capable of modeling dynamic routing based on the provided traveler information. Drivers with access to information are assumed to be able to compare their current routes with the new routes. If the difference in the travel time is greater than a pre-defined threshold, drivers are assumed to switch to the new route. The route diversion could be occurring at any junction along their routes including the DMS locations.	Assumptions: - Travelers are assumed to be assigned to their historical routes. - The percentage of travelers with access to en-route information is assumed given. - Travelers can modify their routes along any node along their original path. Logic: - At each shortest path update interval, the shortest paths from all origin nodes to all destinations are determined. - For all travelers with access to information, if the travel time (cost) of the new path is less than the time of the current path by a pre-defined threshold, the traveler is assumed to switch to the new path.

Adaptive Traffic Signal Control or Dynamic Signal Timing	The DIRECT model allows modifying the signal timing plan for all or a subset of the intersections in the network at any point of time during the simulation horizon. A signal control scheme is described in terms of its activation start and end times and the timing plan for all intersections considered in this scheme. Multiple schemes could be defined a priori for the simulation horizon. These schemes are implemented in the simulation based on their activation times. If a traffic management module is used to generate a control scheme at any point in time, this scheme can also be deployed in the network according to its activation time.	Assumption: An integrated traffic control scheme includes a set of the intersections in the network. A new timing plan could be generated for all intersections in this scheme.
		if (new scheme is gnerated) {
		for (all intersections in this scheme) {
		for (all signal phases at this junction) {
		GreenInterval = newGreen
		RedInterval = newRed
		Offset = newOffset
		}
		}
		}

Dynamic Shoulder Lane

This strategy allows traffic to use the shoulder lane during the duration of an incident where one or more regular lanes are closed. The lane could be open for traffic usage just after the incident is detected, and remain open for any pre-specified period after the incident is cleared. Figure 4-5 illustrates a typical scenario for shoulder lane usage. Two regular lanes are closed because of the incident causing a vehicle queue to form upstream the incident. As the shoulder lane (in blue) is opened for traffic usage, a portion of the vehicles shift to the shoulder lane which substitutes part of the lost capacity due to the incident.

DIRECT represents highway traffic movements along the different links at the lane level. Each link is defined in terms of its lanes. If the dynamic shoulder lane strategy is activated, one lane is added to each freeway link where the strategy is activated. Vehicles on the lane adjacent to the shoulder could shift to the shoulder lane. The shoulder lane is treated as a regular lane during the strategy activation period. At the time the strategy is deactivated, the vehicles on the shoulder lane are shifted to the adjacent lane. The shoulder lane is eliminated as one of the open lanes for the link. It is worth mentioning that DIRECT adopts mesoscopic simulation logic. As such, lane changing behavior is implicitly modeled through updating the traffic density on each lane during every simulation interval. The corresponding average speed for the traffic moving on each lane then determined for each lane based on its level of traffic density.

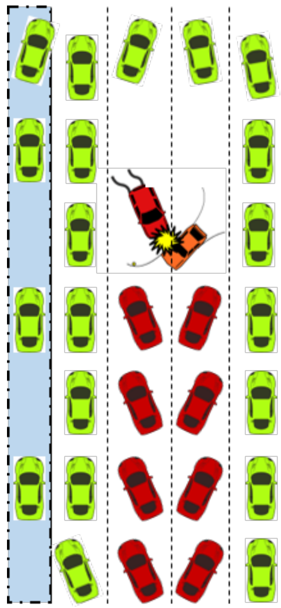


Figure 4-5: Dynamic Shoulder Lane Strategy [Source: SMU]

Adaptive Ramp Metering

The adaptive ramp metering is a freeway management strategy which reduces the overall freeway congestion by managing the amount of traffic entering the freeway. Figure 4-6 shows an example of ramp metering strategy with different rates of vehicles that are allowed to enter the freeway from the on-ramp. Each ramp is modeled in DIRECT as a link with a pre-defined maximum outflow capacity (i.e., saturation flow rate). To model different metering rates, the outflow capacity is reduced to represent the recommended ramp metering rate. Based on the adjusted outflow rate, the number of vehicles that can enter the freeway through the ramp in each simulation interval is determined. If the number of vehicles that need to enter the freeway exceeds this maximum number of vehicles allowed in a simulation interval, a queue is formed and the vehicles join this queue. Vehicles are discharged from the queue based on the first-in-first-out queue order.

As explained above, several feasible metering rates are pre-specified for each ramp (as illustrated in Figure 4-6). The traffic management module specifies the optimal rate for each ramp as part of the integrated ATDM response plan. In other words, the optimal metering rate is determinate externally to the DIRECT simulation model. However, the model can simulate the metering rate recommended by the traffic management module.

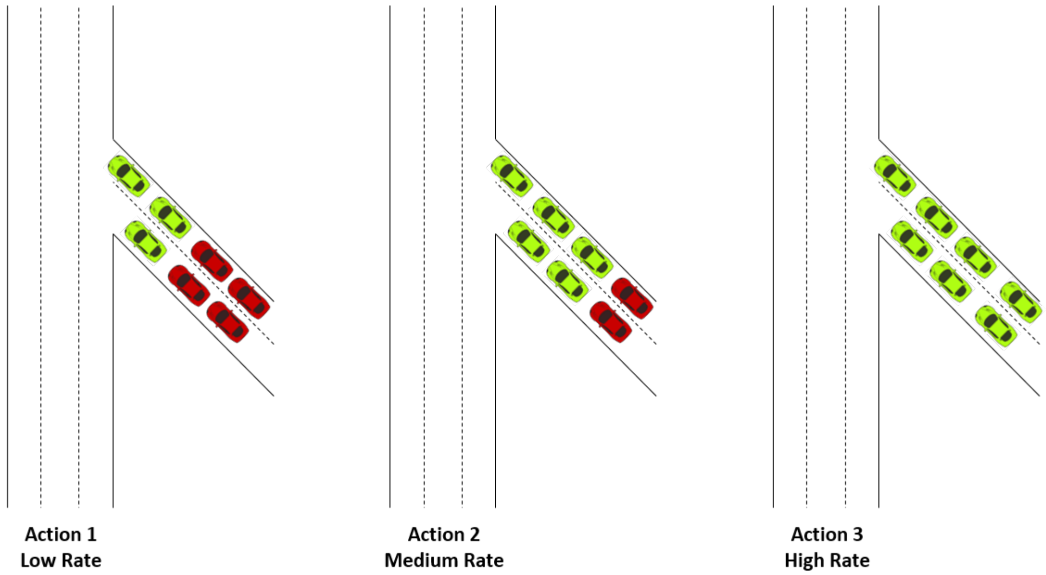


Figure 4-6: Adaptive Ramp Metering Strategy with Different Metering Rates [Source: SMU]

Dynamic Routing

The dynamic routing strategy warns drivers of congestion ahead and recommends diversion to alternative routes. This information could be disseminated to drivers through Dynamic Message Signs (DMS), in-vehicle information, or social media. In all cases, new diversion routes are recommended to the drivers from their current locations to their final destinations. Drivers compare the travel time of the new routes against that of their habitual routes. If the travel time saving is greater than a pre-defined threshold, drivers are assumed to switch to the new routes. The new routes typically detour the drivers around the incident location to avoid the congestion. Figure 4-7 shows an example of DMS that recommends different diversion rates. Depending on the displayed message and the duration of displaying this message, different diversion rates could be achieved (e.g., 10%, 20%, and 30%). For a given diversion rate, drivers on the freeway are picked randomly according to this rate and provided the diversion routing information. As the diversion rate increases, more vehicles are expected to leave the freeway and use the recommended diversion routes.

Similar to the ramp metering logic, several diversion rates are pre-defined for each DMS. The traffic management module determines the optimal diversion rate to be adopted at each DMS. The optimal diversion rate is determined such that the total travel time in the network is minimized. As this optimal rate is determined, the simulation activates the DMS and the recommended route diversion rate is simulated as described above.

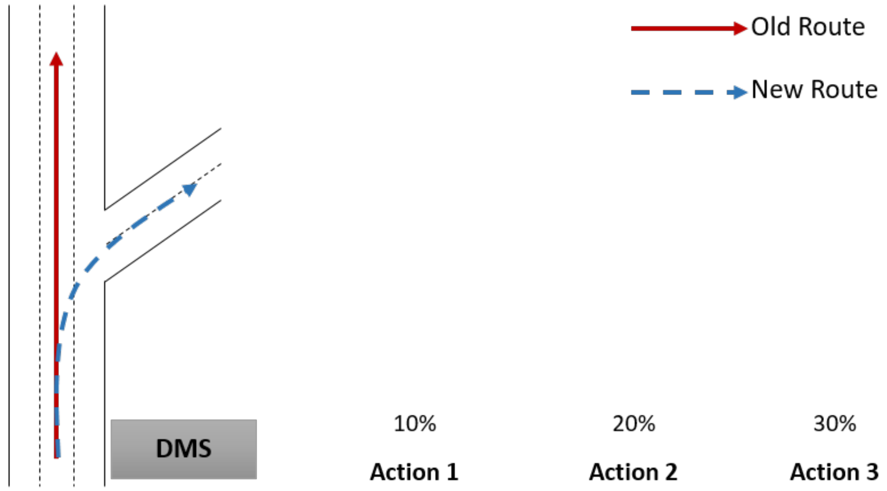


Figure 4-7: Dynamic Routing Strategy with Different Diversion Ratios [Source: SMU]

Adaptive Traffic Signal Control

The dynamic signal timing strategy modifies the signal timing for all or a subset of the intersections along the diversion routes in order to provide additional capacity to accommodate the diverting traffic. A pre-timed signal control is adopted for all intersections in the corridor. To model the pre-timed signal control logic in DIRECT, a time scheduler is assumed to track the start and end of the green interval for each phase. As the green interval is assigned to a phase, for all simulation intervals falling after the start of the green interval, all lanes served during this phase are assumed to have an outflow capacity that is equal to their saturation flow rate. As the green interval ends, the outflow capacity is reduced to zero for all simulation intervals within the red interval. A queue is formed for each lane and vehicles are stored in that queue waiting for the next green interval to start. The length of the queue is updated based on number of vehicles in the queue.

Figure 4-8 illustrates an example of the different settings at one intersection. The figure shows the different signal timing plans at a hypothetical intersection. These plans are different in the amount and green assigned for one of the phases. Similarly, several feasible timing plans (phasing, green and red intervals for each phase and offsets) are defined for each intersection as an input to the traffic network manager. Using the GA search logic, the traffic network manager determines the optimal timing for each intersection as part of the integrated scheme. The new timing plans overwrite the old one defining new setting values. The logic described above is again used to simulate the intersections considering these new settings.

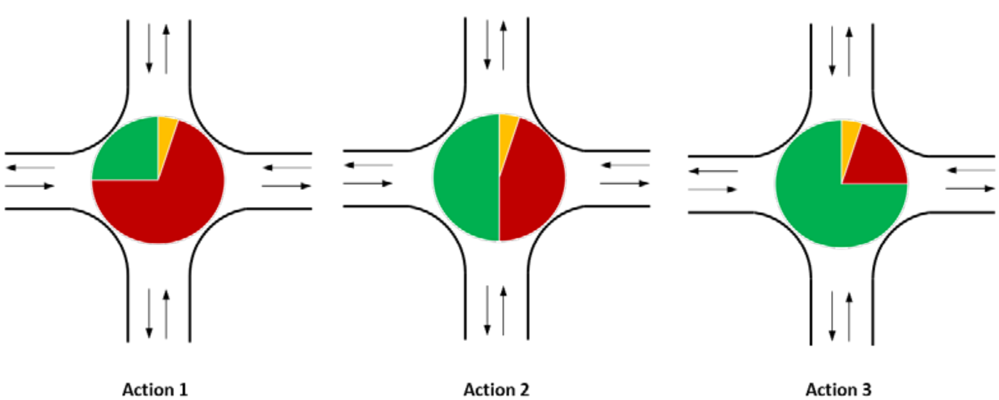


Figure 4-8: Different Feasible Timing Plans Defined at an Intersection [Source: SMU]

4.1.3 Active Parking Management Strategies

In order to evaluate Dynamically Priced Parking strategy using the Dallas Testbed, a time-dependent pricing scheme is assumed for the parking lots near the commuters' destinations. Higher parking cost is usually adopted in the peak period with the goal is to influence the behavior of commuters. As commuter try to avoid the high parking cost, they either a) change their departure times to the off-peak period; or b) abandon their private cars and switch to transit, if available.

The DIRECT modeling platform is used to model the effect of a dynamic parking pricing scheme on the commuter's departure time and travel choice decisions and the cumulative effect of such decisions on the overall network performance. Following the dynamic route assignment logic in DIRECT, travelers are assigned to routes that minimize a generalized cost measure. This measure is in the form of a weighted linear function which includes the total travel time and the total travel cost. The generalized cost includes I) route's travel time, II) vehicle operation cost (as a function of trip distance), and III) any out-of-pocket cost elements (e.g., parking cost, tolls). The set of optimal routes are periodically updated to capture congestion dynamics in the network as well as changes in the parking cost associated with implementing a dynamic parking pricing scheme. Figure 4-9 illustrates the overall framework used to model the commuters' departure time and mode choice decisions. As shown in the figure, the framework adopts a rolling horizon approach that represents the commuters' within-day trip planning logic. The rolling horizon framework implements a look-ahead logic in which commuters with later habitual departure times are allowed to evaluate their departure times to earlier or later times.

A hierarchal choice mechanism is proposed in this research which as presented in Figure 4-10. Commuters are assumed to first evaluate the option to change their departure time. The total travel costs, including the parking cost at the destination, are compared for the different departure times. If the saving is greater than a pre-defined threshold, commuters are assumed to modify their departure time. A commuter that decided to modify her/his departure time is assumed to use her/his private car. If the commuter decided not to change the departure time, the cost of the trip using a transit mode, if any, is compared to that of the private car. If the saving is less than a certain threshold, the commuter is assumed to abandon her/his private car and use transit.

Different parameters are considered to model the commuters' choice decisions under a dynamic parking pricing scheme. There model parameters include:

1. The dynamic pricing pattern at each parking lot.
2. Percentage of the commuters who seek for the parking spots at the end of their trips (e.g., 20% of the travelers need the parking).
3. The length of look-ahead and backward intervals that commuters consider to change their original departure time. For example, if a commuter original departure time is t, this traveler considers modifying her/his departure time to any time in the interval [$t - \Delta$: $t + \Delta$] in order to avoid the high parking cost.
4. The threshold in the travel cost saving that commuters that commuters consider to modify their departure times or mode of travel (e.g., saving is more than 20%).
5. Number of parking lots with dynamic parking pricing.

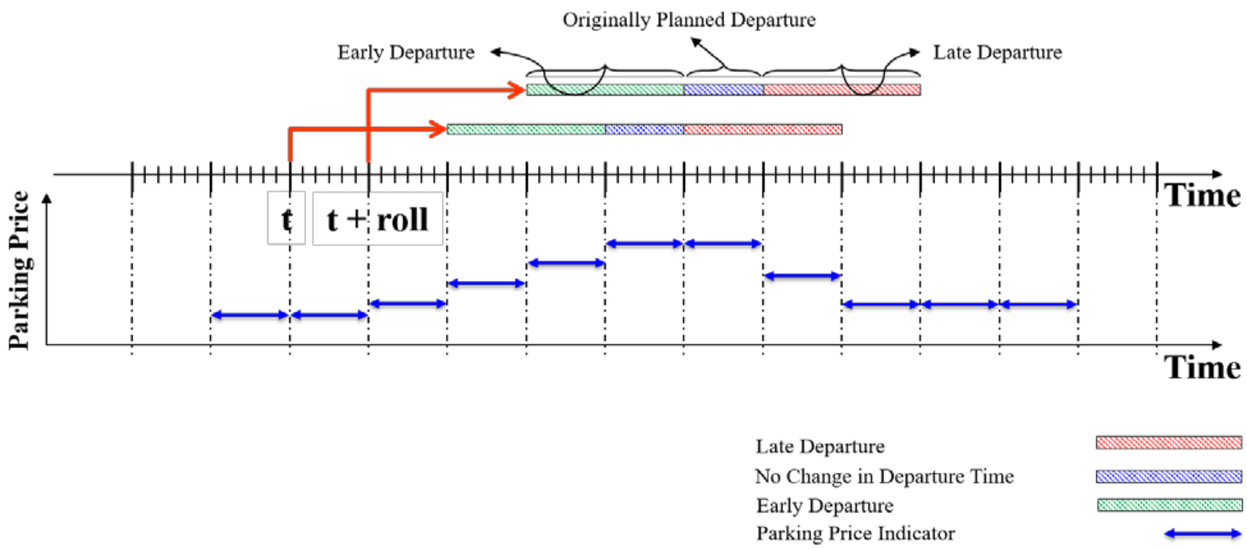


Figure 4-9: A Rolling Horizon Approach for Modeling Trip Planning Decisions [Source: SMU]

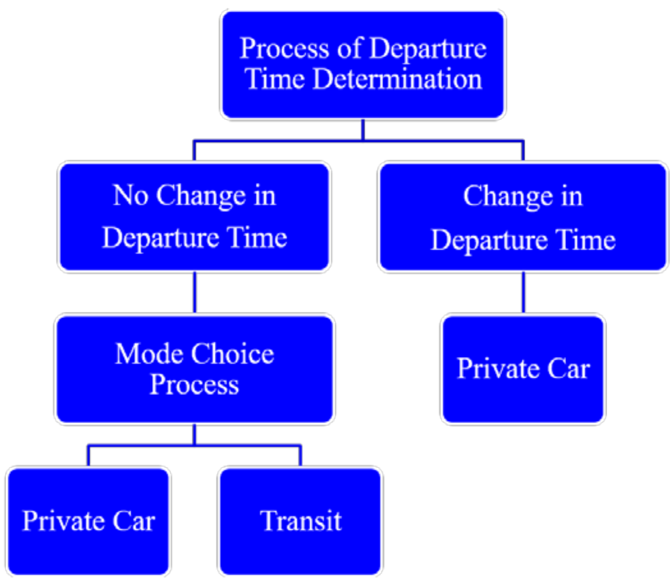


Figure 4-10: Hierarchal Departure Time and Model Choice under Dynamic Parking Pricing Scheme [Source: SMU]

4.2 Phoenix Testbed Modeling Approach

Phoenix Testbed was used to evaluate four ATDM strategies: Adaptive Signal Control, Adaptive Ramp Metering, Dynamic Routing and Predictive Traveler Information System. The Testbed team used different tools to simulate different strategies using a Multi-Resolution Simulation Platform, since the testbed was on a DTALite platform and required external tools to integrate Ramp Metering and Adaptive Signal Control.

Ideally, all the four ATDM strategies should run together on the same network work under different configurations. However, this is not realistic in the scope of this project due to lack of a single simulator suitable for all four strategies. As a result, multiple traffic simulators were adopted in this task. As shown in Figure 4-11, in addition to the standard DTALite simulator, a special version of DTALite was also developed to allow external adaptive ramp metering strategy to change the ramp metering rate according to the real-time traffic condition extracted from the special DTALite. The third DTA simulator was also derived from a parallel project and enhanced to meet the requirements for adaptive signal control in mesoscopic simulation (i.e., second-by-second, high-fidelity modeling within intersections). Since the HD-DTA is closely coupled with the signal emulator Advanced System Controller (ASC)/3 in microscopic Vissim, which in turn becomes a media for external adaptive signal control strategies to be reflected into HD-DTA, HD-DTA, ASC/3 (Vissim) and adaptive signal control all composes of a multi-resolution simulation platform, referred to as MRSP.

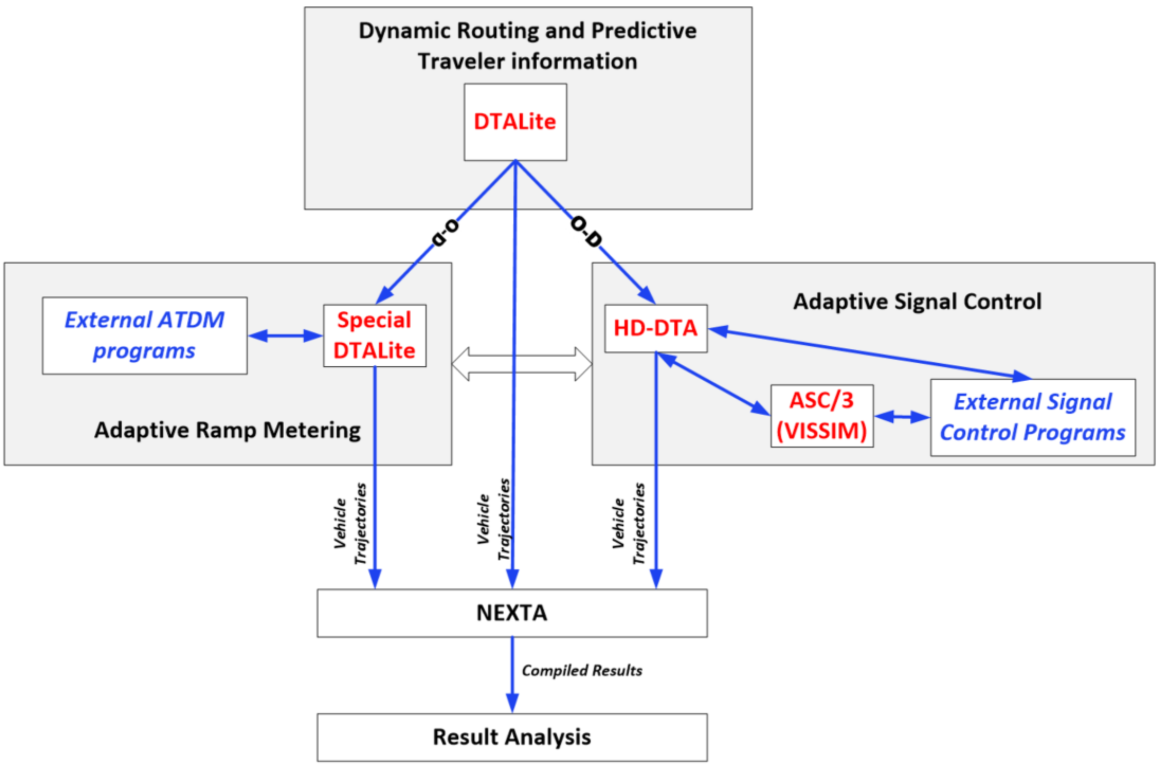


Figure 4-11: Phoenix Testbed Modeling Framework [Source: ASU]

The tools utilized are listed below:

1. **DTALite**: DTALite is an open-source dynamic traffic assignment model that is based on a mesoscopic simulation-assignment framework. DTALite uses a computationally simple but theoretically rigorous traffic queuing model in its lightweight mesoscopic simulation engine. To reduce data preparation efforts, it only requires a minimal set of static traffic assignment data and some time-dependent OD demand pattern estimates. DTALite was used for the overall predictive traveler information and dynamic routing system.
2. **HD-DTA**: High-Definition DTA is a version of Dynamic Traffic Assignment model which is higher resolution than DTALite and was require to interface DTALite with Vissim microscopic simulation tool.
3. **Vissim**: PTV Vissim is a microscopic multi-modal traffic flow simulation software package developed by PTV Planung Transport Verkehr AG in Karlsruhe, Germany. Vissim was used to interface HD-DTA with RHODES, which was the Adaptive Signal Control program used in this testbed.

4. **RHODES**: Real-time Hierarchical Optimizing Distributed Effective System is an adaptive traffic control system that is based on decomposing the control-estimation problem into three hierarchical levels: (1) intersection control; (2) network control; and (3) network loading.
5. **NEXTA**: NEXTA (Network EXplorer for Traffic Analysis) is a graphical user interface to facilitate preparation, post-processing and analysis of simulation-based dynamic traffic assignment datasets was used for visualization and post-processing.

Due to this architecture, the required simulation resolution, network details and scope and network fidelities are very different. Specifically, adaptive ramp metering strategies typically need to update the ramp metering rate every 10 to 300 seconds and therefore mesoscopic traffic simulators are suitable for adaptive ramp metering simulation. Adaptive signal control strategy is in nature microscopic and requires high resolution, network details and fidelities. In contrast, dynamic routing and predictive traveler information systems are relatively more flexible in terms of simulation resolution and fidelity.

All simulators use the same traffic network converted from the microscopic simulations and all based on the same O-D demands. Nonetheless, the loading processes are very different within various simulators and so are the corresponding results. Standard DTALite allows a certain portion of travelers to recalculate their paths to avoid congestions as well as allows using historical travel times and real-time travel times to predict future link travel time. As such, standard DTALite is suitable to simulate dynamic routing and predictive traveler information systems. A feature of adaptive ramp metering is to adjust the ramp metering rate dynamically. This feature can be simulated through adjust the ramp link capacities in DTA simulator. Given that it is complicated to change the kernel of standard DTALite simulator, the ASU project team decided to modify the standard DTALite to allow interactions between DTALite and external programs. In doing so, various control strategies can be evaluated with ease. At each period, the real-time traffic conditions are exported to intermediate files with time stamp, such as the travel demand, agent positions. On the other hand, the external control program will calculate the appropriate ramp metering rates according to its own strategy and feed new ramp link capacities back to DTALite to continue the simulation.

The adaptive signal control strategy cannot be simulated within DTALite or special DTA because the minimum time step of existing DTA simulator(s) is six seconds which cannot meet the requirement of adaptive signal control strategies. As such, the ASU project team developed an enhanced version of DTA simulator, referred to as high-definition DTA (HD-DTA), which has one-second simulation resolution as well as interfaces for external control algorithms. Through the interfaces, HD-DTA is coupled with the high-fidelity signal emulator, ASC/3, included in the microscopic simulation engine, Vissim. The inherent control algorithm in ASC/3 can be further overridden by other adaptive signal control algorithms via the standard communication protocol for traffic signal controls.

It is desired to evaluate the adaptive ramp metering and adaptive signal control together to see the joint performance in urban areas. After the early efforts, the project team determined that simulating both adaptive ramp metering and adaptive signal control simultaneously is not realistic and therefore the team designed an iterative approach between to approximate the joint simulation of adaptive signal control and adaptive ramp metering. After simulation runs are finished, the raw outputs are all sent into the post-processing program, NeXTA to analyze and visualize the MOEs of our interest.

During the course of this task, the project team first identified a scope of work for this task. Although it is possible to evaluate dynamic routing and predictive traveler information system on a city-wide network, it is neither realistic nor practical to implement city-wide adaptive signal control and adaptive ramp metering in near future within the project scope and schedule. Without loss of generality, the project team decided to extract three intersections along the McClintock Rd and freeway 101 between Rio Salado Parkway and Broadway Road in the city of Tempe. The selected subnetwork is fully connected which allows travelers for multiple alternative routes to reach their destinations. In summary, the new subnetwork includes: 985 links; 914 nodes, 3 signalized intersections and 3 interchanges.

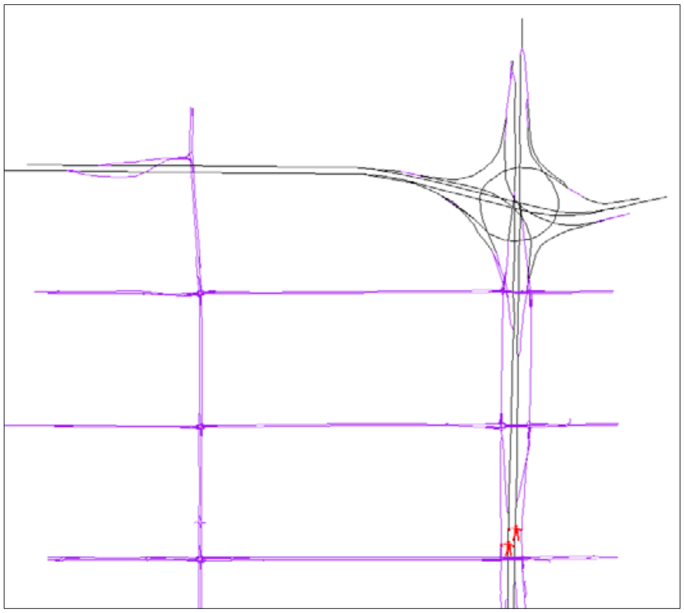


Figure 4-12: Scope of ATDM Strategy Evaluation in Tempe [Source: ASU]

As for the travel demands and O-D pairs for four scenarios were also extracted with the tool, the O-D cut, which was also used to extract O-D demands of the City of Tempe from the greater Phoenix area during the evaluation of EnableATIS previously. Within this new scope, there are around 160,000 vehicles during the 5 hours of evening peak period simulation among all four operational conditions. The total length of the traffic networks for ATDM evaluations is about 48 miles.

4.2.1 Predictive Traveler Information and Dynamic Routing

With the predictive traveler information and dynamic routing strategies, travelers could not only get the real-time link travel times, but also the short-term prediction travel times along the routes. Such information would allow travelers to switch to the alternative routes to avoid congestions. While the travelers are calculating new best routes periodically, it is very important to not only adopt the latest experienced travel time, but also the predicted travel time in near future for the downstream links that travelers have not arrived yet. Several preliminary simulation runs were performed to create a historical trend of link travel time changes. It is assumed that all travelers seek the least-cost paths from their origins to destinations and most travelers would like to switch their paths if necessary to avoid congestions.

To model these ATDM strategies, an effective network representation and efficient algorithms to get the appropriate paths for travelers are necessary. The team used a space-time network representation to formulate traveler path and thereby easily optimize routes and predict travel-times. In the following sub-sections, details on this representation and the decentralized algorithm to optimize routes is provided.

Consider a directed, connected traffic network (N, E), where N is a finite set of nodes, and E is a finite set of traffic links between different adjacent nodes. The planning time horizon is discretized into a set of small time slots, denoted by $T = \{t_0, t_0 + \sigma, t_0+2\sigma, \ldots, t_0+M\sigma\}$. Symbol t_0 specifies the given departure time from the origin node O, and σ represents a short time interval (e.g. 6 s) during which no perceptible changes of travel times are assumed to take place in a transportation network. M is a sufficiently large positive integer so that the time period from t_0 to $t_0+M\sigma$ covers the entire planning horizon.

For a given physical network, a corresponding space-time expanded network was constructed, denoted by (V, A), expanded from the physical network (N, E) and time-varying link travel time. Specifically,

$V=\{(i,t)|i \in N, t \in T\}$ represents the set of time-dependent nodes, where $(i,t) \in V$ indicate the state of node *i* at time stamp *t* and each state will be treated as a separate node. The set of time dependent arcs is represented as $V=\{(i,j,t,s)|(i,j) \in E,\ t_0 \le t \le s \le t_0 + M\sigma\}$, where time dependent arc (i,j,t,s) occur in the space-time network when one can travel from physical node *i* at timestamp *t* and arrive at physical node *j* at timestamp *s*. As shown in Figure 4-13, the plot on the left hand side exemplifies a physical network with assumed 1-min travel time for each link, while the right hand side depicts its corresponding space-time network with a horizontal time dimension. Waiting arcs are introduced to model the situation of traveling agents staying at a node from one timestamp to the next, represented by dash lines in Figure 4-13.

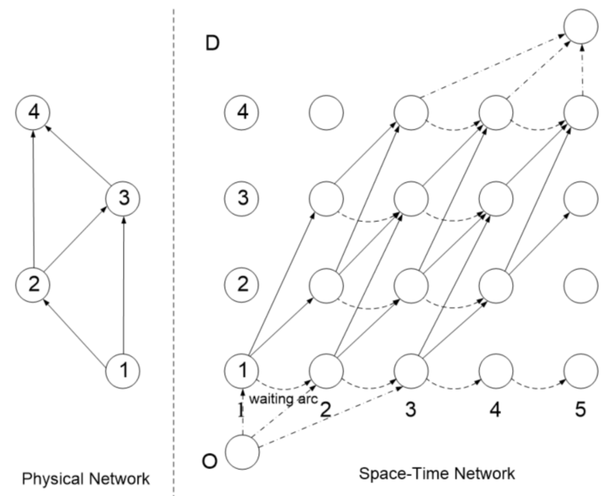


Figure 4-13: Physical Network compared to Space-Time Network [Source: ASU]

We also added source/sink node as well as super arcs from the super source and to the super sink (represented by dot-dash lines). For simplicity, our model first considers a point-queue model where each traveling agent is assumed to travel through a link at free-flow speed and waiting at the end node of the link if the inflow capacity of the subsequent link is unavailable. The point queue model can be relatively easy extended to the spatial queue and kinematic wave model[14]. This space-time structure can be also easily incorporated in the implementation for a dynamic network loading problem using agents.

The DTALite's dynamic routing model utilizes an agent-based simulation optimization model which finds global optimum for all travelers to reach their destination using minimum travel time (objectified as cost). Lagrangian Relaxation-based Heuristic Approach is used for the optimization for its speed an ability to narrow down solution-space using heuristic data available from the DTALite model. The optimization is subject to multiple constraints as listed below:

1. Constraints on time-dependent network flows stating that the input should be same as output at each node.
   a. Flow balance constraints on origin node
   b. Flow balance constraints on destination node
   c. Flow balance constraints on intermediate node
2. Constraints on network propagation enables agent propagation by controlling link and node's capacities.
   a. Inflow capacity constraints
   b. Continuous Flow constraints

[14] Zhou, X., Taylor, J. (2014). DTALite: A queue-based mesoscopic traffic simulator for fast model evaluation and calibration. Cogent Engineering, 1(1): 1-19.

3. Constraints on information provision constraints the amount of information available to vehicles/agents to control their dynamic routing, by controlling their short-term/long-term experiences, available VMS and other information.
    a. Information Activation Constraints
    b. Historical Information Provision Constraints
    c. Real-time Information Provision Constraints
    d. Node Information Provision Constraints
    e. Budget Constraints
    f. Information Start Time Constraints
    g. Detour Constraint

The final optimization solution approach is provided in Figure 4-14.

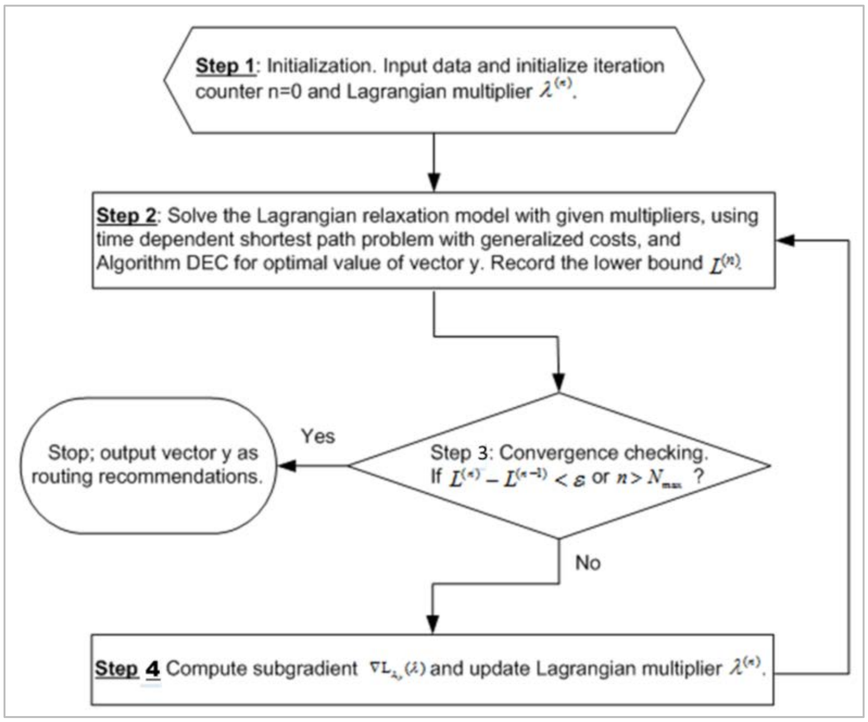


Figure 4-14: Solution Procedure for Lagrangian Relaxation-based Heuristics [Source: ASU]

The overall algorithm is described in the following steps:

Step 1: (Initialization) Set n =0; Perform dynamic network loading using DTALite with initial path of each agent; initialize the Lagrangian multiplier $\lambda^{(n)}$, evaluate the objective function value $L^{(n)}$ of Lagrangian Relaxation problem (17). Go to Step 2.

Step 2: (Solve the relaxed model)

Given Lagrangian multiplier $\lambda^{(n)}$ and current results from network loading, solve the problem (19) using a modified label correcting algorithm for time dependent least cost path problem, and Algorithm DEC, to find current optimal value for vector y.

Update the objective function value $L^{(n)}$ of Lagrangian Relaxation problem (17).

Go to Step 3.

Step 3: (Convergence checking) If $L^{(n)} - L^{(n-1)} < \varepsilon$ or $n > N_{\max}$, terminate the iteration and output current solution of vector y. Otherwise, go to step 4.

Step 4: Compute subgradient with Eq. (22) and update Lagrangian multiplier using Eq. (23). Go to step 2.

4.2.2 Adaptive Ramp Metering

The purpose of ramp metering is to limit vehicles on ramps to enter the mainline freeway and reduce the interferences in weaving areas and increase the throughput. The adaptive ramp metering is to dynamically adjust metering rate according to the mainline traffic on freeways. In order to simulate the adaptive ramp metering strategies, a customized version of DTALite was developed. DTALite will not only measure the observed travel demand but also predicts the near-future demand based on historical data. Therefore, the reported real-time travel demands at each time period are a mixture of real-time and historical future data and therefore in essence proactive. This feature also makes the proposed adaptive ramp metering strategy proactive. The project team added hypothetical incidents to the network, since the extracted smaller Tempe network was devoid of any recorded incidents as shown in Figure 4-15. The introduced incidents took place after the on ramps (blue lines) where ramp metering will most likely have the best performance. When incidents occur, the mainline capacities near three interchanges (from north to south) were on average reduced by 20%, 40% and 60% respectively. It was assumed that if only adaptive ramp metering strategy is considered, there was no effect on the mainline travel demand, unless other ATDM strategies are in place, such as dynamic routing strategy.

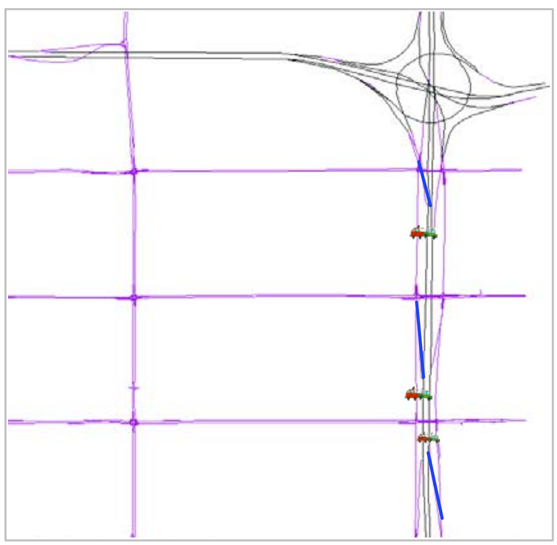


Figure 4-15: Locations of Incidents for Phoenix Testbed [Source: ASU]

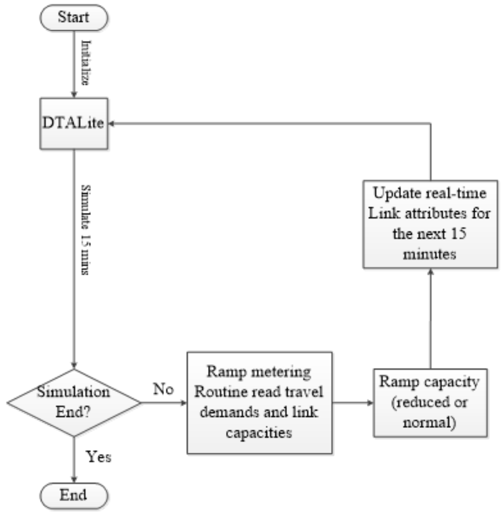


Figure 4-16: Workflow of Adaptive Ramp Metering [Source: ASU]

Through measuring the mainline travel demand at several locations, it was possible to ascertain if the traffic volume has exceeded or will exceed the reduced road capacities. The goal of the adaptive ramp metering in this context is always to keep the mainline traffic volume lower than the (reduced) road capacity and reduce the interferences between mainline traffic and vehicles on ramps. To achieve that goal, the capacities on the corresponding ramp links are reduced by (D_(main_Line)+D_ramp-C_(a%)) where D is the time-dependent travel demand and C is the time-dependent link capacity reduced by α% during incidents. Figure 4-17 shows the work flow of adaptive ramp metering implementation in the special version of DTALite. Once the total demand on the main line and on ramps exceeds the link capacities, including during the incidents, the ramp metering strategy will be activated. The ramp metering strategy was set up such that the total demand on the mainline plus ramps is always equal to or lower than the mainline capacity. In doing so, the interference in weaving areas is minimized and traffic mobility is improved.

The standard DTALite does not contain adaptive ramp metering mechanism. For this project, a special version of DTALite was developed to output the real-time travel demands on certain links to other program as well as to update the ramp metering rate from the external program. Specifically, while this special DTALite is running, it will periodically output the travel demand on selected links into text files stamped by time and will not proceed until the updated ramp metering rate generated by external program can be read. On the other hand, the adaptive ramp metering strategy cannot proceed either unless it finds the latest travel demand in the time stamped text files. This allowed dynamically changing the ramp capacities (to reflect ramp metering rate) when DTALite is running.

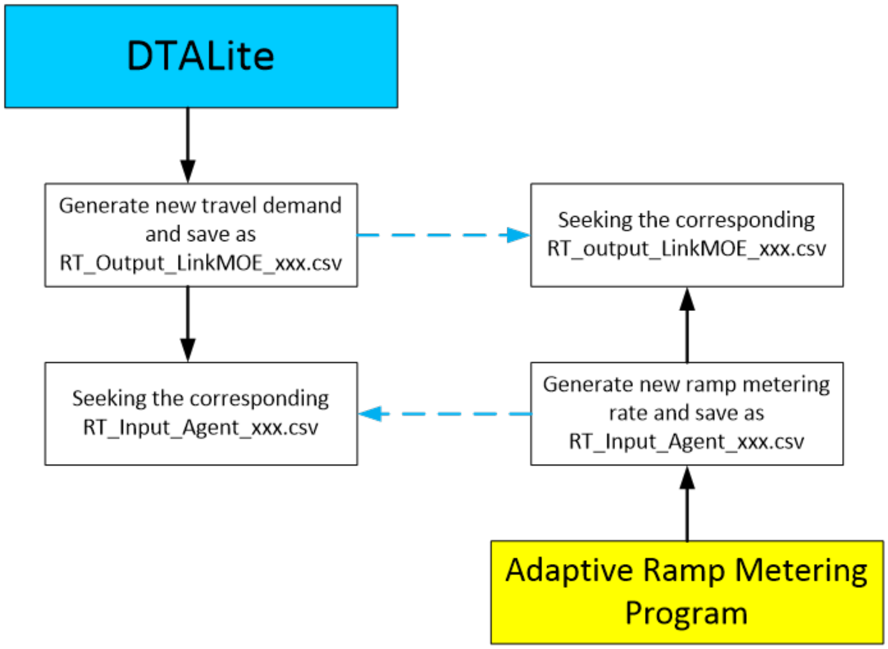


Figure 4-17: Demonstration of DTALite-Ramp Metering Program Interface [Source: ASU]

4.2.3 Adaptive Traffic Signal Control

The adaptive traffic signal control used is Real-time Hierarchical Optimizing Distributed Effective System (RHODES). RHODES does not employ defined traffic cycles or signal timing plans. It utilizes traffic flow models that predict vehicle arrivals at the intersection, and adjust the timing of each phase to optimize an objective function such as delay. Because it emphasizes on traffic prediction, this system can respond to the natural statistical variations in traffic flow as well as to flow variations caused by traffic incidents or other unpredictable events. Intersection control equipment for adaptive systems is often more complex than for the other control categories.

For this project, three intersections are modeled as shown in Figure 4-18. The time-dependent arriving vehicles and turning ratios are derived from the calibrated HD-DTA models of City of Tempe. Given the adopted signal control strategy is driven by advance detector calls, it is necessary to assume that the travel time between advance detectors and stop line are constant. In addition, there are no vehicles existing the road between advance detectors and stop lines neither new vehicles entering the road between advance detectors and stop lines.

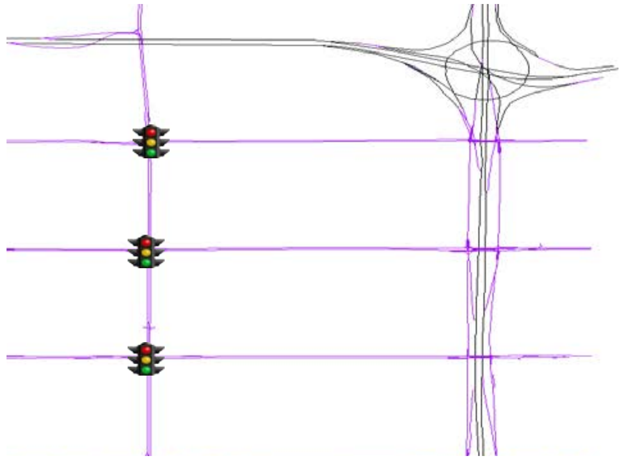


Figure 4-18: Locations of Adaptive Traffic Signal Control Implementation [Source: ASU]

Figure 4-19 shows the overall work flow of RHODES. In order to mimic the real-world sensing and transmission technologies, the RHODES architecture introduces measurement noise as shown in Figure 4-19 prior to utilizing it for signal strategy calculations. RHODES will first process the newly incoming information, such as new detections of vehicles, and predict those vehicles' trajectories for a short-term, including toward which direction those new vehicles will move (left-turn, through or right turn) and how soon they will join the queue. After that, the short-term prediction of traffic states $\hat{x}(t)$, will be created. At this point, the core module of RHODES begins to optimize to determine which approach should be given green time in sequence and how long the green times should be.

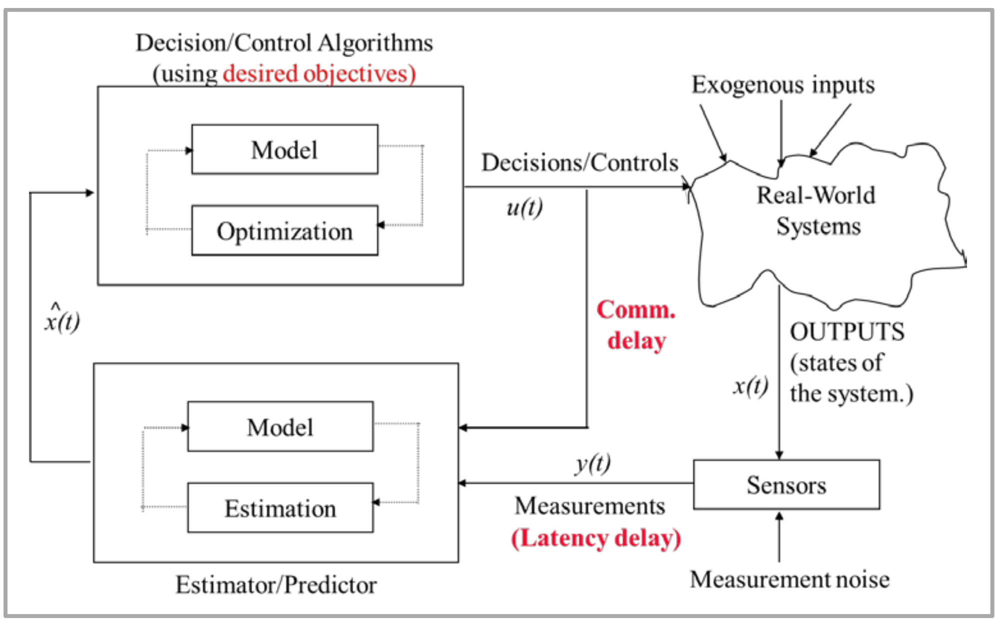


Figure 4-19: Workflow of RHODES Application [Source: ASU]

There are three important inputs for RHODES to work: road saturation rate (i.e., discharge rates), travel time from advance detectors to stop lines and turning ratios. (Figure 4-20)

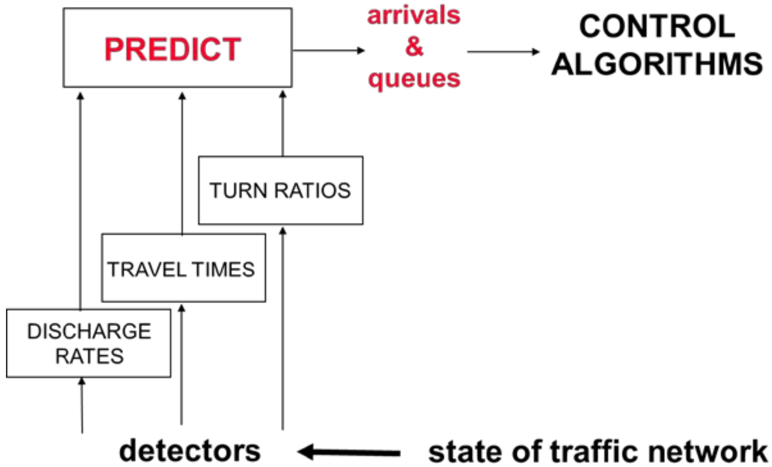


Figure 4-20: Inputs Required for Adaptive Signal Control Strategy [Source: ASU]

The optimization solution in RHODES was developed based on dynamic programming and combinatorial optimization. The idea is to select the best solutions among millions of feasible signal timings from now to the end of time horizon (e.g., 15 minutes from now). Each feasible solution (shown as examples in Figure 4-21) is composed of a phasing sequence and each phase has a green time from the minimum green to the maximum green. Since whenever an approach is given green, all other conflict approaches must be given red, creating control delays, a phasing sequence over time will resulting a total delay. Through the dynamic programing (DP), the RHODES can quickly reach the best signal timings and implement it in the field. To further improve the predicting accuracy, RHODES also adopted the rolling horizon technique to suppress the data randomness. As shown in Figure 4-22, for each optimization, the time horizon is longer, such as 15 minutes, to evaluate the total control delays under a feasible signal timing. After this timing plan is implemented, it only lasts 5 minutes before a new optimization process begins based on the newly incoming traffic data. This approach can effectively diminish the bias created by the traffic randomness. Traditionally adaptive signal control strategies were simulated and evaluated in the microscopic simulation environment. However, in this project, it is necessary to evaluate the integral performance of adaptive signal control in junction of other ATDM strategies. As such, we developed a multi-resolution simulation platform to enable adaptive signal control mechanism in DTA-type simulator.

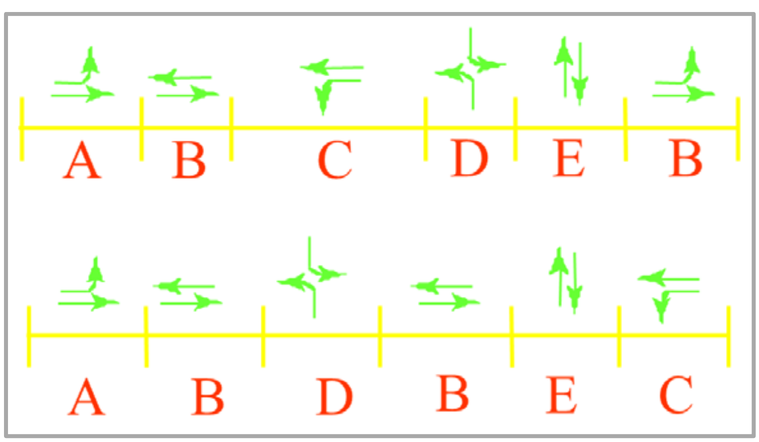


Figure 4-21: Examples of Two Feasible Signal Timing Plans [Source: ASU]

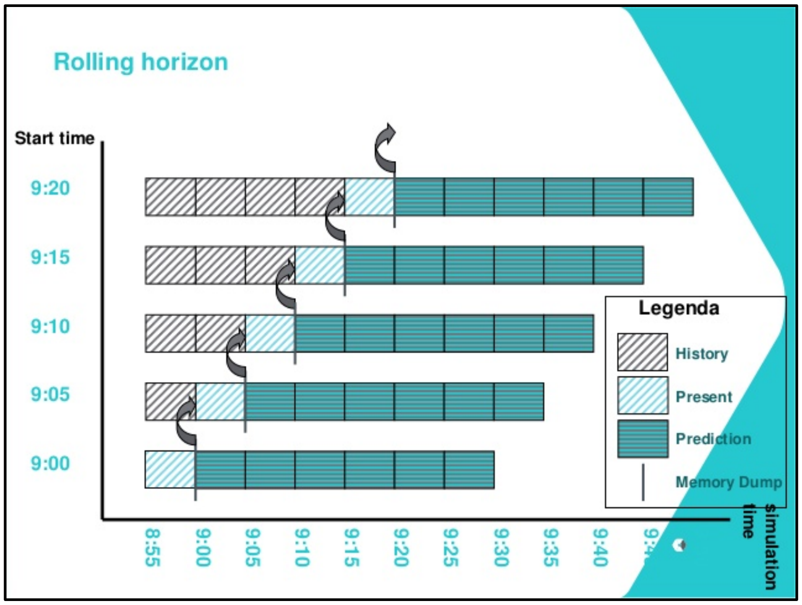


Figure 4-22: Concept of Rolling Horizon in RHODES [Source: ASU]

The project team used HD-DTA to help integrate a low-resolution DTALite model with a high-resolution Vissim model. HD-DTA is similar to DTALite but with higher simulation resolution (second-by-second). Since red light is in essence to prohibit vehicles to enter the intersection or prohibit a particular movement within intersections, the team first defined a group of special links within intersections to match them with particular signal phase(s), as demonstrated in Figure 4-23. The signal links will be opened and closed alternatively according to exogenous signal control mechanism. Additionally, the team also developed a synchronous link between HD-DTA and Vissim.

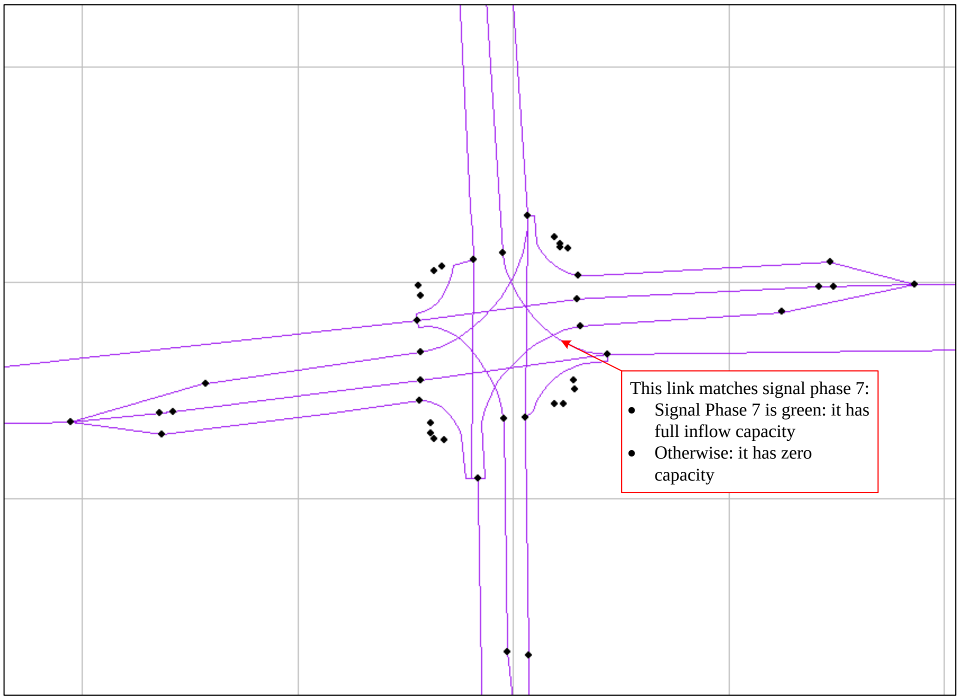


Figure 4-23: Matching Signal Phases Between HD-DTA and Vissim [Source: ASU]

At each simulation step, Vissim will send all real-time signal phase status generated by its signal emulator to HD-DTA simulator. Through a mapping data structure, HD-DTA will decide which signal links should be open and which close accordingly. Please note that the signal phase in Vissim can be either determined based on the inherent control logic in ASC/3 or overridden by the external control logic (in our case, the external control logic is RHODES). This new approach can eventually have RHODE-determined adaptive signal phase statuses reflected in HD-DTA simulation.

The HD-DTA-Vissim interface also replicated detector calls for RHODES according to on-going traffic conditions. Since Vissim is only used as a carrier of ASC/3 signal emulator, all detector calls must be generated in HD-DTA. According to the attributes of detectors, whenever a HD-DTA agent enter a link on which detectors are placed, a future detector call will be scheduled according to the travel time from the link start to the detector location. With time elapsing, this scheduled detector call will be sent to RHODES to let RHODES a new vehicle is approaching. Figure 4-24 shows the concept of how to place detector calls.

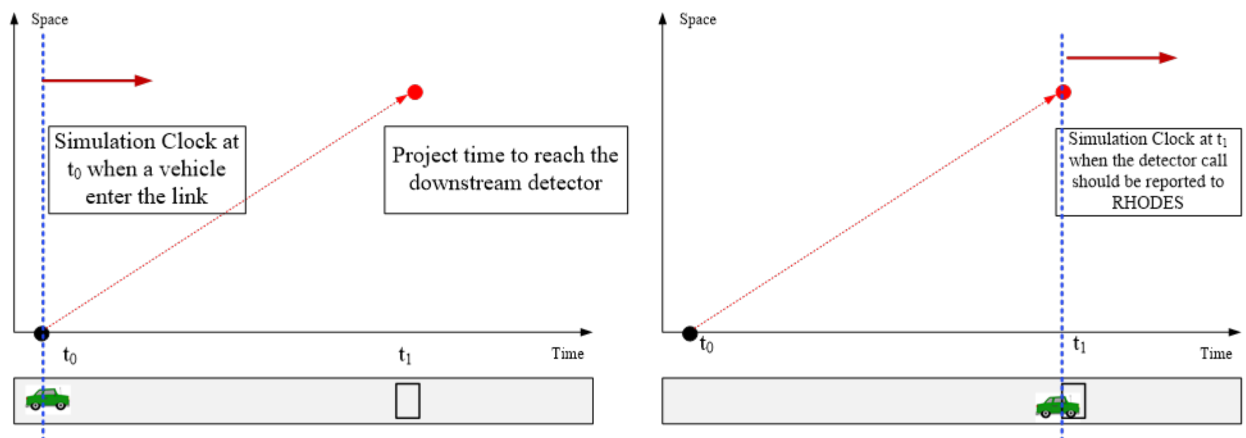


Figure 4-24: Detector Placement in HD-DTA and RHODES [Source: ASU]

Since the benefits of adaptive signal control are on urban streets, the project team evaluated the benefits of adaptive signal control along the three intersections. The major Measure of Effectiveness (MOE) in the evaluation is the travel time along the whole arterial (3 intersections). For each scenario (derived from the cluster analysis), two signal control strategies were simulated: standard actuated signal timing corresponding to the travel demand (baseline); adaptive signal control strategy. There are also some differences regarding the detector configurations. Compared to the standard signal control strategies, adaptive signal control needs additional advance detectors to predict.

4.2.4 Strategy Combinations

Integrating Adaptive Ramp Metering with Adaptive Signal Control requires, either further modifying special DTALite to be compliant with Adaptive Signal Control (by introducing more data structure and reducing the resolution to 1 second), or modifying HD-DTA to be able to simulate Adaptive Ramp Metering (by introducing ARM module as well as other functions in DTALite). Neither option was realistic given the project timeline and resources. Hence, the project team decided to propose an approximated approach to model the two ATDM strategies together. Specifically, DTALite with Adaptive Ramp Metering and HD-DTA with Adaptive Signal Control strategy were iteratively simulated with one simulator providing inputs for the other simulator. Compared to the original proposed all-in-one simulation, this new approach lowers the complexity of simulation platform development while introduce possible bias to the results of joint simulation of adaptive ramp metering and adaptive signal control. In the meantime, convergence of iterations (i.e., ensure the improving direction of iterations) is also tricky and in need of engineering judgement.

Figure 4-25 shows the architecture of this new simulation framework, referred to as Multi-Resolution Simulation Platform (MRSP). There are four major components on MRSP: DTALite/NEXTA, High-Definition (HD) DTA simulator, ASC3 signal control emulator (Vissim) and RHODES adaptive traffic signal control system. The HD-DTA provides the traffic propagation analogous to DTALite/NexTA.

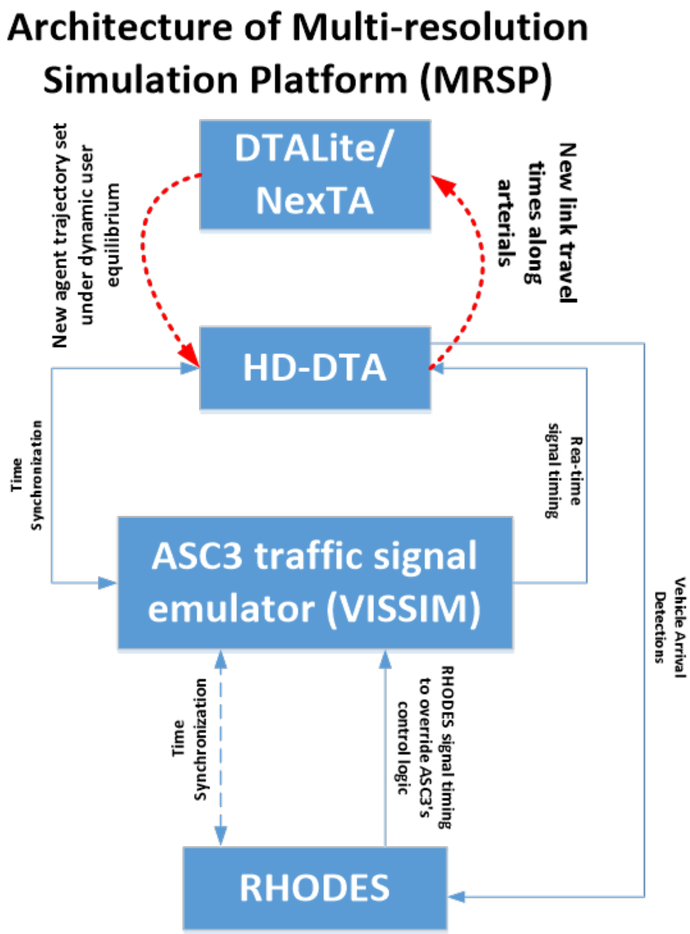


Figure 4-25: Multi-Resolution Simulation Platform Architecture [Source: ASU]

There are several necessary coupling links within MRSP to synchronize simulation clocks and establish real-time data exchange. The following paragraphs explain how those coupling links are set up.

Link 1: Time synchronization between HD-DTA and ASC/3 (Vissim)

Using any of APIs provided in Vissim, such as signal API, driving behavior API or emission API, it is possible to open a synchronous connection and continuously listen to any connections while Vissim is launching. In the meantime, HD-DTA also populates a synchronous port to couple with Vissim while launching. Through correct configuration, at each simulated second, HD-DTA need to correctly connect and communicate with Vissim in order to proceed both HD-DTA and Vissim. Through this synchronous connection, the clock synchronization is achieved.

Link 2: Real-time signal timing exchange between HD-DTA and ASC/3 (Vissim)

The latest version of ASC/3 in Vissim also includes a fully functional communication module like in the real hardware ASC/3 signal controller. This new feature makes efficiently reading real-time signal status in ASC/3 using external programs possible. Taking advantages of this feature, at each time stamp, the HD-DTA collects signal status from ASC/3 using NTCIP commands and then translate them into the open or close status of the corresponding signal links. If a signal link is open, then vehicles are allowed to enter intersections whereas if a signal link is close, then vehicles will have to wait at stop lines the signal link is re-opened.

Link 3: Time synchronization between ASC/3 (Vissim) and RHODES

There are additional challenges to synchronize the clocks between ASC/3 (Vissim) and RHODES in that there might be many RHODES-controlled intersections in reality and, if we set up an independent synchronous connection for each intersection, the communication overheads might significantly slow down the simulation speed. To address this issue, a different solution was adopted. From preliminary experiments, it was found out that microscopic simulation engine, Vissim, is almost always slower than RHODES' speed. In other words, RHODES optimization routines have to wait for Vissim to finish it current simulation step and proceed. This phenomenon provides us with the possibility of setting up an asynchronous server to broadcast Vissim's simulation step and RHODES does not proceed until it was notified so. Specifically, any APIs provided in Vissim can be used to establish a separate connection to broadcast the current simulation step, all RHODES-controlled intersections continuously monitor that broadcast simulation time to decide if it's ready to proceed. In this way, the clock synchronization is established between Vissim and all RHODES routines.

Link 4: Data Exchange between RHODES and ASC/3 and HD-DTA

In general, RHODES needs to two data sources to fulfill its optimization task: the on-going traffic signal status and the newly incoming vehicle detectors. Using NTCIP commands, RHODES retrieves real-time traffic signal status from ASC/3 (Vissim) which is also the on-going signal timing in HD-DTA simulation. On the other hand, RHODES sets up another data exchange link with HD-DTA. As described before, HD-DTA schedules detector calls according to agent movements and detector configurations on certain links. At each time step, the HD-DTA will send all detector events reaching the scheduled time at that time step to the corresponding RHODES. RHODES will translate the incoming detector calls into vehicle arrivals on various approaches and then estimate the queue lengths of left-turn, through and right-turn on each approach. Figure 4-26 shows the linking mechanism.

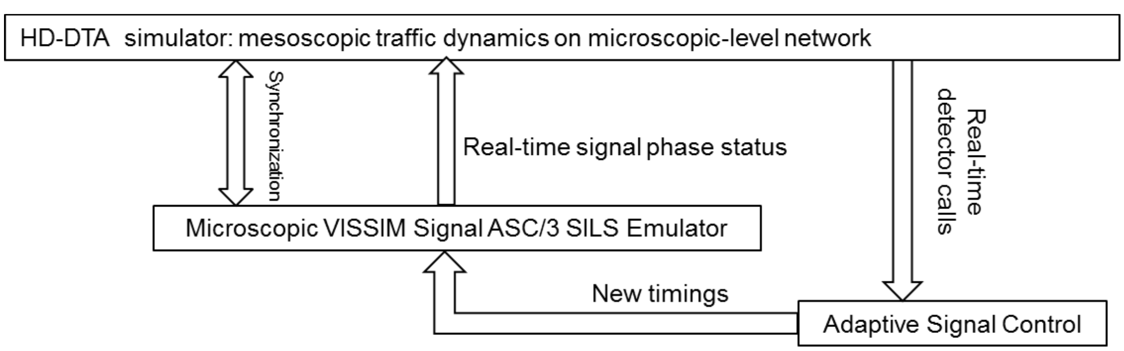


Figure 4-26: HD-DTA to ASC/3 to RHODES Interface [Source: ASU]

Link 5: Data Exchange between HD-DTA and DTALite

At this time, the DTALite for Adaptive Ramp Metering and HD-DTA for Adaptive Signal Control are not coupled through automated data exchange. Instead, the data exchange between DTALite and HD-DTA was established through manual file exchange. Specifically, in each iteration, DTALite will provide a new agent trajectory set satisfying the dynamic User Equilibrium. The agent trajectory set will be loaded into

HD-DTA network to create new travel demand along the arterial. Since HD-DTA can provide high-fidelity signal control mechanism and the resulting travel time along the arterial is likely reduced. At the end of simulation, the HD-DTA will generate updated link travel times along the arterial. Then some of the link travel times in DTALite will be updated based on the HD-DTA output and a new user equilibrium can be reached and a new set of agent trajectories will be created as well. This process is iteratively repeated between DTALite and HD-DTA until certain threshold is satisfied.

4.3 Pasadena Testbed Modeling Approach

Figure 4-27 illustrates the overall framework of the ATDM strategies implementation with the prediction component for the Pasadena testbed. The framework was designed to virtually emulate the decision-making process in a traffic management center. The framework describes main processes detection, communications, and control/advisory information dissemination technology; and system management decisions.

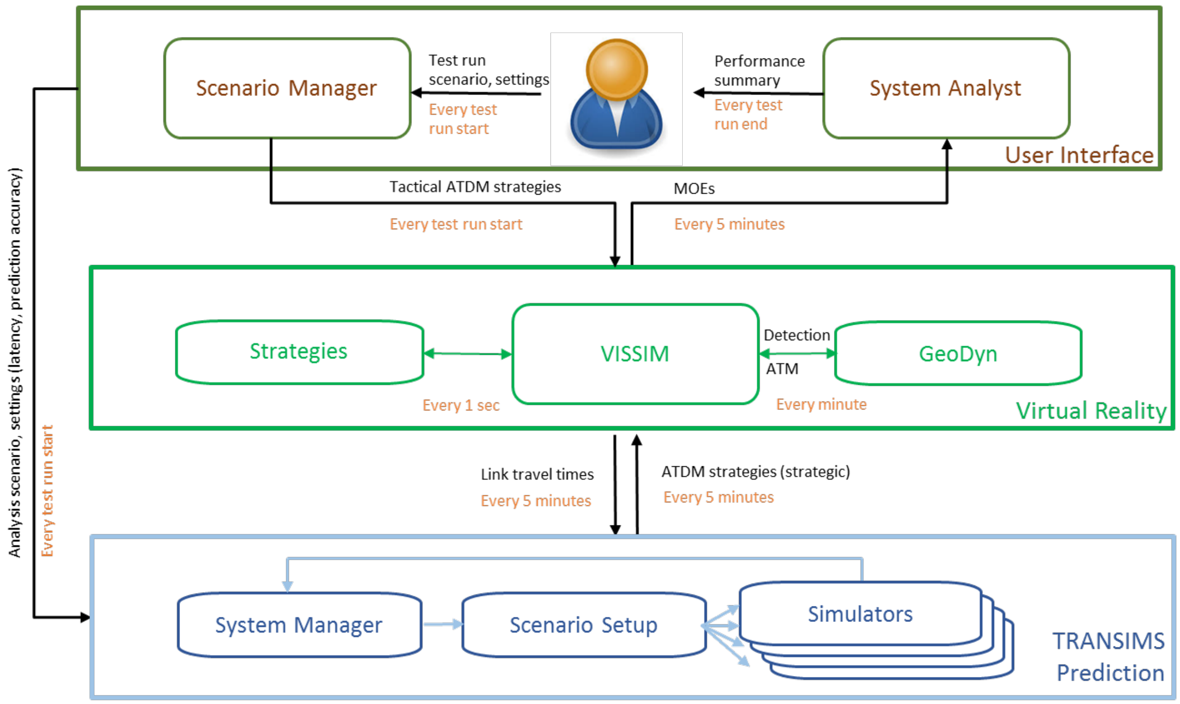


Figure 4-27: Analysis Framework for Pasadena Testbed [Source: HBA]

PTV VISSIM was used as the microscopic traffic simulation tool used to model virtual real world conditions within the Pasadena Testbed. Together with VISSIM, the testbed team also utilized PTV VISUM for DTA modeling and overall model development and management. This multi-resolution modeling toolset represents the transportation network vehicular flow simulator and the travel demand simulator in the generalized AMS testbed framework.

TRANSIMS was used as the anticipated traffic management center to evaluate the operational effectiveness of each strategy in isolation or combination. TRANSIMS receives information from VISSIM and adjusts its network's link performance parameters using the link travel time data received. Using that given information, TRANSIMS simulates the operational performance using several defined prediction parameters and recommends the strategy with the best operational performance. TRANSIMS simulates its vehicle agents at a mesoscopic level.

Several important aspects of VISSIM capabilities are used in developing the Pasadena Testbed:

- Multi-resolution modeling and model development: This is accomplished by two aspects of the VISUM/VISSIM interface: 1) the compatibility between the dynamic traffic assignment model (VISUM) and corresponding path flow (OD and path) transfer into VISSIM; 2) detailed geometric and intersection control data transferrable into corresponding modeling elements in VISSIM, for example, speed limits and signal timing plans.
- Traffic demand and routing were developed from the DTA model in VISUM for the whole testbed network. With the above multi-resolution modeling approach, VISSIM baseline models took the traffic demand and routing directly from VISUM DTA model, instead of the lengthy DTA convergence process in VISSIM microscopic simulation.
- VISSIM's RBC signal control emulator was customized to permit the change of pre-computed signal timing patterns. This allowed the testbed to analyze the Dynamic Traffic Signal Control strategy where active signal timing patterns are selected by the System Manager based on their predicted performance as determined by the Prediction System.

4.3.1 Active Traffic Management (ATM) Control

ATM control by GeoDyn2 represented the freeway management decision support system (ATDM strategies) in the generalized AMS testbed framework. The tool and included suite of algorithms for modeling ATM strategies was GeoDyn2. ATM control strategies for Pasadena Testbed included dynamic speed limits, queue warning, and adaptive ramp metering. GeoDyn2 has been successfully migrated to a testbed environment with VISSIM (http://www.hbamerica.com/index.php?id=86). Figure 4-28 shows the screen capture of GeoDyn2 testbed demo.

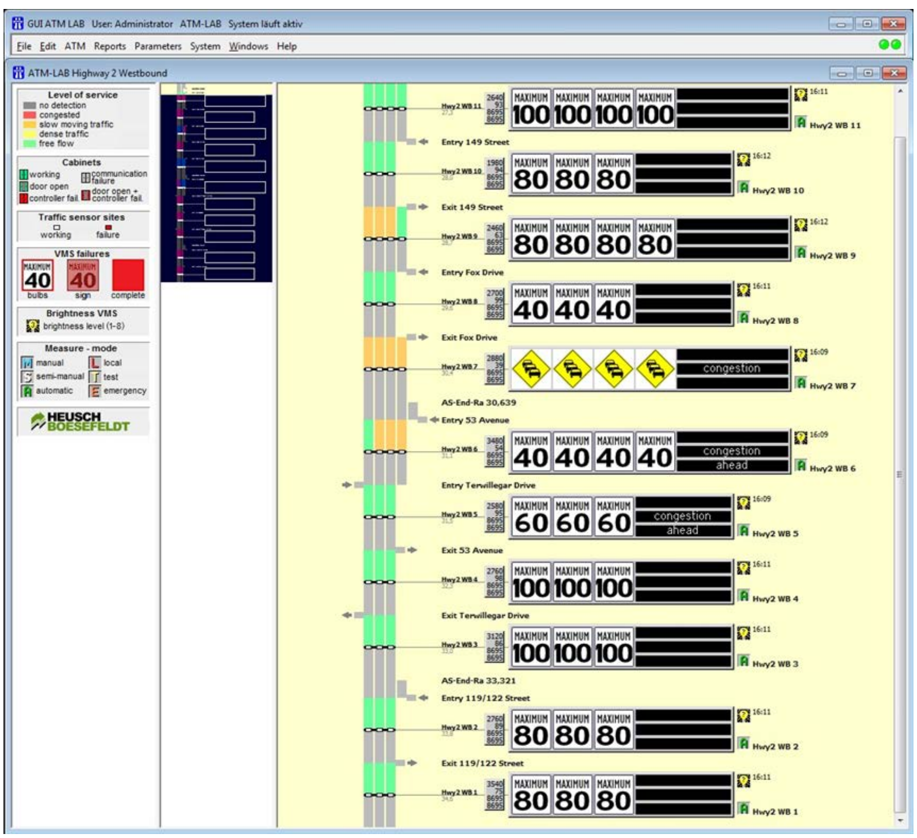


Figure 4-28: Demo GeoDyn2 Application in a Virtual ATM Lab Setup [Source: TTS]

Adaptive ramp metering plan selection is controlled by GeoDyn2 and the decision plan implementation is unique to each on-ramp for the freeway. Ramp detectors are setup at four locations within proximity for each on-ramp to provide traffic information to select the optimal plan. The detector locations are setup at the following locations: 1) Immediate entrance from the collector roads to the ramps; 2) Immediately before the stop bar; 3) Immediately after the stop bar; and 4) Along the freeway segment before the merge or weave zone. The traffic data allows GeoDyn2 to optimize the on-ramp flowrate without causing significant isolated turbulence on the freeway while not allowing vehicles to spill into the immediate collector road. Flowrate into the freeway is controlled by the change in red-signal duration between each cycle length. The individual plans for each on-ramps are revisited at a frequency of once every minute by GeoDyn2. The following are the strategy actions for ARM:

- ARM Action 1: Activate GeoDyn2 to consider Adaptive Ramp Metering

Dynamic speed limit (DSL) and queue warning (QW) is also controlled by GeoDyn2. For the Pasadena testbed, the information communicated by the DSL and QW were instrumented through dynamic lane control signs. The design guideline used for instrumenting the infrastructure is the VicRoads design guideline[15]. The overall Pasadena testbed has a total of 126 gantries placed and coded in VISSIM throughout the whole freeway. The DSL and QW identifies isolated speed congestions and distributes them over a longer segment to reduce abrupt/rapid speed differences. Freeway speed profiles are sent to GeoDyn2 via the gantries. TRANSIMS does not perform prediction for DSL and QW. GeoDyn2 proactively changes the speed limit at each gantry locations every 1-minute iteration.

The Hard Shoulder Running (HSR) and Dynamic Junction Control (DJC) are used in combination for the Pasadena testbed. The HSR strategy has two individual plans where the shoulders are opened for traffic use at limited sections or all sections. The DJC is used to manage favorable flowrates to allow increased capacity from either the I-210 southbound approach or the SR 134 approach to the I-210 eastbound freeway. The DJC dynamically changes the junction alignment at the I-210 at SR 134 interchange to manage the flowrates. A business rule was introduced for any implementation of HSR and DJC to reflect a realistic real world deployment scenario. The business rule indicates that HSR and DJC strategy must remain activated for a minimum of 30-minutes unless the plan escalates. If the plan selection escalates, the succeeding plan implementation will have a minimum activation time of 30-minutes. The HSR and DJC plans are activated via variable message signs to inform drivers of the changes in lane configurations, designations, and accessibility. The 30-minute minimum business rule was selected to provide drivers a more realistic HSR and DJC configuration expectation by avoiding frequent lane opening and closing within short durations. A 30-minute minimum activation was selected based on the lower limit of prediction horizon used for TRANSIMS. The following are strategy actions for DJC and HSR:

- DJC Action 1: Activate Dynamic Junction Control to Favor I-210 Traffic
- HSR Action 1: Activate Hard Shoulder Running Section 1
- HSR Action 2: Activate Hard Shoulder Running Section 1, 2, and 3

There are 60 signal controls within the Pasadena testbed network coded with Dynamic Signal Control (DSC) capabilities. There are three defined signal plans for the 60 DSC intersection to operate throughout the PM peak hour. The signal plans are selected through TRANSIMS recommendations and are implemented for a minimum of 5-minutes before the signal plans are reevaluated. The cycle lengths will remain the same across all available plans with adjustments to the green phases allocated to the prioritized progression associated with the plans. The following are the strategy actions for DSC:

- DSC Action 1: Activate Signal Plan Timed for Network Optimal
- DSC Action 2: Activate Signal Plan Timed for Eastbound (Peak Direction) Progression

[15] https://www.vicroads.vic.gov.au/business-and-industry/technical-publications/road-design

- DSC Action 3: Activate Signal Plan Timed for Eastbound-Westbound Progression

4.3.2 Active Demand Management System

Dynamic route guidance (DRG) is the only active demand management system used throughout the Pasadena testbed. The current DRG plans developed is to minimize the number of vehicles entering the freeway from the arterials when congestion is detected. The DRG reroutes drivers on the arterials planning to take the freeway to take route along a parallel arterial to bypass freeway congestion before reentering the freeway further downstream. There are incident DRG developed are to reroute vehicles currently on the arterials planning to enter the freeway to a route along a parallel arterial before entering the freeway from a ramp located downstream of a detected incident. The congestion DRG plans are aimed at directing vehicles on arterials to avoid congestions before entering the freeway while the incident plans are aimed to direct vehicles on arterials to avoid an incident before entering the freeway. The following are the strategy actions for DRG:

- DRG Action 1: Eastbound reroute around congestion on I-210 eastbound
- DRG Action 2: Northbound-southbound reroute around congestion on I-210 eastbound
- DRG Action 3: Eastbound-northbound-southbound reroute around congestion on I-210 eastbound
- DRG Action 4, 5, 6: Reroute around incident

DRG Action 4, 5, and 6 are customized by operational condition due to the difference in incident location. Operational condition 1 has action 4, 5, and 6 for incidents. Operational condition 2 only has action 4 for incidents. Operational condition 3 only has action 4 and 5 for incidents.

4.3.3 Prediction System

Prediction in the Pasadena Testbed included two parts, a Demand Adjustor and a Simulator, both implemented in TRANSIMS. The Demand Adjustor was based on the TRANSIMS router and while the Simulator used TRANSIMS' mesoscopic simulator. During a testbed run, the router used the current traffic state combined with assumed prediction scenario to predict OD path flows. These OD path flows, alongside other expected operational condition changes and employed ATDM strategies, were simulated by the VISSIM simulator to provide the predicted network performance metrics. There are four prediction parameters that TRANSIMS assesses when performing its prediction iteration. The following listed are the parameters with their definition and assessed values:

- Prediction Horizon: The time TRANSIMS will simulate into the future to assess traffic operations for the individual strategy plans under consideration. The prediction horizons assessed are: 15-minutes; 30-minutes; and 60-minutes.
- Prediction Latency: The time lag before any recommendations by TRANSIMS is implemented by VISSIM. The prediction latencies assessed are: 5-minutes; and 10-minutes.
- Prediction Accuracy: The percent of detector data made available to TRANSIMS to use to adjust its like performance function to adjust to the most current traffic state. The prediction accuracy assessed are: 50%, 90%, and 100%.
- Traveler Compliance: The percent of travelers that will comply with the recommendations made by TRANSIMS when assessing the strategy deployment. Under TRANSIMS prediction, this parameter only applies to DRG to reflect on the number of vehicles diverting from entering the freeway to using the arterials for a longer route to avoid congestion or incident before entering the freeway.

There are total of 10 scenarios with various isolated and combination of strategies assessed, but only seven strategy scenarios that require TRANSIMS prediction. The seven scenarios are listed as follows with the associated available plans:

Strategy Scenario 1 (ARM):

- Plan 0: Do Nothing
- Plan 1: ARM Action 1

Strategy Scenario 2 (DSC):

- Plan 0: Do Nothing
- Plan 1: DSC Action 1
- Plan 2: DSC Action 2
- Plan 3: DSC Action 3

Strategy Scenario 3 (HSR + DJC):

- Plan 0: Do Nothing
- Plan 1: HSR Action 1
- Plan 2: HSR Action 1 + DJC Action 1
- Plan 3: HSR Action 2 + DJC Action 1

Strategy Scenario 5 (DRG):

- Plan 0: Do Nothing
- Plan 1: DRG Action 1
- Plan 2: DRG Action 2
- Plan 3: DRG Action 3
- Plan 4: DRG Action 4
- Plan 5: DRG Action 5 (OC 1 and OC 3)
- Plan 6: DRG Action 6 (OC 1)

Strategy Scenario 6 and 9 (ARM + HDR + DJC):

- Plan 0: Do Nothing
- Plan 1: ARM Action 1 (Freeway Congestion is Not Heavy)
- Plan 2: ARM Action 1 + DJC Action 1 (Freeway Congestion is Not Heavy)
- Plan 3: HSR Action 1 + ARM Action 1 (Freeway Congestion is Heavy)
- Plan 4: HSR Action 1 + DJC Action 1 + ARM Action 1 (Freeway Congestion is Heavy)
- Plan 5: HSR Action 2 + DJC Action 1 + ARM Action 1 (Freeway Congestion is Heavy)

Strategy Scenario 7 (DSC + DRG):

- Plan 0: Do Nothing
- Plan 1: DRG Action 1
- Plan 2: DRG Action 2
- Plan 3: DRG Action 3
- Plan 4: DRG Action 1 + DSC Action 1 (Freeway Congestion is Heavy)
- Plan 5: DRG Action 2 + DSC Action 1 (Freeway Congestion is Heavy)
- Plan 6: DRG Action 3 + DSC Action 1 (Freeway Congestion is Heavy)
- Plan 7: DRG Action 4 + DSC Action 2 (Traffic Incident)
- Plan 8: DRG Action 5 + DSC Action 2 (Traffic Incident)
- Plan 9: DRG Plan 6 + DSC Plan 2 (Traffic Incident)

Strategy Scenario 8 and 10 (ARM + HSR + DJC + DSC + DRG):

- Plan 0: Do Nothing

- Plan 1: DRG Action 1
- Plan 2: DRG Action 2
- Plan 3: DRG Action 3
- Plan 4: DJC Action 1 + DRG Action 3 + DSC Action 1 + ARM Action 1
- Plan 5: DJC Action 1 + HSR Action 1 + DSC Action 1 + ARM Action 1
- Plan 6: DJC Action 1 + HSR Action 2 + DSC Action 1 + ARM Action 1
- Plan 7: DJC Action 1 + DRG Action 4 + DSC Action 2 + ARM Action 1
- Plan 8: DJC Action 1 + DRG Action 5 + DSC Action 2 + ARM Action 1
- Plan 9: DJC Action 1 + DRG Action 6 + DSC Action 2 + ARM Action 1

4.3.4 Traffic System Manager and Communication Simulator

The Traffic System Manager module represents the system manager and their decision emulator while the Communication Simulator in Pasadena Testbed represents the wireless communication emulator in the generalized AMS testbed framework. Both tools were implemented within TRANSIMS. The System Manager emulates the decision processes of a typical traffic management center operator. These decisions will include:

- Select the strategic ATDM strategy set to be evaluated by the prediction system.
- Determine and initiate the implementation of the most appropriate ATDM strategy set based on predictive evaluation results.
- Broadcast of incident messages processed by the Communication Simulator.

The Communication Simulator primarily provides the representation of data loss and latency, two key aspects that affect the ATDM implementation. The Prediction System and the Traffic System Manager/Communication Simulator are closely linked with both systems forming one inner data loop, as depicted in blue in Figure 4-29. The featured prediction loop including TRANSIMS router and simulator can evaluate multiple instances in parallel; each instance representing one ATDM strategy set from the System Manager. The goal of this loop is to identify the best ATDM strategy set for implementation in VISSIM (virtual real world).

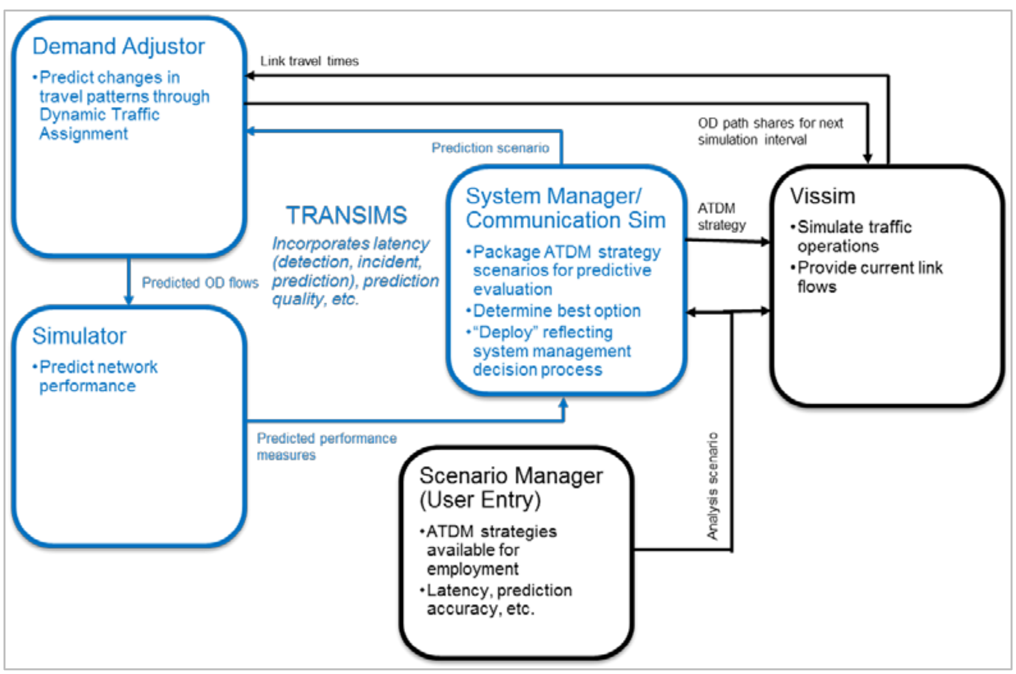


Figure 4-29: Pasadena Testbed Prediction System Architecture [Source: HBA]

4.3.5 Scenario Manager

The Scenario Manager is the Pasadena Testbed run-time control module. The Scenario Manager is provided with a graphical user interface for easy operation control of the testbed. Each testbed run is initiated by the Scenario Manager. The specific evaluation parameters, including tested ATDM strategies, latency, prediction quality, will be broadcasted to all subsystems.

The functions of Scenario Manager include:

- Selection of tactical ATDM
- Selection of available strategic ATDM strategies and DMA applications
- Selection of prediction and communication test parameters
- Start/end testbed sessions

The Scenario Manager was custom developed for the Pasadena Testbed. It controls a two combination sets of predefined strategies and prediction parameters. The strategies can be selected in isolation or in combination. Figure 4-30 shown a screenshot of the Scenario Manager GUI used to manage the simulated parameters and handle the packaged information sent to TRANSIMS and apply the plan recommendations sent from TRANSIMS.

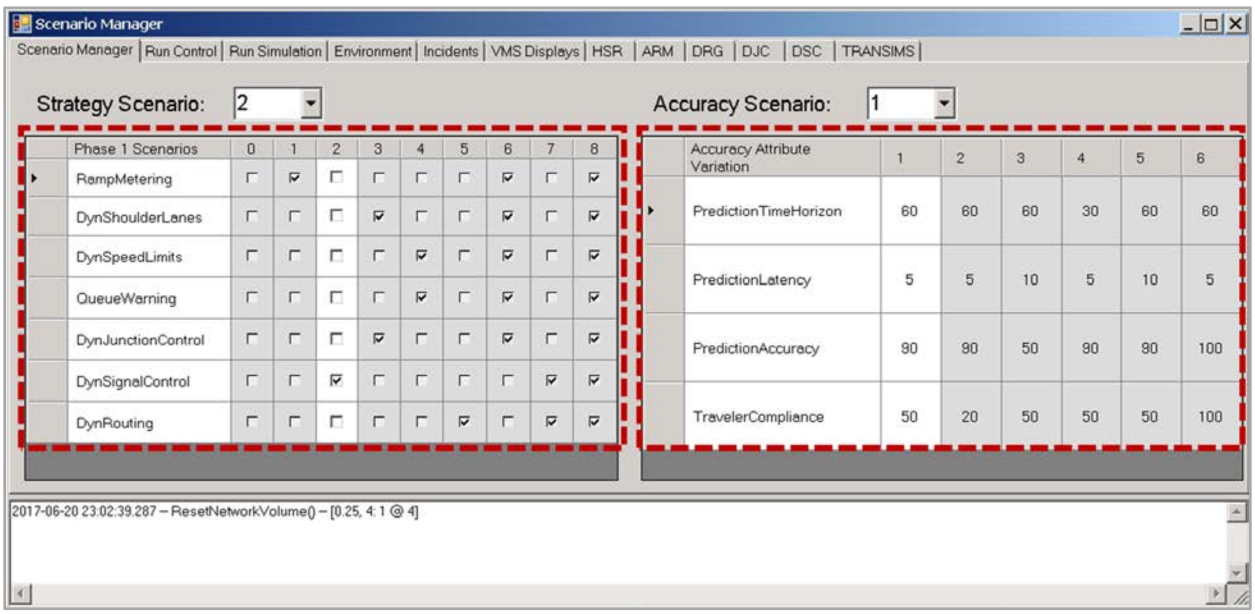


Figure 4-30: Pasadena Testbed Scenario Manager GUI [Source: HBA]

4.4 Chicago Testbed Modeling Approach

The Chicago Testbed is modeled in DYNASMART, a (meso) simulation-based intelligent transportation network planning tool. It simulates and visualizes dynamic traffic assignment under certain circumstances. The model can be configured to run offline or online. The offline model (DYNASMART-P) includes dynamic network analysis and evaluation, while the online model (DYNASMART-X) adds short term and long term prediction capabilities.

DYNASMART models the evolution of traffic flows in a traffic network resulting from the travel decisions of individual drivers. The model is also capable of representing the travel decisions of drivers seeking to fulfill a chain of activities, at different locations in a network, over a given planning horizon. It is designed for use in urban areas of various sizes (large and small) and is scalable, in terms of the geometric size of the network, with minimal degradation in performance. DYNASMART can also model the fine details of transportation networks such as zones (any number of zones), intersections, links, origins and destinations. The user can specify any zonal configuration for the network, as long as it is consistent with the origin-destination demand matrix. Links may be modeled as freeways, highways, ramps, arterials, and high occupancy toll lanes, etc. Each link is represented by its length, number of lanes, existence of left-turn bays, maximum traffic speeds, etc. Two-way lane roads are modeled as two links, i.e. no overtaking is allowed by taking space in the opposing lane. Link junctions with different signalized and non-signalized control options are also modeled. Finally, DYNASMART-P can represent trip origins, destinations and even intermediate destinations for trip chaining.

Inheriting the core simulation components from DYNASMART-P, the primary distinction of the online operational tool (DYNASMART-X) is its capability of interacting with multiple sources of information and providing reliable estimates of network traffic conditions and predictions of network flow patterns. A comprehensive DYNASMART-X simulation is triggered by the following six algorithmic modules:

- Network State Estimation (RT-DYNA) module provides up-to-date estimates of the current state of the network. It has the full simulation functionality as DYNASMART-P, and its execution is synchronized to the real-world clock.
- Network State Prediction (P-DYNA) module provides future network traffic states for a pre-defined horizon, as an extension from the current network state estimated by RT-DYNA.
- OD Estimation (ODE) module uses a Kalman filtering approach to estimate the coefficients of a time-varying polynomial function that is used to describe the structural deviation of OD demand in addition to a historical regular pattern.
- OD Prediction (ODP) module uses the predicted OD coefficients provided by ODE to calculate the demand that is generated from each origin to each destination at each departure time interval. The predicted time dependent OD matrices are used for both current (RT-DYNA) and future (P-DYNA) stages.
- Short Term Consistency Checking (STCC) module uses the link densities and speeds of the simulator to evaluate the consistency of the flow propagation with the real-world observations and correct the simulated speeds.
- Long Term Consistency Checking (LTCC) module compares the simulated and observed link counts to calculate scaling factors that are used to adjust the demand level in both RT-DYNA and P-DYNA.

Note that STCC is executed much more frequently than LTCC. The purpose of these two levels of consistency checking is to minimize the deviation or discrepancy between what is estimated by the system and what is occurring in the real world, in an effort to control error propagation.

The algorithmic components described above form the main structure of the DYNASMART-X system. The interconnection between these components and the basic data flow model are illustrated in Figure 4-31.It also includes the interaction between DYNASMART-X system and external real world, as STCC, LTCC, and ODE form the data interface which receive measurements (count, speed, and occupancy) continuously from traffic detectors.

The graphical user interface (GUI) is another supporting component in DYNASMART-X, which aims to provide a convenient environment for executing the algorithms by allowing users to enter input data, and enables users to view and analyze simulation results "on the fly". Figure 4-32 presents a snapshot of DYNASMART-X system running for an example network of Chicago Testbed. The three windows in the user interface display the prevailing traffic conditions, a predicted traffic condition without implementing traffic management strategy, and a predicted traffic condition with management strategy.

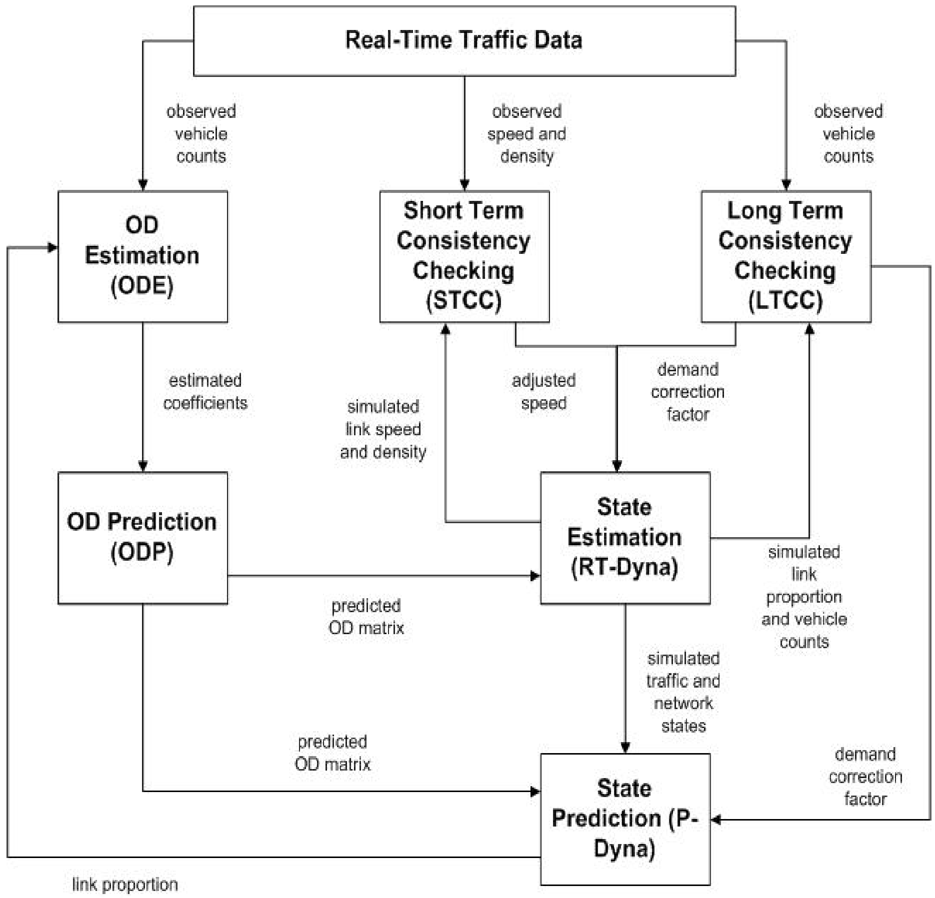


Figure 4-31: System structure of DYNASMART-X and data flow [Source: NWU]

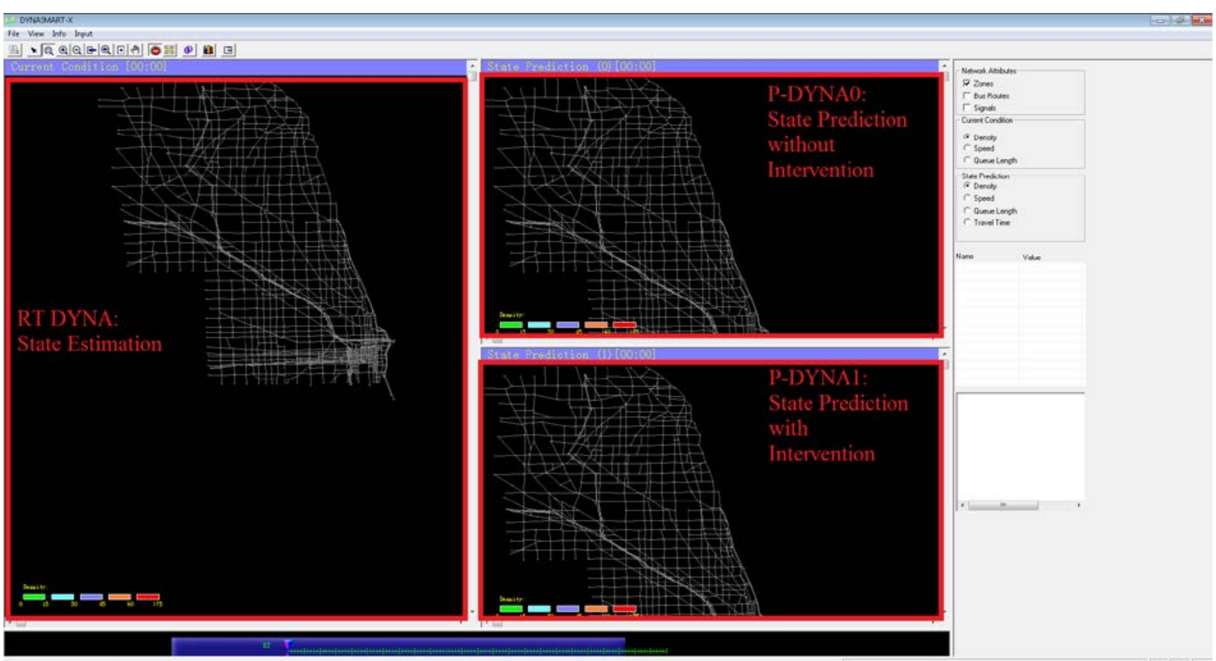


Figure 4-32: The Chicago Testbed Network as Displayed in DYNASMART-X GUI {Source: NWU]

4.4.1 Conceptual Framework

Figure 4-33 illustrates the overall modeling framework. The framework adopts a rolling horizon approach, which integrates: (1) a traffic network estimation model that emulates the real-world traffic conditions; (2) a traffic network prediction model that predicts the traffic demand and network performance given prevailing traffic conditions; and (3) a decision support system that is responsible for evaluating the estimated and predicted traffic states and generating or adjusting traffic management operations.

The network state estimation and prediction modules are developed based on the state-of-the-art TrEPS models (Ben-Akiva, Bierlaire, Koutsopoulos, & Mishalani, 2002; H. S. Mahmassani, 1998; H. S. Mahmassani & Zhou, 2005). It uses a simulation-based dynamic traffic assignment (DTA) approach for real-world traffic estimation and prediction, and is capable of capturing the network dynamics resulting from the network's demand-supply interaction. The DTA simulation model is coded in DYNASMART, a (meso) simulation-based intelligent transportation network planning tool. The model can be configured to run offline or online. Offline model (DYNASMART-P) includes dynamic network analysis and evaluation, and online model (DYNASMART-X) adds short-term and long-term prediction capabilities. In this study, DYNASMART-X is adopted as the TrEPS model for demand and state prediction.

As is shown in Figure 4-33 , the closed-loop framework consists of six modules: (1) network state estimation module, (2) demand estimation module, (3) demand prediction module, (4) network state prediction module, (5) system evaluation module, and (6) decision making module. Modules (1), (5) and (6) are conducted within the offline model, and Modules (2), (3) and (4) are implemented in the online model. The offline model and online model are connected to transfer information. The link volume and speed from the offline model, which emulates the real-world traffic conditions, are treated as traffic flow observation and sent into the online model as the reference to adjust estimated and predicted traffic demand and state. The predictive traffic information from the network prediction module in the online model is sent back into the offline model for system evaluation and decision making.

Both simulation and evaluation are conducted with a moving horizon to predict and feedback the network performance. As illustrated in Figure 4-33 (a), the network performance that covers a pre-defined horizon (e.g., 30 minutes) is continuously collected and transferred every roll period (e.g., 5 minutes). The offline simulation of real world does not stop and wait for the feedback from online prediction, and thus a latency may occur due to the calculation time and information transfer. At the interval that the offline model receives predictive information, the system evaluation and decision making modules are triggered to generate appropriate adjustment for the current traffic management strategies. The adjustments include updating route choices for ADM strategies, changing the service direction on reversible lanes or opening shoulder lanes for ATM strategies, and generating new snowplow route when weather-related Strategies are triggered. It is worth mentioning that the pre-defined horizon may be extended for the weather-related strategies when snow accumulation exceeds the threshold within one prediction stage (Figure 4-33 (b)). The long-time prediction (e.g., 3 hours) is required to calculate the snowplow routes given the assumption that the snowplow vehicle is expected to accomplish a round trip and return to the depot within 3 hours, but the ATDM strategies do not need long-time prediction to update the strategies. The longer prediction horizon takes longer calculation time and may lead to larger latency. Therefore, to save computational cost and reduce information transfer latency, the prediction horizon is extended if and only if the weather-related strategies are required.

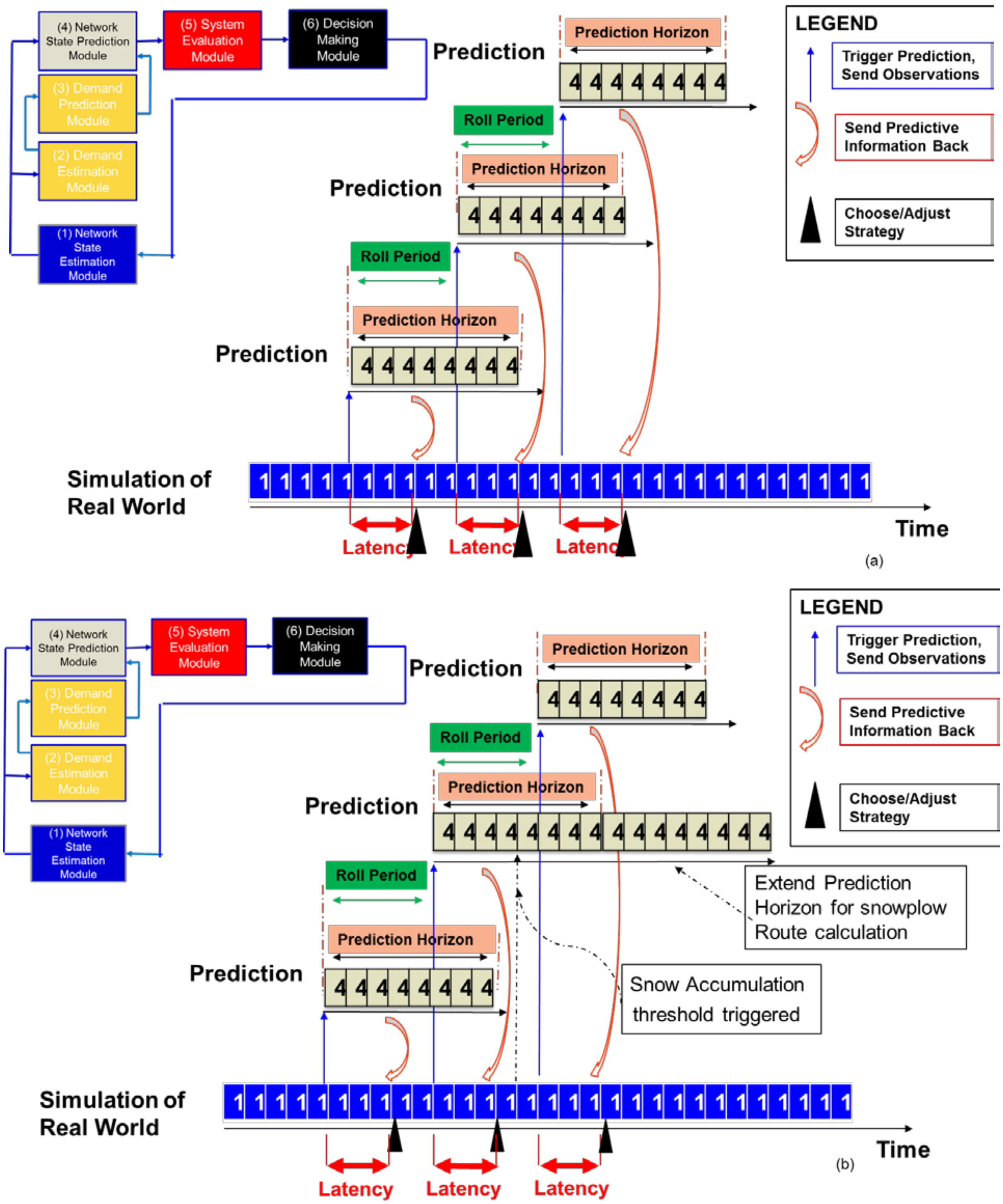


Figure 4-33: (a) Framework for traffic network management system with decision making capabilities; (b) Framework for traffic network management system with decision making capabilities for weather-responsive strategies. [Source: NWU]

4.4.2 Active Traffic Management Strategies

The adaptive traffic signal control in this context takes into consideration the real-time and predictive traffic demand in order to adjust corresponding phase's green time The adaptive traffic signal control, as with actuated type of control, requires a minimum (G-min) and a maximum (G-max) green time set up for each of the signalized intersections. To allow for preferential treatment of vehicles traversing in the major direction, G-min for major approaches and G-max for minor approaches were set to correspond to green times obtained from pre-timed signal timing plans (and weather-responsive signal timing plan, if applicable). These values determined the upper and lower boundary of the minimum and maximum green times. The approach essentially applies the same actuated operation principle, however, based on predicted real-time traffic conditions it updates each corridor's coordinated signal timing plans

Dynamic Shoulder Lanes

The dynamic shoulder lanes allow vehicles to drive on the shoulder lanes during the specific time of day. The period to open shoulder lanes is the peak hour on the weekdays, i.e. 5-9 AM for the inbound direction and 3-7 PM for the outbound direction for weekdays, when general traffic is moving at less than 35 mph. This operational setting is based on the I-55 Bus-on-Shoulder Demonstration program suggested by the Illinois Department of Transportation. More details can be found at the website for this program (http://www.idot.illinois.gov/transportation-system/Network-Overview/transit-system/i-55-bus-on-shoulder). In order to move the most people through congestion and promote public transportation, the shoulder option was an added feature that can be used when available.

Note that the shoulder was closed in during maintenance. For this study, winter maintenance was evaluated. Thus, the primary lanes of the highway, ramps and interchanges are the first priority for snow removal. As a result, the shoulder may not be available for several days during and immediately after a winter storm. Shoulders are plowed and cleared of snow as soon as conditions allowed after a snowstorm. The shoulder lanes are not available during the medium and heavy snow conditions.

Modeling Approach

As shown in Figure 4-34, there are several freeway segments in the Chicago testbed: I-94 to the northern suburban areas, I-90 to the northwestern suburban areas, I-290 to the western suburban areas, and I-90 and I-94 merges and connects to the downtown area. In addition, the Lake Shore Drive connects the downtown area and the northern part of the Chicago city. Among these segments, Lake Shore Drive does not have the shoulder lanes, and I-90/94 is parallel to the Kennedy Expressway, which is the reversible lane in the Chicago testbed. As such, the candidates for the dynamic shoulder lane strategy are I-90, I-94 and I-290 segments. As with I-290, 95% of the segments are wider than 8 inches, 77% of the segments are with shoulder lanes wider than 10 inches, and over 62% are wider than 12 inches. The details of the shoulder widths are listed in Table 4-2 ("Roadway Existing Conditions," 2013). The shoulder lanes are paved and with rumble strips at the edge.

Along northbound and southbound I-90/94, the existing shoulder widths vary between four and five feet. In order to build the I-90 "Golden Corridor"(Val, 2016) and "Smart Corridor" (Rossi, 2015), the I-90 project allows express buses on the shoulder. The Illinois Tollway has included beefed-up shoulders as part of its reconstruction and widening of I-90 from the Kennedy in Chicago to Barrington Road in Hoffman Estates. The Tollway hopes to try out "connected technology" on the 10 bus routes that will be operating on the shoulder of the new I-90 (Figure 4-35). Therefore, the dynamic shoulder lane strategy was implemented on I-290 and I-90.

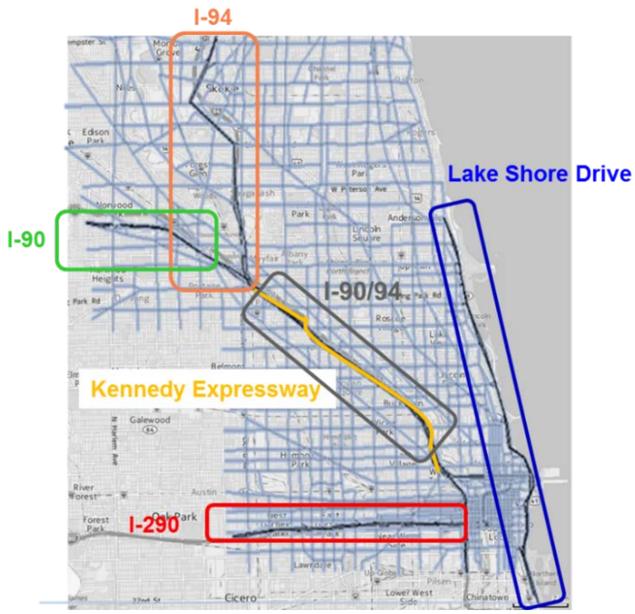


Figure 4-34: Freeway segments in the Chicago Testbed {Source: NWU]

Table 4-2: Existing Mainline Shoulder Widths [Source: NWU]

Shoulder Width	Westbound				Eastbound				Overall	
	Left		Right		Left		Right			
2' to < 4'	1,620	8%	0	0%	0	0%	0	0%	1,620	2%
4' to < 6'	463	2%	0	0%	293	1%	0	0%	756	1%
6' to < 8'	792	4%	0	0%	891	4%	0	0%	1,683	2%
8' to < 10'	11,425	53%	584	3%	911	4%	773	5%	13,693	18%
10' to < 12'	7,076	33%	232	1%	3,036	14%	1,068	7%	11,412	15%
12' to < 14'	0	0%	9,570	55%	15,713	72%	13,823	86%	39,106	51%
14'	0	0%	7,044	40%	1,077	5%	445	3%	8,566	11%
Total	21,376		17,430		21,921		16,109		76,836	

Overall right shoulder lengths are less than left shoulder lengths due to ramps entrances and exits.

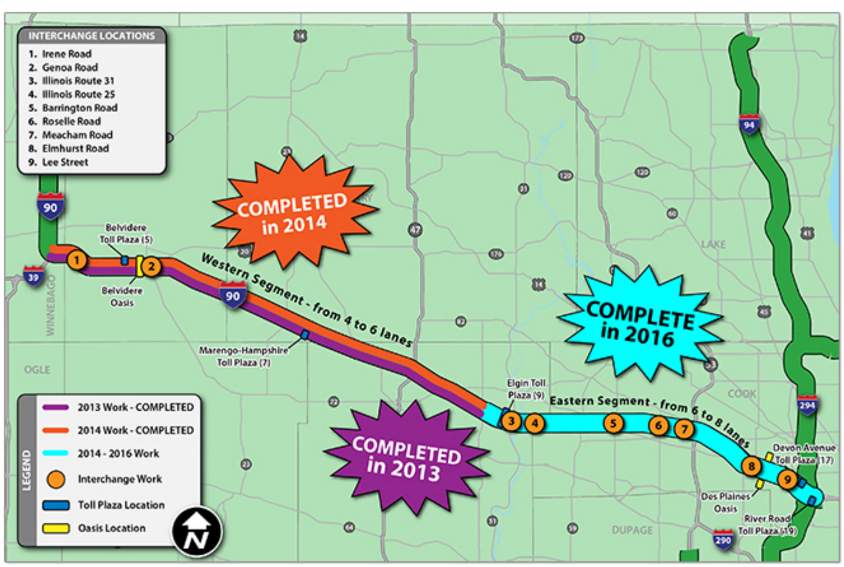


Figure 4-35: The new I-90 of the Chicago metropolitan area [Source: NWU]

Figure 4-36 shows the procedure to implement this strategy. The implementation is involved within both estimation and prediction module according to the schedule of dynamic shoulder lane to open shoulder lanes is the peak hour on the weekdays. The schedule is predefined same as I-55 Bus-on-Shoulder program, which allows vehicles traveling on shoulder lane during 5-9 AM for the inbound direction and 3-7 PM for the outbound direction for weekdays. If the module is triggered to implement this strategy, the module is checking the current status of shoulder lane and compared it with the predefined schedule so that Variable Message Sign (VMS) informs whether shoulder lane is available or not.

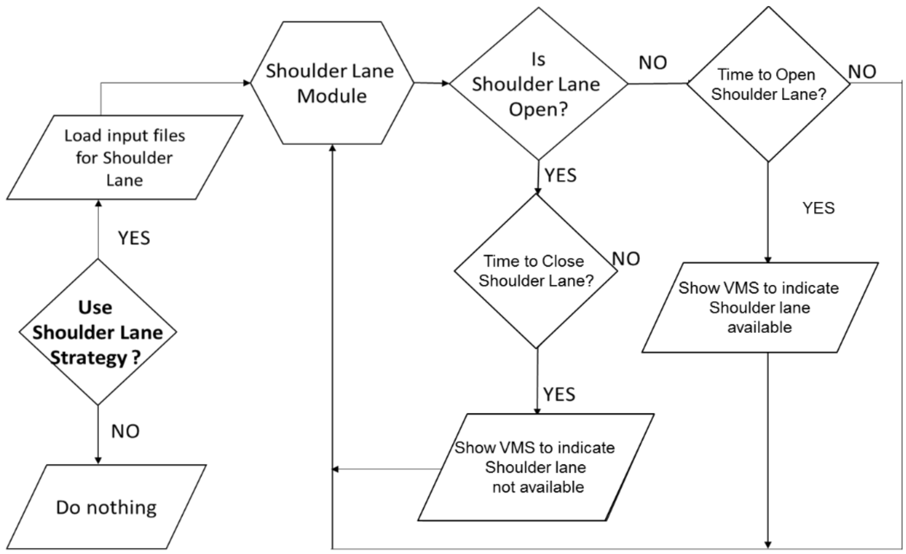


Figure 4-36: Flowchart of dynamic shoulder lane [Source: NWU]

Dynamic Lane Use Control

The dynamic lane use control is defined as the dynamic reversible lane in the Chicago testbed. To follow the reality in the Chicago testbed, the reversible lane is proposed to be the real-world Kennedy Expressway. The Kennedy Expressway is operated based on both a schedule (shown in Table 4-3) and the real-time schedule is available from checking the website http://www.kennedyexpresslanes.com/. However, the direction for service changes in response to special events, weather conditions, and incidents on the highway

The reversible lanes affect a large portion of the downtown expressway network, not just the Kennedy Expressway itself. The reversible lanes almost always open in the direction of higher volume of vehicles although the corresponding travel time may be lower due to the extra lanes going in the direction of that higher volume.

Table 4-3: Kennedy Reversible Schedule

Day of Week	From	To	Target Start
Monday - Thursday	Inbound	Outbound	12:30 PM
Friday	Inbound	Outbound	1:30 PM
Monday - Friday	Outbound	Inbound	11:00 PM
Saturday	Inbound	Outbound	2:00 PM
	Outbound	Inbound	5:00 PM
	Inbound	Outbound	8:30 PM
Sunday	Outbound	Inbound	12:01 AM
	Inbound	Outbound	2:00 PM
	Outbound	Inbound	11:00 PM

Note that the Friday afternoon schedule may be altered to accommodate heavy inbound travel times in reality. In those instances, the flip from outbound to inbound may occur as early as 6:00 PM based on congestion, impacts to other facilities, incidents and special events. However, in this study, the default schedule is followed as the Friday scenario is calibrated with medium level demand (OC 5) and no incident or special event occurs.

Modeling Approach

Figure 4-37 shows the procedure to implement this strategy. To guarantee the availability when reversing the direction for service, vehicles are "flushed" to take a detour from the expressway segment. The clearance time is 10% more than the expected travel time for the segment. Note that this strategy is implemented when the TrEPS model predicts the traffic condition for the prediction horizon as well as the system is simulating the real world. In other words, the implementation is involved within both estimation and prediction module.

If reversible lane strategy is implemented, the reversible lane module is triggered with specific input files. Within any simulation (including estimation and prediction) interval, the module is checking where any onramp to reversible lane is already open first. If not, the module checks if it is time to open reversible lane according to the schedule. As the reversible lane should be always open for one direction, the answer should be YES to this question. Before open any direction service, the system should always check if there is any vehicle on the other direction. If not, it is safe to open; otherwise, the vehicles should be flushed first to the exit (i.e. the nearest off-ramp of reversible lane). On the other hand, if there is any direction already open for service, the module calculates the clearance time and predicts time to close onramps and stop provide more service. Besides, if the clearance time is estimated to be longer than scheduled time, the module decides to flush vehicles so that the other direction can be open on time.

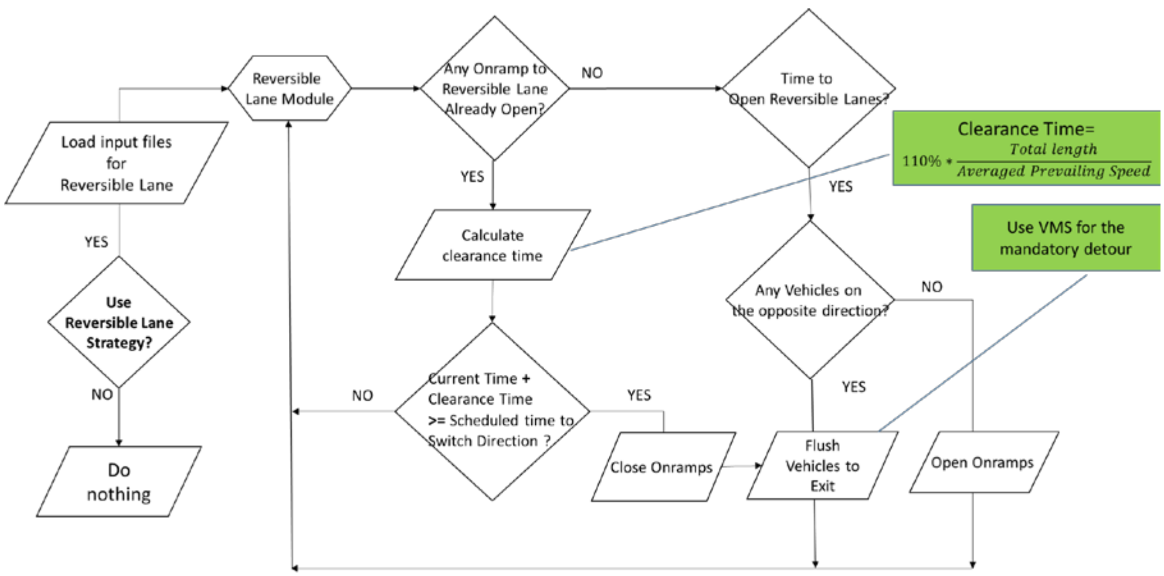


Figure 4-37: Flowchart of dynamic lane use control [Source: NWU]

Dynamic Speed Limit

Dynamic speed limit is a process of updating the speed limits in response to the predictive and prevailing traffic conditions. It can take into account the weather condition and other local geometries and road conditions. For the Chicago Testbed, the dynamic speed limit is generated according to the decision tree and implementation flowchart designed for speed harmonization.

Adaptive Traffic Signal Control

The adaptive traffic signal control refers to (vehicle) actuated signal control operation which favors major direction vehicle progression. It takes into consideration the real-time and predictive traffic demand in order to adjust corresponding phase's green time. The adaptive traffic signal control requires a minimum (G-min) and a maximum (G-max) green time set up for each of the signalized intersections. DYNASMART continues to extend the green (beyond G-min) up to G-max, as along as vehicles are detected at the stop bar. To allow for preferential treatment of vehicles traversing in the major direction, G-min for major approaches and G-max for minor approaches were set to correspond to green times obtained from pre-timed signal timing plan (and weather-responsive signal timing plan, if applicable).

Modeling Approach

Each corridor consists of a number of fully actuated signalized intersections. Specific features of the three corridors are described below.

- Case 1: W Peterson Avenue. It is a 4-mile corridor with 8 signalized intersections connecting I-94 Freeway and Lakeshore Drive Highway. The intersection spacing ranges between 0.17 and 1 mile with an average spacing of 0.56 miles
- Case 2: W Chicago Avenue. It is a 4-mile corridor with 11 signalized intersections connecting I-90 Freeway to the city. The intersection spacing ranges between 0.13 and 0.62 miles with an average spacing of 0.35 miles
- Case 3: McCormick Boulevard. It is a 4-mile corridor with 9 signalized intersections. This corridor is located in the city and is relatively away from the freeways and highways. The intersection spacing ranges between 0.24 and 0.52 miles with an average spacing of 0.45 miles

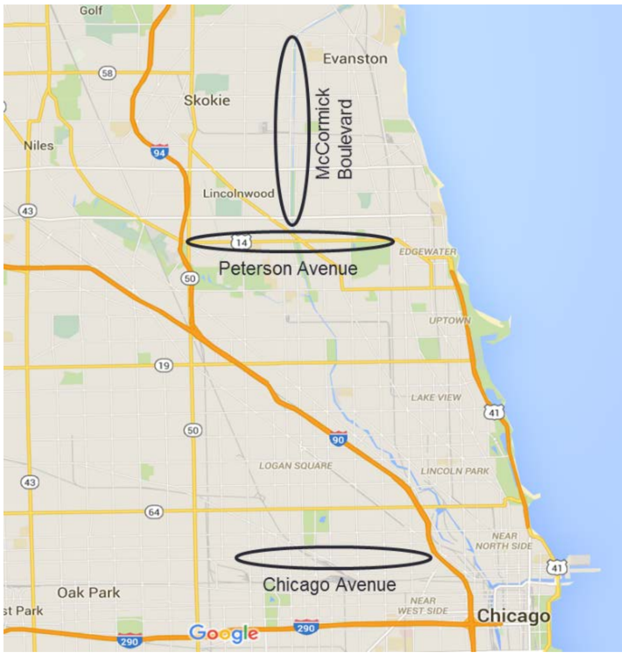


Figure 4-38: Corridors with adaptive traffic signal control [Source: NWU]

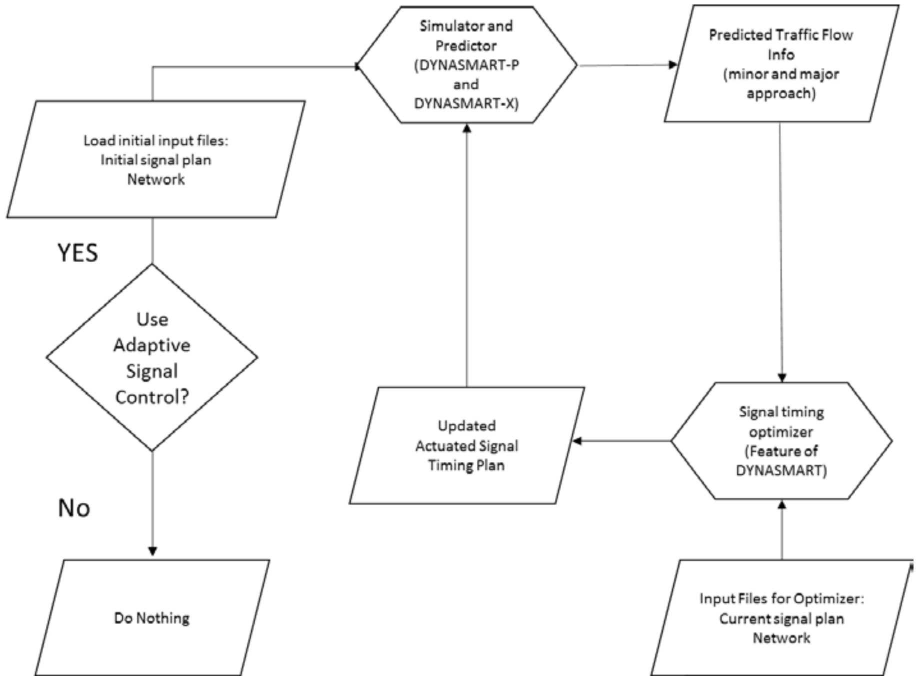


Figure 4-39: Flowchart of adaptive signal control [Source: NWU]

Figure 4-39 introduces the implementation procedure of the adaptive signal control strategy. To implement the strategy under any operational condition, the simulator and predictor loads initial input files to generate and update traffic flow information for the signal timing optimizer. Meanwhile, the optimizer requires the current signal plan and network features to generate an updated actuated signal plan for the simulator and predictor. The procedures are conducted in a loop to simulate the traffic conditions and optimize the signal plan.

4.4.3 Active Demand Management Strategies

Active Demand Management Strategies (ADM) bundle include two individual ATDM strategies, which are predictive traveler information and dynamic routing. The ADM strategies are implemented as a bundle. The travel time (cost) to calculate time-dependent shortest path for dynamic routing is obtained from predictive traveler information within a pre-defined prediction horizon, which also belongs to prediction features to be evaluated and tested in this study.

Predictive Traveler Information

The prediction traveler information is calculated by TrEPS which predicts the traffic state, including traffic flow, travel time, speed, and other parameters for a predefined prediction horizon and helps choose and adjust the traffic management strategy and operations.

Modeling Approach

To implement this strategy, we emphasize how to connect the prediction results and the emulation of the real-world. To do so, we adopt the DYNASMART-X as the predictor and DYNASMART-P as the emulator, which is capable of reproducing traffic conditions given either traffic origin-destination matrix or individual trip data. To implement and evaluate the strategies, the DYNASMART-P and DYNASMART-X are running simultaneously, but DYNASMART-P, regarded as the real world, loads demand from individual trip data, where we provide vehicle departure information and the original paths; DYNASMART-X loads from OD matrix to simulate the real-world in DYNASMART-P. At the beginning of each prediction stage, DYNASMART-P is sending the link volume and speed to DYNASMART-X as the real-world observations to adjust the estimation status in DYNASMART-X, and after prediction finishes, DYNASMART-X will send the travel time and turn penalty back to DYNASMART-P as the predictive traveler information. Note that vehicles that have access to the predictive traveler information are able to update their routes to the new shortest path calculated by the dynamic routing strategy.

Dynamic Routing

The dynamic routing strategy calculates the shortest path for the vehicle from its current node to its destination. The shortest path can achieve both user equilibrium and system optimum. In this study, we adopt the user equilibrium and the Variable Message Sign (VMS) as the main constraint to generate the shortest path.

Modeling Approach

Once the predictive travel cost is available from online model, the shortest path (SP) calculation becomes dynamic with involvement of time-dependent travel time. In a static simulation environment where predictive travel cost is not available, the SP is calculated with prevailing travel time and assigned for individual vehicles. If a vehicle able to receive en-route information, the route of this vehicle is updated when the travel cost of the new calculated SP is less than the pre-specified path and the cost savings exceed the threshold (e.g. 1 minute or 5 minutes for the entire trip). Once the predictive travel cost is available from online model, the shortest path calculation becomes dynamic with involvement of time-dependent travel time. The difference between static SP and dynamic SP lies in that the travel time $t(l)$ for link l keeps the same during the static SP calculation when the vehicle is moving, but in the dynamic SP calculation, the travel time $t(l,\tau)$ for link l keeps updating according to the arrival time τ at link l. As such, the dynamic SP with predictive travel information provides a better emulation than the static SP assignment.

The predictive information strategy and dynamic routing strategy are implemented in a bundle according to the design framework shown in Figure 4-40. Note that the predictive information will be sent back to the simulation of the real world from the predictor, but it is not guaranteed that every driver in the transport system can have access to the information. If some drivers have access to the predictive information, they can decide whether to update their route choice according to their individual route choice rule.

If ADM strategy bundle is implemented, the ADM module is triggered with specific input files. Every prediction roll period, the ADM module refers to the traffic prediction, gets predictive link travel time, and calculates the new SP. But the new SP are only provided for the drivers who have access to predictive traveler information. For these part of drivers, they can check whether the saving time is larger enough and decide whether to update their path; other drivers can only follow the old SP.

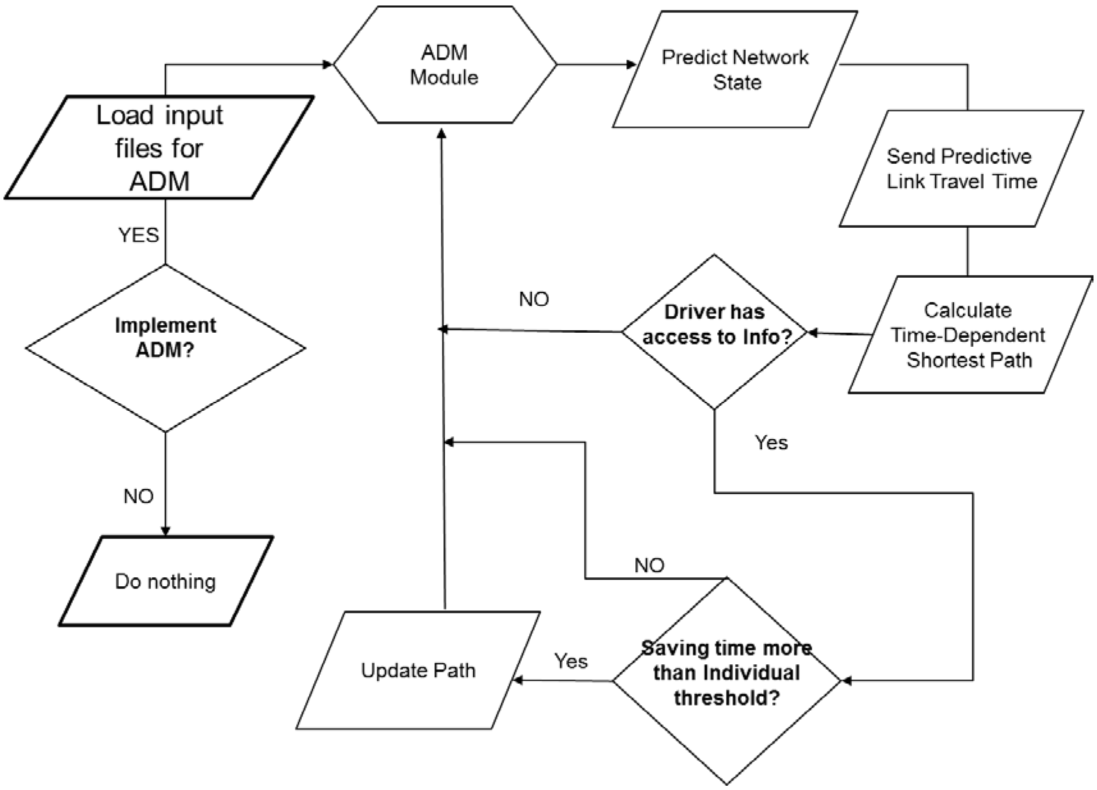


Figure 4-40: Flowchart of Active Demand Management strategies [Source: NWU]

4.4.4 Weather-Related Strategies

Weather related strategies includes snow emergency parking management, traffic signal priority for winter maintenance vehicles, and snowplow routing. To simulate the weather-related strategies a Winter Maintenance Module (WMM) was incorporated with a mesoscopic simulation tool. The logic of WMM is shown in Figure 4-41. Throughout the simulation horizon, the WMM continuously reads the predicted weather information for the next 3 hours and predicts the road surface condition and snow depth without anti-icing operation. When the road surface condition deteriorates to a predefined threshold, the WMM generates a maintenance plan and simulates it.

First, the emergency parking ban on arterial roads is enforced to ensure enough space for snowplow operation. Then the snowplow routing is generated based on road surface condition and predictive traffic volume and link speed for the next 3 hours. The objective function of snowplow routing is formulated to serve maximum traffic volume, where the links to be plowed are categorized with service hierarchy according to maintenance rule. After the snowplow routes are generated, signals at critical intersections are reset to give the priority to maintenance vehicles. During the snowplow operation, a link’s capacity and density will be affected. It was assumed that a lane is blocked by the maintenance vehicle during plowing and cannot be accessed by other vehicles. All other things being equal, the snowplow operation would reduce a link’s capacity and increase the density. The anti-icing/deicing operation is done in conjunction with the plowing operation by spreading chemicals to the surface of road. The chemicals can lower the freezing-point of water, melt the remaining ice and snow on the road surface and prevent the formation of bonded snow and ice in the future.

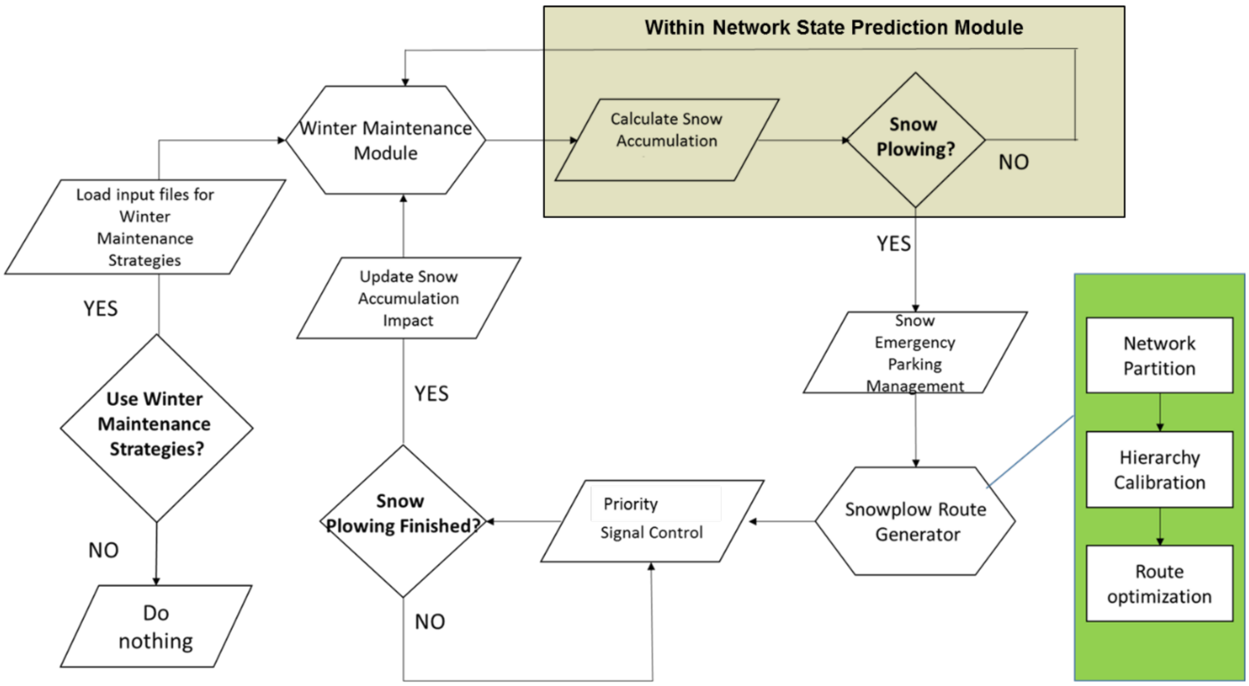


Figure 4-41: Implementation procedures of Weather-responsive strategy [Source: NWU]

Modeling Approach

First, the emergency parking ban on arterial roads is enforced to create enough space for snowplow operation. The emergency parking ban goes into effect on the arterial roads that are marked as blue in Figure 4-42 when at least 2 inches of snow falls on the street. The vehicles park on the arterial when the ban is enforced will be ticketed or towed. Within the modeling framework, if the parking ban is violated on any specific link, then it will not be accessed and plowed by the snowplow.

Then the snowplow routes are generated based on road surface condition and real-time traffic volume and link speed. We define the problem on a connected and directed graph G=(V, A), where V={0,…,n} is the vertex set and A={(i,j): i,j∈V and i≠j} is the arc set. The network is served by a homogeneous snowplow fleet R= {1, 2, …, M}. Vertex 0 is the depot where M snowplow vehicles are based. An additional vertex v_a represents an artificial depot, used as the start and end point of all routes. For every arc (i,j) ∈ A, let n_{ij} be the number of lanes, l_{ij} be the arc length and p_{ij} be the priority weight of arc ij. We incorporate the service hierarchy in the objective function by defining the priority weight p_{ij} which is calibrated both by the link volume and the type of arc. Highway, freeway, bus routes and hospital routes have the highest priority. *VOT* is defined as the average value of time of all travelers within the network. Each arc has an associated required service time t_{ij} and an associated traverse time t'_{ij}. $st(t)$ is the liquid water equivalent (LWE) snow intensity at time *t*. The LWE of snow is defined as the depth of water if one melts the snow to be measured. Depending on the snow density, the actual snow depth ranges from 4 to 10 times the LWE depth. For more information about liquid water equivalent measurement, please see (U. S. D. o. T. F. A. Administration, 2015). d_{ij}^t is the LWE of snow accumulated on the surface of arc (i,j) at time *t*. The relationship among snow depth, link speed reduction and capacity reduction is complicated. Due to the limitation of literature, we made the simplified assumptions showed in Table 4-4. d_{ij}^t is defined as following：

$$d_{ij}^{t} = \begin{cases} \int_{0}^{t} st_t dt & if\ t < t_{ijm}^{k} \\ \int_{t_{ijm}^{k}}^{t} st_t dt & if\ t > t_{ijm}^{k} \end{cases} \tag{4-1}$$

To simulate the real time traffic condition on an arc (i,j) ∈ A at time t, let $v_{ij}(t)$ denote expected average speed without any snowplow operation and $q_{ij}(t)$ represent the predicted traffic volume. $v_{ij}'(t, t_{ijm}^{k})$ is the predicted speed on an arc (i,j) at time t if the arc is scheduled to be plowed at t_{ijm}^{k}. $v_{ij}'(t, t_{ijm}^{k})$ is different from the $v_{ij}(t)$ because the snow accumulation reduces speed or/and capacity. All snowplow operation starts at t_0 when the snow accumulation surpasses a threshold and must be completed within the required service time window before t_e.

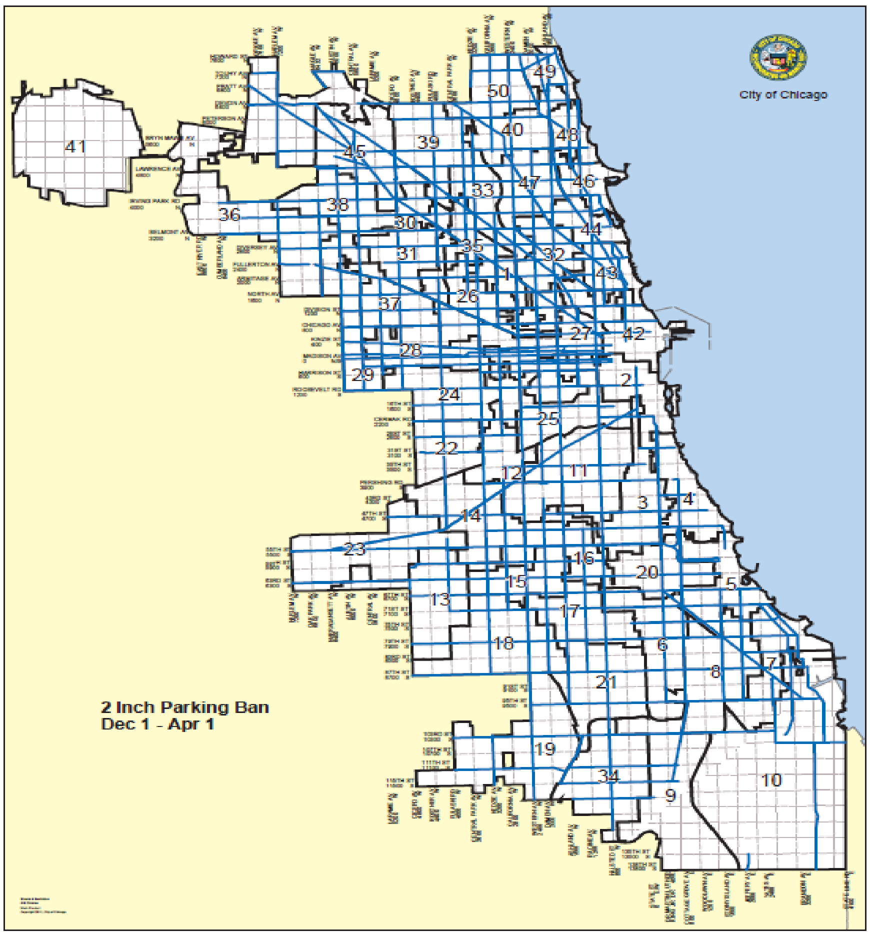


Figure 4-42: 2-inch parking ban map [Source: NWU]

Table 4-4: Snow Accumulation VS. Speed Reduction and Capacity Reduction

d_{ij}^{t} (inches LWE)	Speed Reduction	Capacity Reduction
$(\mathbf{0}, \mathbf{0.2}]$	11%	None
(0.2,0.4]	16%	None
(0.4,0.8]	20%	50%
(0.8,∞)	Lane closure	Lane closure

We define three decision related variables similar to (22):

- x_{ijm}^{k}: binary variable equals to 1 if and only if arc (i,j) is served by snowplow m and appears in the kth position of its route
- y_{ijm}^{k}: binary variable equals to 1 if and only if arc (i,j) is traversed by vehicle m and appears in the kth position of its route while deadheading
- t_{ijm}^{k}: is the start time of service or traversal of arc (i,j) by vehicle *m* and this arc appears in the kth position of the route.

The problem can be formulated mathematically as follows:

$$minimize \sum_{(i,j)\in A} D\left(t_{ijm}^{k}, q_{ij}\right) * VOT * p_{ij} - \sum_{(i,j)\in A} y_{ijm}^{k} * t'_{ij} * TraverseCost \quad \textbf{\textit{(4-2)}}$$

$$D\left(t_{ijm}^{k}, q_{ij}\right) = \int_{t0}^{te} \left(\frac{l_{ij}}{v_{ij}^{t}} - \frac{l_{ij}}{v'_{ij}\left(t, t_{ijm}^{k}\right)}\right) * q_{ij}(t)dt \quad \textbf{\textit{(4-3)}}$$

Constraints:

$$t_{ijm}^{k} + t_{ij}x_{ijm}^{k} + t'_{ij}y_{ijm}^{k} = \sum_{(h,j)\in A} t_{jhm}^{k+1}\left(x_{jhm}^{k+1} + y_{jhm}^{k+1}\right) \quad \textbf{\textit{(4-4)}}$$

$$\sum_{m\in R,k\in K} \left(x_{a0m}^{k} + y_{a0m}^{k}\right) = M \quad \textbf{\textit{(4-5)}}$$

$$\sum_{m\in R,k\in K} \left(x_{oam}^{k} + y_{oam}^{k}\right) = M \quad \textbf{\textit{(4-6)}}$$

$$\sum_{(i,j)\in A}\left(x_{ijm}^{k} + y_{ijm}^{k}\right) = \sum_{(j,h)\in A}\left(x_{jhm}^{k+1} + y_{jhm}^{k+1}\right) \quad \textbf{\textit{(4-7)}}$$

$$\sum_{k,r} x_{ijm}^{k} = n_{ij} \quad \textbf{\textit{(4-8)}}$$

$$\sum_{(i,j)\in A}\left(x_{ijm}^{k} + y_{ijm}^{k}\right) \leq 1 \quad \textbf{\textit{(4-9)}}$$

$$x_{ijm}^{k} \in \{0,1\} \quad \textbf{\textit{(4-10)}}$$

$$y_{ijm}^{k} \in \{0,1\} \quad \textbf{\textit{(4-11)}}$$

$$t_{ijm}^{k} > 0 \quad \textbf{\textit{(4-12)}}$$

The objective function consists of two parts: the benefit of plowing and the operational cost of maintenance. The benefit is calculated as the difference between the total predictive travel times with and without plowing multiplied by the value of time. Although the operation cost consists of service cost and deadheading cost, we only include the deadheading cost in the objective function because the service cost is constant that won't change under different scenarios (Corberán & Prins, 2010). Constraints (4-4) guarantees time consistency of service and traversal times. Constraints (4-5) and (4-6) ensure all paths start and end at the depot. Constraint (4-7) enforces flow conservation. Constraint (4-8) states that all lanes of arc ij must be served. Constraint (4-9) requires that each position of a route can only be assigned one arc.

After the snowplow routes are generated, signals at critical intersections are reset to enable priority for snowplows. The snowplow operation on a link would reduce the link capacity and increase the density. It was assumed that a lane is blocked by the maintenance vehicle during plowing and cannot be accessed by other vehicles and cannot be accessed by other vehicles. Given a link *i*, let n_i denote the number of lanes; m_i represent the link length; C_i be the link capacity, and q_i be density. When a snowplow is plowing the link and locates x miles from the upstream node, the reduced capacity is estimated as $C_i' = C_i(1 - \frac{x}{n_i l_i})$ and the lane density is calculated as $q_i = \frac{number\ of\ vehicles}{n_i l_i - x}$.

The plowing and deicing/anti-icing operation are conducted in conjunction. Snowplows spread the chemicals to the road surface while servicing the road. The chemicals melt the reset of the snow and ice on the pavement and prevent further formation of ice and snow bond. The performance of chemical is subject to various factors such as air temperature, humidity, wind, solar radiation, rate and type of precipitation, pavement type as well as traffic condition. It is hard, if not impossible, to calculate the actual performance of chemicals on the fields without conducting field tests. For this research, it is assumed that the chemicals can keep the road free of ice for one hour.

4.5 San Diego Testbed Modeling Approach

The traffic simulation tool that was used for the San Diego Testbed is Aimsun, developed by TSS-Transport Simulation Systems. Aimsun is a multi-resolution traffic modeling platform that includes macroscopic, mesoscopic, microscopic and hybrid mesoscopic-microscopic modelling engines. The microscopic simulator is the one used for the San Diego Testbed.

Aimsun features an Advanced Programming Interface (API) that allows implementing processes that during the simulation read outputs and implement changes to the infrastructure (signals, ramp meters, lane closures, etc.), or interfacing Aimsun with external processes. The API was used to model ITS devices that are already operational in the corridor: San Diego Ramp Metering System (SDRMS), Congestion Pricing System (CPS), Changeable Express Lane System (CELS).

ATDM strategies were modeled using the standard Traffic Management functionality provided by the software, which allows to code changes affecting the infrastructure (e.g. lane closure, turn closure, change of speed limit) or the vehicle behavior (e.g. forced turn, forced re-routing) at specific times or when a triggering condition occurs during the simulation. Details on how these strategies were implemented are provided below.

4.5.1 Active Traffic Management Strategies

The three ATM strategies implemented in the San Diego testbed are Dynamic Lane Use, Dynamic Speed Limits and Dynamic Merge Control.

Dynamic Lane Use/Reversal

This strategy involves dynamically closing or opening of individual traffic lanes as warranted and providing advance warning of the closure(s) (typically through dynamic lane control signs), in order to safely merge traffic into adjoining lanes. The I-15 corridor features a total of four HOT lanes that normally operate in a 2 northbound and 2 southbound lane configuration. The Changeable Express Lane System (CELS) allows modifying the lane configuration to 1 northbound and 3 southbound or 3 northbound and 1 southbound lanes, thereby replicating the Dynamic Lane Reversal strategy.

This was implemented in Aimsun using the Traffic Management functionality. A change from the standard 2 northbound and 2 southbound lane configurations to 1 northbound and 3 southbound lanes for Operational Conditions 1 and 2 (AM) or 3 northbound and 1 southbound lanes for Operational Conditions 3 and 4 (PM) is performed using this system. The configuration is generally activated throughout the simulation and is generally coupled with Dynamic HOV/Managed Lanes to promote the usage of the additional HOT lane.

Dynamic Speed Limits

This strategy adjusts speed limits based on real-time traffic, roadway, and/or weather conditions. Dynamic speed limits can either be enforceable (regulatory) speed limits or recommended speed advisories, and they can be applied to an entire roadway segment or individual lanes. This was implemented in Aimsun using the variable speed limit algorithm ACISA-1 (Algorismes de Control I Senyalització Automàtics – 1) designed by ACISA (Aeronaval de Construcciones e Instalaciones) in 2009 for the C-31 and C-32 motorways accessing Barcelona.

The corridor (I-15 mainline) is divided into segments, where each segment is defined as the stretch between an entrance ramp and the next exit ramp, or between an exit ramp and the next entrance ramp.

The logic to set the speed of each segment is the following:

- Every 5 minutes, starting from the last segment downstream, calculate an average of the speed measured by all the active detectors on top of sections belonging to the segment, weighted with the count; then round up to the closest multiple of 5 mph.
- Apply the segment a speed limit equal to the minimum between the average speed as computed above and average speed of the segment immediately downstream plus 5 mph. If the value is greater or equal to the general speed limit, do not apply any variable speed limit.

The rounding by excess ensures that the logic doesn't produce any wind-down effect, in which a speed limit is applied, then because vehicles are complying with it and possibly driving a bit slower, a lower speed gets calculated for the next time interval with no reason.

Dynamic Merge Control

This strategy (also known as dynamic late merge or dynamic early merge) consists of dynamically managing the entry of vehicles into merge areas with a series of advisory messages (e.g., displayed on a dynamic message sign [DMS] or lane control sign) approaching the merge point that prepare motorists for an upcoming merge and encouraging or directing a consistent merging behavior. Applied conditionally during congested (or near congested) conditions, dynamic merge control can help create or maintain safe merging gaps and reduce shockwaves upstream of merge points. San Diego Association of Governments (SANDAG) has identified a single location where the Dynamic Merge Control could potentially be deployed: the entrance of SR-78 into I-15.

This was implemented in Aimsun using the Traffic Management functionality. The activation of a closure of the rightmost lane on I-15 upstream of the entrance is triggered when the occupancy of the ramp from SR-78 exceeds 80% and turned off when the occupancy goes below 80%.

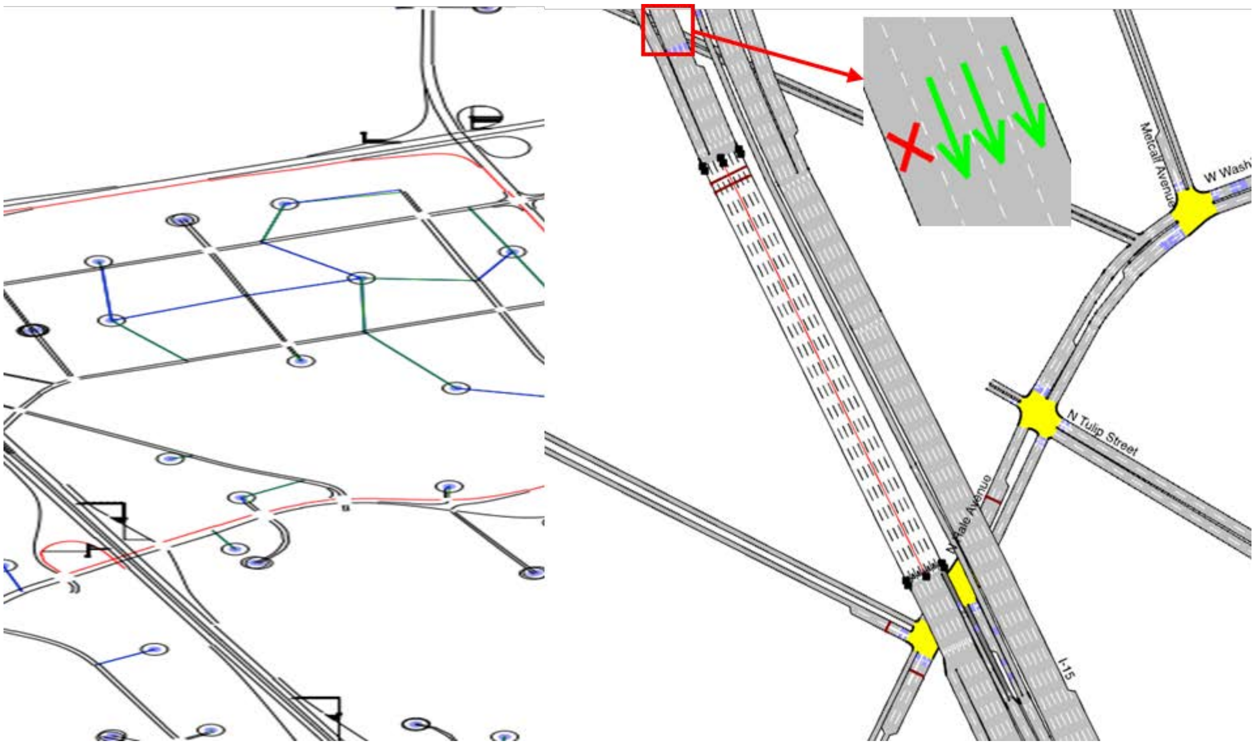


Figure 4-43: Location of Dynamic Merge Control [Source: TSS]

Since only one location has been identified, and it is in the southbound direction, this strategy has been tested only under the first two Operational Conditions.

4.5.2 Active Demand Management Strategies

The three ADM strategies implemented and evaluated in the San Diego Testbed are Predictive Traveler Information, Dynamic HOV/Managed Lanes and Dynamic Routing strategies. Their modeling approach is provided below.

Predictive Traveler Information

This strategy involves using a combination of real-time and historical transportation data to predict upcoming travel conditions and convey that information to travelers before and during their trips to influence travel behavior. The I-15 corridor features an Integrated Corridor Management (ICM) application that constantly produces predicted travel time information and provides a simulation-based Decision Support System (DSS) to evaluate the best response plans to apply when an unexpected incident occurs.

The project team implemented a testing framework that consists of the I-15 ICM Aimsun Offline system connected to a virtual reality simulation instead of a real-time detection data feed (Figure 4-44).

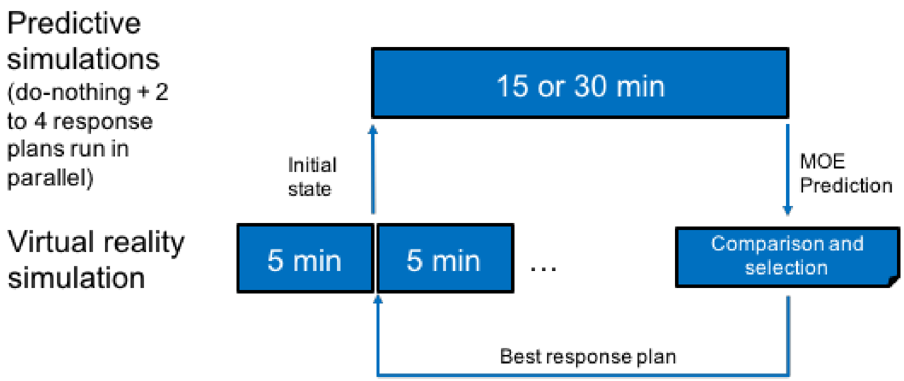


Figure 4-44: Testing framework for the Predictive Traveler Information strategy [Source: TSS]

Starting from 10 or 25 min before the incident occurring in each scenario, the virtual reality simulation pauses every 5 minutes and sends the current simulation state to the Aimsun Online instance. The Aimsun Online instance performs a simulation-based prediction, at 15 or 30 min, for alternative options: do-nothing and a fixed set of response plans (whose number and specification depends on the scenario).

At the end of this parallel simulation runs, the Aimsun Online instance reads the delay time within 5 miles upstream and downstream of the incident, and picks the response plan that produces the lowest result (or the do-nothing). The virtual reality simulation applies this response plan and advances for other 5 min, when it repeats the process described above.

A comparison with the architecture of the real I-15 ICM system shows two simplifications:

- In the real system, the data taken from reality are real-time counts, while in this testing framework the predictive simulations are fed with a full snapshot of the state of the vehicles in the virtual reality simulation.
- The real system includes a comprehensive set of response plans designed to deal with a broad range of incidents and features a business rules engine capable of selecting which response plans are most suitable for a given event.

Taking from reality real-time counts, and configuring the demand for the predictive simulations with a procedure involving pattern matching, analytic predictions, demand selection from a library and real-time dynamic demand adjustment, requires a significant warm-up period and therefore cannot work with a virtual reality simulation that covers only four hours. For this reason, in the proposed testing framework both the virtual reality simulation and the predictive simulations access the same Aimsun model document file, where the demand and the incident are already defined, and the data taken by the predictive simulations from the virtual reality simulation is a full snapshot of the state of the vehicles.

Since the business rules engine in the ICM system is provided by a component developed by a third party and external to the Aimsun Online modules, TSS has no access to this functionality. For this reason, the testing framework doesn't include a business rules engine and always tests a predefined set of response plans for each Operational Condition. We consider that both simplifications are acceptable for this evaluation and do not invalidate the results of the analysis, because the testing framework must deal with four specific Operational Conditions with fixed and predefined traffic demand and incidents, rather than with any conditions throughout the year and any incidents, like the real ICM system. In these four Operational Conditions, the testing framework should produce similar results to those of the real system.

It's worth noting that each Operational Condition has a response plan that was applied during the incident, on the real-deployment day. In the Predictive Traveler Information simulations, the do-nothing case will deactivate the response plan that was originally applied.

Dynamic HOV/Managed Lanes

The HOV lanes on the I-15 corridor feature a Congestion Pricing System (CPS) that updates the cost of accessing the HOV lanes for SOVs based on the current congestion level. This was implemented in Aimsun using the Traffic Management functionality. A "free-to-all" scenario, in which SOVs[16] have free access to the HOV lanes was emulated for this strategy. The free access is granted in the southbound direction for Operational Conditions 1 and 2 (AM) and in the northbound direction for Operational Conditions 3 and 4 (PM).

Dynamic Routing

Dynamic Routing provides a set of alternative routes for the vehicles to avoid the area affected by the incident in each operational condition. These alternative routes are evaluated either with Predictive Traveler Information as a set of alternative response plans evaluated in parallel, or with current travel times, when no predictions are available.

Operational Condition 1

The Dynamic Routing options are based on two diversion routes, one for vehicles coming from I-15 and one for vehicles coming from SR-78, and two percentages of vehicles following them, 3% and 6%. They produce a total of six response plans to test (plus the do-nothing): activating only one diversion route or both, and affecting 3% or 6% of the vehicles. In the first rerouting option, vehicles coming from I-15 go towards SR-78 eastbound, exit SR-78 at Centre City Parkway and reenter I-15 at West Valley Parkway (Figure 4-45). In the second rerouting option, vehicles coming from SR-78 exit at Nordahl Road, follow Auto Parkway and reenter I-15 at 9th Ave. These diversion routes are complemented by change of signal plans at the signalized intersections along the routes (9 signals and 5 signals respectively), and by an increase of the metering rate at West Valley Parkway and 9th Ave southbound entrances on I-15.

[16] The demand is segmented into HOVs (which have always free access to HOV lanes), SOV-toll (which are SOVs that may be willing to pay to get access to HOV lanes) and SOV-no-toll (which are SOVs that are never willing to pay to get access to HOV lanes). The "free-to-all" scenario makes all SOV-toll and 20% of the SOV-no-toll consider the option to use the HOV lanes (for free).

Figure 4-45: The two rerouting options under Operational Condition 1 [Source: TSS]

Operational Condition 2

The Dynamic Routing options are based on two diversion routes, one for vehicles coming from I-15 and one for vehicles coming from SR-78, and two percentages of vehicles following them, 3% and 6%. They produce a total of six response plans to test (plus the do-nothing): activating only one diversion route or both, and affecting 3% or 6% of the vehicles. In the first rerouting option, vehicles coming from I-15 go towards SR-78 eastbound, exit SR-78 at Centre City Parkway and reenter I-15 at 9th Ave (Figure 4-46). In the second rerouting option, vehicles coming from SR-78 exit at Nordahl Road, follow Auto Parkway and reenter I-15 at 9th Ave. These diversion routes are complemented by change of signal plans at the signalized intersections along the routes (10 signals and 5 signals respectively), and by an increase of the metering rate at 9th Ave southbound entrance on I-15.

Figure 4-46: The two rerouting options under Operational Condition 2 [Source: TSS]

Operational Condition 3

The Dynamic Routing options are based on three diversion routes for 3% of the vehicles traveling northbound on I-15. They produce a total of four response plans to test (plus the do-nothing): activating only one diversion route or the three concurrently. In one diversion route vehicles exit at Bernardo Center Drive and reenter at Rancho Bernardo Road. In another diversion route vehicles exit at Camino del Norte and reenter at Rancho Bernardo Road. In the last diversion route vehicles exit at Carmel Mountain and reenter at Rancho Bernardo Road (Figure 4-47). These diversion routes are complemented by change of signal plans at the signalized intersections along the routes (6 signals, 6 signals and 5 signals respectively), and by an increase of the metering rate at Rancho Bernardo northbound entrance on I-15.

Figure 4-47: The three rerouting options under Operational Condition 3 [Source: TSS]

Operational Condition 4

The Dynamic Routing options are based on two diversion routes for 3% of the vehicles traveling northbound on I-15 towards SR-78 westbound. They produce a total of three response plans to test (plus the do-nothing): activating only one diversion route or both concurrently. In one diversion route vehicles exit I-15 at 9th Ave and enter SR-78 at Centre City Parkway. In the other diversion route vehicles exit I-15 at 9th Ave and enter SR-78 at Nordahl Road (Figure 4-48). These diversion routes are complemented by change of signal plans at the signalized intersections along the routes (9 signals and 8 signals respectively), and by an increase of the metering rate at Centre City Parkway and Nordahl Road westbound entrances on SR-78.

Figure 4-48: The two rerouting options under Operational Condition 4 [Source: TSS]

Chapter 5. Synergies and Conflicts

This chapter documents the research findings regarding the synergies and conflicts among different ATDM strategies. Specifically, this chapter addresses the question of which strategies are more beneficial when they are combined with other strategies and which strategies are better off implemented in isolation. Dallas and Phoenix Testbeds were used to answer these questions.

5.1 Research Questions and Hypotheses

Primarily three research questions will be answered in this chapter. They are:

1. Are ATDM strategies more beneficial when implemented in isolation or in combination (e.g., combinations of ATM, ADM, or APM strategies)?
2. Which ATDM strategy or combinations of strategies yield the most benefits for specific operational conditions?
3. What ATDM strategies or combinations of strategies conflict with each other?

Our preliminary research hypothesis is that the ATDM strategies that are synergistic (e.g., ADM, APM, ATM) will be more beneficial when implemented in combination than in isolation. An ATDM strategy and a certain combination of strategies will yield higher benefits only under certain operational conditions. Certain ATDM strategies will be in conflict with each other, resulting in no benefits or reduced benefits.

5.2 Dallas Testbed Analysis Approach

The modeling framework presented in Figure 4-2 is used to examine the overall network performance considering the deployment of different ATDM strategy combinations. As mentioned above four different strategies are considered in this analysis including: a) dynamic routing; b) dynamic signal timing; c) dynamic shoulder lane; and d) dynamic ramp metering. As explained earlier, the Dynamic Routing Strategy provides recommendation for the traffic upstream of the incident to divert from the freeway to the arterial streets to bypass the incident. The dynamic signal timing Strategy allows the dynamic modification of the signal timing plans for all intersections along the diversion routes recommended for the traffic. The dynamic shoulder lane Strategy allows vehicles to utilize the shoulder lane during the duration of the incident. The implementation of this strategy is expected to significantly alleviate the congestion associated with the incident due to the increase in the freeway capacity associated with opening the shoulder as a lane for traffic. Finally, the dynamic ramp metering strategy allows implementing time-varying metering rates for the freeway's on-ramps located upstream of the incident.

As mentioned above, the decision support module is capable to deploy single traffic management strategy, or generate a ATDM response plan that integrates multiple ATDM strategies. We use such capabilities to compare the overall network performance when the ATDM strategies mentioned above are deployed in isolation or combined with each other. As presented hereafter, different combinations are considered in this analysis to obtain insight on their synergy and conflict. In this analysis, the traffic network conditions are represented by operational scenario MD-LI. As described earlier, this scenario represents a highly-congested network with low incident severity and dry weather conditions.

The analysis has also been extended to examine the dynamic parking pricing strategy. Hypothetical scenarios are modeled in which several parking lots close to the downtown area in the southern section of the corridor are assumed to adopt dynamic pricing schemes. These schemes are assumed to be published and available to travelers prior to starting their trips. Considering the parking cost at the different times, travelers evaluate their travel options and decide to a) follow their habitual departure times and use their private cars; b) adjust their departure times to avoid high parking cost while using their private cars, and c) keep their departure times and use transit instead of the private cars to save parking cost at the destination. In this third case, travelers could use transit for the entire trip (i.e., pure transit) or use transit as part of an intermodal trip in which the traveler uses her private car for the first portion of the trip to access the transit service and then use transit to reach the destination.

It should be noted that the dynamic parking pricing strategy is not currently adopted in Dallas. Parking lots are mostly privately owned with fixed rate pricing, and there is generally a parking surplus in the downtown. As such, the analysis performed in this study to examine the effectiveness of the dynamic parking pricing strategy is based on hypothetical scenarios in terms of parking lots that adopt the dynamic parking strategy and the pricing schemes deployed at each parking lot.

Sensitivity analysis is performed to examine the effectiveness of the dynamic parking pricing strategy. As the dynamic parking strategy is designed primarily to influence the travelers' behavior in the morning peak period, an additional operational scenario that represents a morning peak period is considered in this analysis. It is worth mentioning that the operational scenario has not been developed based on the cluster analysis conducted as part of this study which focused only on the network congestion pattern in the evening peak period. Therefore, an operational scenario that was developed as part of the Integrated Corridor Management demonstration study for the US 75 Corridor is used to examine the effectiveness of the dynamic parking pricing strategy. The morning peak operational scenario considered in this analysis represents moderate congestion condition with medium severity incident and dry weather conditions.

As described above, the moving horizon approach is used to report the total network performance measures assuming a roll period of five minutes and a backward horizon of 30 minutes. In all experiments, two scenarios are compared. In the first scenario, no ATDM response plans are deployed and all travelers are assumed follow their habitual routes and experience the delay due to the incident (i.e., the baseline scenario). In the second scenario, the traffic management system is activated to manage the incident through deploying ATDM response plans that integrate different combinations of the strategies mentioned above. The traffic management module is activated with the start of the incident through 30 minutes after its clearance. The benefits of the traffic management system are reported in terms of saving in the total network travel time, fuel consumption and emissions as percentages of their corresponding values under the baseline scenario.

5.2.1 Traffic Management Strategies

This section provides the results of the experiments conducted to examine synergy/conflict among different ATDM traffic management strategies. Figure 5-1 through Figure 5-4 depict the network performance measures obtained for these set of experiments. Figure 5-1 gives the percentage savings total network travel time, Figure 5-2 gives the corresponding saving in the total fuel consumption, and Figure 5-3 and Figure 5-4 give the savings in the emissions of carbon dioxide and nitrogen oxide, respectively. These figures also provide the corresponding values of these performance measures under the baseline scenario. The results of eight different operational scenarios (A to H) are shown in each of these figures. The first three scenarios (A to C) show the network performance resulting from adopting one ATDM strategy at a time. The other five scenarios (D to H) represent the activation of ATDM response plans that integrate different ATDM combinations.

Several main observations can be made based on these results:

- More travel time savings are generally observed by integrating multiple ATDM strategies in the generated ATDM response plans. Operational scenarios in which the more ATDM strategies are integrated in the generated schemes resulted in more travel time savings compared to the scenarios in which each of these ATDM is solely adopted.
- The dynamic shoulder lane strategy has significant impact on alleviating the congestion associated with the incident. A significant travel time saving is observed in all scenarios in which this strategy is adopted as part of the generated ATDM response plans. A peak saving of about 2.5% (for a horizon of 30 minutes is observed) in the scenario in which the dynamic shoulder lane strategy is activated along with the dynamic signal timing, dynamic routing, and ramp metering strategies. As shown in Table 5-1, in this operational scenario, the corresponding total travel time saving is recorded at 75,304 minutes.
- To examine the statistical significance of the obtained results, the simulation runs are replicated for the scenario in which the HD-MI operational conditions and the dynamic signal timing and dynamic routing strategies are activated. The travel time savings are recorded for ten simulation runs considering changing the simulation random seed for each run. An average travel time saving value of 76,910 minutes and corresponding standard deviation of 9,474 minutes are recorded for these ten replications. Thus, the corresponding 95% confidence range is defined as $58{,}341 \text{ minutes} < \mathrm{X} < 95{,}479 \text{ minutes}$. This 95% confidence range includes the travel time saving reported for this scenario which is 75,304 minutes.

Compared to other strategies, the dynamic signal timing strategy is not generally effective if it is deployed on its own. While slight travel time saving is observed in the first part of the horizon, congestion builds up later in the horizon. The travel time saving was limited to 0.25%. However, more benefits could be achieved when it is integrated with the dynamic routing strategy.

Table 5-1 provides a summary of these results. For each operational scenario, the table gives the total travel network time saving records considering the entire horizon. It also gives the maximum observed travel time saving in any 30 minutes' period across the entire horizon. For example, a total travel time saving of 223 minutes is recorded for the dynamic signal timing strategy. This saving increased to 75,304 minutes when all four control strategies are integrated to generate one ATDM response plan.

Figure 5-2 provides the corresponding saving in the fuel consumption associated with the eight operational scenarios considered in the analysis. Several main observations can be made based on the results in this figure.

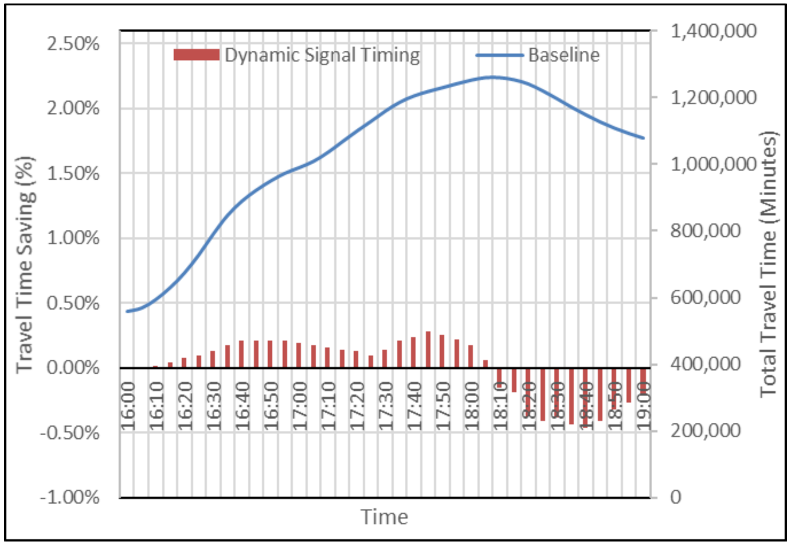
- As mentioned above, adopting the dynamic signal timing by itself does not achieve significant travel time savings. The same pattern is observed for fuel consumption pattern. While minor fuel consumption saving is recorded in the first part of the horizon, the strategy is shown to shift the congestion to subsequent periods resulting in more fuel consumption compared to the baseline scenario.
- Also, similar to the results obtained for the travel time savings, adopting the dynamic shoulder lane helps in achieving considerable saving the fuel consumption.
- The highest level of fuel consumption savings is obtained in Scenario F in which the dynamic shoulder lane, the dynamic routing and the dynamic signal timing strategies are integrated in the generated scheme, implying solid synergy among these three strategies. The percentage saving reaches to above 1% for a period of 30 minutes and remained close to that range for a considerable portion of the horizon. A corresponding fuel consumption saving of about 71.0 tons is recorded for this scenario. However, as the ramp metering strategy is included as part of the schemes, a significant drop in the amount of fuel consumption saving (about 7.0 tons) is observed as shown in scenario H indicating conflict between the ramp metering strategy and other strategies.

- While the ramp metering strategy helps in enhancing the performance in terms of network travel time savings, adopting such strategy as part of the ATDM response plans is shown to slightly reduce the saving in the amount of fuel consumption. For instance, comparing operational scenarios E and F (without ramp metering) against scenarios H and G (with ramp metering), one can observe that including the ramp metering strategy as part of the generated schemes reduces the percentage saving along the horizon. In these scenarios, the additional fuel consumption resulting from stopping the traffic on the on ramps of the freeway (and associated congestion on the frontage road) outperforms the savings associated with improving the flow on the freeways.

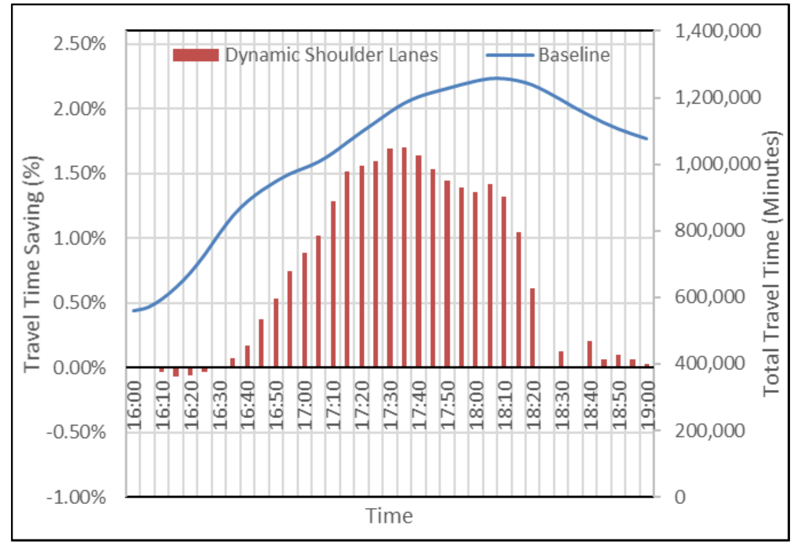
Figure 5-3 and Figure 5-4 give the results for environmental measure of performance for deploying different traffic management strategies. Figure 5-3 gives the percentage saving in the carbon dioxide, while Figure 5-4 gives the percentage saving the nitrogen oxide. The emission savings patterns are generally similar to that recorded for the fuel consumption savings. For example, the dynamic signal timing by itself is not an effective strategy. In addition, scenario F in which the dynamic shoulder lane, the dynamic routing, and the dynamic signal timing strategies are integrated as part of the scheme generally provides the highest emission savings. The ramp metering strategy conflicts with these three strategies resulting in a drop in the amount of emission savings.

Table 5-1: Deploying Different ATDM Traffic Management Strategies on Dallas Testbed under Medium Demand and Low Incident Severity Conditions

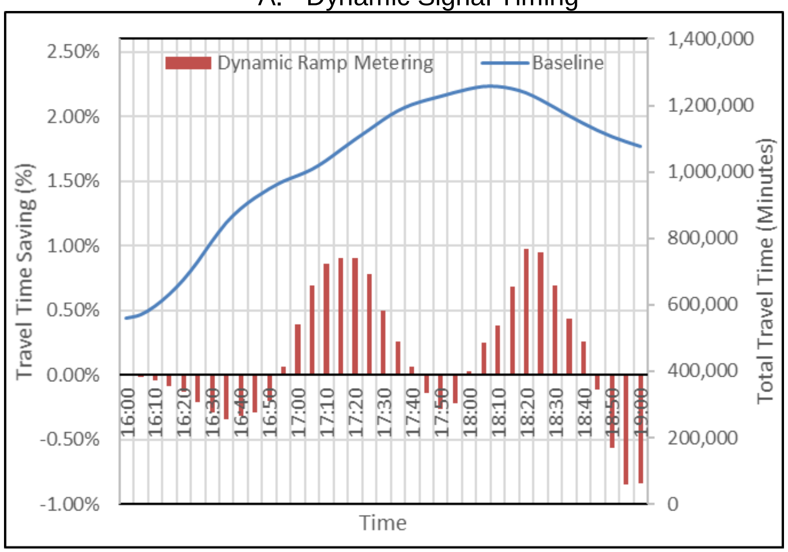
Scenario	ATDM Strategy Implemented				Total Network
	Dynamic Signal Timing	Dynamic Shoulder Lanes	Dynamic Ramp Metering	Dynamic Routing	Travel Time Savings (minutes)
S1/A	✓				223
S2/B		✓			48,630
S3/C			✓		10,923
S4/D		✓		✓	44,210
S5/E	✓			✓	15,125
S6/F	✓	✓		✓	53,871
S7/G	✓		✓	✓	22,926
S8/H	✓	✓	✓	✓	75,304



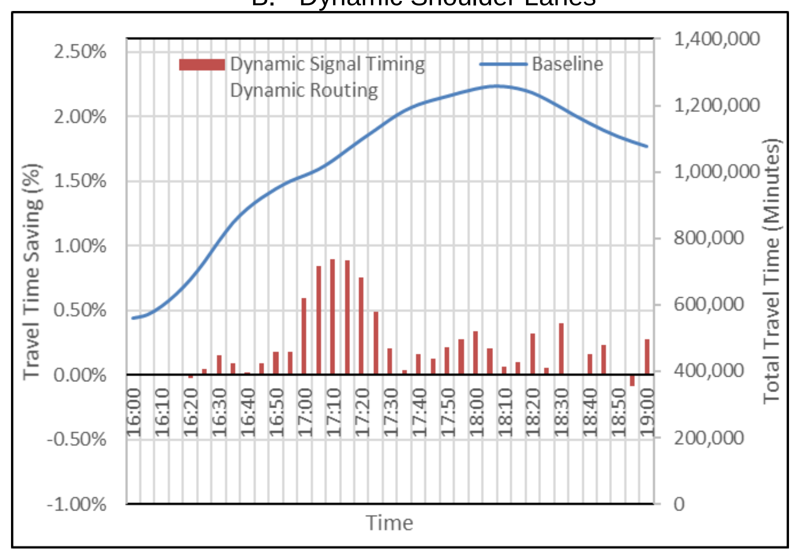
A. Dynamic Signal Timing



B. Dynamic Shoulder Lanes



C. Dynamic Ramp Metering



D. Dynamic Signal Timing + Dynamic Routing

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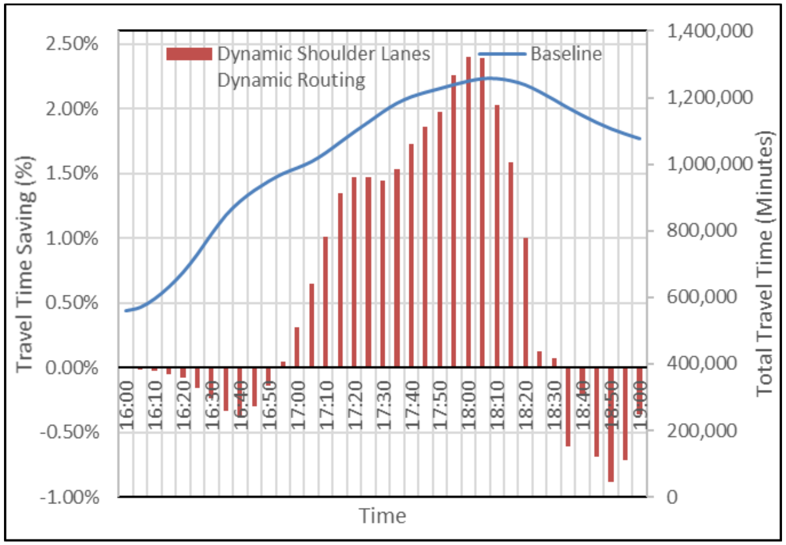
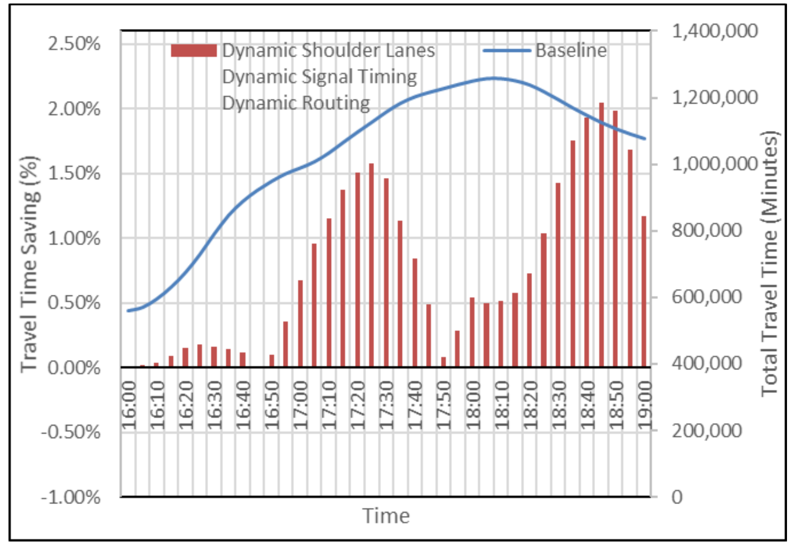
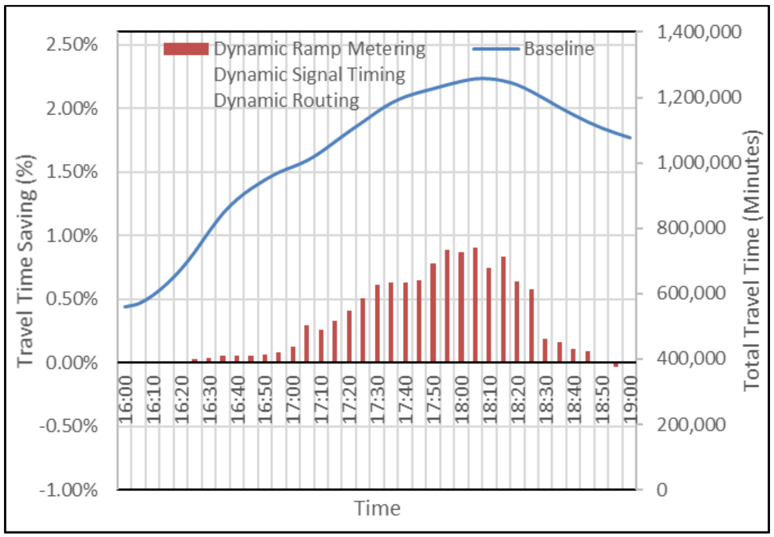


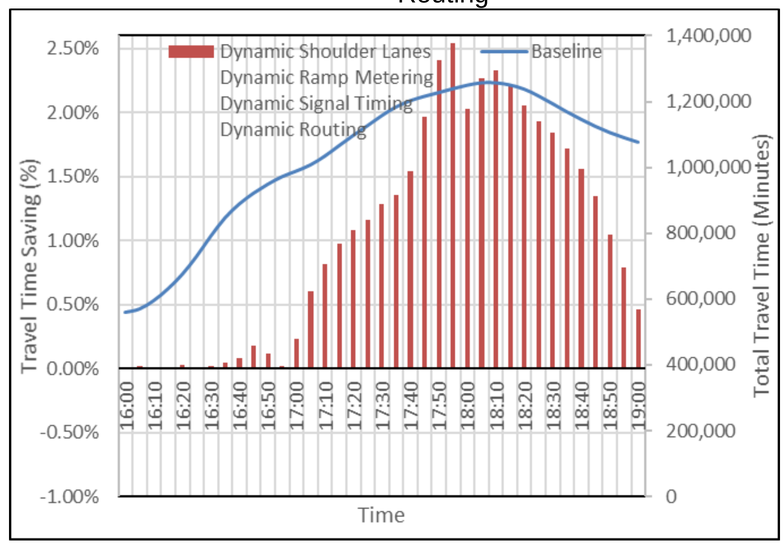
E. Dynamic Shoulder Lanes + Dynamic Routing



F. Dynamic Shoulder Lanes, Dynamic Signal Timing, Dynamic Routing

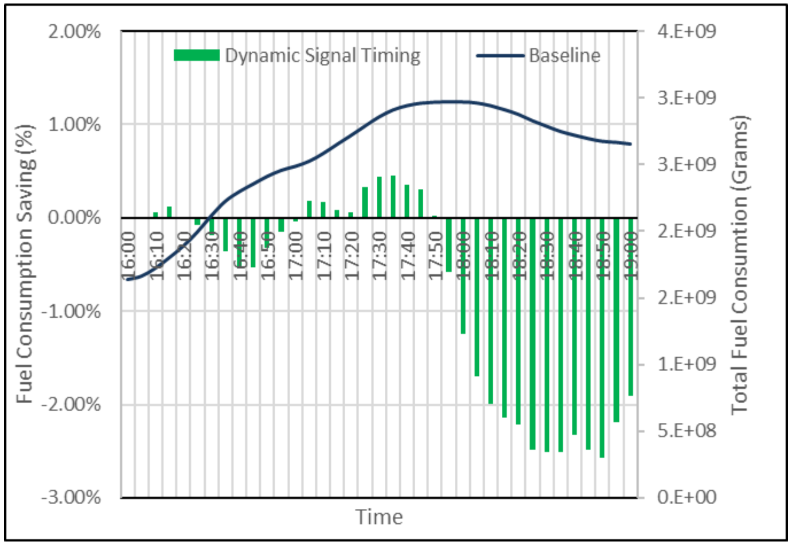


G. Dynamic Ramp Metering, Dynamic Signal Timing, Dynamic Routing

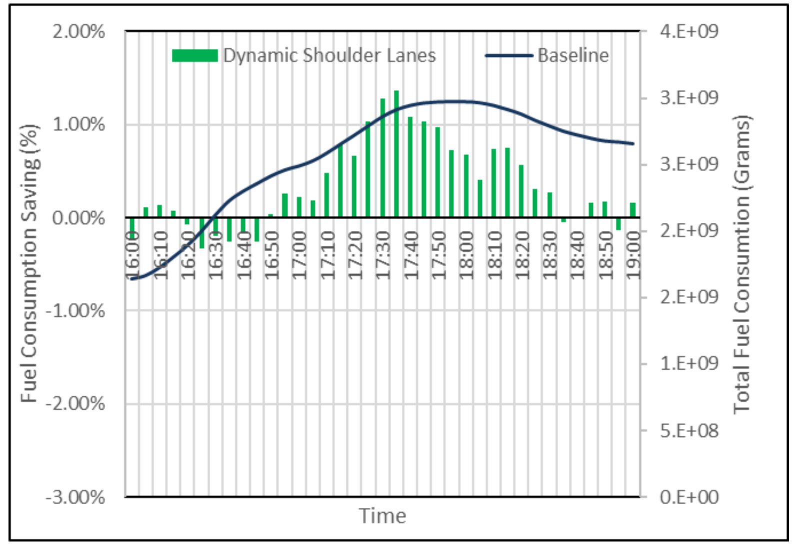


H. Dynamic Shoulder Lanes, Dynamic Ramp Metering, Dynamic Signal Timing, Dynamic Routing

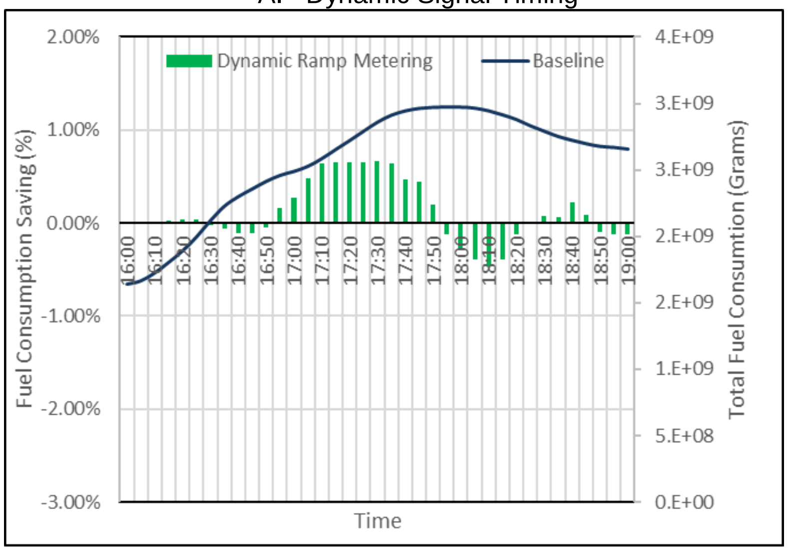
Figure 5-1: Total Travel Time Saving Deploying Different Strategy Combinations on Dallas Testbed under MD-LI Condition [Source: SMU]



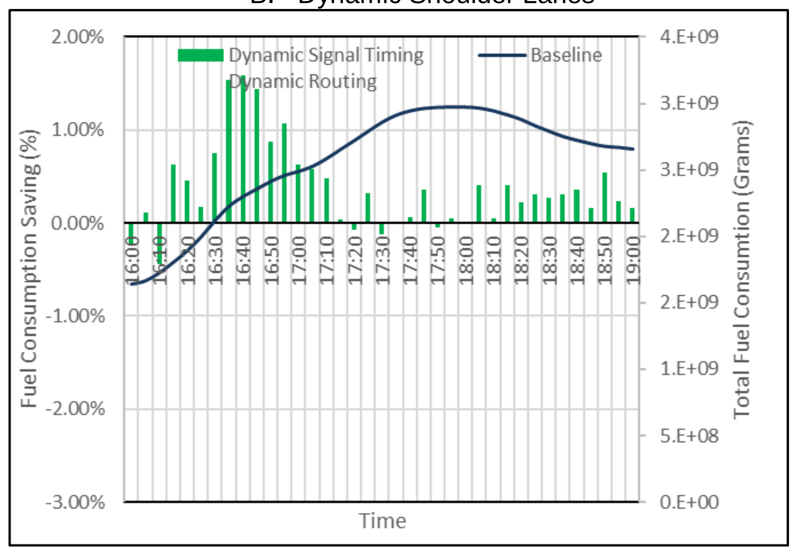
A. Dynamic Signal Timing



B. Dynamic Shoulder Lanes



C. Dynamic Ramp Metering



D. Dynamic Signal Timing + Dynamic Routing

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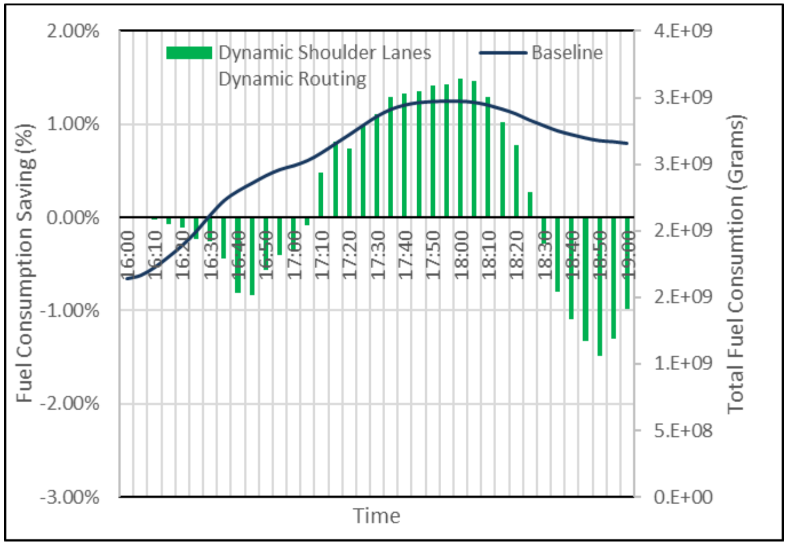
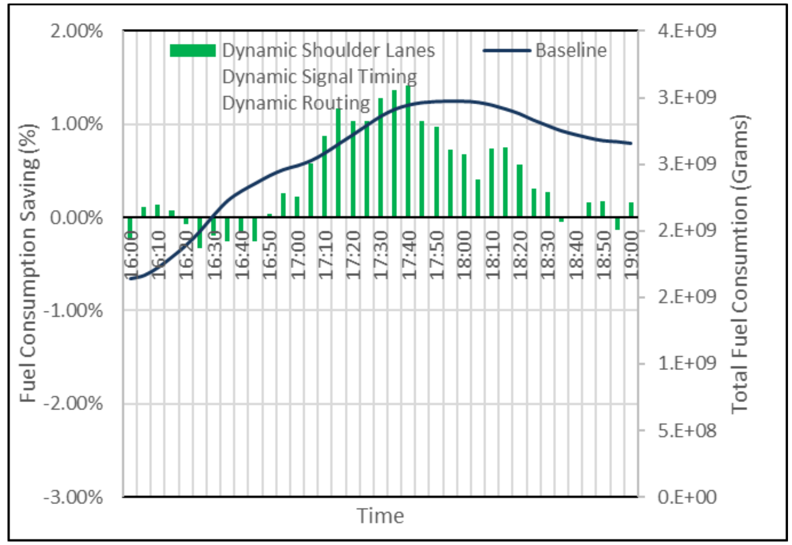
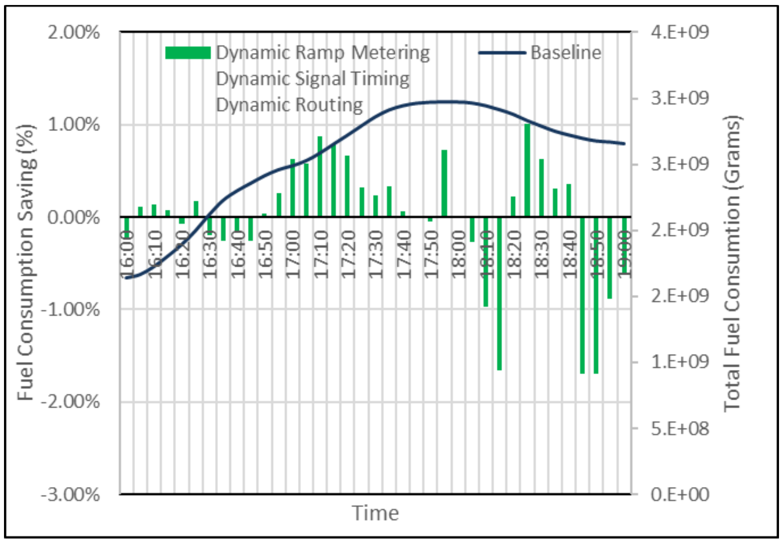


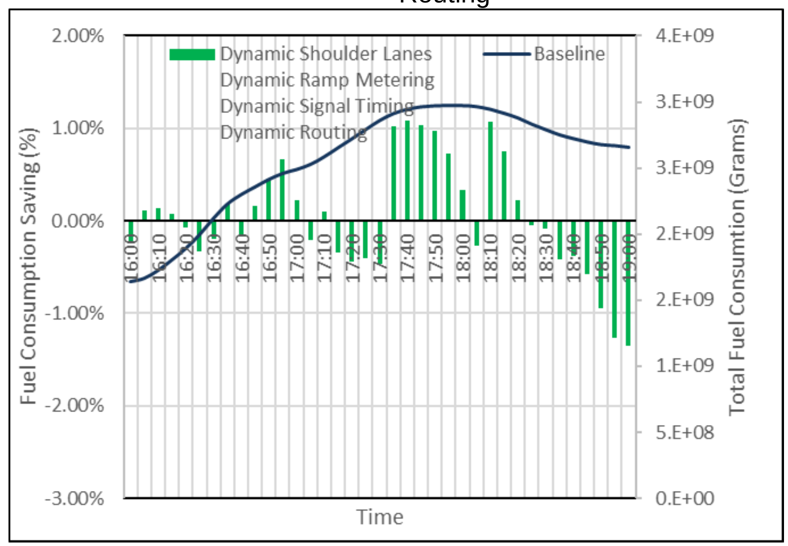
E. Dynamic Shoulder Lanes + Dynamic Routing



F. Dynamic Shoulder Lanes, Dynamic Signal Timing, Dynamic Routing

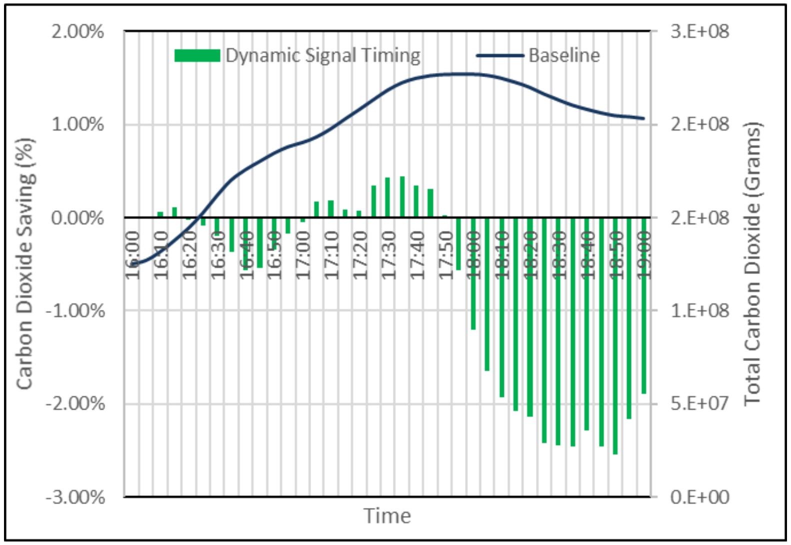


G. Dynamic Ramp Metering, Dynamic Signal Timing, Dynamic Routing

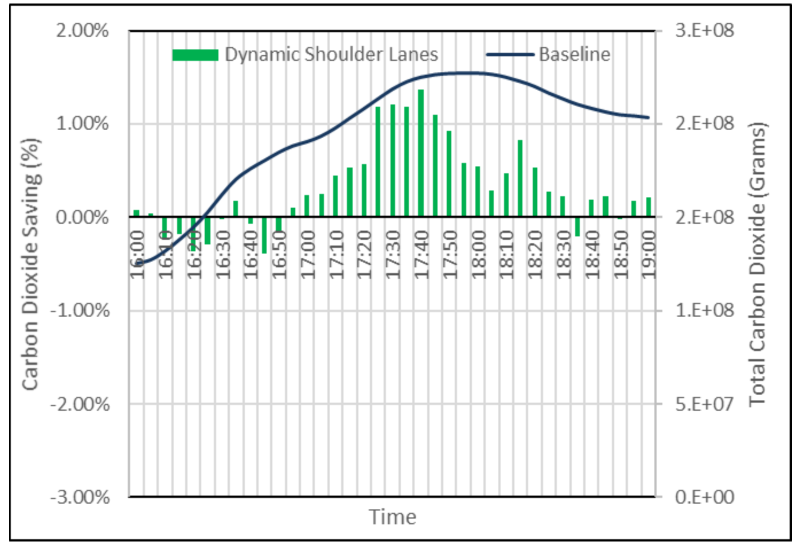


H. Dynamic Shoulder Lanes, Dynamic Ramp Metering, Dynamic Signal Timing, Dynamic Routing

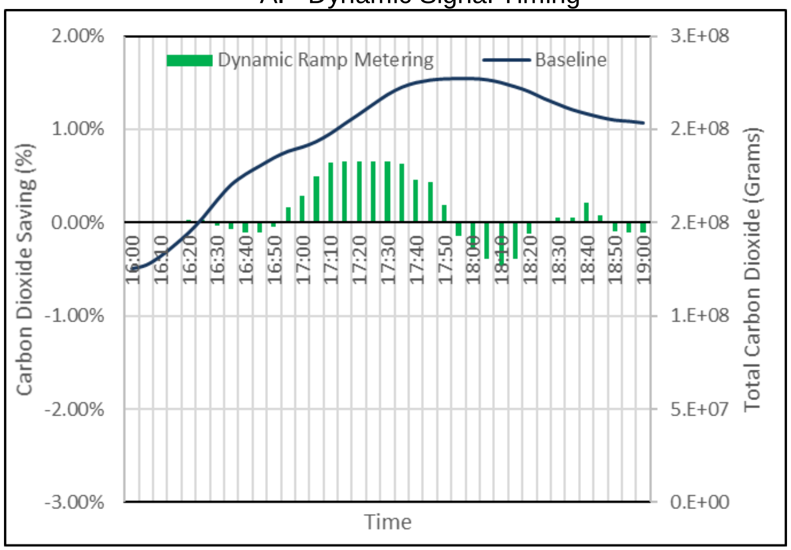
Figure 5-2: Total Fuel Consumption Saving Deploying Different Strategy Combinations on Dallas Testbed under MD-LI Condition [Source: SMU]



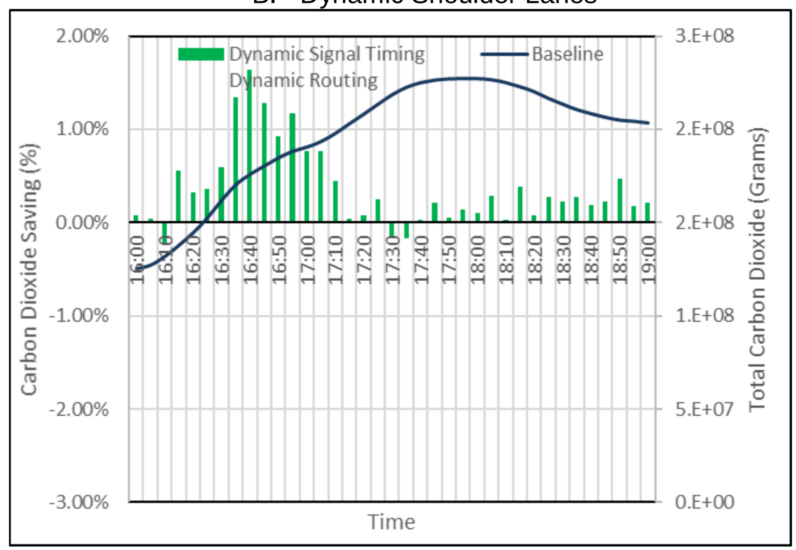
A. Dynamic Signal Timing



B. Dynamic Shoulder Lanes



C. Dynamic Ramp Metering



D. Dynamic Signal Timing + Dynamic Routing

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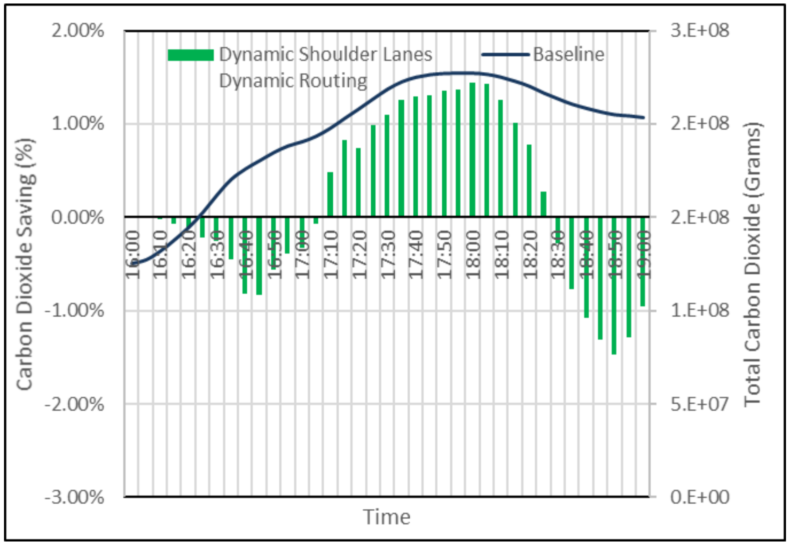
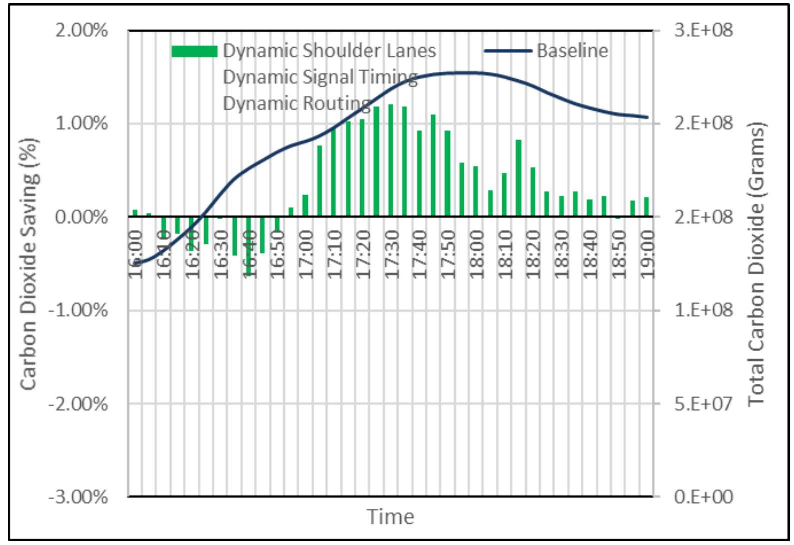
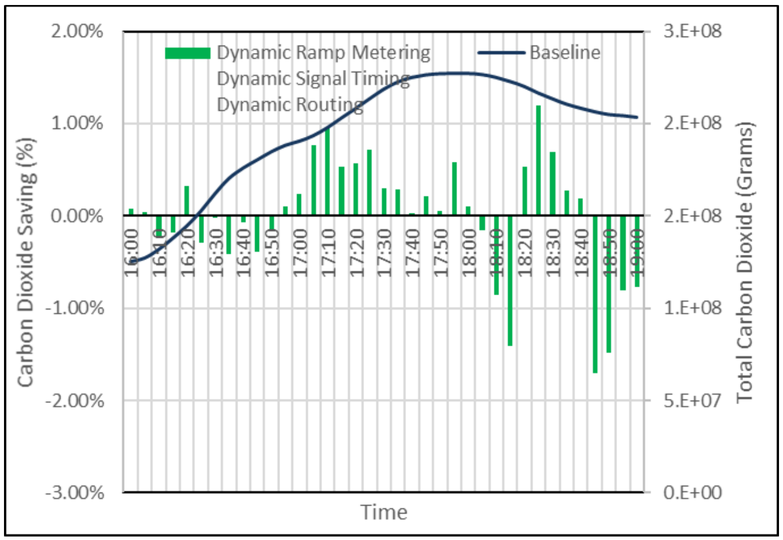


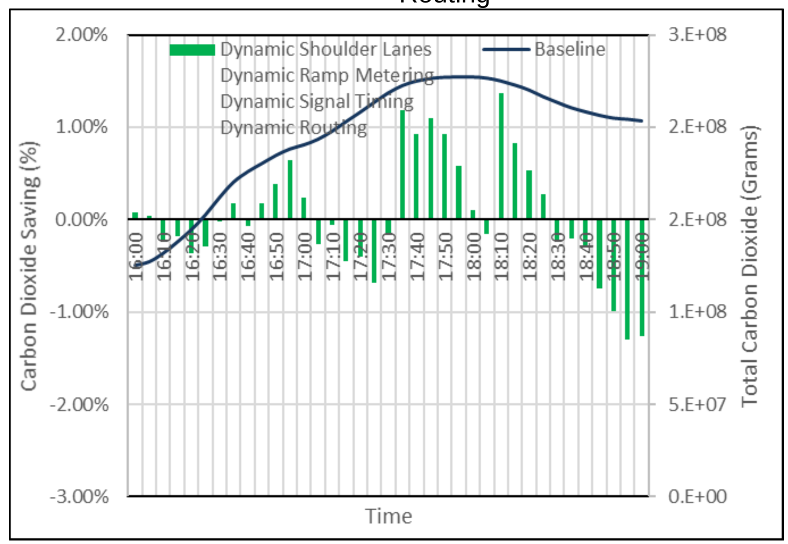
E. Dynamic Shoulder Lanes + Dynamic Routing



F. Dynamic Shoulder Lanes, Dynamic Signal Timing, Dynamic Routing

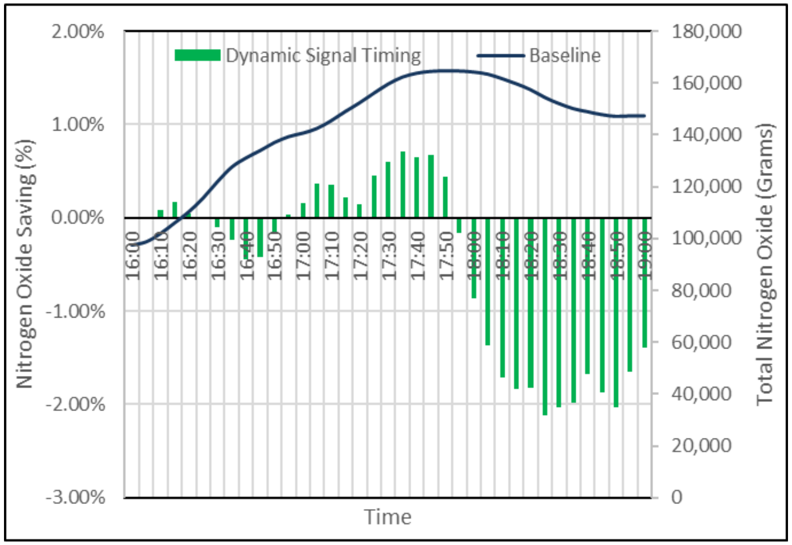


G. Dynamic Ramp Metering, Dynamic Signal Timing, Dynamic Routing

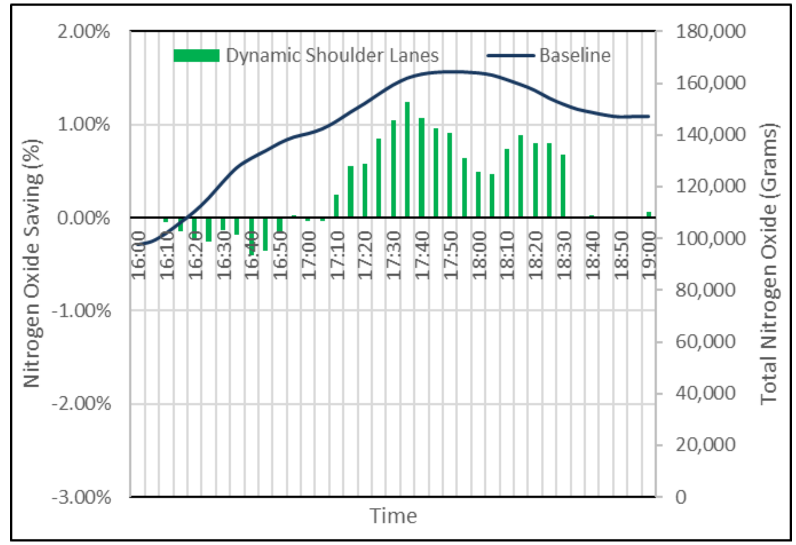


H. Dynamic Shoulder Lanes, Dynamic Ramp Metering, Dynamic Signal Timing, Dynamic Routing

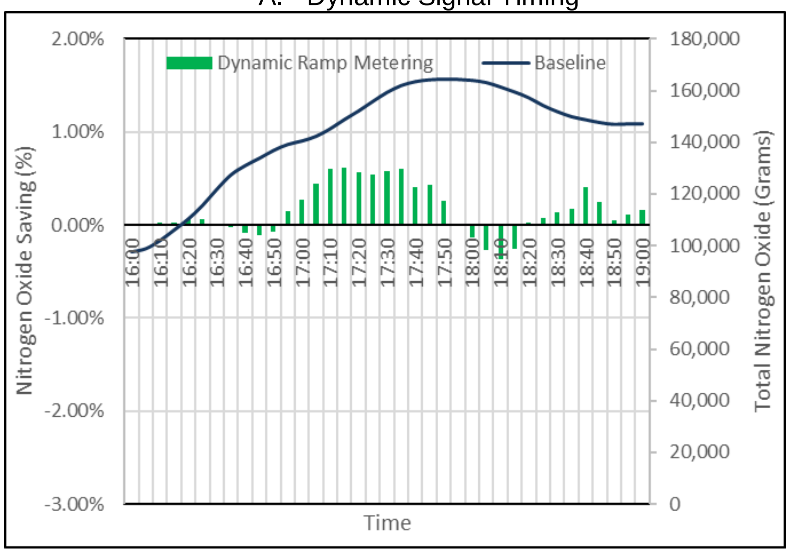
Figure 5-3: Total Carbon Dioxide Saving Deploying Different Strategy Combinations on Dallas Testbed under MD-LI Condition [Source: SMU]



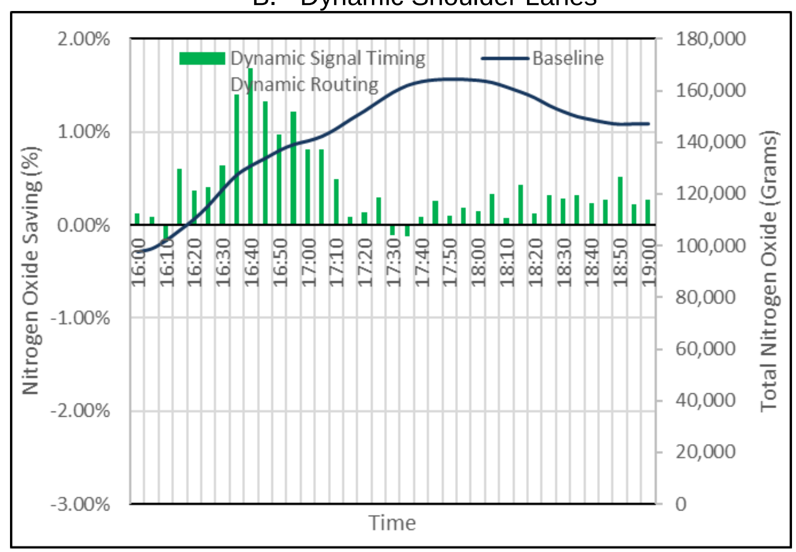
A. Dynamic Signal Timing



B. Dynamic Shoulder Lanes



C. Dynamic Ramp Metering



D. Dynamic Signal Timing + Dynamic Routing

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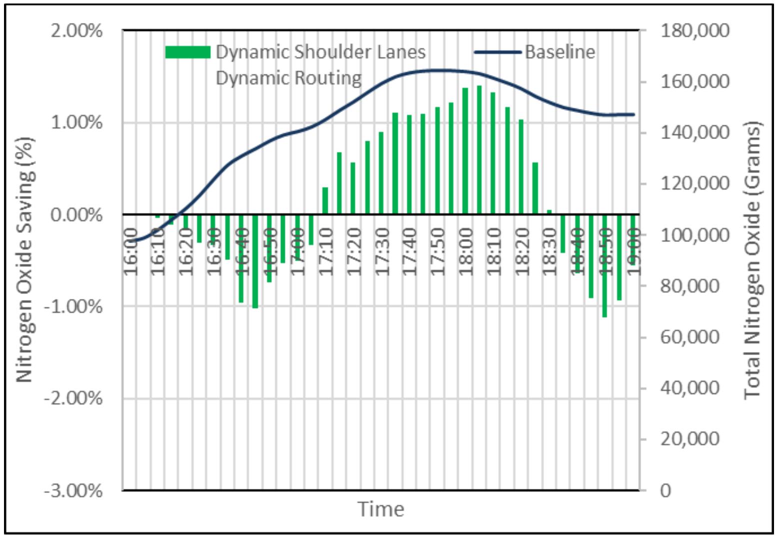
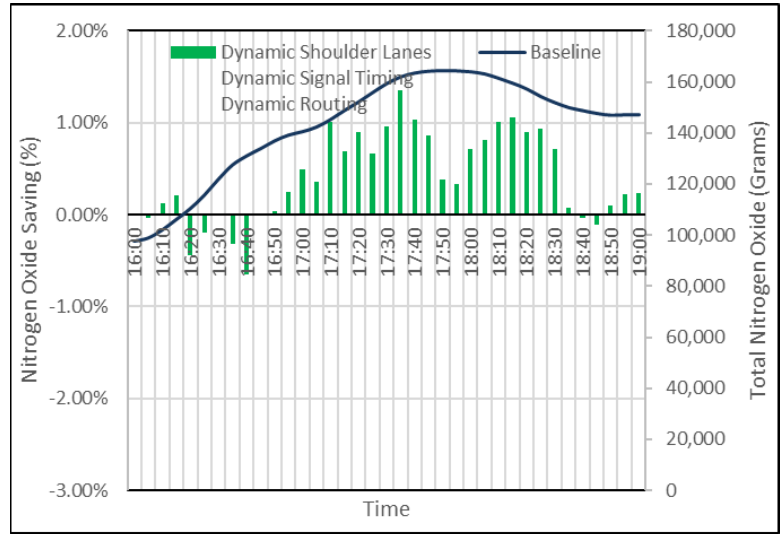
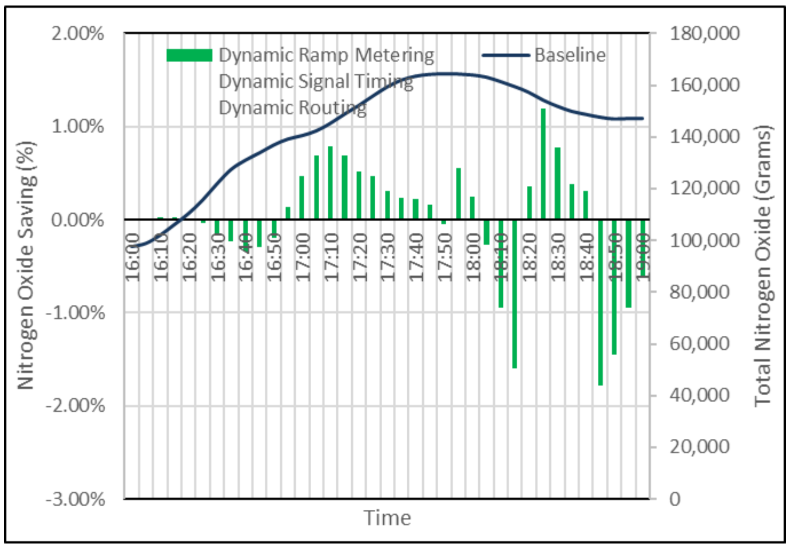


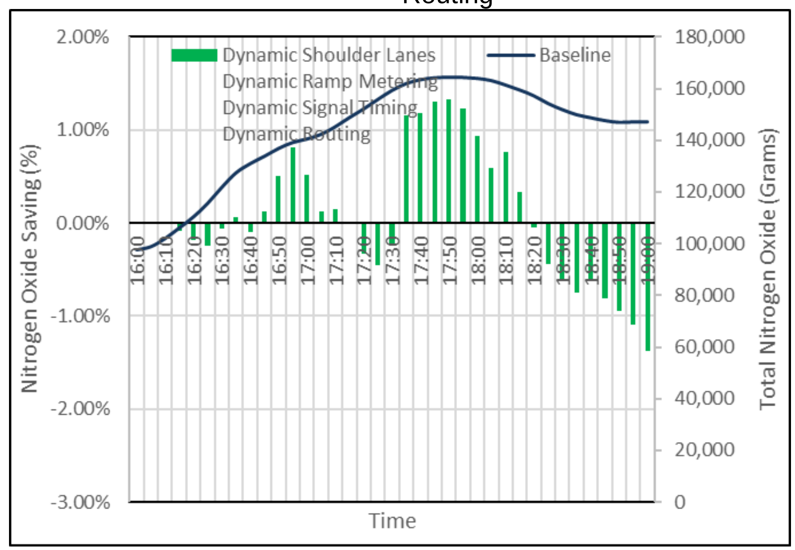
E. Dynamic Shoulder Lanes + Dynamic Routing



F. Dynamic Shoulder Lanes, Dynamic Signal Timing, Dynamic Routing



G. Dynamic Ramp Metering, Dynamic Signal Timing, Dynamic Routing



H. Dynamic Shoulder Lanes, Dynamic Ramp Metering, Dynamic Signal Timing, Dynamic Routing

Figure 5-4: Total Nitrogen Oxide Saving Deploying Different Strategy Combinations on Dallas Testbed under MD-LI Condition [Source: SMU]

Table 5-2: Total Environmental Performance in Different ATDM Traffic Management Strategies on Dallas Testbed under Medium Demand and Low Incident Severity Conditions

Scenario	ATDM Strategy Implemented				Fuel Consumption Savings (tons)	Carbon Dioxide Savings (tons)	Nitrogen Oxide Savings (tons)
	Dynamic Signal Timing	Dynamic Shoulder Lanes	Dynamic Ramp Metering	Dynamic Routing			
S1/A	✓				131.05	9.84	4.75
S2/B		✓			62.94	4.51	3.05
S3/C			✓		17.92	1.34	1.44
S4/D		✓		✓	34.50	2.56	1.90
S5/E	✓			✓	56.27	4.17	3.50
S6/F	✓	✓		✓	71.27	4.84	3.88
S7/G	✓		✓	✓	2.06	7.10	0.06
S8/H	✓	✓	✓	✓	7.94	0.67	0.89

Figure 5-5 and Figure 5-6 demonstrate the effect of different ATDM strategy combinations on the travel time reliability. In these figures, the standard deviation of the time-dependent travel time values, which is recorded every five minutes for the entire simulation horizon, are recorded for the US-75 northbound and southbound directions, respectively. The standard deviation of the time-dependent travel time for the baseline scenario is also given for both freeway directions. The results are given for activating the ATDM strategies considering the HD-MI operational conditions. As shown in Figure 5-5, which provides the results for the northbound direction where the incident is reported, activating the ATDM strategies resulted in reducing the travel time variation across the horizon implying more reliable travel time along the northbound direction. For example, in the scenario in which the dynamic signal timing, the dynamic should lane, the dynamic ramp metering and the dynamic routing strategies are activated, the standard deviation is recorded at about 11.7 minutes, compared to 13.0 minutes for the baseline scenario. The results given in Figure 5-6 for the southbound directions indicate that there is no significant change in the travel time variability. Such results are expected as no incidents are reported on the southbound direction of the freeway.

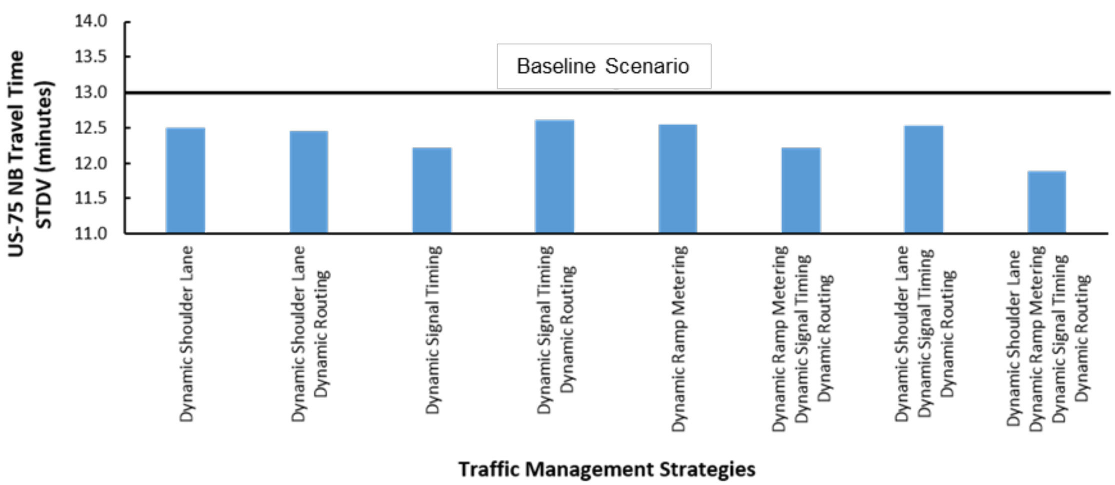


Figure 5-5: US-75 Northbound Travel Time Standard Deviation under different Traffic Management Strategies (Dallas Testbed under Medium Demand and Low Incident Severity Conditions) [Source: SMU]

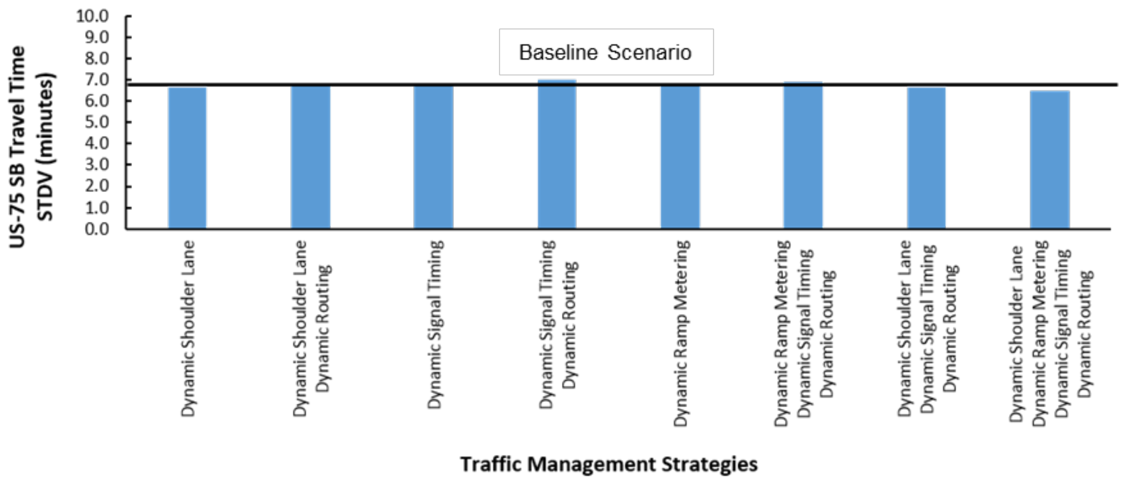


Figure 5-6: US-75 Southbound Travel Time Standard Deviation under different Traffic Management Strategies (Dallas Testbed under Medium Demand and Low Incident Severity Conditions) [Source: SMU]

5.3 Phoenix Testbed Analysis Approach

For the Phoenix Testbed, two combinations of strategies were assessed for synergies and conflicts by comparing the cases where individual strategies were implemented in simulation and compared them with results for a combinatorial implementation. They are provided below.

5.3.1 Adaptive Ramp Metering and Adaptive Traffic Signal Control

In order to compare the impact of Adaptive Ramp Metering (ARM) and Adaptive Traffic Signal control (implemented as RHODES) and their combinations, DTALite, HD-DTA and the multi-resolution simulation platform were utilized respectively to makes sure the results comparable. Adaptive Ramp Metering was assessed for different operational conditions using DTALite and the Adaptive Signal Control (ASC) strategy (RHODES) was assessed using HD-DTA. The measure of effectiveness compared was average travel-time of vehicles in the network including arterials and freeways. For analyzing the impact of isolated strategies with respect to combinations, these strategies were assessed using different operational conditions. Additional conditions will be evaluated in the following chapters.

Figure 5-7 and Figure 5-8 shows the isolated benefits of Adaptive Ramp Metering and Adaptive Signal Control on the network. The bar-plots in Figure 5-7 shows the average travel time of vehicles on the freeway in the baseline model and when Adaptive Ramp Metering is implemented. As shown by the yellow-line, which shows the percentage savings from baseline, this strategy is most effective under High Demand, Medium Incident and Wet Weather condition, where the strategy was able to reduce travel time by up to 18 percent. High Demand and High Incident showed least benefits. The bar-plots on Figure 5-8 shows the average arterial travel time when Adaptive Signal Control (RHODES) was implemented under different operational conditions using the HD-DTA platform. As shown in the figure, RHODES was able to reduce the travel time of vehicles on the arterial significantly. As for RHODES, the maximum benefit was found to be for the High Demand, Medium Incident and Wet Weather operational condition, where RHODES reduced the travel time of vehicles on the arterial by nearly 19 percent. Under Low Demand Low Incident conditions, the reduction in travel time was the least (nearly 11 percent).

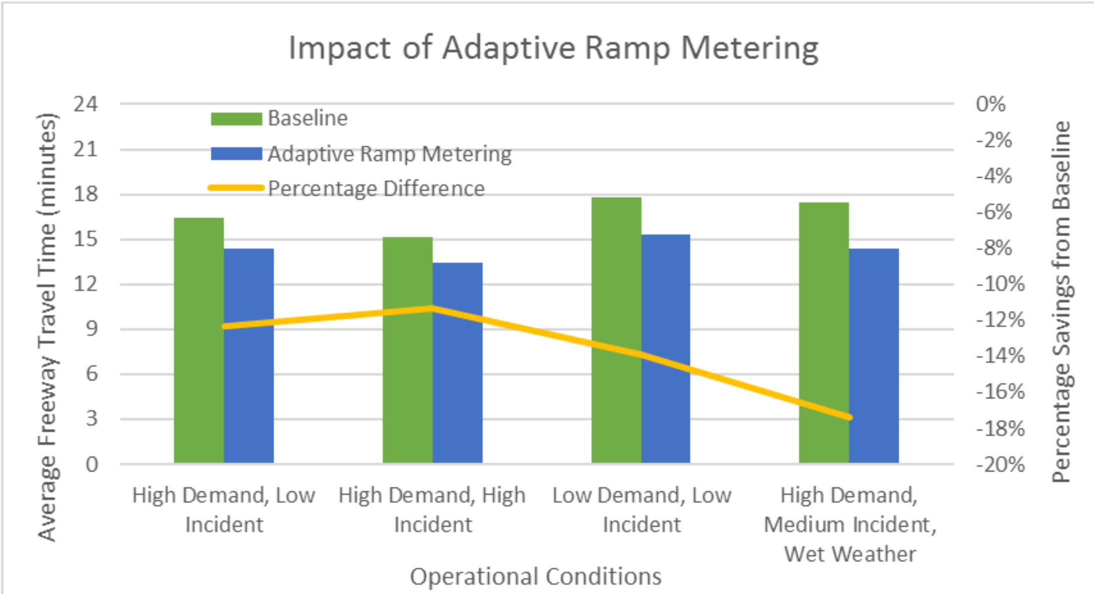


Figure 5-7: Freeway Travel Time with Adaptive Ramp Metering (Phoenix Testbed)[Source: Booz Allen]

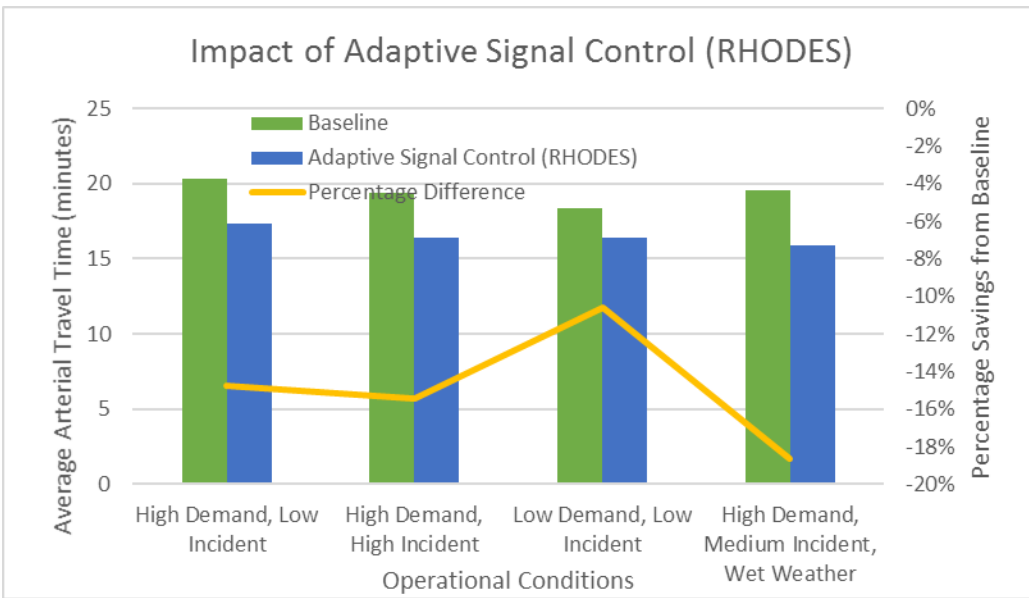


Figure 5-8: Arterial Travel Time with Adaptive Signal Control (Phoenix Testbed) [Source: Booz Allen]

Based on the Multi-Resolution Simulation Platform (MRSP), the project team evaluated the possible benefits, in terms of travel time savings along the freeway and arterial, under the joint application of adaptive signal control and adaptive ramp metering strategies. This is done by comparing the results with a base-line model in which no ATDM strategy is used. For each operational condition, multiple iterations of simulation were conducted. In each iteration, the baseline condition was re-simulated in DTALite/NexTA platform while the adaptive ramp metering strategies at three interchanges were turned on. A new user equilibrium was reached because of the impact of adaptive ramp metering strategy on the freeways. The most comprehensive output of DTALite is in the form of agent trajectories including both paths and times. Those agent trajectories were then filtered and re-loaded in the multi-resolution simulation platform. Since RHODES would reduce the travel times along the arterial, the resulting travel times along the arterials was also changed, resulting in the violation of the user equilibrium between the arterial and freeway. At this point, one iteration was completed. In the next iteration, the DTALite/NexTA would reached a new user equilibrium based on the updated link travel times along the arterials and adaptive ramp metering and then send the new set of agent trajectories into the multi-resolution simulation platform.

Five iterations were simulated between MRSP (multi-resolution simulation platform) and DTALite for each operational condition. After some preliminary experiments, the team decided to introduce additional accidents along the freeway segment in order to examine the performance of the combined Adaptive Ramp Metering and RHODES together. Otherwise, the benefits were nearly unrecognizable due to the relatively low travel demand compared with the available highway resources in Phoenix. Figure 5-9 shows the change in performance measures when Adaptive Ramp Metering and Adaptive Signal Control was implemented in isolation and in combination. The percentage change in performance measures for ARM was freeway travel time and for ASC was arterial travel time, both of which are shown as percentage deviation from the baseline (when no strategy was implemented).

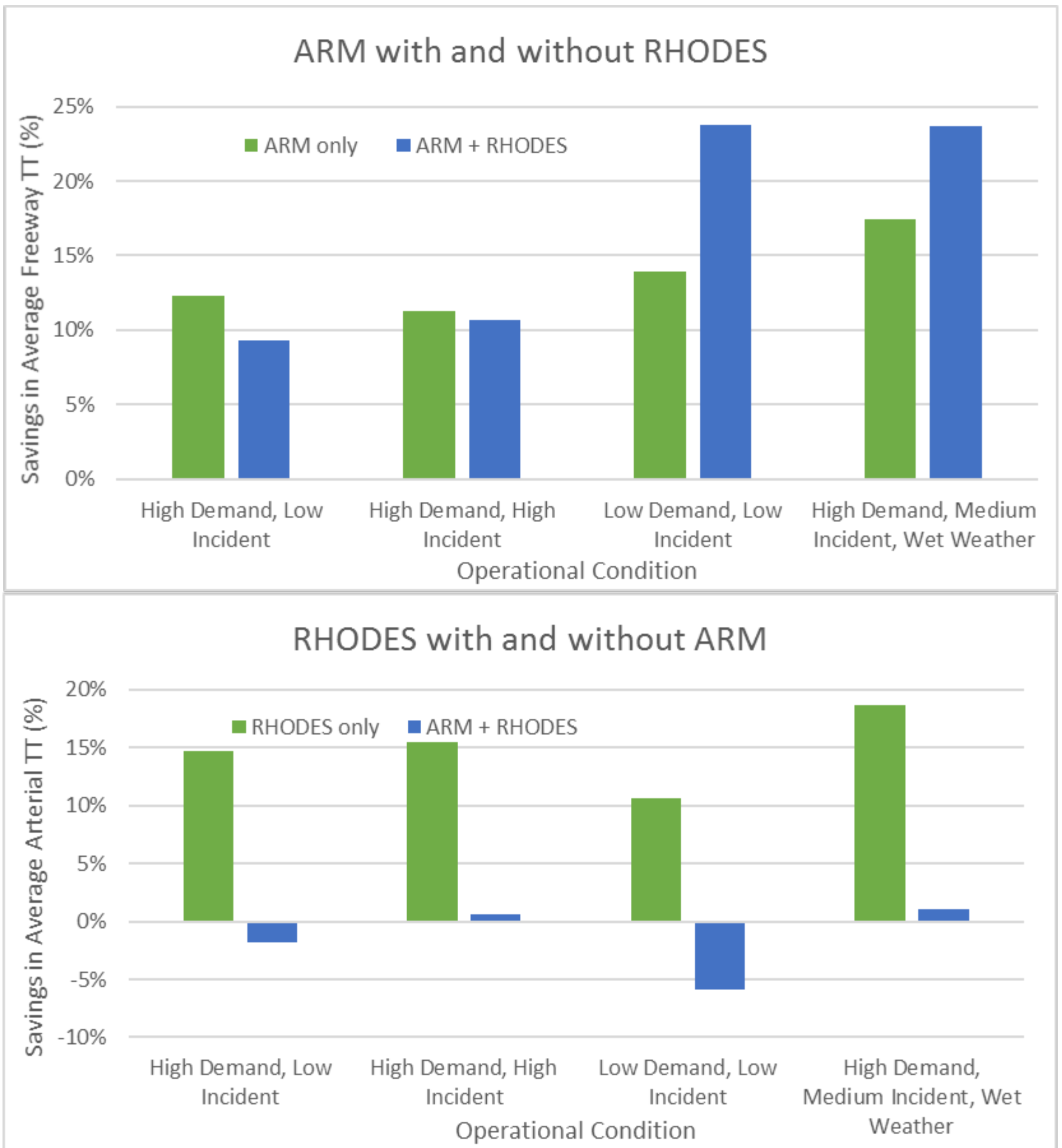


Figure 5-9: Performance of ARM and ASC under isolation and combination. (Phoenix Testbed) [Source: Booz Allen]

For the Adaptive Ramp Metering, it was shown that the combination with ASC was providing lesser benefits than in isolation under high demand, dry weather operational conditions. Under the operational conditions with low demand and wet weather, the combination provided more benefits than ARM alone. For the RHODES strategy, it was shown that the combination with ARM was providing much lesser benefits, and in many cases dis-benefits than when implemented in isolation. From the simulation results, it appears that the overall traffic mobility can be increased by 5%~15% in terms of average freeway travel-time when ARM and RHODES are implemented together. Based on the agent samples which went through the whole freeway segment or went through the whole northbound and southbound arterial mainline, it was noticed that the simulated travel time under control of RHODES had increased. After carefully examined the simulation results both in DTALite and in MRSP, it was seen that DTALite, like many other DTA-type simulators, realized traffic signal control approximately and, as a result, it might have overestimated the link capacities around signalized intersections. In contrast, the MRSP platform adopts high-fidelity traffic signal emulator close to the reality and so exactly estimated the link capacities. Consequently, the travel time along the arterial was witnessed to increase rather than decrease. For each scenario, the MRSP platform was iterated five times and the iteration which has the best simulation outputs were selected.

5.3.2 Dynamic Routing and Predictive Traveler Information

Dynamic Routing and Predictive Traveler Information systems are crucial to active travel demand management. Through these systems, travelers can be guided and suggested to switch to alternative routes to reach their destinations according to the predicted traffic states. In doing so, travel demand can be re-distributed temporarily and spatially. There are two types of dynamic routing in the scheme of ATDM, Variable Message Signs (VMS) focusing on route switching at specific locations; in-vehicle-device-based dynamic routing system focusing on provide individual travelers with better routes in a wider range. In practice, it is highly recommended to adopt dynamic routing and predictive traveler information systems together because good routing policies rely on good traveler information systems. On the other hand, good traveler information systems require high quality data sources, such as vehicle trajectories and origin-destinations which could be provided by the dynamic routing users. The Phoenix testbed focused on the in-vehicle-device-based dynamic routing system integrated with predictive traveler information system using modules that are standard in DTALite. During the preliminary simulation runs to reach user equilibrium, the DTALite recorded the time-dependent historical travel time on all links. During the Dynamic Routing scenarios, a portion of travelers are allowed to recalculate their routes to the scheduled destination according to the latest traffic conditions. The real-time link travel times are calculated based on the latest link travel times as well as the future link travel times predicted from historic data. If an agent could find a considerably better route than its original route, it may choose to change the route.

By default, the DTALite allows a user-defined portion (0%~50%) of total travelers to switch their routes to avoid congestions and reach their destinations. In the meantime, during the preliminary runs of DTALite, historical travel time is also recorded so as to provide proactive link travel time information during the formal simulation runs. The baseline (0% dynamic routing travelers) case was compared with the case where 20% of the travelers had dynamic routing travelers with predictive traveler information under all four operational conditions. From the preliminary simulation runs, it is found that the heaviest congestion occurred around incident sites and the dynamic routing users will switch their routes to avoid those congestions. Figure 5-10 shows the benefits of dynamic routing and predictive traveler information system in terms of average travel time under the four different operational conditions.

As shown, Dynamic Routing was able to reduce the network-wide travel time by up to 40 percent. It should be pointed out that such benefits may be less due to the possible bias generated in model calibration. Specifically, the calibration algorithm underestimated the traffic volumes along arterials due to lack of traffic data along arterials and the traffic volume along arterials are unrealistically low and leave excessive capacity for vehicles from freeways with generate traffic delays. The arterials may also be congested and could not hold that much additional vehicles. As far as the operational conditions are concerned, travel-time savings are shown in almost all the selected conditions with the highest saving when there is highest incident severity and lowest saving when there is lowest incident severity.

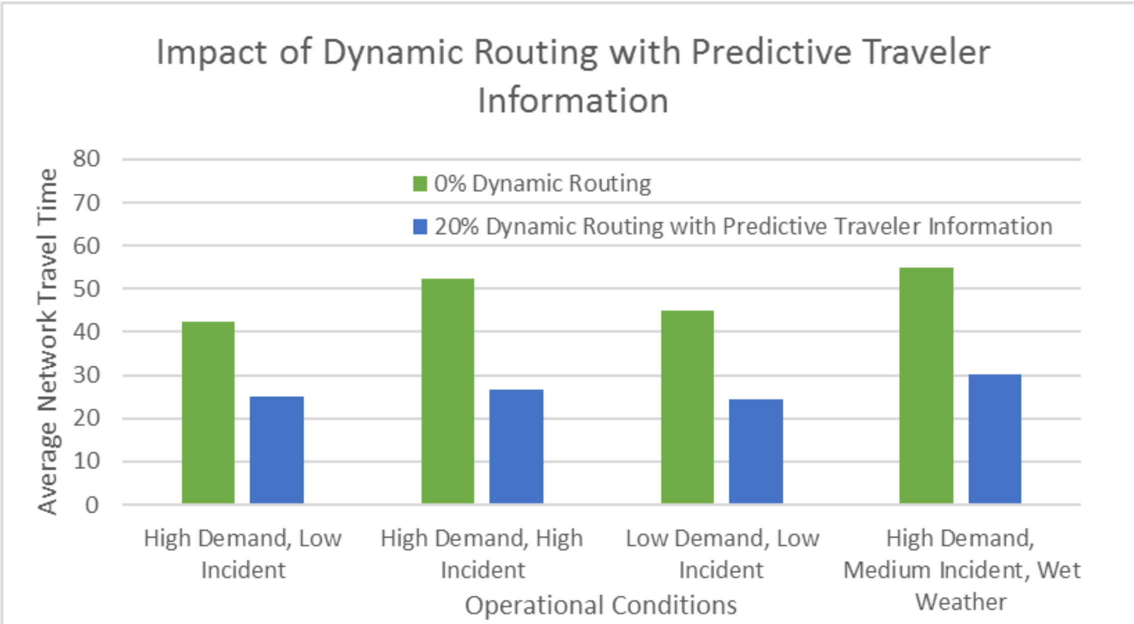


Figure 5-10: Average Network Travel Time Under Dynamic Routing and Predictive Traveler Information Systems (Phoenix Testbed) [Source: Booz Allen]

5.4 Pasadena Testbed Analysis Approach

The ATM strategies included in this analysis are: a) Adaptive Ramp Metering; b) Dynamic Signal Control; c) Hard Shoulder Running; d) Dynamic Junction Control; e) Dynamic Speed Limit plus Queue Warning; and f) Dynamic Route Guidance.

As mentioned in the previous Chapter, TRANSIMS assess all available plans for each of the predefined activated individual or combination ATM strategies from the analysis scenario and makes a recommendation to VISSIM through the System Manager for implementation. TRANSIMS makes its recommendation based on the strategy with the best network performance. The analysis discussed in this section was performed using Operational Condition 1 which is defined by high demand, low to medium incident frequency/severity, medium corridor travel times and dry weather.

The period of analysis for each of the strategies and combination is over a 4-hour period during the weekday PM peak from 3:00PM to 7:00PM. All strategies were assessed under the same prediction scenario and traveler compliance.

5.4.1 Analysis Results

Figure 5-11 shows a general summary of the network travel time for each scenario assessed while Figure 5-12 shows the network travel time savings over the assessment period in 5-minute intervals. Figure 5-12 also shows the recommended plan from TRANSIMS at each 5-minute interval. Table 5-3 shows a separate statistical analysis of each individual strategies to identify if their network, freeway, and arterial impacts are considered statistically significant. Detailed discussion of each plan associated with each strategy scenarios were discussed in Chapter 4.

The results yield the following observation:

- In increasing order, the tabulated results listed in Table 5-3 shows when the following strategies yield positive network travel time savings: DSC, ARM, DRG, and HSR + DJC. The only strategy that yields negative network travel time savings is DSL + QW.
- Through an iterative process, it was determined that DSC only yields positive network travel time savings when implemented during heavy congestion periods (5:00PM to 7:00PM for OC 1).
- The combination arterial focused strategy between DSC with DRG yield a network travel time saving of 2.11% which is a small increase from the isolated DRG strategy of 2.10% and a larger increase from the isolated DSC strategy of 0.77%.
- The results for the freeway focused strategy, ARM + HSR + DJC combination, shows a network travel time savings of 6.64% which is lower than the isolated HSR + DJC strategy at 7.77% but significantly higher than the isolated ARM strategy at 2.45%. This result does not indicate there is a conflict between ARM with HSR + DJC due to the predefined plan deployment discussed in Chapter 4 which limits the use of HSR to only heavy congestion periods (5:00PM to 7:00PM).
- The combination of arterial and freeway focused strategies, ARM + HSR + DJC + DSC + DRG, shows a slight improvement at 6.68% network travel time savings compared to the freeway only focused strategy, ARM + HSR + DJC, at 6.64% but a significant improvement from the arterial only focused strategy, DSC + DRG, at 2.11%.
- The DSL + QW shows negative travel time savings due to the distribution of traffic congestion from an isolated location over a larger segment distance to promote a more gradual change in speed.

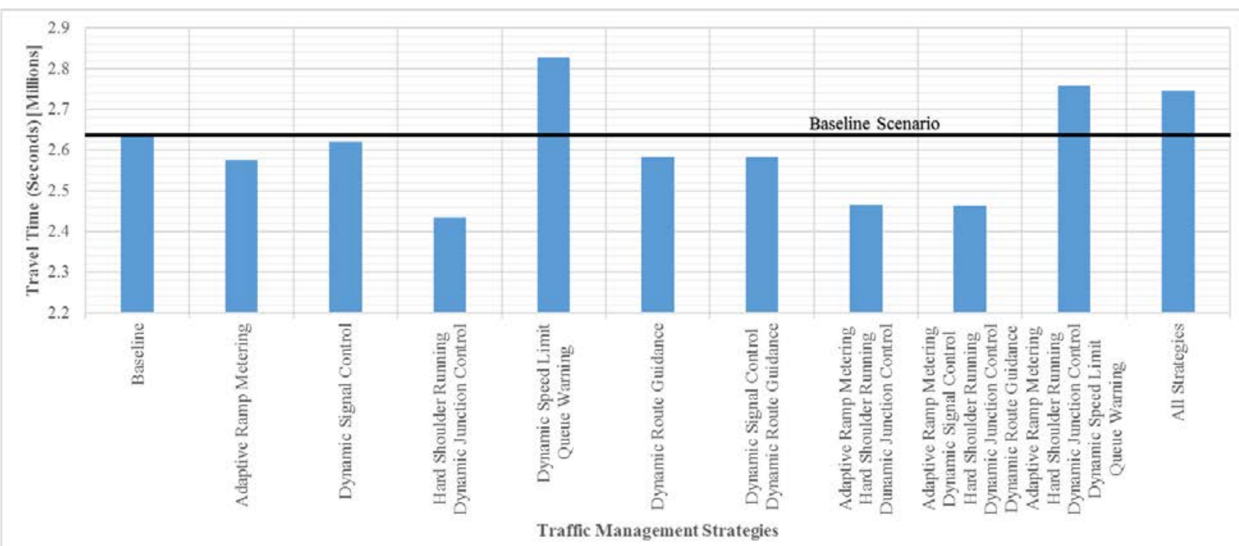


Figure 5-11: Network Travel Time for Individual and Combination ATDM Strategies [Source: Booz Allen]

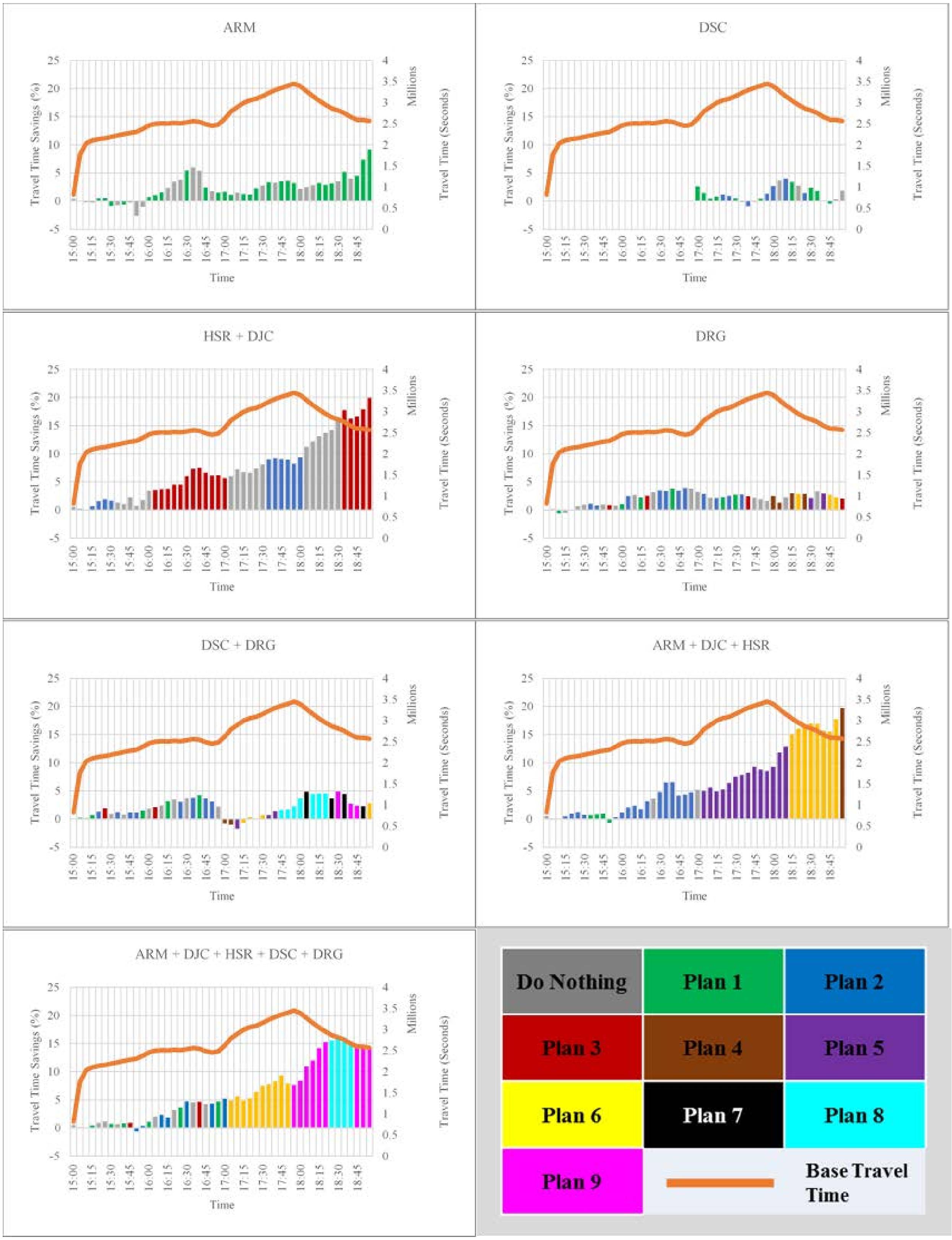


Figure 5-12: Network Travel Time for Individual and Combination ATDM Strategies over 4 Hours [Source: Booz Allen]

Table 5-3: Statistical Analysis of Individual Strategies

Strategy	Performance Measure	Sample Size	Mean (Baseline)	Std. Dev. (Baseline)	Mean (Strategy)	Std. Dev. (Test)	Computed t-Statistic	P-Value	Statistical Significance
ARM	Network Travel Time	5	2605566	41189.18	2578367	21169.86	1.3133	0.1185	No
	Network VMT/VHT	5	27.65	0.3981	27.85	0.1617	-1.0779	0.1651	No
	Freeway Travel Time	5	1065139	41688.59	1023646	24649.38	1.9157	0.0423	Yes
	Arterial Travel Time	5	1540428	6853.094	1554720	14691.6	-1.9714	0.0481	Yes
DSC	Network Travel Time	5	2605566	41189.18	2595655	28881.91	0.4405	0.3364	No
	Network VMT/VHT	5	27.65	0.3981	27.71	0.2413	-0.2903	0.3901	No
	Freeway Travel Time	5	1065139	41688.59	1031745	26181.35	1.5168	0.0866	No
	Arterial Travel Time	5	1540428	6853.094	1537910	34178.4	0.8063	0.1032	No
HSR + DJC	Network Travel Time	5	2605566	41189.18	2411702	31562.66	7.9934	4.59E-05	Yes
	Network VMT/VHT	5	27.65	0.3981	29.67	0.3669	-7.9862	4.61E-05	Yes
	Freeway Travel Time	5	1065139	41688.59	952713	49696.62	3.619	0.0056	Yes
	Arterial Travel Time	5	1540428	6853.094	1458988	45055.67	3.582	0.0186	Yes
DSL + QW	Network Travel Time	5	2605566	41189.18	2876724	44088.36	1.94318	4.02E-05	Yes
	Network VMT/VHT	5	27.65	0.3981	23.35373	0.296745	18.77476	1.51E-07	Yes
	Freeway Travel Time	5	1065139	41688.59	1294654	41002.8	-8.28248	3.65E-05	Yes
	Arterial Travel Time	5	1540428	6853.094	1602070	11072.64	-9.74123	9.69E-05	Yes
DRG	Network Travel Time	5	2605566	41189.18	2555538	35639.32	1.8115	0.0258	Yes
	Network VMT/VHT	5	27.65	0.3981	28.15	0.3077	-2.0064	0.0199	Yes
	Freeway Travel Time	5	1065139	41688.59	1016635	32128.54	1.9709	0.0447	Yes
	Arterial Travel Time	5	1540428	6853.094	1530580	5001.518	2.4894	0.0208	Yes

The adaptive ramp metering strategy shows a statistically insignificant change from the baseline at the network travel time savings. At the freeway and arterial level, adaptive ramp metering shows a statistically significant improvement for the freeway and a statistically significant degradation at the arterials (P-value < 0.05). The isolated DSC strategy does not show statistically significant improvements.

The HSR + DJC and DRG isolated strategies show statistically significant improvement from the baseline for the network, freeway, and arterial levels. The results show that HSR has the highest benefit impact on the operational performance of the network. A closer investigation into the simulated scenarios show the combination strategies of ARM + HSR + DJC and ARM + HSR + DJC + DSC + DRG can achieve very close magnitude of improvements to the isolated HSR + DJC strategy with lower HSR activation time period as shown in Table 5-4.

Table 5-4: Comparison of Network Travel Time Savings to Duration when HSR was Activated

Strategies	Duration when Hard Shoulder Running was Activated	Network Travel Time Savings
HSR + DJC	195 minutes	7.77%
ARM + HSR + DJC	110 minutes	6.64%
ARM + HSR + DJC + DSC + DRG	50 minutes	6.68%

5.5 Chicago Testbed Analysis Approach

Table 5-5 shows the design of experiment tests. The average travel time on the Chicago testbed is no more than 30 minutes, and the shorter roll period is expected to provide more accurate predictive information. In testing the first two research questions, the default settings for prediction features were applied, with a prediction horizon of 30 minutes, and a roll period of 5 minutes. The experiments to test the research questions on Synergies and Conflicts are designed to test all possible combinations of strategies. Note that the Weather-related strategies are only applicable to OC 3 through OC6, as the snow accumulation cannot reach the threshold to trigger the Weather-Related strategies in OC2.

However, to select the optimized setting of the percentage of vehicles which have access to predictive information, the net penetration level of 0% (do nothing), 30% and 50% are tested in OC1 (a clear day scenario) before conducting the test scenarios to address questions for Synergies and Conflicts. Note that the net penetration rate in the test scenarios for the experiment factor of combination of strategies is set at 30% in the table. This choice is made according to the simulation tests for the network penetration, which is described in detail in the section 9.2.2.

Table 5-5: Experiment Scenarios for Research Questions of Synergies and Conflicts

Experiment Factor	Tests	Strategy	Net Penetration Level	Roll	Horizon	Latency
Percentage of vehicles that have the access to predictive information for ADM	OC1 (Clear Day)	Doing nothing	0 %	-	-	-
		ADM	30 %	5	30	0
		ADM	50 %	5	30	0
Combination of strategies	OC1 (Clear Day); OC2 (Rain to Snow)	Do nothing	0 %	-	-	-
		ADM	30%	5	30	0
		ATM	0%	5	30	0
		ADM +ATM	30%	5	30	0
	OC3, 4 (Moderate Snow); OC5 (Heavy Snow); OC6 (Moderate Snow + Incident)	Do nothing	0 %	-	-	-
		ADM	30%	5	30	0
		ATM	30%	5	30	0
		WR	30%	5	30	0
		ADM + WS	30%	5	30	0
		ADM +ATM + WS	30%	5	30	0

5.5.1 Analysis Results

Several observations can be made on the results shown on Figure 5-13 to Figure 5-19. First, for the net penetration effect in Figure 5-13, the penetration rate of 30% yields more benefits than the rate of 50% in terms of system performance for the entire day, but the higher rate contributes more benefits on the morning peak traffic. This phenomenon was also verified in literature (see (Zockaie, Chen, & Mahmassani, 2014) where the traffic network with high penetration rate requires coordination in vehicle routing to achieve maximal effect; otherwise, conflicts among route choices may occur, leading to a less improved traffic state.

To test the scenarios in terms of Synergies and Conflicts, 3 h operational conditions were plotted, including (1) improvement in the % cumulative throughput compared with the baseline scenario with no strategy implemented, (2) improvement in the actual number of the cumulative throughput compared with the baseline scenario with no strategy implemented, and (3) the actual number of cumulative demand and cumulative throughput under the baseline scenario and the scenario with the most beneficial strategy or combination of strategies.

Figure 5-14 and Figure 5-15 refer to the results for clear day and rain to snow scenario. It can be concluded that under clear day or rain to snow scenario, where influence from weather effect is not significant, the combination of ATM and ADM shows considerable synergies, especially for peak hours, where the effect is better than the just sum of the individual strategies. Note that ATM brings some negative effect around noon, when the shoulder lane is not available to provide more supply. Meanwhile, due to the continuously high demand, dynamic speed limit is always functional on the main highway segments, limits the traffic volume and thus leads to the network throughput drop. The throughput gets recovered after 3PM when dynamic shoulder lane is open again.

Under the snow affected scenarios, if the travel demand is high (e.g. OC 3 and OC 5) in Figure 5-16 and Figure 5-18, the best strategy comes from the Weather-related strategy described in section 2.1 and 4.3, and it is compatible with ADM and ATM with most synergies.

If the travel demand is low (i.e. OC 4) in Figure 5-17, ATM and the Weather-related strategy can bring negative effect when implemented individually. The reasons could be (a) dynamic shoulder lanes are not functional on weekend for OC 4, producing no extra capacity, (b) speed limits due to safety issue under snow may reduce the network throughput in a less congested network when demand is low, and (c) the recovered capacity from the Weather-related strategy is not effective for OC 4 due to low demand, but it brings disadvantages from lane closure during implementation.

Under the snow and incident affected scenario (OC 6) in Figure 5-19, ATM shows the most benefits as an individual strategy since it brings more capacity with dynamic shoulder lanes and controls local demand with speed limit. Meanwhile, compared with OC 3 do-nothing scenario, the loss of capacity due to incident is observed, and the combination of strategies contributes to not only recovering the capacity but improving it compared with pre-incident capacity.

Figure 5-13: Simulation tests for CV market penetration [Source: NWU]

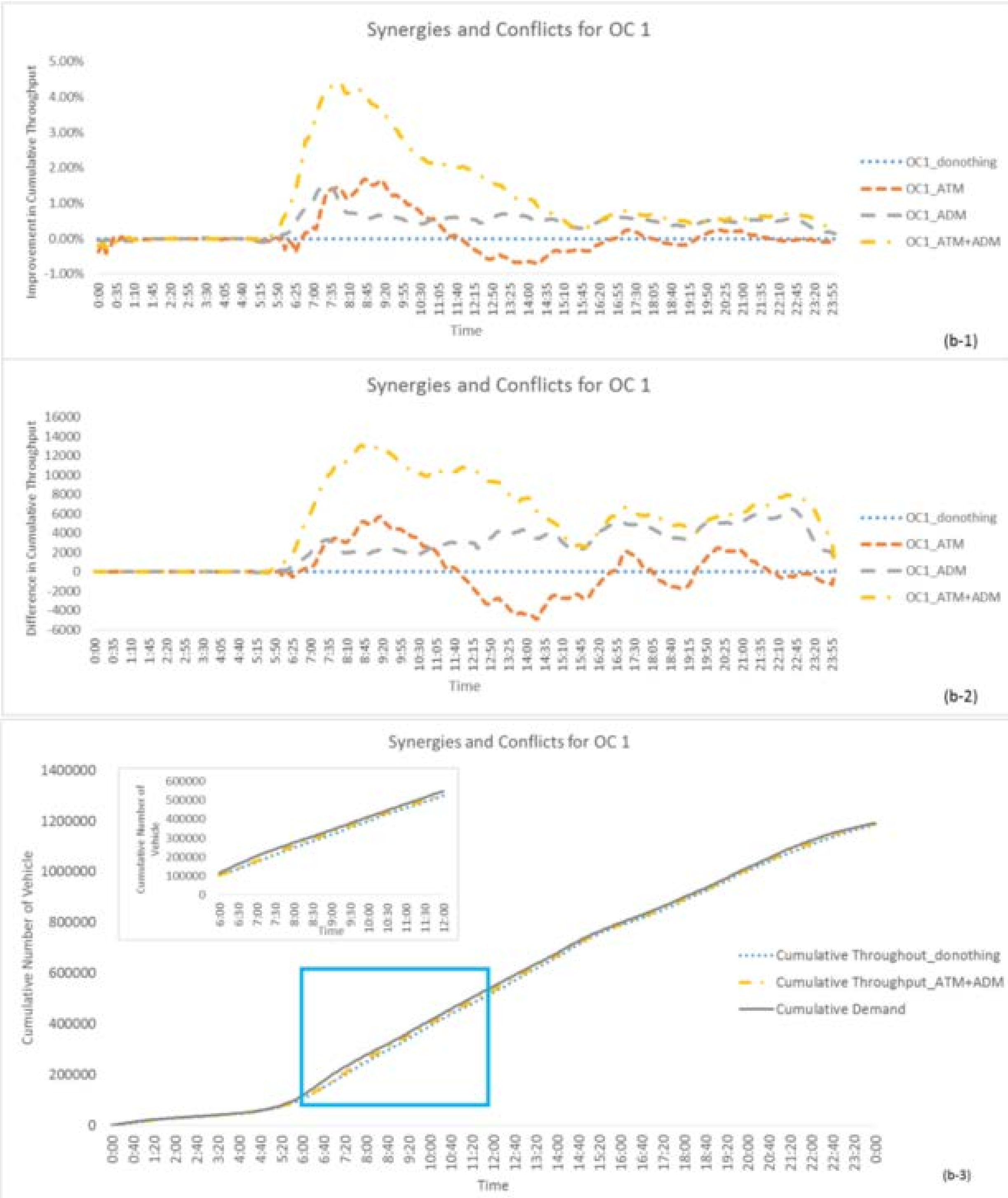


Figure 5-14: Simulation tests for synergies and conflicts for OC1 [Source: NWU]

Figure 5-15: Simulation tests for synergies and conflicts for OC2 [Source: NWU]

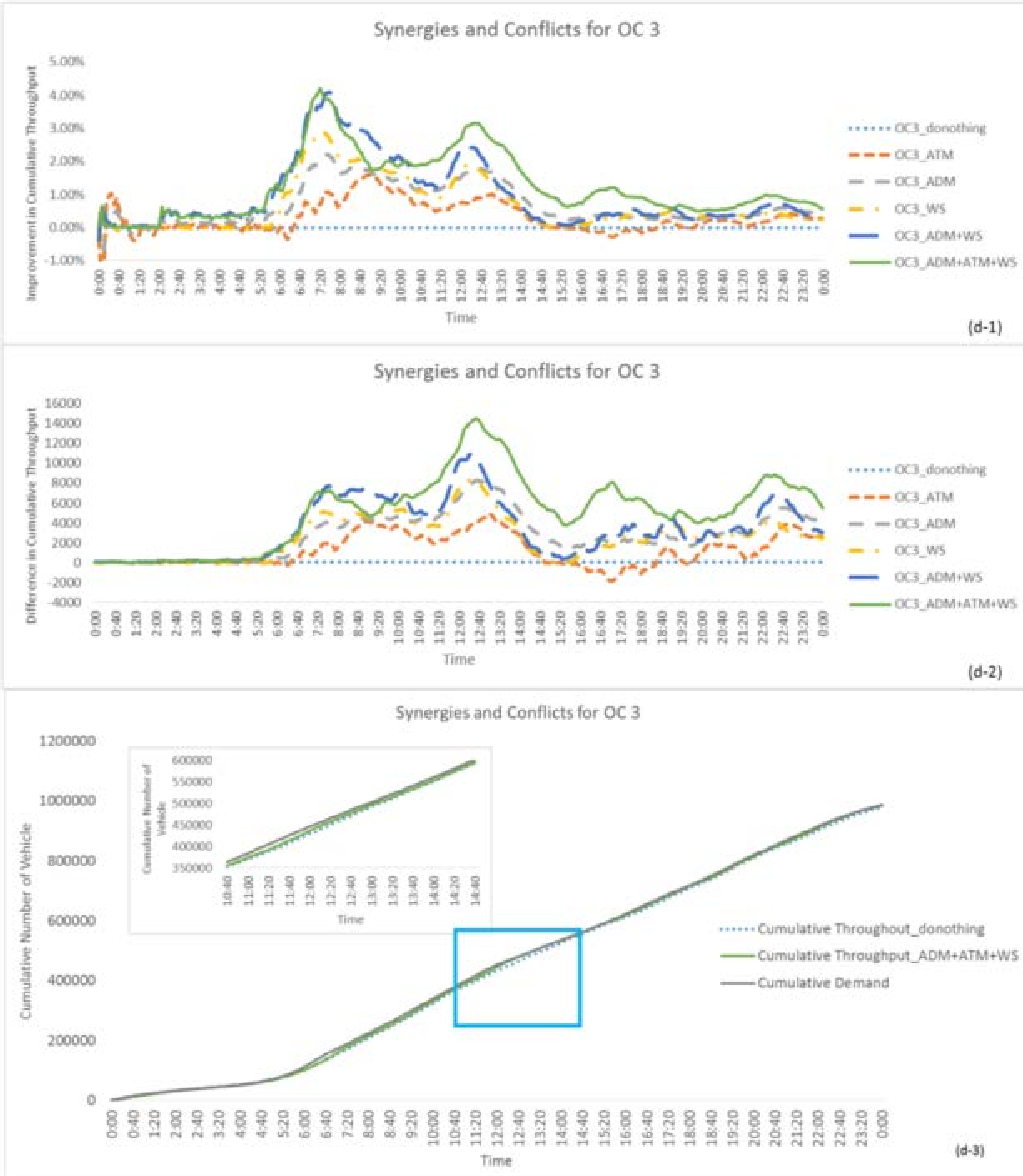


Figure 5-16: Simulation tests for synergies and conflicts for OC3 [Source: NWU]

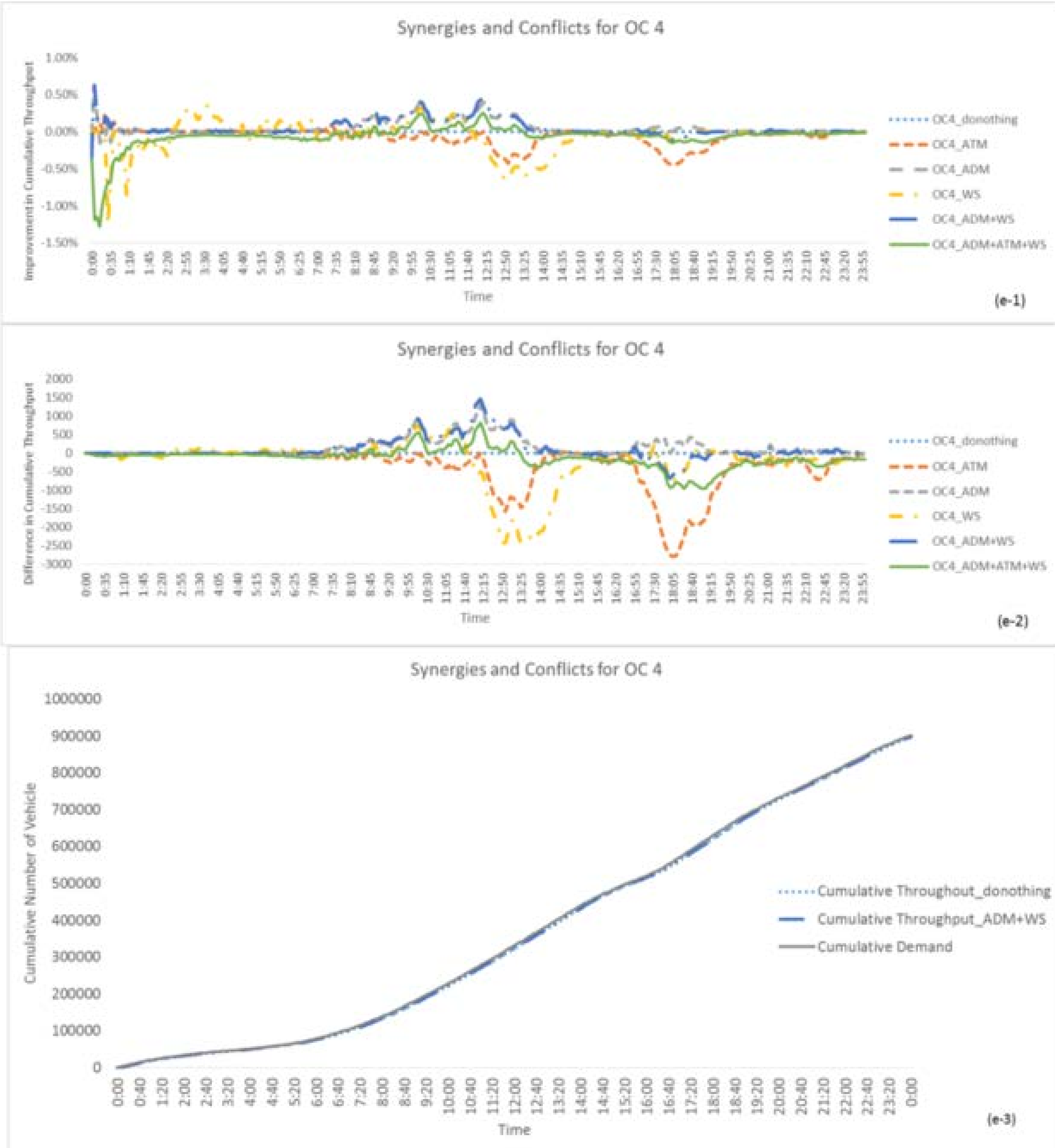


Figure 5-17: Simulation tests for synergies and conflicts for OC4 [Source: NWU]

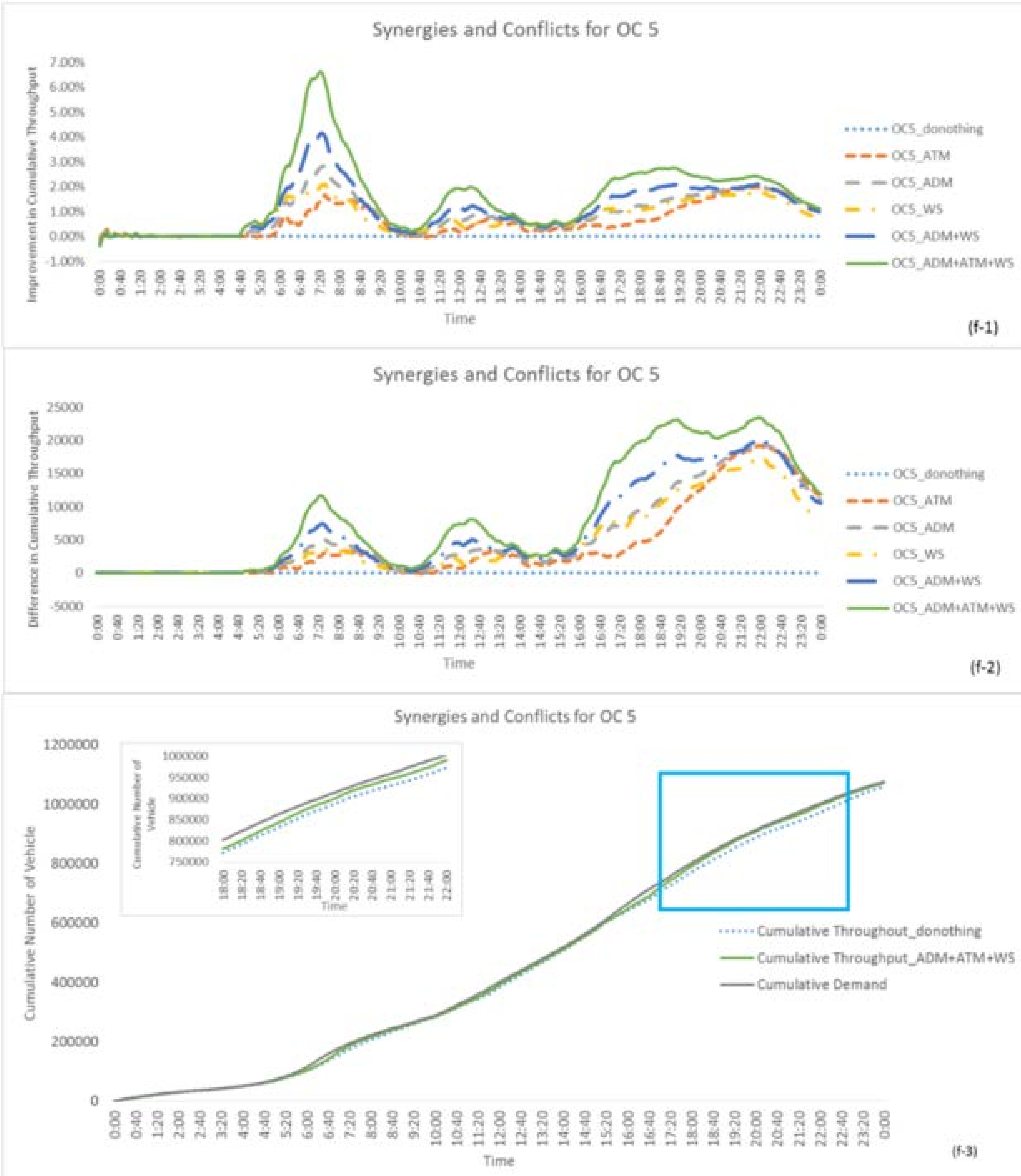


Figure 5-18: Simulation tests for synergies and conflicts for OC5 [Source: NWU]

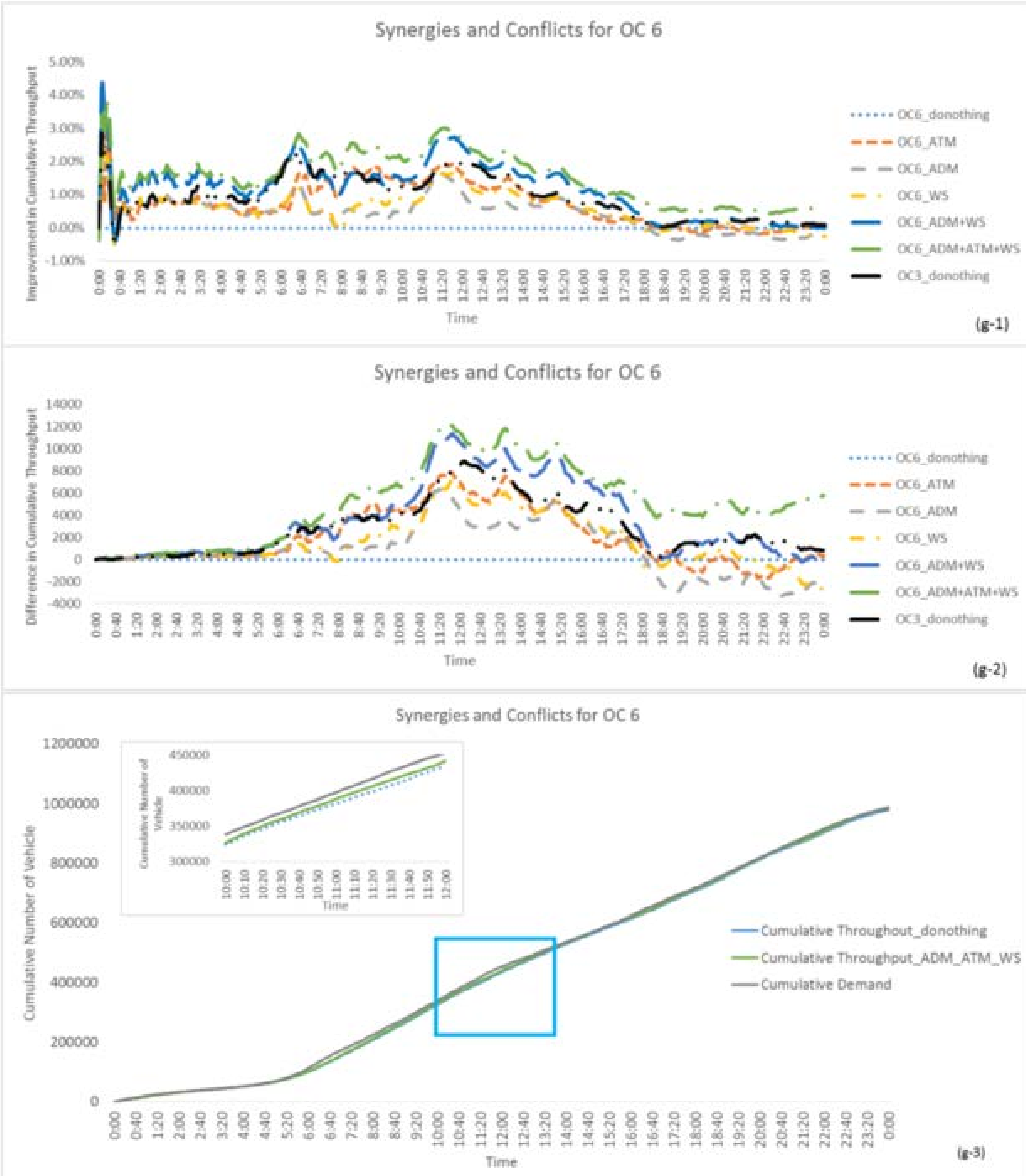


Figure 5-19: Simulation tests for synergies and conflicts for OC6 [Source: NWU]

5.6 San Diego Testbed Analysis Approach

Operational condition 1 was used to evaluate combinations of different ATDM strategies to find synergies and conflicts. Specifically, the scenarios that have been evaluated are:

- Dynamic Lane Use, Dynamic HOV/Managed Lanes and Dynamic Speed Limits
- Dynamic Merge Control and Dynamic HOV/Managed Lanes
- Dynamic Merge Control, Dynamic HOV/Managed Lanes and Dynamic Routing

Simulations were conducted activating concurrently ATDM strategies. The performance measures obtained in these simulations have been compared both with the baseline case, in which no ATDM strategies are active, and with the results of the scenarios in which an individual ATDM strategy was active.

5.6.1 Dynamic Lane Use, Dynamic HOV/Managed Lanes and Dynamic Speed Limits

A set of simulations was run with a 3+1 configuration of the HOV lanes along I-15 in the southbound direction (see 0), no toll for SOVs that would use the HOT lanes in the southbound direction (see 0), and dynamic speed limits sets according to the ACISA-1 algorithm (see 0).

A comparison of the speed contour on I-15 in the southbound direction with the baseline conditions shows that dynamic speed limits produce a “dilution” of the congestion over space and time (Figure 5-20), which suggests an improvement in safety.

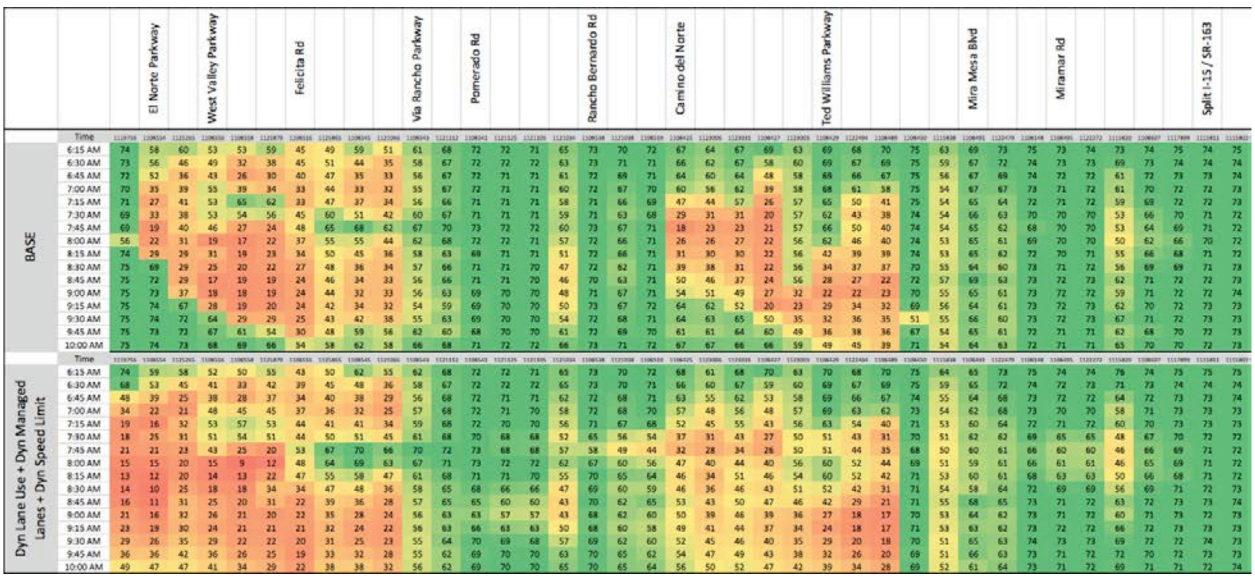


Figure 5-20: Speed contour with Dynamic Lane Use, Dynamic HOV/Managed Lanes and Dynamic Speed Limits compared with the baseline case [Source: TSS]

If we compare network-wide traffic performance measures with Dynamic Lane Use, Dynamic HOV/Managed Lanes and Dynamic Speed Limits concurrently active with the baseline condition and with the case of only Dynamic Lane Use and Dynamic HOV/Managed Lanes or only Dynamic Speed Limits active (Table 5-6 and Figure 5-21), we can notice that the results are similar to the situation with Dynamic Speed Limits only, with a slightly better throughput and slightly longer travel time.

Table 5-6: Performance measures with Dynamic Lane Use, Dynamic HOV/Managed Lanes and Dynamic Speed Limits compared with the baseline case and with the activation of individual ATDM strategies

Network Statistics	Base	Dyn Lane Use + Dyn Managed Lanes + Dyn Speed Limit	Difference	Dyn Lane Use + Dyn Managed Lanes	Difference	Dynamic Speed Limit	Difference
Vehicle Miles Traveled (mi)	2,320,947	2,297,710	-1.0%	2,325,470	0.2%	2,295,970	-1.1%
Total Travel Time (h)	61,946	64,029	3.4%	60,953	-1.6%	63,713	2.9%
Passenger Hourly Travel Time (h)	78,635	81,614	3.8%	77,591	-1.3%	80,972	3.0%
VMT/VHT (mi/h)	37.47	35.89	-4.2%	38.15	1.8%	36.04	-3.8%

Figure 5-21: Performance measures with Dynamic Lane Use, Dynamic HOV/Managed Lanes and Dynamic Speed Limits compared with the baseline case and with the activation of individual ATDM strategies [Source: TSS]

In summary, the results show neither a significant conflict nor a significant synergy between these ATDM strategies. The increase of congestion at the entrances and exits of the HOV lanes due to the increase of demand triggered by Dynamic Lane Use, Dynamic HOV/Managed Lanes is sensed by Dynamic Speed

Limits, which extends the congestion over a larger space and longer time in order to avoid abrupt speed changes. This increase of safety is obtained at the expense of throughput and travel time. Dynamic Lane Use and Dynamic HOV/Managed Lanes alone would produce better traffic performance, at the expense of safety. Dynamic Speed Limits alone would produce an increase of safety, but with a more pronounced reduction of throughput.

5.6.2 Dynamic Merge Control and Dynamic HOV/Managed Lanes

A set of simulations was run with no toll for SOVs that would use the HOT lanes in the southbound direction (see 0) and dynamic merge control at the entrance of SR-78 into I-15 southbound (see 0). A comparison of the speed contour on I-15 in the southbound direction with the baseline conditions shows that the spatial and temporal extension of congestion is essentially unchanged (Figure 5-22).

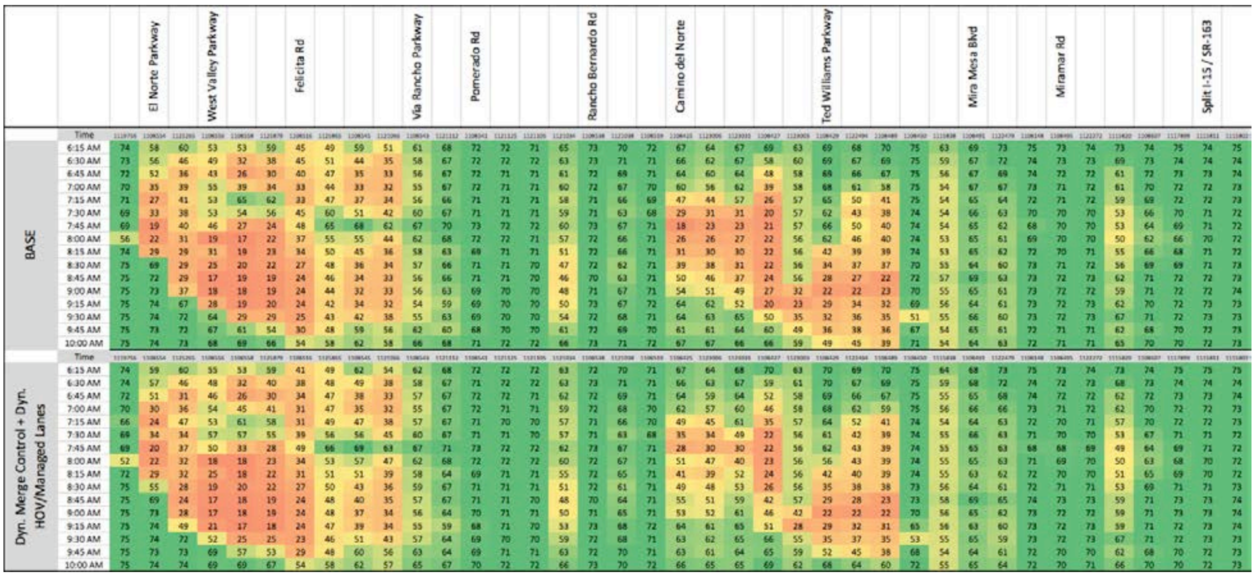


Figure 5-22: Speed contour with Dynamic Merge Control and Dynamic HOV/Managed Lanes compared with the baseline case [Source: TSS]

If we compare network-wide traffic performance measures with Dynamic Merge Control and Dynamic HOV/Managed Lanes concurrently active with the baseline condition and with the case of only Dynamic Merge Control or only Dynamic HOV/Managed Lanes and Dynamic Lane Use active (Table 5-7 and Figure 5-23), we can notice that the results are similar to the baseline situation.

Table 5-7: Performance measures with Dynamic Merge Control and Dynamic HOV/Managed Lanes compared with the baseline case and with the activation of individual ATDM strategies

Network Statistics	Base	Dyn. Merge Control + Dyn. HOV/Managed Lanes	Diff.	Dyn Lane Use + Dyn Managed Lanes	Diff.	Dynamic Merge Control	Diff.
Vehicle Miles Traveled (mi)	2,320,947	2,321,332	0.0%	2,325,470	0.2%	2,315,264	-0.2%
Total Travel Time (h)	61,946	61,543	- 0.7%	60,953	-1.6%	65,191	5.2%
Passenger Hourly Travel Time (h)	78,635	78,300	- 0.4%	77,591	-1.3%	83,511	6.2%
VMT/VHT (mi/h)	37.47	37.72	0.7%	38.15	1.8%	35.52	-5.2%

Figure 5-23: Performance measures with Dynamic Merge Control and Dynamic HOV/Managed Lanes compared with the baseline case and with the activation of individual ATDM strategies [Source: TSS]

In summary, the results show a synergy between these ATDM strategies. Dynamic HOV/Managed Lanes compensate the slightly negative effect in terms of traffic performance caused by Dynamic Merge Control, which facilitates the entrance from SR-78, at the expense of penalizing traffic coming from the northern boundary of the I-15 corridor in the southbound direction.

Dynamic HOV/Managed Lanes alone hasn't been evaluated (it has been evaluated at minimum in combination with Dynamic Lane Use); it is expected that combining additionally Dynamic Lane Use the synergy of the three ATDM strategies would increase. However, Dynamic HOV/Managed Lanes and Dynamic Lane Use show the best traffic performance. Therefore, the decision to activate Dynamic Merge Control or not should be dictated purely by the need to reduce queueing on the ramp coming from SR-78 rather than by overall traffic performance benefits. If Dynamic Merge Control is activated, Dynamic HOV/Managed Lanes would compensate its slightly negative impact.

5.6.3 Dynamic Merge Control, Dynamic HOV/Managed Lanes and Dynamic Routing

A set of simulations was run with dynamic merge control at the entrance of SR-78 into I-15 southbound (see 0), no toll for SOVs that would use the HOT lanes in the southbound direction (see 0), and dynamic routing based on current (not predicted) travel times (see 0).

A comparison of the speed contour on I-15 in the southbound direction with the baseline conditions shows that the spatial and temporal extension of congestion is essentially unchanged (Figure 5-24).

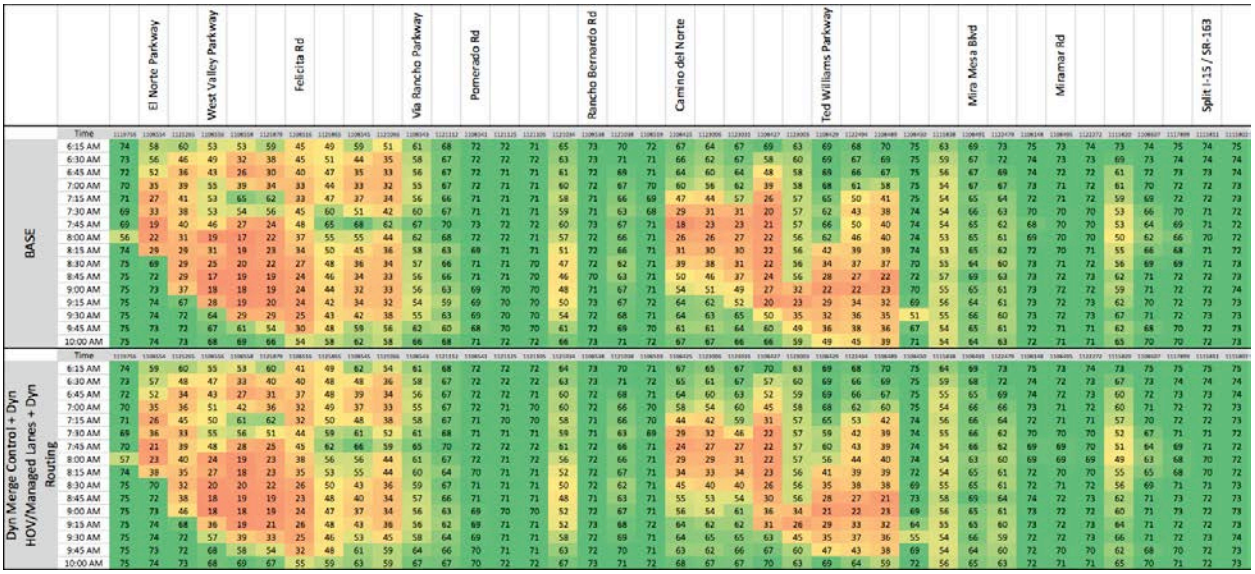


Figure 5-24: Speed contour with Dynamic Merge Control, Dynamic HOV/Managed Lanes and Dynamic Routing compared with the baseline case [Source: TSS]

If we compare network-wide traffic performance measures with Dynamic Merge Control, Dynamic HOV/Managed Lanes and Dynamic Routing concurrently active with the baseline condition and with the case of only Dynamic Merge Control or only Dynamic HOV/Managed Lanes and Dynamic Lane Use active (Table 5-8 and Figure 5-25), we can notice an almost negligible increase of throughput with a slight decrease of travel time.

Table 5-8: Performance measures with Dynamic Merge Control, Dynamic HOV/Managed Lanes and Dynamic Routing compared with the baseline case and with the activation of individual ATDM strategies

Network Statistics	Base	Dyn Merge Control + Dyn HOV/Managed Lanes + Dyn Routing	Diff.	Dyn Lane Use + Dyn Managed Lanes	Diff.	Dynamic Merge Control	Diff.
Vehicle Miles Traveled (mi)	2,320,947	2,323,165	0.1%	2,325,470	0.2%	2,315,264	-0.2%
Total Travel Time (h)	61946	61,240	-1.1%	60,953	-1.6%	65,191	5.2%
Passenger Hourly Travel Time (h)	78635	77,829	-1.0%	77,591	-1.3%	83,511	6.2%
VMT/VHT (mi/h)	37.47	37.94	1.2%	38.15	1.8%	35.52	-5.2%

Figure 5-25: Performance measures with Dynamic Merge Control, Dynamic HOV/Managed Lanes and Dynamic Routing compared with the baseline case and with the activation of individual ATDM strategies [Source: TSS]

In summary, the results show a synergy between these ATDM strategies. Dynamic HOV/Managed Lanes and Dynamic Routing compensate the slightly negative effect in terms of traffic performance caused by Dynamic Merge Control, which facilitates the entrance from SR-78, at the expense of penalizing traffic coming from the northern boundary of the I-15 corridor in the southbound direction.

Dynamic HOV/Managed Lanes alone hasn't been evaluated (it has been evaluated at minimum in combination with Dynamic Lane Use) nor or Dynamic Routing alone (it has been evaluated with Predictive Traveler Information); it is expected that combining additionally Dynamic Lane Use the synergy of the three ATDM strategies would increase. However, Dynamic HOV/Managed Lanes and Dynamic Lane Use show the best traffic performance. Therefore, the decision to activate Dynamic Merge Control or not should be dictated purely by the need to reduce queueing on the ramp coming from SR-78 rather than by overall traffic performance benefits. If Dynamic Merge Control is activated, Dynamic HOV/Managed Lanes and Dynamic Routing would compensate its slightly negative impact.

5.7 Results Summary

This chapter analyzes the impact of combining different strategies and implementing them together in an active traffic management context and to find out synergistic and conflicting strategies. To assess the impact of combination of different ATDM strategies, the proposed strategies were assessed in isolation and in combination. It was found that these strategies are synergistic in nature, with combination of strategies showing better performance measures than isolation.

The results from the Dallas Testbed shows that all the ATDM strategies improve the overall network performance during non-recurrent congestion scenario. Integrated ATDM strategies such as Dynamic Signal Timing, Dynamic Routing, Adaptive Ramp Metering and Dynamic Shoulder Lane could have significant benefits in terms of congestion reduction. As mentioned earlier, the system periodically reports the performance of the network in terms of travel time savings for 30 minutes rolling horizon. Careful examination of the entire results reveals that travel time savings of over 1,250 hours have been reached at some instances. For example, when multiple strategies are integrated in one scheme, more than 75,000 minutes' savings in travel time was seen at the most congested time in the network. The results of environmental network performance show the ATDM strategies has positive impact on the fuel consumption and other pollution measures in the network. Among all the strategies, dynamic shoulder lanes strategy has significant impact on reducing the fuel consumption, and pollution in the entire network. However, the adaptive ramp metering strategy usually increases the fuel consumption and pollution in the total network. The integrated ATDM strategies such as dynamic signal timing, dynamic routing, and dynamic shoulder lane was the most successful scenario in terms of reducing the fuel consumption, carbon dioxide emission, and nitrogen oxide emission. Shown in Table 5-9, Dynamic Shoulder Lanes strategy contributed to the highest benefits, in isolation and in combination. Most of the strategies were synergistic.

Table 5-9: Deploying Different ATDM Traffic Management Strategies (Dallas Testbed)

Scenario	***ATDM Strategy Implemented***				***Total Network Travel Time Savings (minutes)***
	Dynamic Signal Timing	***Dynamic Shoulder Lanes***	***Dynamic Ramp Metering***	***Dynamic Routing***	
S1	✓				223
S2		✓			48,630
S3			✓		10,923
S4		✓		✓	44,210
S5	✓			✓	15,125
S6	✓	✓		✓	53,871
S7	✓		✓	✓	22,926
S8	✓	✓	✓	✓	75,304

Based on the Phoenix Testbed analysis, it was seen that Adaptive Ramp Metering system was beneficial in all congested conditions, especially when there are incidents on the mainline and the mainline travel demand becomes higher than remaining road capacities. Adaptive Signal Control was also beneficial to improve the traffic mobility along the arterials in terms of travel time reductions. When Adaptive Ramp Metering and Adaptive Signal Control in a road network composed of both urban freeways and arterials are deployed together, it is more likely that they will be jointly beneficial rather than harmful to the overall traffic mobility. Dynamic Routing/Predictive Traveler Information System was shown to help travelers avoid bottlenecks and therefore considerably reduce their overall travel delays.

Based on the results from the Pasadena Testbed, it can be seen that the freeway facility focused strategies yield significantly more benefits than the arterial focused strategies. The addition of an additional lane on the freeway and flow management by the HSR and DJC strategies yield the highest operational benefits at the network level. Looking at the combination scenarios, the initial observation for travel time savings shown in Table 5-10 indicates that HSR + DJC strategy implemented in isolation yields the highest travel time savings at 7.77%. A closer investigation into the total duration when the

HSR strategy was deployed for the for this isolated strategy was a total of 195 minutes. Comparing the travel time savings for the isolated strategy with the combination scenario, the ARM + HSR + DJC combination scenario has a HSR activation duration of 110 minutes (43.6% less than isolated) but yields a network travel time savings of 6.64%. The final combination strategy of ARM + HSR + DJC + DSC + DRG combination scenario has a HSR activation duration of 50 minutes (74.4% less than isolated) but yields a network travel time savings of 6.68%. The result comparison suggests there are synergies when combining freeway focused strategies, HSR + DJC with ARM, and even higher synergies when combining additionally with arterial focused strategies, DSC and DRG. The combination yields high network travel time savings with the lower needs to frequently activating an additional shoulder lane for freeway traffic. Freeway traffic represents a significant portion of traffic for the Pasadena testbed as demonstrated by the travel time savings impact by HSR + DJC and DSL + QW. The DSL + QW strategy implemented in isolation and combination yields negative travel time savings but shows patterns of traffic safety improvements as discussed in Chapter 7.

Table 5-10: ATDM Strategies Network Travel Time Savings Summary (Pasadena)

Scenario	ATDM Strategy Implementation					Network Travel Time Savings (Seconds)	Network Travel Time Savings (Percent)
	ARM	DSC	HSR + DJC	DSL + QW	DRG		
S1	✓					64,663	2.45
S2		✓				20,322	0.77
S3			✓			205,075	7.77
S4				✓		-187,920	-7.12
S5					✓	55,425	2.10
S6		✓			✓	55,689	2.11
S7	✓		✓			175,251	6.64
S8	✓	✓	✓		✓	176,370	6.68
S9	✓		✓	✓		-118,769	-4.50
S10	✓	✓	✓	✓	✓	-105,573	-4.00

From the Chicago Testbed results, we can conclude that the low-medium penetration rate yields the most benefits for system performance, while the high penetration rate requires coordination in vehicle routing to achieve benefits. Therefore, for the ADM involved scenarios, we recommend the net penetration level could be set with the low-medium penetration rate. In terms of synergies and conflicts, it is observed that (1) the ATM, ADM and the Weather-related strategies are synergistic for clear day and rain-to snow day scenarios; (2) the ATM, ADM and the Weather-related strategies are synergistic for high demand snow day scenarios and (3) the ATM and the Weather-related strategy may not be effective when applied jointly for the low demand, snow day scenario considered. The analyses showed the most beneficial strategy or combination of strategies.

In the San Diego Testbed, Dynamic Lane Use, Dynamic HOV/Managed Lanes and Dynamic Speed Limits show neither a significant conflict nor a significant synergy. The increase of congestion at the entrances and exits of the HOV lanes due to the increase of demand triggered by Dynamic Lane Use, Dynamic HOV/Managed Lanes is sensed by Dynamic Speed Limits, which extends the congestion over a larger space and longer time in order to avoid abrupt speed changes. This increase of safety is obtained at the expense of throughput and travel time. Dynamic Lane Use and Dynamic HOV/Managed Lanes alone would produce better traffic performance, at the expense of safety. Dynamic Speed Limits alone would produce an increase of safety, but with a more pronounced reduction of throughput. The combined effect of having an increase of safety with less reduction of throughput can be interpreted as a good compromise, which can be considered a synergy. Dynamic Merge Control and Dynamic HOV/Managed Lanes show a synergy: Dynamic HOV/Managed Lanes compensate the slightly negative effect in terms of traffic performance caused by Dynamic Merge Control, which facilitates the entrance from SR-78, at the expense of penalizing traffic coming from the northern boundary of the I-15 corridor in the southbound direction. In other words, the decision to activate Dynamic Merge Control or not should be dictated purely by the need to reduce queueing on the ramp coming from SR-78 rather than by overall traffic performance benefits, and if Dynamic Merge Control is activated, Dynamic HOV/Managed Lanes would compensate its slightly negative impact on throughput. Dynamic Merge Control, Dynamic HOV/Managed Lanes and Dynamic Routing show also a synergy: Dynamic HOV/Managed Lanes and Dynamic Routing compensate the slightly negative effect in terms of traffic performance caused by Dynamic Merge Control, which facilitates the entrance from SR-78, at the expense of penalizing traffic coming from the northern boundary of the I-15 corridor in the southbound direction. Again, the decision to activate Dynamic Merge Control or not should be dictated purely by the need to reduce queueing on the ramp coming from SR-78 rather than by overall traffic performance benefits, and if Dynamic Merge Control is activated, Dynamic HOV/Managed Lanes and Dynamic Routing would compensate its slightly negative impact on throughput.

Chapter 6. Prediction and Active Management

This chapter documents the analysis using ATDM strategies based on the accuracy of prediction in terms of demand as well as other prediction attributes such as length of prediction horizon and geographic coverage. Both Dallas and Phoenix Testbeds are used to answer the research questions that concerns this topic.

6.1 Research Questions and Hypotheses

The following research questions are answered using this analysis:

1. Which ATDM strategy or combination of strategies will benefit the most through increased prediction accuracy and under what operational conditions?
2. Are all forms of prediction equally valuable, i.e., which attributes of prediction quality are critical (e.g., length of prediction horizon, prediction accuracy, prediction speed, and geographic area covered by prediction) for each ATDM strategy?
3. Are the investments made to enable more active control cost-effective?
4. Which ATDM strategy or combinations of strategies will be most benefited through reduced latency and under what operational conditions?

As far as experiment hypotheses is concerned, the team expects that improvements in prediction accuracy will yield higher benefits for certain ATDM strategies and combinations of strategies than for others. An ATDM strategy or combinations of strategies will yield the most benefits with improvements in prediction accuracy only under certain operational conditions. Increased prediction accuracy is more critical for certain ATDM strategies over others, with certain attributes (e.g., length of prediction horizon, prediction accuracy, prediction speed, and geographic area covered by prediction) of prediction quality being most critical. Incremental improvements in latency will result in higher benefit-cost ratio for certain ATDM strategy or combinations of strategies up to a certain latency threshold, after which benefit-cost ratio will be reduced. Reductions in latency will yield higher benefits for certain ATDM strategies and combinations of strategies than for others. An ATDM strategy or combinations of strategies will yield the most benefits with reduced latency only under certain operational conditions.

The following sections provide a descriptive analysis of prediction accuracy and other attributes of prediction from a Testbed perspective.

6.2 Dallas Testbed Analysis

This section describes the settings and results of the experiments that are conducted to examine the effect of the prediction quality on the performance of the traffic network management process. Several prediction attributes are considered in this analysis including a) demand prediction accuracy, b) length of the prediction horizon, c) decision making latency, and d) geographical area covered by the prediction module.

The overall modeling framework follows the rolling horizon framework described in Figure 4-2. In this set of experiments, the ATDM response plans generated using the traffic management module includes the dynamic routing and the dynamic signal timing strategies. The generated ATDM strategy is assumed to consist of retiming a subset of the signalized intersections along parallel arterials and activating the Dynamic Message Signs (DMSs) upstream of the incident location. The parallel arterials are used as alternative routes during the incident. Eleven different signal timing plans are assumed to be pre-approved for each intersection. One plan is optimally selected based on the amount of diverting traffic at the intersection. As described earlier, DMSs are assumed to be equipped with several messages so that different traffic diversion percentages can be achieved. In all experiments, the operational conditions represented by operational condition MD-LI are used. As mentioned earlier, this scenario represents a highly congested network with moderate incident severity and dry weather conditions.

Two scenarios are compared. In the first scenario (baseline scenario) no ATDM response plans are deployed, and all travelers are assumed to follow their habitual routes and experience the delay due to the incident. In the second scenario, the traffic management system is activated to manage the incident through deploying ATDM response plans that integrate dynamic routing and dynamic signal timing control as mentioned above. The traffic network management module uses the traffic network state prediction to develop ATDM response plans. The effectiveness of ATDM response plans is evaluated for a pre-specified prediction horizon, and the most efficient ATDM response plan is selected to be deployed in the main traffic network. As discussed above, the quality of traffic network prediction affects the efficiency of traffic network management schemes. Several experiments are conducted to measure the quality of prediction on the effectiveness of the developed traffic network management schemes. Similar to the results in the previous Chapter, the moving horizon approach is used to report the total network performance measures assuming a roll period of five minutes and a backward horizon of 30 minutes. The benefits of the traffic management system are reported in terms of saving in the total network travel time, fuel consumption and emissions as percentages of their corresponding values under the baseline scenario.

6.2.1 Effect of Demand Prediction Accuracy

In this analysis, we examine the effect of different levels of demand prediction inaccuracy on developing efficient ATDM response plans. In the scenario with perfect demand prediction, the estimation module, which emulates the real-world, and the prediction module are assumed to have the same time-dependent demand pattern (similar to analysis presented in the previous chapter). Demand inaccuracy is represented by altering (overestimating or underestimating) the demand of the prediction module from that of the estimation module. Figure 6-1 illustrates the procedure of generating inaccurate demand for the prediction module. Assume the accurate demand (D^{acc}) for a pre-specified future horizon H is given at time t. Also the percentage of demand prediction inaccuracy e is given. Thus, the difference in the number of travelers generated in the horizon H between accurate demand and inaccurate demand settings is calculated as follows:

$$\boldsymbol{E} = \boldsymbol{D}^{\boldsymbol{acc}} \times \boldsymbol{e} \qquad (6\text{-}1)$$

As shown in Figure 6-1, initially the predicted demand used by the prediction module for the horizon H is set to be equal the estimation module. Then, this demand is altered to introduce a pre-defined level of inaccuracy e. Given the discrepancy in number of travelers E, individual travelers are selected randomly from the original demand. Those selected travelers are either removed from the demand matrix for the demand underestimation scenario or duplicated as new travelers for the demand overestimation scenario. Given an inaccurate demand prediction scenario, the traffic management module is activated to develop the

ATDM response plans. Similar to the presented results in the previous chapter, the efficiency of the ATDM response plans is evaluated through comparing the network performance against that of the baseline scenario in which the traffic management module is not activated.

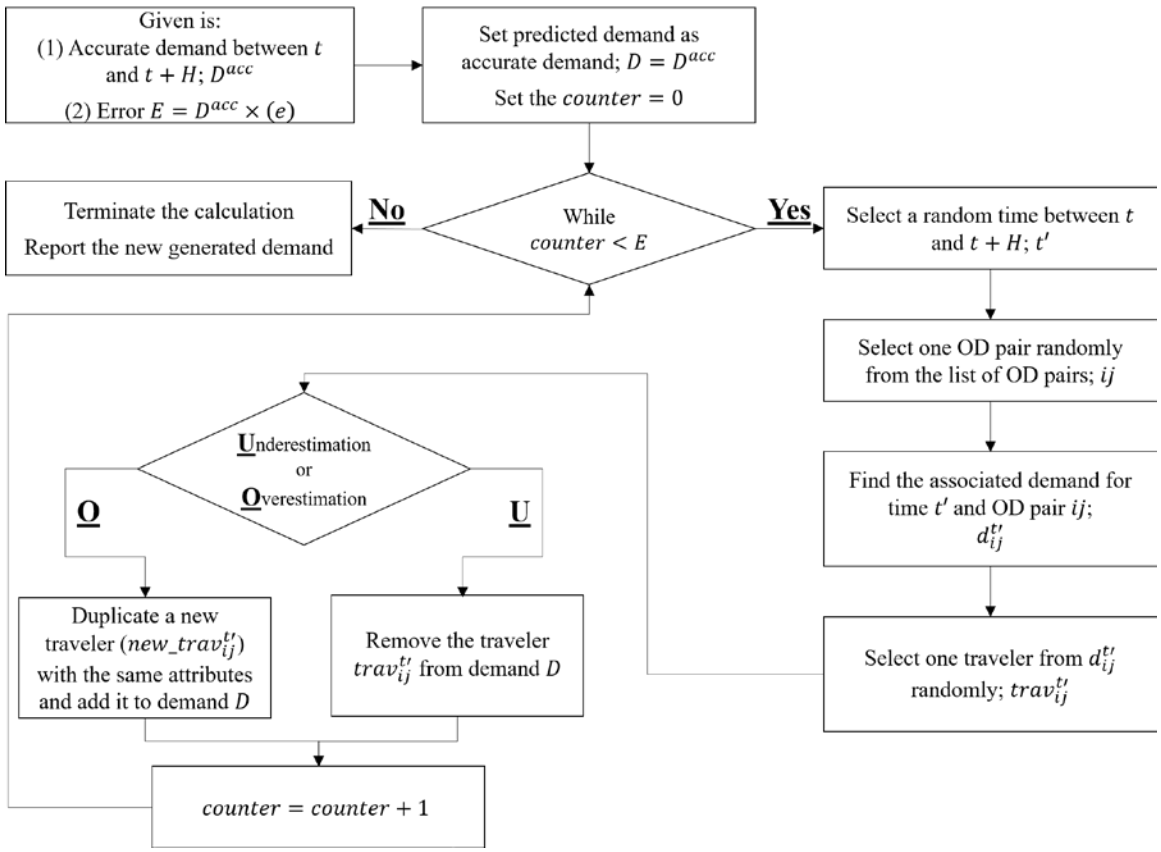


Figure 6-1: Modeling Inaccurate Demand Prediction [Source: SMU]

Figure 6-2 and Figure 6-3 represent the results for demand underestimation and overestimation, respectively. The figures compare the effectiveness of the ATDM strategy in three different demand prediction accuracies; I) Perfect Demand Prediction, II) Demand Prediction with 5% Error, and III) Demand Prediction with 10% Error. As mentioned above, the ATDM strategy in all the analysis is a combination of dynamic routing and dynamic signal timing control. Table 6-1 summarizes gives total network travel time saving in minutes for the different scenarios. The following observations can be made based on these results:

- A superior network performance is obtained for the case in which perfect demand prediction is assumed.
- The network performance gradually worsens with the increase in the level of demand prediction error. For example, savings of 7,806 and 12,341 minutes are recorded for the scenarios with 5% demand prediction error in the underestimation and overestimation cases, respectively. As the error increases to 10%, the savings are reduced to 2,252 and 3,298 minutes, respectively.

Figure 6-3 provides the corresponding saving in the fuel consumption associated with developing ATDM strategies under inaccurate demand prediction. The results show that the amount of fuel consumption increases in the scenarios in which the demand is inaccurately predicted. In other words, inability to accurately predict the demand has resulted in ATDM response plans that fail to achieve fuel consumption savings. For example, in the scenario with underestimated demand with 5% error scenario, an increase of 70.39 tons of fuel consumption is recorded. Similarly, for the 10% error scenario, the fuel consumption increased by 75.39 tons. Figure 6-4 and Figure 6-5 give the results for environmental measure of performance for deploying traffic management strategies under inaccurate demand prediction. Figure 6-4 gives the percentage saving in the carbon dioxide, while Figure 6-5 gives the percentage saving in the nitrogen oxide. The emission savings patterns are generally similar to that recorded for the fuel consumption savings. In addition, Table 6-2 gives the amount of fuel consumption, and carbon dioxide and nitrogen oxide emissions for different levels of demand prediction accuracy.

Table 6-1: Traffic Management Strategies with Different Prediction Accuracy (Dallas Testbed under Medium Demand and Low Incident Severity)

Scenario Description	Total Network Travel Time Savings (minutes)
Perfect Demand	15,125
5% Underestimated Demand	7,806
10% Underestimated Demand	2,252
5% Overestimated Demand	12,341
10% Overestimated Demand	3,298

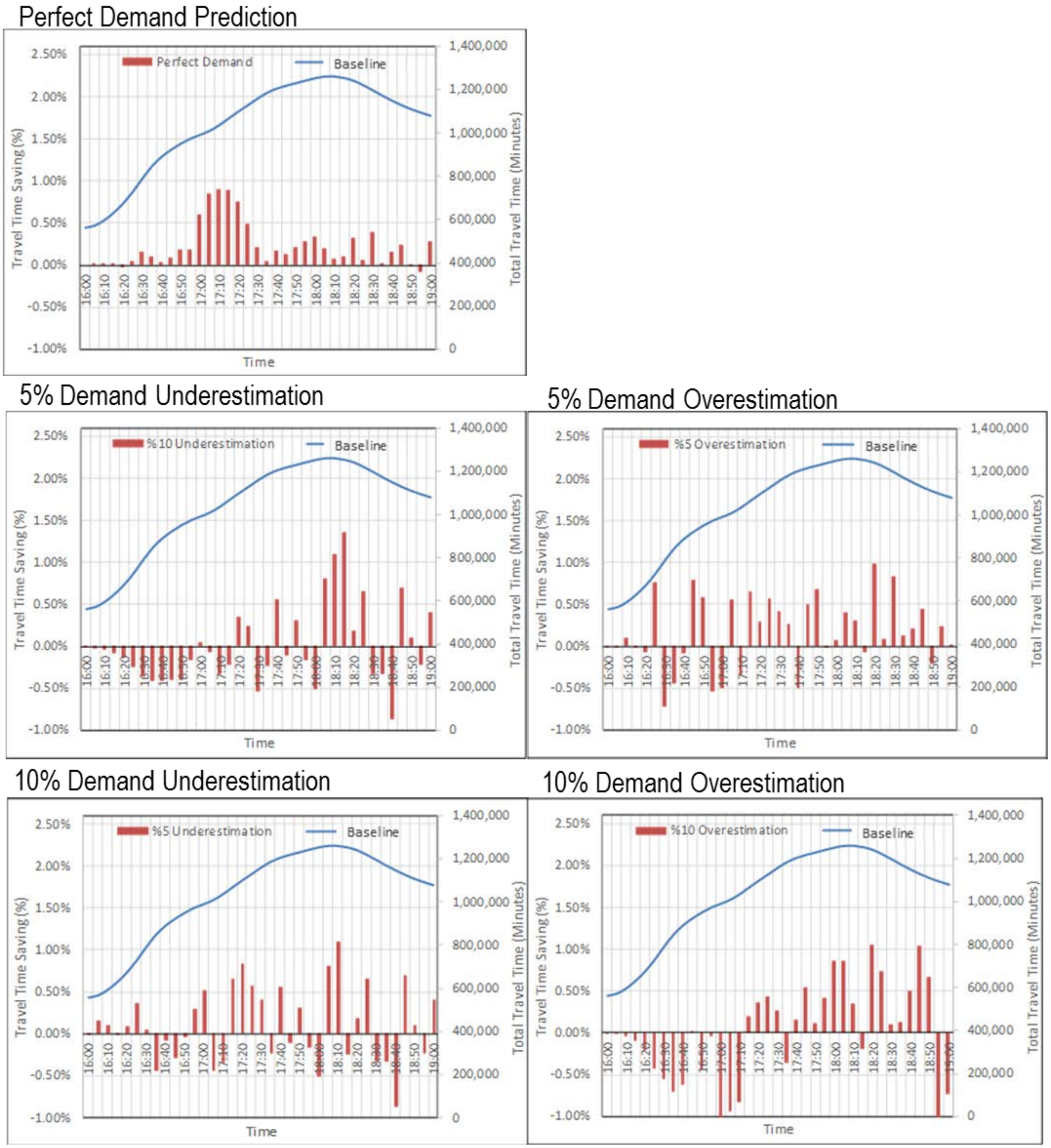


Figure 6-2: Effect of Inaccurate Demand Prediction in Total Network Travel Time Savings (Dallas Testbed under Medium Demand and Low Incident Severity) [Source: SMU]

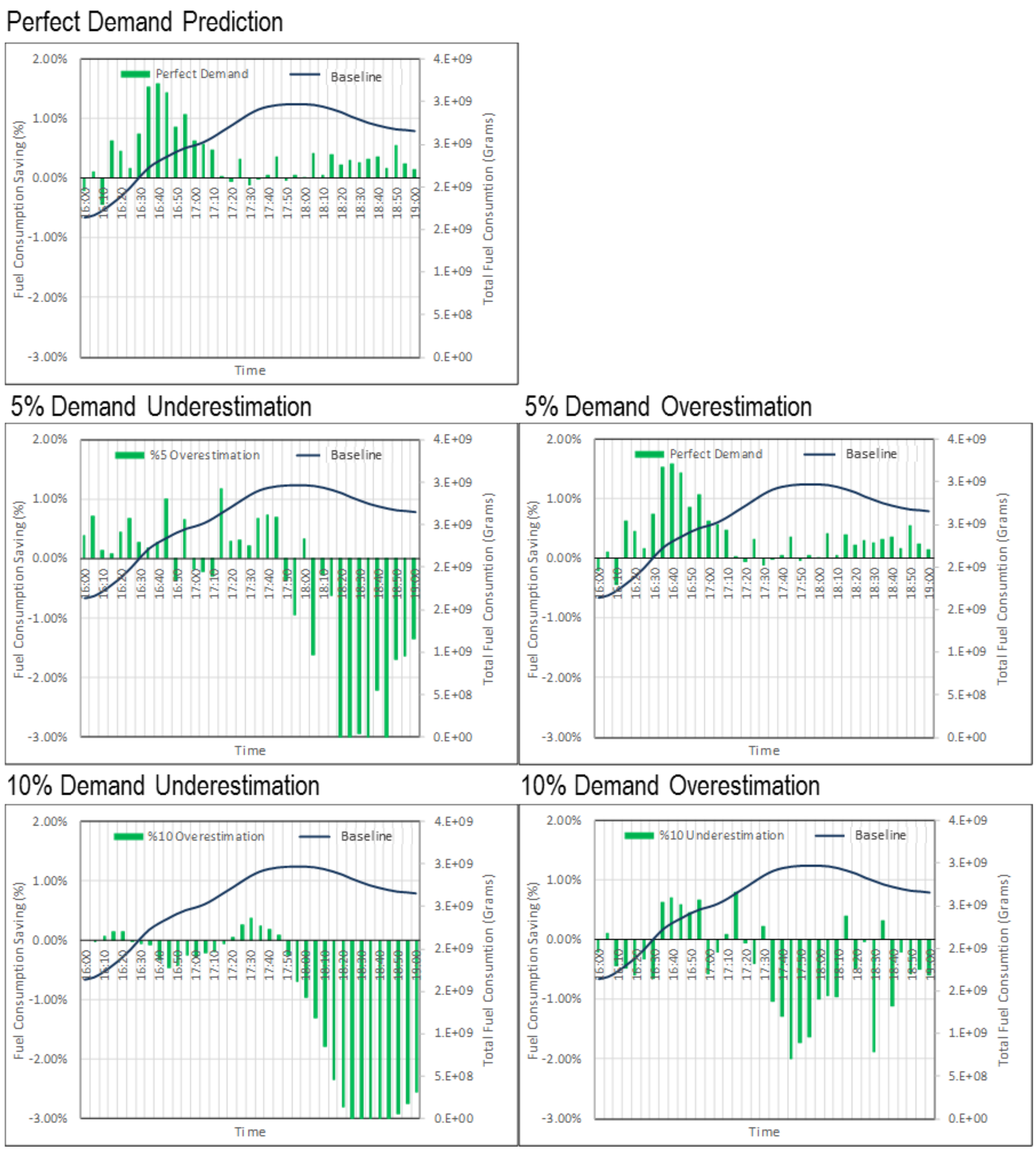


Figure 6-3: Effect of Inaccurate Demand Prediction in Total Fuel Consumption (Dallas Testbed under Medium Demand and Low Incident Severity) [Source: SMU]

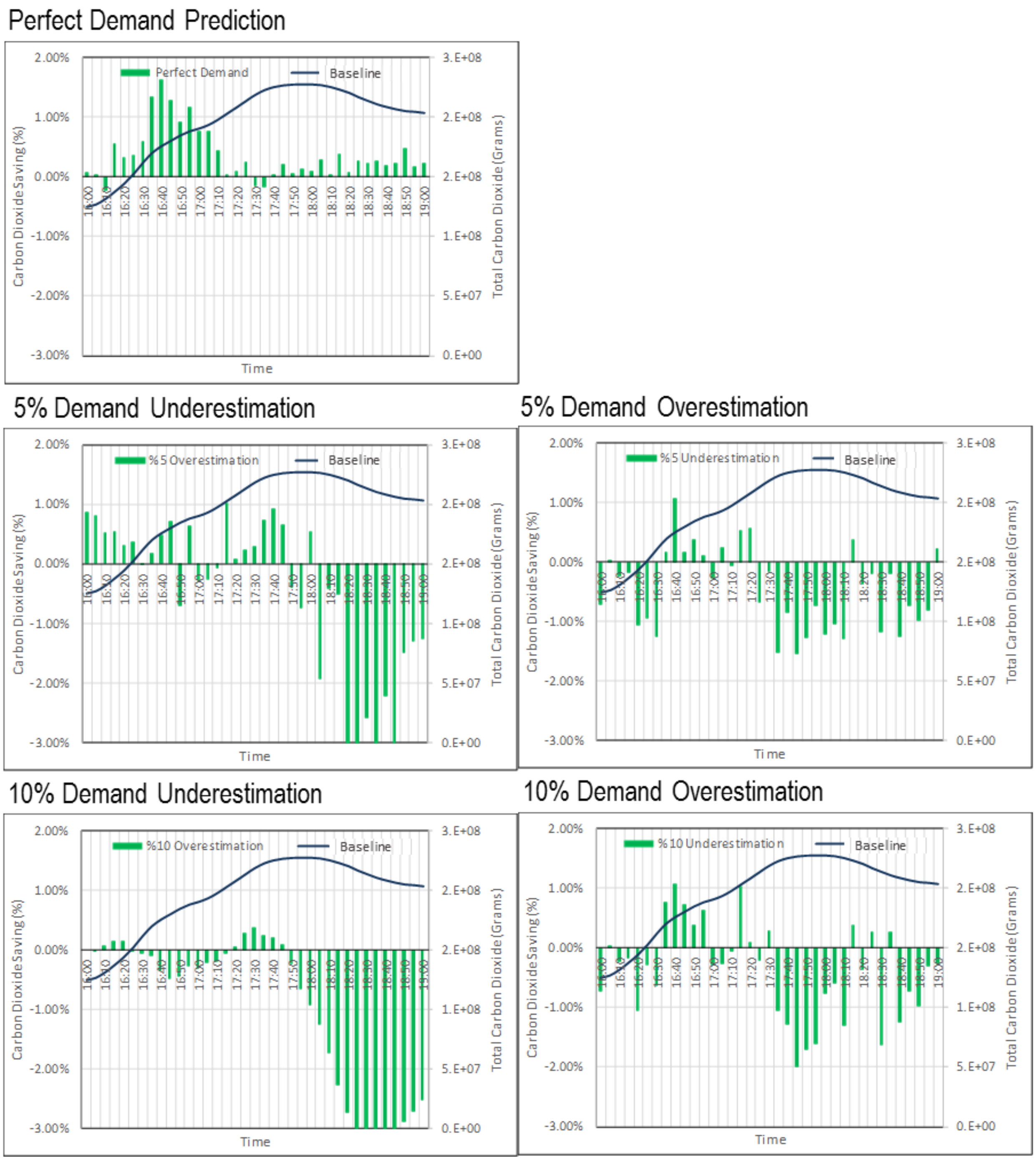


Figure 6-4: Effect of Inaccurate Demand Prediction in Total Carbon Dioxide Emission (Dallas Testbed under Medium Demand and Low Incident Severity) [Source: SMU]

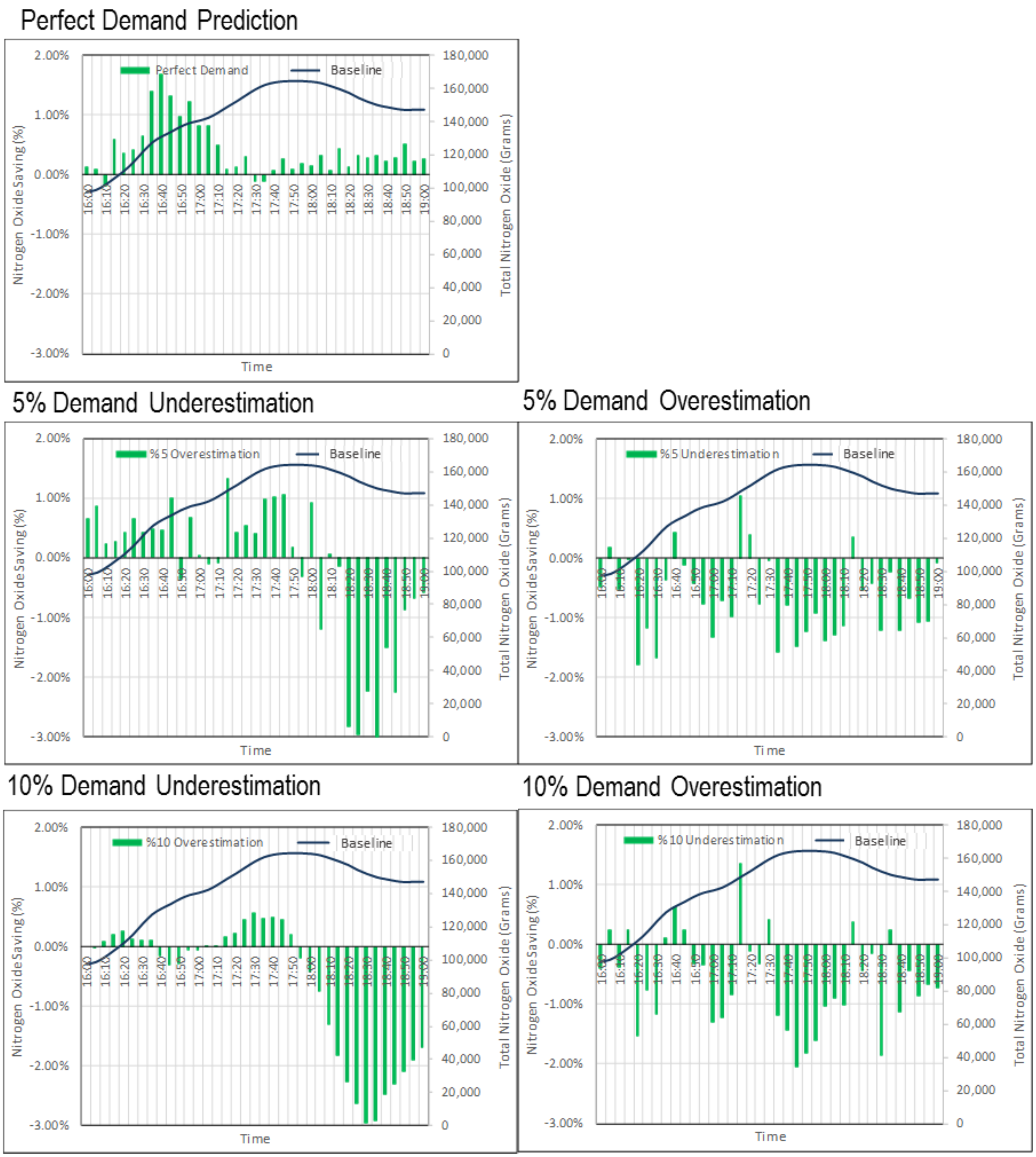


Figure 6-5: Effect of Inaccurate Demand Prediction in Total Nitrogen Oxide Emission (Dallas Testbed under Medium Demand and Low Incident Severity) [Source: SMU]

Table 6-2: Fuel Consumption and Environmental Performance considering Different Levels of Demand Prediction Accuracy (Dallas Testbed under Medium Demand and Low Incident Severity)

Scenario Description	Fuel Consumption Saving (tons)	Carbon Dioxide (tons)	Nitrogen Oxide (kilograms)
10% Underestimated Demand	-75.39	-5.83	-6.14
05% Underestimated Demand	-70.39	-4.99	-5.58
Perfect Demand	56.27	4.17	3.50
05% Overestimated Demand	-95.24	-6.83	-1.89
10% Overestimated Demand	-166.62	-12.46	-5.78

6.2.2 Effect of Length of Prediction Horizon

The experiments of this subsection examine the effect of the length of prediction horizon on the effectiveness of the ATDM strategies considering different prediction horizons (15, 30, and 60 minutes). In this set of experiments demand prediction was assumed to be accurate. In addition, the developed ATDM response plans for all experiments consider a combination of dynamic routing and dynamic signal timing strategies.

Figure 6-6 presents the results of total network travel time saving for three different lengths of prediction horizon at 15, 30, and 60 minutes. In addition, Table 6-3 gives the corresponding total network travel time saving for all scenarios.

The following observations can be made as follows:

- The network performance generally improves as the length of the prediction horizon increases. As the horizon is increased, assuming perfect prediction accuracy, the generated schemes are more effective.
- Positive correlation is observed between increasing the length of prediction horizon, and total travel time savings in the network. For example, using 15-minute prediction horizon resulted in less travel time savings compared to that obtained for the scenario in which 60-minute prediction horizon is considered. For the 15-minute prediction horizon, a saving of 9,114 minutes is recorded. This saving increased to 21,586 minutes when the prediction horizon increased to 60 minutes.

Figure 6-7 also provides the corresponding saving in the fuel consumption for the three different lengths of prediction horizon. In addition, Figure 6-8 and Figure 6-9 give the results for environmental measures of performance for deploying traffic management strategies considering different lengths of prediction horizon such as total Carbon Dioxide and Nitrogen Oxide emissions. Table 6-4 gives a summary of these results.

Table 6-3: Traffic Management Strategies with Different Lengths of Prediction Horizon (Dallas Testbed under Medium Demand and Low Incident Severity)

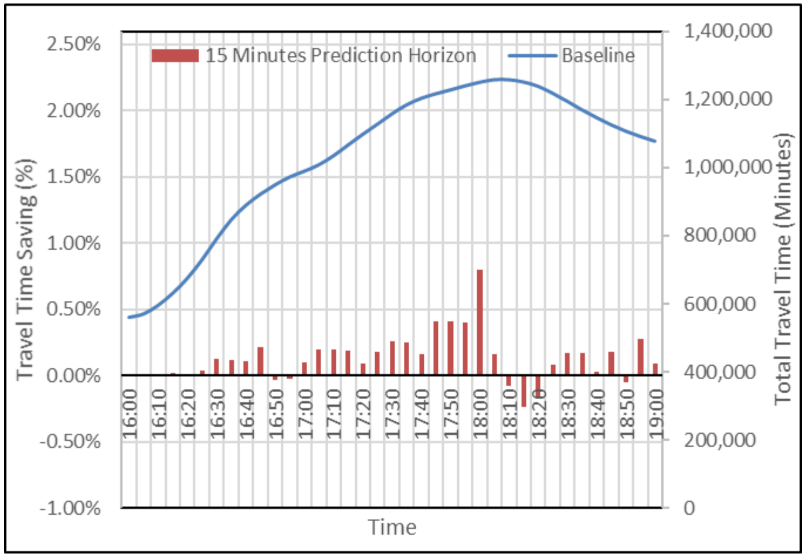
Scenario Description	Total Network Travel Time Savings (minutes)
15-minutes Prediction Horizon	9,114
30-minutes Prediction Horizon	15,125
60-minutes Prediction Horizon	21,586

Table 6-4:Total Environmental Performance with Different Lengths of Prediction Horizon (Dallas Testbed under Medium Demand and Low Incident Severity)

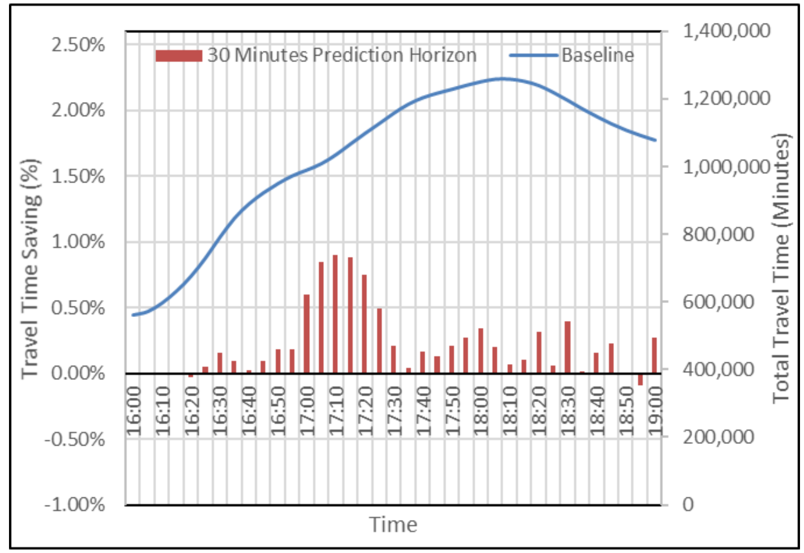
Scenario Description	Fuel Consumption Saving (tons)	Carbon Dioxide (tons)	Nitrogen Oxide (kilograms)
15-minutes Prediction Horizon	-34.65	-2.56	-0.37
30-minutes Prediction Horizon	56.27	4.17	3.50
60-minutes Prediction Horizon	64.61	5.34	3.68

The following observations can be made:

- Similar saving patterns are observed for the fuel emission, the carbon dioxide emission, and the nitrogen oxide emission.
- As shown in the table, the amount of savings generally increases with increasing the length of prediction horizon used to develop the ATDM response plans. For example, in increase in the fuel consumption of 34.65 tons is recorded for the 15-minutes horizon. As the horizon increased to 60 minutes, a saving of 64.61 tons is recorded. Similar results are obtained for the carbon dioxide and nitrogen oxide emissions.
- As most trips in the corridor have duration less than one hour, one should not expect the total travel time saving to increase with increasing of the prediction horizon beyond one hour. In other words, the marginal saving will tend to diminish with the increase in the length of the prediction horizon.
- There is significant improvement in the environmental measure of performance with increasing the length of the prediction horizon from 15 minutes to 30 minutes. However, there is slight improvement as this horizon is further increased to 60 minutes.

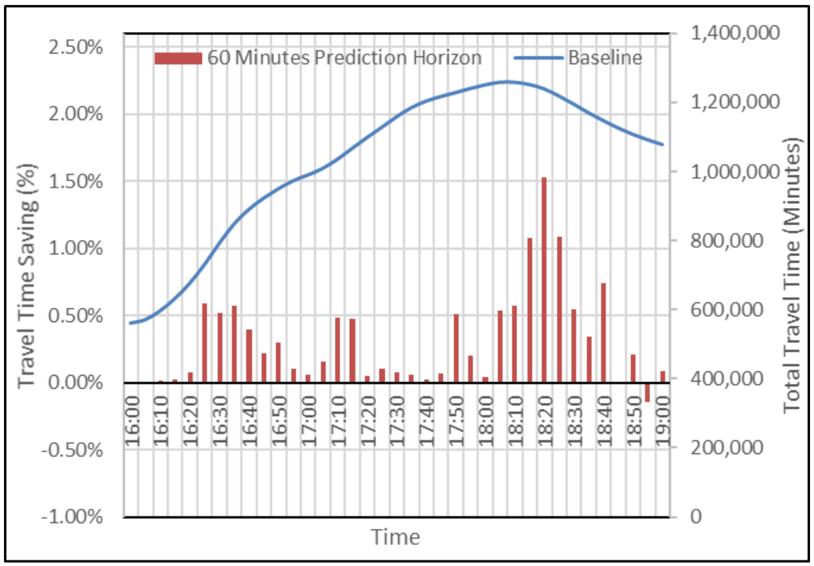


15-minute Prediction Horizon



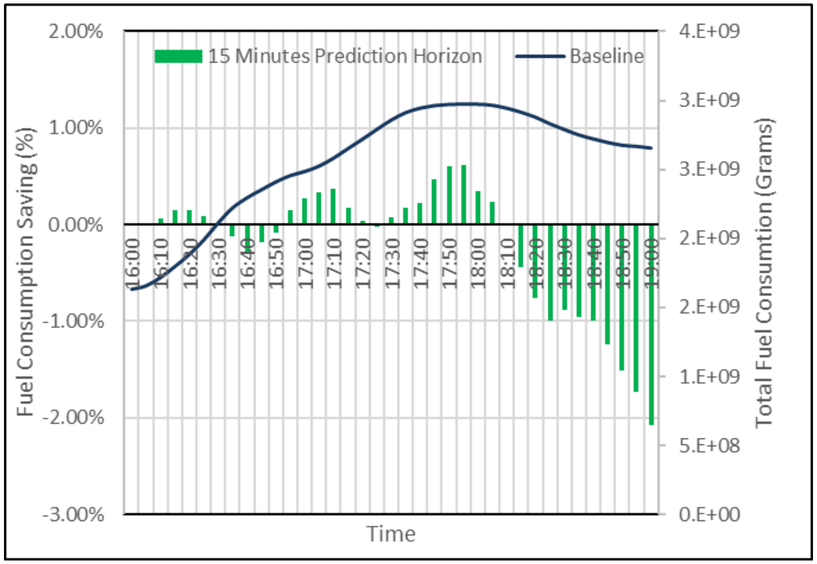
30-minute Prediction Horizon

(Dallas Testbed under Medium Demand and Low Incident Severity)

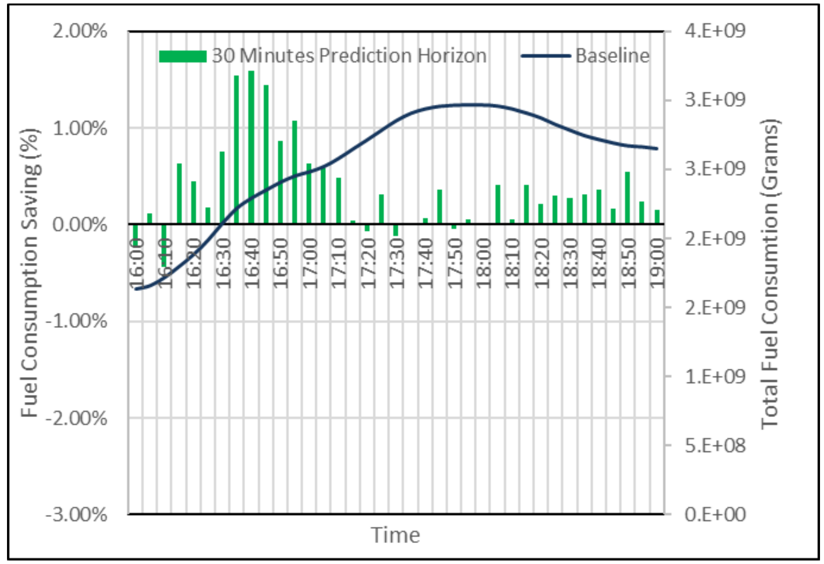


60-minute Prediction Horizon

Figure 6-6: Effect of the Length of Prediction Horizon on Total Network Travel Time Saving [Source: SMU]

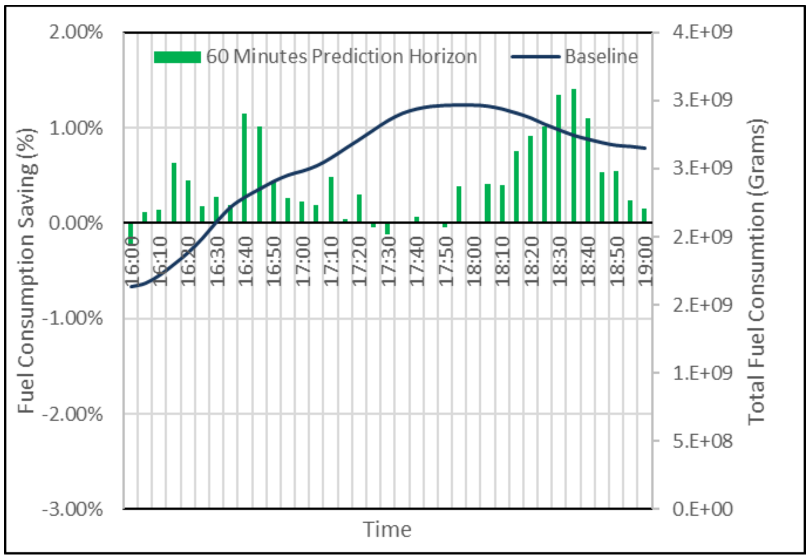


15-minute Prediction Horizon



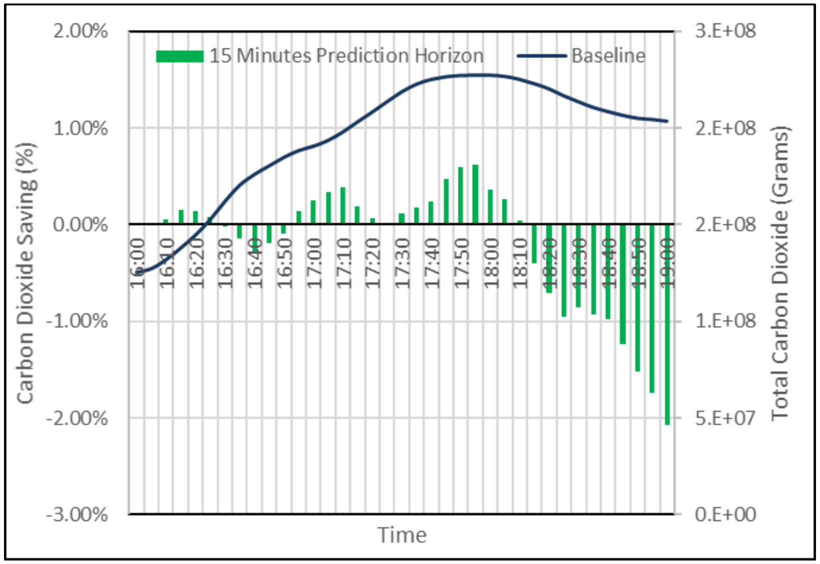
30-minute Prediction Horizon

(Dallas Testbed under Medium Demand and Low Incident Severity)

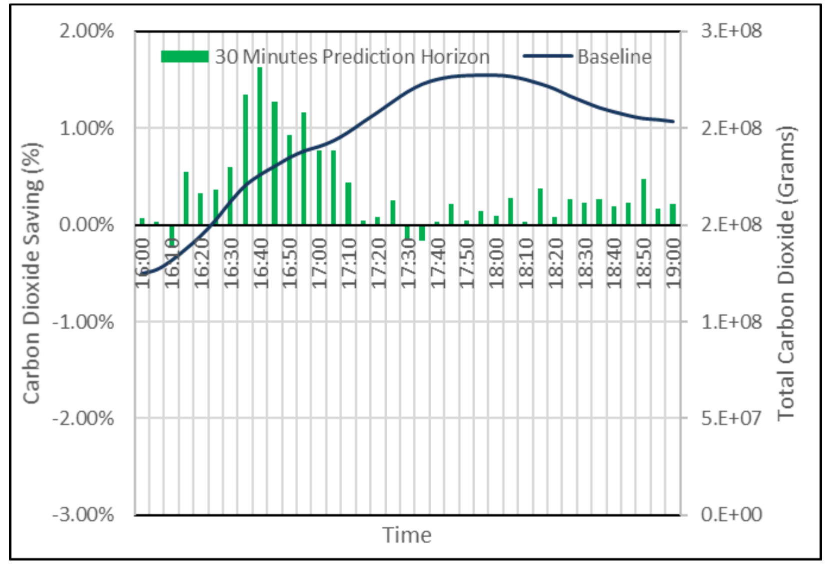


60-minute Prediction Horizon

Figure 6-7: Effect of the Length of Prediction Horizon on Total Fuel Consumption [Source: SMU]

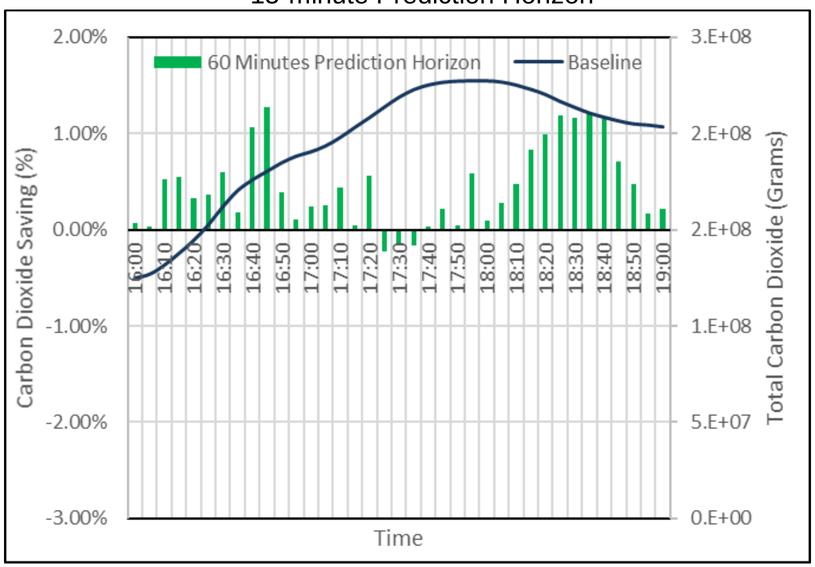


15-minute Prediction Horizon



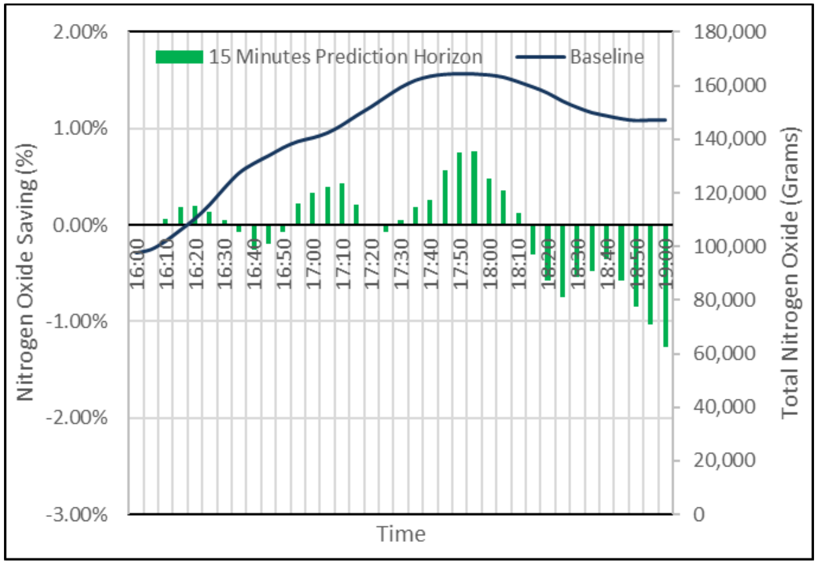
30-minute Prediction Horizon

(Dallas Testbed under Medium Demand and Low Incident Severity)

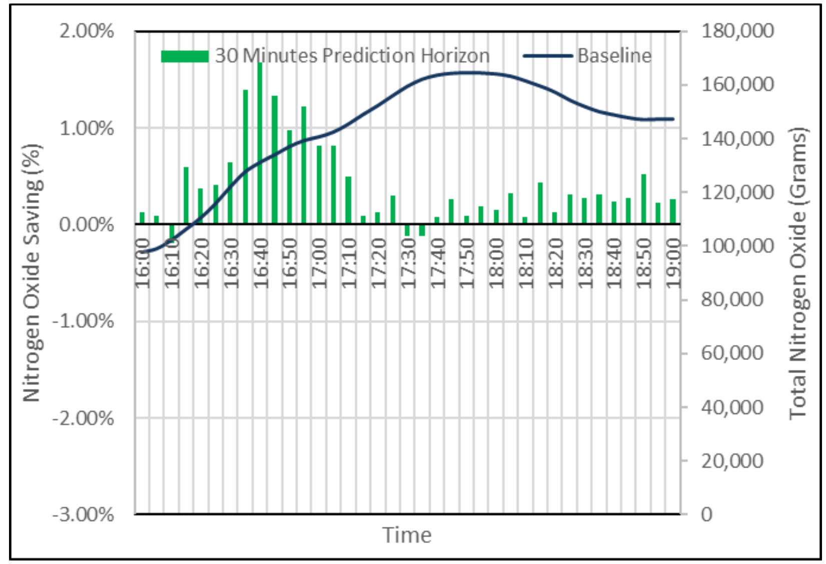


60-minute Prediction Horizon

Figure 6-8: Effect of the Length of Prediction Horizon on Total Carbon Dioxide [Source: SMU]

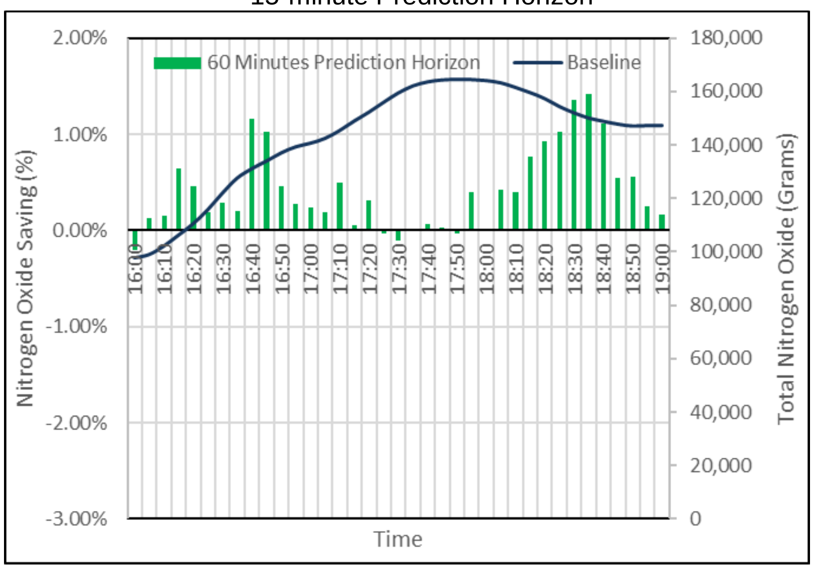


15-minute Prediction Horizon



30-minute Prediction Horizon

(Dallas Testbed under Medium Demand and Low Incident Severity)



60-minute Prediction Horizon

Figure 6-9: Effect of the Length of Prediction Horizon on Total Nitrogen Oxide [Source: SMU]

6.3 Phoenix Testbed Analysis

In order to assess the impact of prediction attributes, Adaptive Ramp Metering strategy was used in the Phoenix testbed, since it is ad-hoc. Nonetheless, the Adaptive Ramp Metering integrated with DTALite is capable of reflecting the impact of several of prediction horizon, prediction accuracy and communication latency. In practice, different prediction horizons may result in different predicting stability, prediction accuracy may be skewed due to various reasons, such as measurement errors and inherent randomness in traffic flows. In the meantime, it may often take a significant amount of time to collect and transmit data, make decision and then download the optimal control strategies, which are combined into what is called latency. In the Phoenix testbed, the different prediction attributes are modeled as described below:

Prediction horizon: In order to model prediction horizon, some preliminary runs were conducted to collect the historical travel demand along the freeway for 5 hours. When the simulation formally runs, whenever a main-line travel demand is collected (For example, the immediately past 5 min), instead of using it directly to calculate the next ramp metering rate, the newly collected data is first combined with the (historical) future data (e.g., travel demand from right now to 10 minutes later). In doing so, the adaptive ramp metering strategy becomes proactive with a particular horizon (e.g., 5 min or 10 min). Figure 6-10 demonstrates this concept. As shown, the predicted demand will look into historical travel demand at different points in future and utilize them as inputs to the Adaptive Ramp Metering system. The two values of prediction horizons used were 5-minute and 10-minute (representing short-term and medium-term predictions).

Prediction accuracy: It is quite normal that traffic data get contaminated during collection and transmission. The prediction may not be accurate due to the poor quality of data. In order to examine whether it will have a negative impact on the performance of ATDM strategies, Phoenix Testbed introduced additional noise to the mainline travel demand measurement. Specifically, right after the mainline travel demand is estimated, it is randomly superimposed certain noise to make the mainline demand deviate from the correct values by -20% to 20% and then the adjusted mainline demand is used to calculate the new ramp metering rate. Therefore, the base-case of no added noise is compared with the test-case of 20% noise is assessed in order to evaluate the impact of prediction accuracy on Adaptive Ramp Metering.

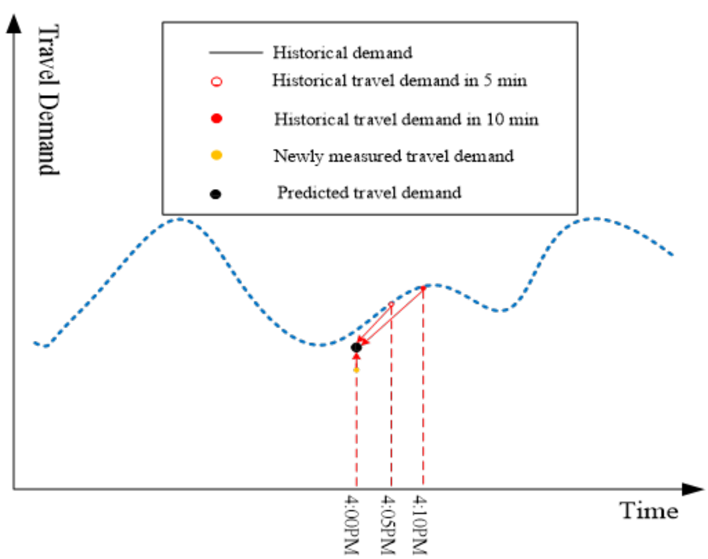


Figure 6-10: Mainline Travel Demand Estimation for Proactive Adaptive Ramp Metering [Source: ASU]

Prediction Latency: It may be very likely that it may take quite a long time for ATDM strategies from collecting data to making decisions in practice. It is also of interest to see if the latency would considerably affect the performance of ATDM strategies. The latency, in an ATDM sense, refers to the time-delay of the prediction system to get the data from the field sensors (or vehicles), run the prediction models and to compute the predicted traffic states at different locations. Additional latency will also occur when traffic scenario managers utilizes this predicted traffic-state to pick a response plan, in real-life. For the Phoenix Testbed, all this is combined into one prediction latency value which is conceptually shown in Figure 6-11.

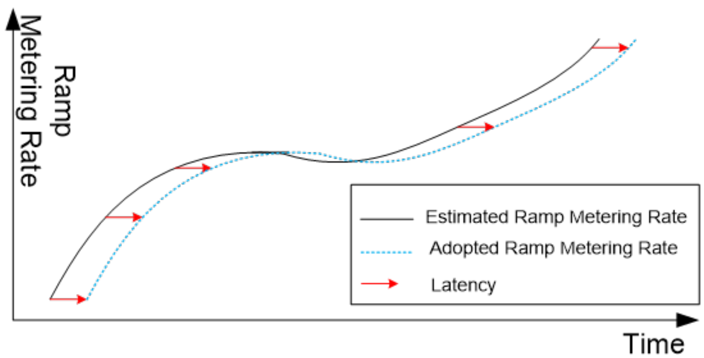


Figure 6-11. Mechanism of Simulating Communication Latency [Source: ASU]

Adaptive Ramp Metering coverage is typically big (at least miles) and therefore the performance of the strategy could very well be affected by the above three factors. Using the special version of DTALite, the project team evaluated the impact of these factors on the Adaptive Ramp Metering strategy. The performance of the Adaptive Ramp Metering in this report is to examine the travel time changes for those vehicles which travel all three interchanges along the freeway 101. Realistic values were selected as: 5 min and 10 min for latency; and 5 min and 10 min for prediction horizons of Adaptive Ramp Metering.

On the simulation platform, the communication latency is simulated by holding the latest ramp metering rate until the latency timer expires. For instance, if the latency is set 5 minutes, then the new ramp metering latency that is calculated at 15:00 hours will not take into place until 15:05 hours. As for the prediction horizon for the Adaptive Ramp Metering, the special DTALite was first run multiple times to get the time-dependent travel demands which are later treated as the historical demand. When the adaptive ramp metering strategy takes place and begin to calculate the appropriate metering rate, it will not only consider the newly measure main-line volume but also combine the next 5-10 min historical travel demand. Both low and high demand operational conditions were used for this assessment.

6.3.1 Prediction Horizon and Communication Latency

Figure 6-12 shows the average travel time along the freeway segment under different prediction horizon (5 min vs. 10 min) for two operational conditions Low Demand + Low Incident and High Demand + High Incident. It appears that the longer prediction horizon will bring the reduction of freeway travel time. This makes sense and is consistent with our experiences. However, the improvement appears marginal as well. After carefully analyzed the simulation results, the team considered that this phenomenon was caused by two reasons. First reason is that travel times does not fluctuated too much with 15 minutes since the time-dependent travel demand is provided every 15 minutes. On the other hand, the overall travel time along the freeway segment is between 10 minutes to 20 minutes in both the operational conditions. Therefore, the gained travel time reduction represents 1%~3% of total travel time. We expect that the total travel time reduction will increase and will be more sensitive to the prediction horizon after the Adaptive Ramp Metering strategies are applied to large areas where travel demand's fluctuation is highly dynamic.

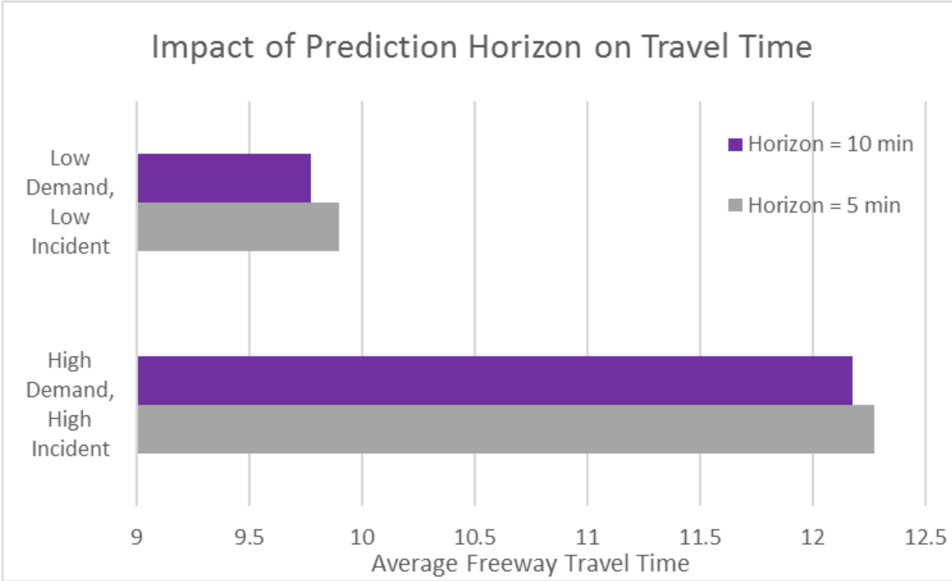


Figure 6-12. Travel Time Comparison Under Different Prediction Horizons for Phoenix Testbed [Source: ASU]

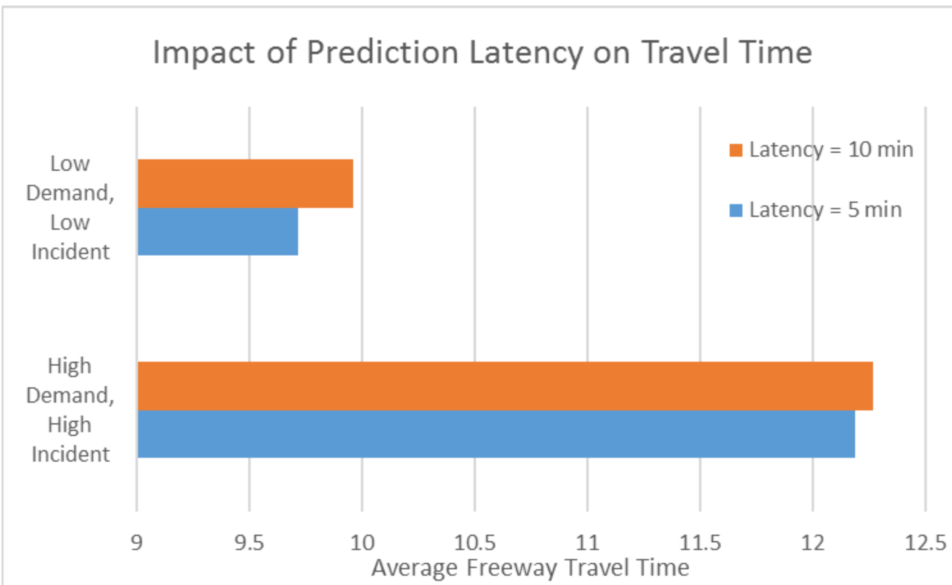


Figure 6-13. Travel Time Comparison Under Different Prediction Latencies for Phoenix Testbed [Source: ASU]

In the meantime, the project team also compared the sensitivity of Adaptive Ramp Metering to the communication latency which is also shown in Figure 6-13. The Figure also shows consistent reduction of travel time if the communication latency is reduced from 10 minutes to 5 minutes. Given the increase of network scope will increase the communication latency and it is expected the latency issue may become more outstanding if the adaptive ramp metering strategies are applied to large areas.

6.3.2 Prediction Accuracy

Prediction accuracy is another major attribute that affects the performance of Adaptive Ramp Metering strategy because the ramp metering rate is dependent on the prediction of mainline travel demand. If the mainline travel demand prediction is erroneous, ARM may over meter or under meter the vehicles on ramps. Although over ramp metering appears to benefit the freeway mobility, it may considerably increase the delay on the adjacent surface streets. In order to estimate the impact of prediction accuracy, after the mainline travel demand is predicted, additional (-20%~20%) random errors are first superimposed into the accurate travel demand and then the metering rates are calculated at three on ramps. Figure 6-14 shows the travel time differences with and without random noises under given configurations. It is obvious that the freeway travel time is highly sensitive to the prediction accuracy, especially when traffic is close to road capacities.

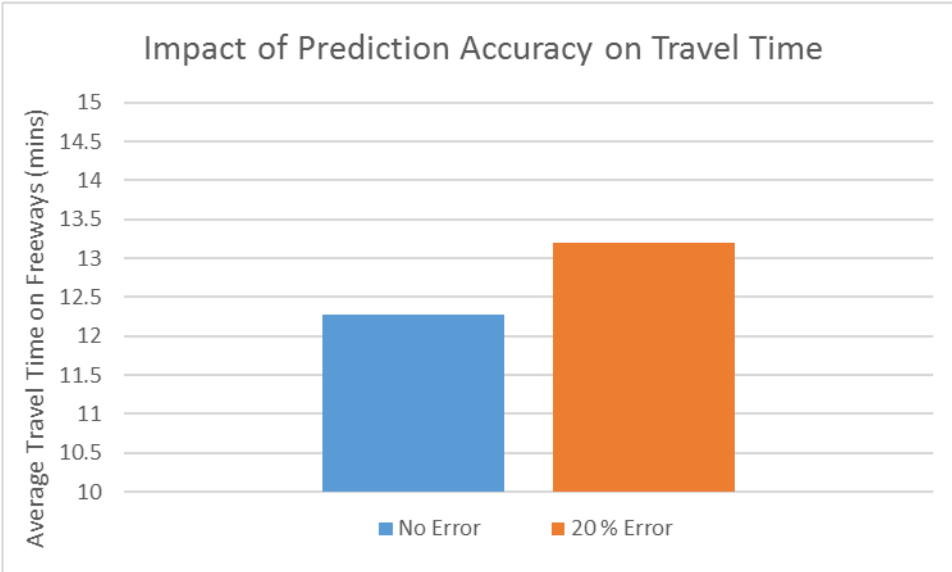


Figure 6-14: Travel Times with and Without Prediction Errors for Phoenix Testbed [Source: Booz Allen]

6.4 Pasadena Testbed Analysis

This section describes the settings and results of the experiments that are conducted to examine the effect of the prediction quality on the performance of the traffic network management process. Several prediction attributes discussed in this section include a) prediction horizon and b) prediction accuracy, covered by the prediction module. This section also assesses the impacts of using ATDM performance prediction versus time-of-day plans for deploying ATDM strategies. The time-of-day plans are meant to replicate "responsive" traffic management where strategies are implemented in response to congestion. In these scenarios, strategies are implemented only when the aggregate network travel time exceeds 3 Million Seconds.

6.4.1 Effects of Prediction

This section compares the travel time savings by comparing the traffic impacts due to the ATDM strategies deployed either by prediction recommendation or predefined time-of-day plans, which are meant to replicate responsive traffic management. The time-of-day plans for each strategy were selected based on the best performing plan if deployed for all 4-hours of the analysis period. For this section of the analysis, the selected plan was deployed for the heaviest congestion period which was determined to be from 5:00PM to 7:00PM (2 hours). The results are summarized in Table 6-5 and Figure 6-15. A detailed comparison of the network travel time savings for each strategy is shown in Figure 6-16. The following observations were made from the analysis:

- All strategies demonstrate an improvement in travel time savings when the strategies were deployed using prediction compared to time-of-day which is only deployed during heavy traffic congestion period.
- The ARM, HSR + DJC, and DRG show a significant improvement when using prediction over time-of-day plans.
- DSC strategy shows a small loss in travel time savings when using time-of-day plan compared to prediction. This result is in part due to the predefined activation of DSC prediction only during the heavy traffic congestion period.
- The prediction capability allows for early deployment of the ATDM strategy before a significant congestion is formed throughout the network.

Table 6-5: ATDM Strategies Network Travel Time Savings with Prediction versus Time-of-day

Strategies	Predictive Traffic Management	Responsive Traffic Management
ARM	2.45%	0.58%
DSC	0.77%	0.47%
HSR + DJC	7.77%	2.01%
DRG	2.10%	0.29%

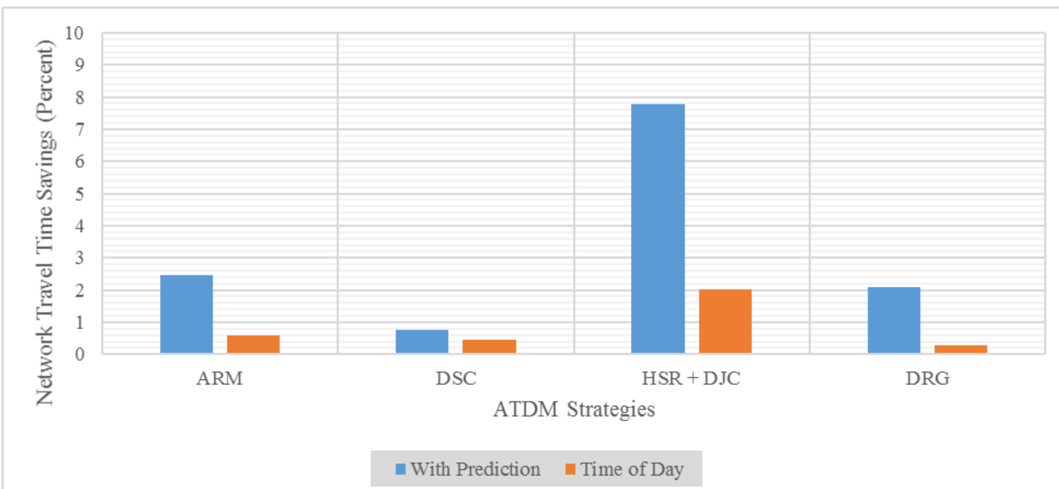


Figure 6-15: Effects of Prediction versus Time-of-Day Plan on ATDM Strategies Network Travel Time Savings [Source: Booz Allen]

Table 6-6: Comparison of Network Travel Time Savings to Duration when HSR was Activated

Strategies	Duration when Hard Shoulder Running was Activated	Network Travel Time Savings
HSR + DJC with Prediction	145 minutes	7.77%
HSR + DJC in a Responsive Manner	120 minutes	2.01%

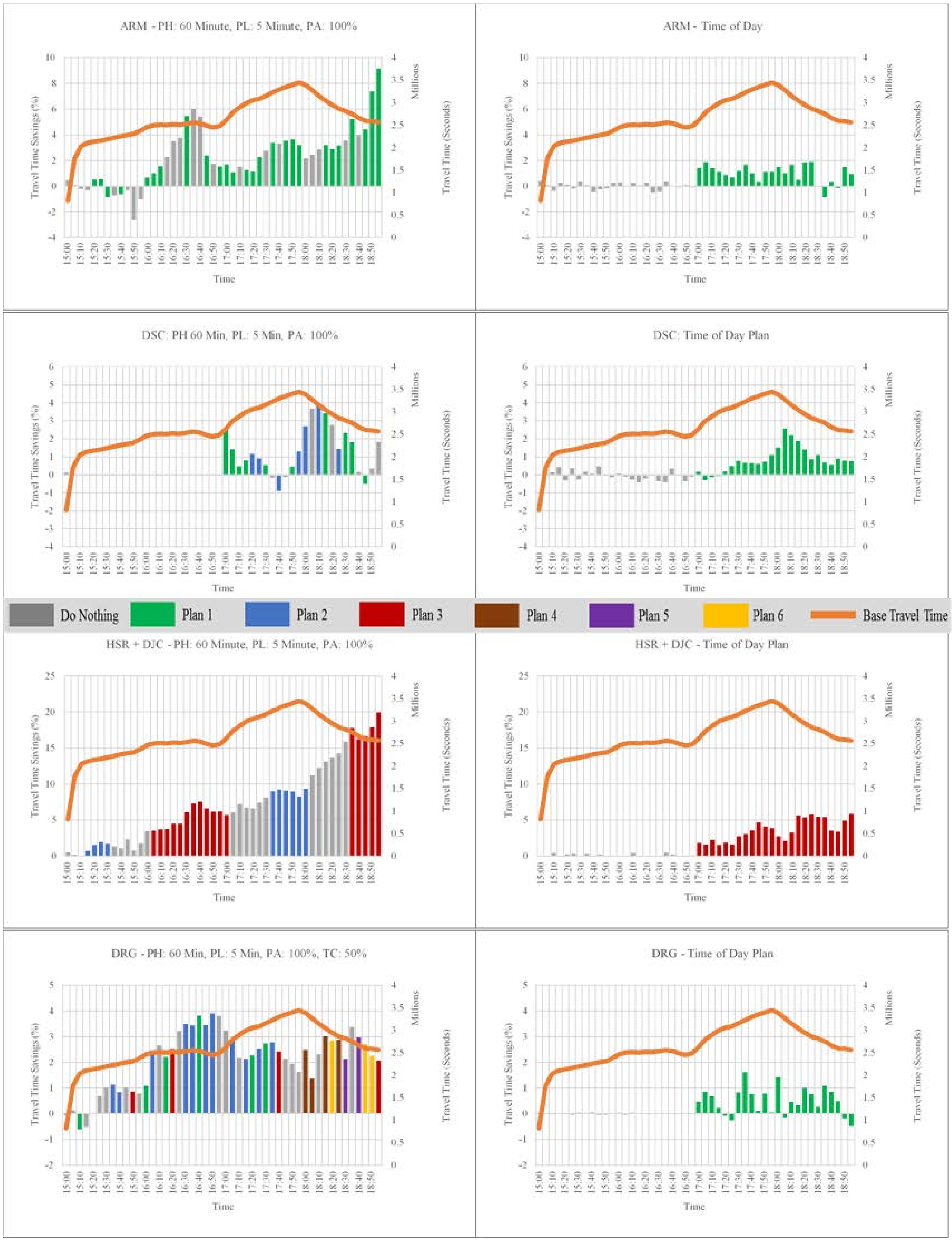


Figure 6-16: Effects of Prediction Horizon on ARM Network Travel Time Savings [Source: Booz Allen]

6.4.2 Effects of Prediction Horizon

The analysis was performed on each isolated ATDM strategy to compare the effects of different prediction horizon on operational performance using the following prediction horizon values: 15 Minutes, 30 Minutes, and 60 Minutes. Only the HSR + DJC strategy was not analyzed using the 15 minutes prediction horizon due to the predefine operating minimum 30 minutes activation rule discussed in Chapter 4. The results from the comparative analysis are summarized in Table 6-7 and Figure 6-17. A more detailed demonstration of travel time savings for each strategy with different prediction horizon are shown in Figure 6-18 to Figure 6-21. The following are the observations from the network operations results:

- All strategies show an increase in operational benefits with the increase in prediction horizon.
- ARM shows a loss in operational benefit, from 2.45% to 0.88%, when prediction horizon is decreased from 60 minutes to 30 minutes. ARM shows very small loss in operational benefit, from 0.88% to 0.87%, when prediction horizon is decreased from 30 minutes to 15 minutes.
- With the decrease in prediction horizon for ARM, TRANSIMS is recommending ARM activation more frequently with 26/48 times at 60 minutes prediction horizon, 43/48 times at 30 minutes prediction horizon, and 46/48 times at 15 minutes prediction horizon.
- Operational benefits for DSC at all Prediction Horizon are below 1% network travel time savings.
- HSR shows a significant loss in operational benefits, from 7.77% to 6.79%, when prediction horizon is decreased from 60 minutes to 30 minutes.
- DRG shows a slight loss in operational benefit, from 2.10% to 2.00%, when prediction horizon is decreased from 60 minutes to 30 minutes. DRG shows a larger magnitude in operational benefit loss, from 2.00% to 0.87%, when prediction horizon is decreased from 30 minutes to 15 minutes.

Table 6-7: ATDM Strategies Network Travel Time Savings with Different Prediction Horizon

Strategies	***Prediction Horizon***		
	15 Minutes	**30 Minutes**	**60 Minutes**
ARM	0.87%	0.88%	2.45%
DSC	0.54%	0.76%	0.77%
HSR + DJC	Not Analyzed	6.79%	7.77%
DRG	1.45%	2.00%	2.10%

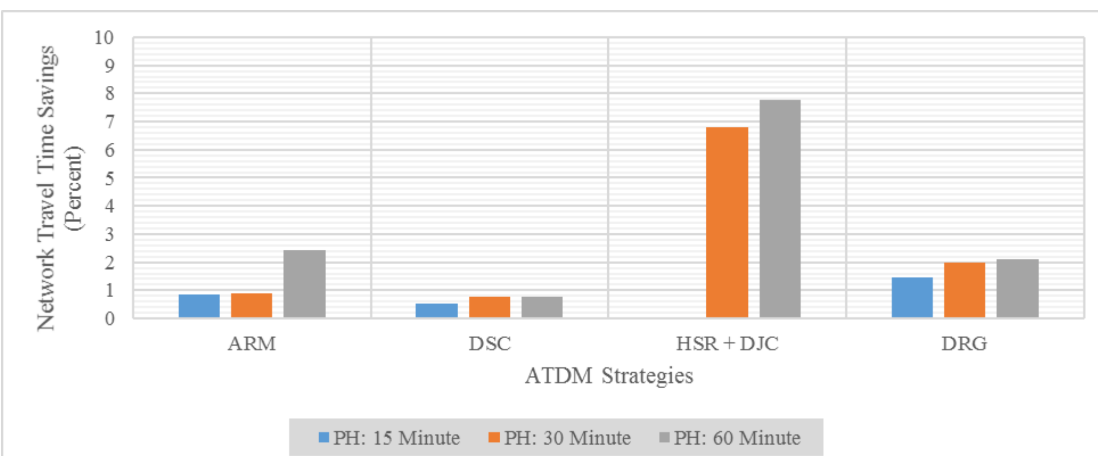


Figure 6-17: Effects of Prediction Horizon (PH) on ATDM Strategies Network Travel Time Savings [Source: Booz Allen]

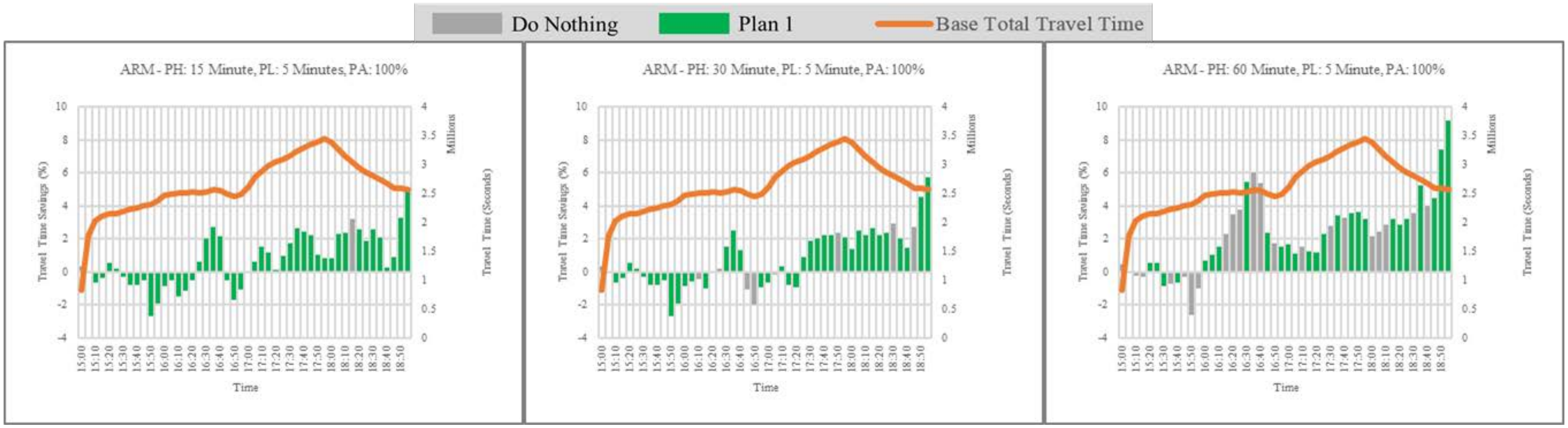


Figure 6-18: Effects of Prediction Horizon on ARM Network Travel Time Savings [Source: Booz Allen]

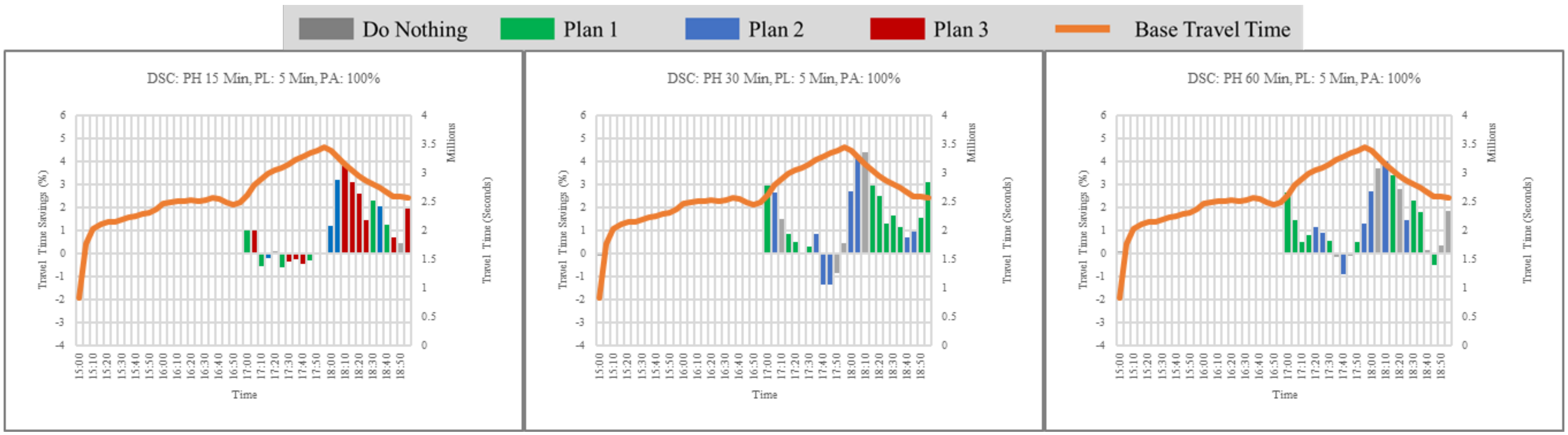


Figure 6-19: Effects of Prediction Horizon on DSC Network Travel Time Savings [Source: Booz Allen]

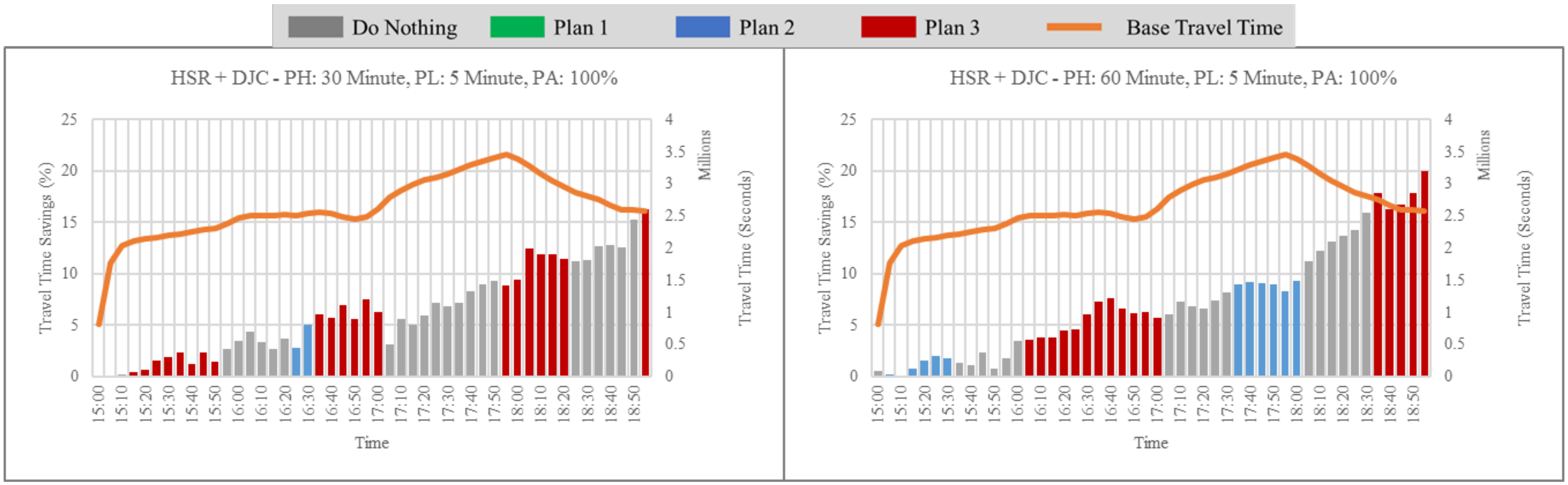


Figure 6-20: Effects of Prediction Horizon on HSR + DJC Network Travel Time Savings [Source: Booz Allen]

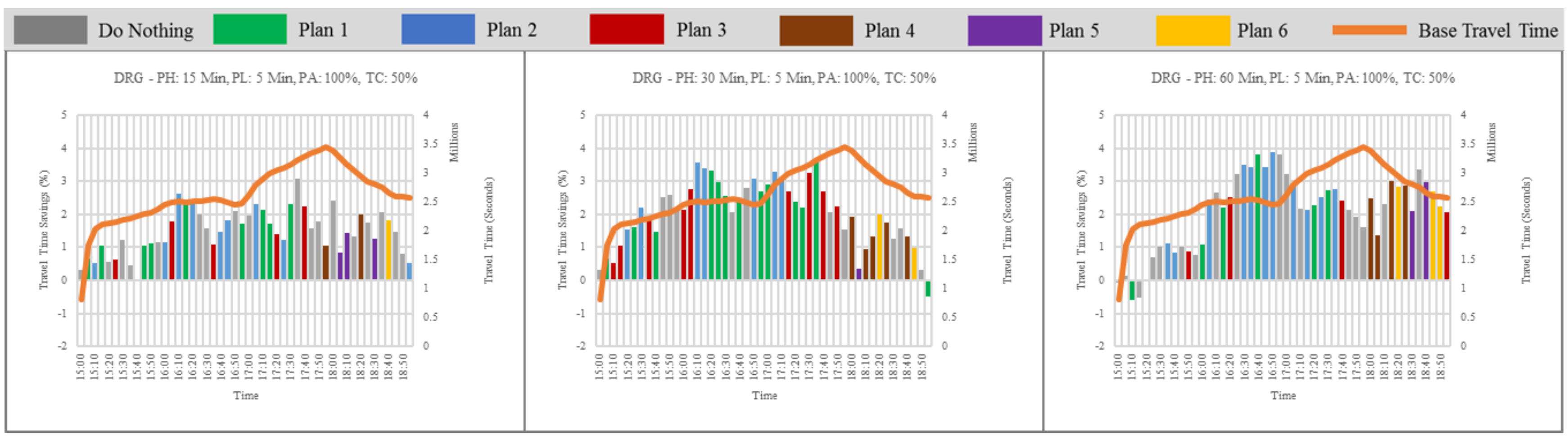


Figure 6-21: Effects of Prediction Horizon on DRG Network Travel Time Savings [Source: Booz Allen]

6.4.3 Effects of Prediction Accuracy

The analysis was performed on each isolated ATDM strategy with different prediction accuracy by assessing their operational performance benefits. The varying prediction accuracy assumes the percent of available data sent from the mock real world traffic infrastructure (VISSIM) to the mock traffic management center (TRANSIMS). The prediction accuracy for this scenario is defined as the percent of available data while the difference is the percent of loss data and is not sent to the mock traffic management center.

- The results from the comparative analysis are summarized in There are minor travel time savings loss for DRG, from 1.72 % to 1.68%, when prediction accuracy is decreased from 100% to 90%. A larger travel time saving loss is observed when the prediction accuracy is reduced from 90% to 50%, from 1.68% to 1.19%.

Table 6-8 and Figure 6-22. A more detailed demonstration of travel time savings for each strategy with different prediction accuracy are shown in Figure 6-23 to Figure 6-26. The following observations from the analyzed results:

- Prediction accuracy has minimal effects on ARM operations.
- There are small travel time savings loss for DSC, from 0.63% to 0.48%, when prediction accuracy is decreased from 100% to 90%. When prediction accuracy is at 50%, DSC strategy yields a traffic operation disbenefit at the network level.
- There are small travel time saving loss for HSR + DJC strategy, from 7.75% to 7.59%, when prediction accuracy is reduced from 100% to 90%. There is a slightly larger effect on travel time loss when prediction accuracy is decreased from 90% to 50% with the savings dropping from 7.59% to 7.08%.
- There are minor travel time savings loss for DRG, from 1.72 % to 1.68%, when prediction accuracy is decreased from 100% to 90%. A larger travel time saving loss is observed when the prediction accuracy is reduced from 90% to 50%, from 1.68% to 1.19%.

Table 6-8: ATDM Strategies Network Travel Time Savings with Different Prediction Accuracy

Strategies	Prediction Accuracy		
	50%	90%	100%
ARM	1.65%	1.67%	1.67%
DSC	-0.19%	0.48%	0.63%
HSR + DJC	7.08%	7.59%	7.75%
DRG	1.19%	1.68%	1.72%

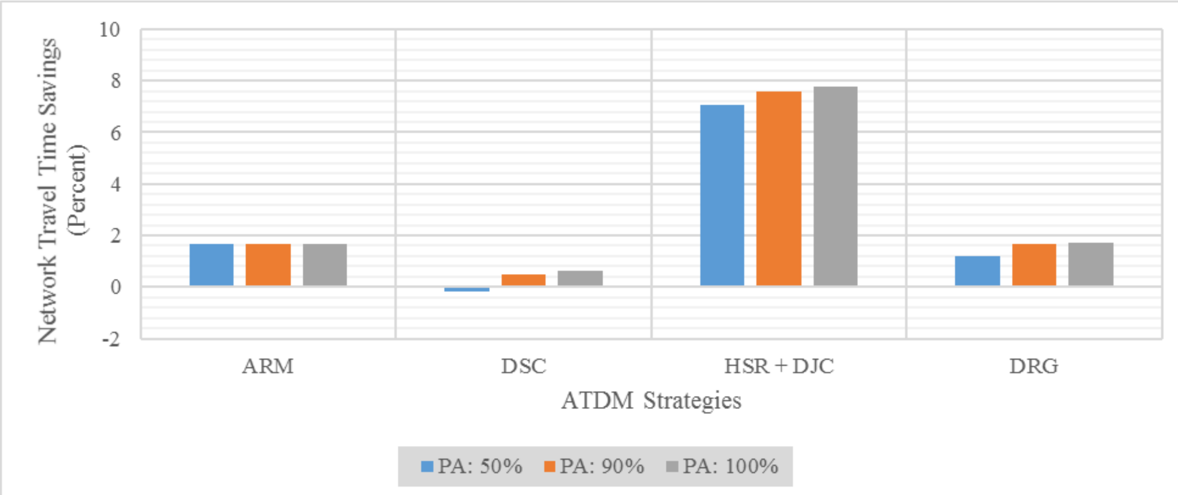


Figure 6-22: Effects of Prediction Accuracy on ATDM Strategies Network Travel Time Savings [Source: Booz Allen]

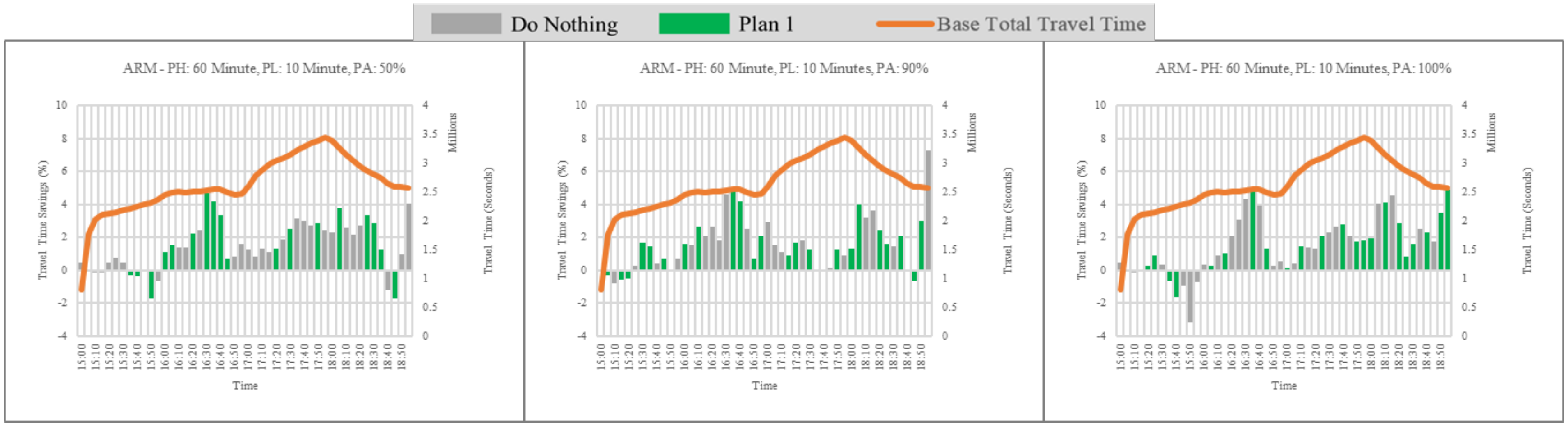


Figure 6-23: Effects of Prediction Accuracy on ARM Network Travel Time Savings [Source: Booz Allen]

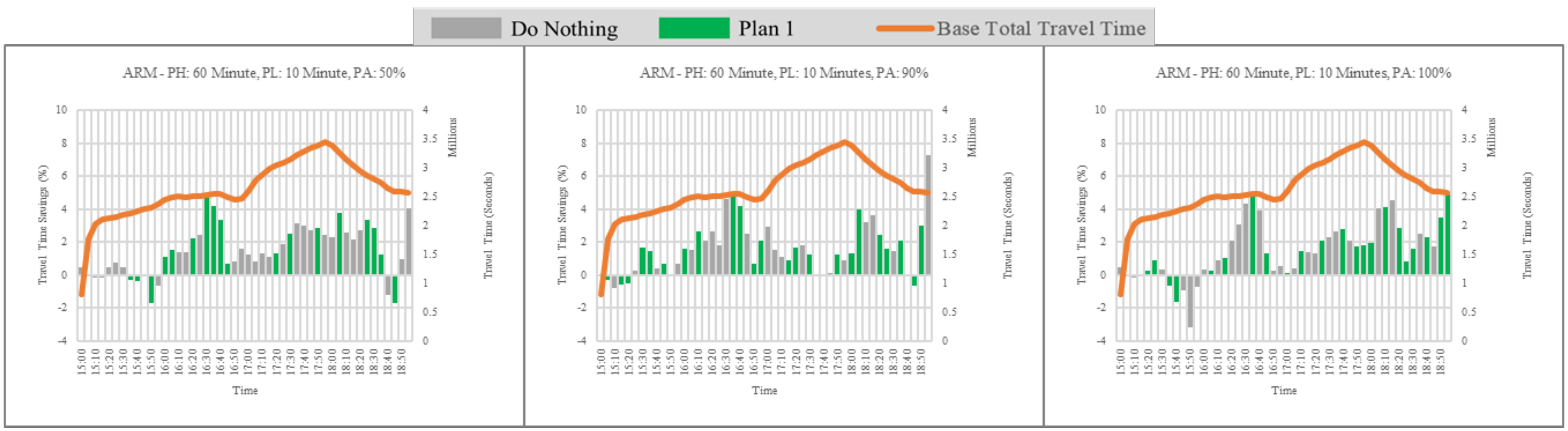


Figure 6-24: Effects of Prediction Accuracy on DSC Network Travel Time Savings [Source: Booz Allen]

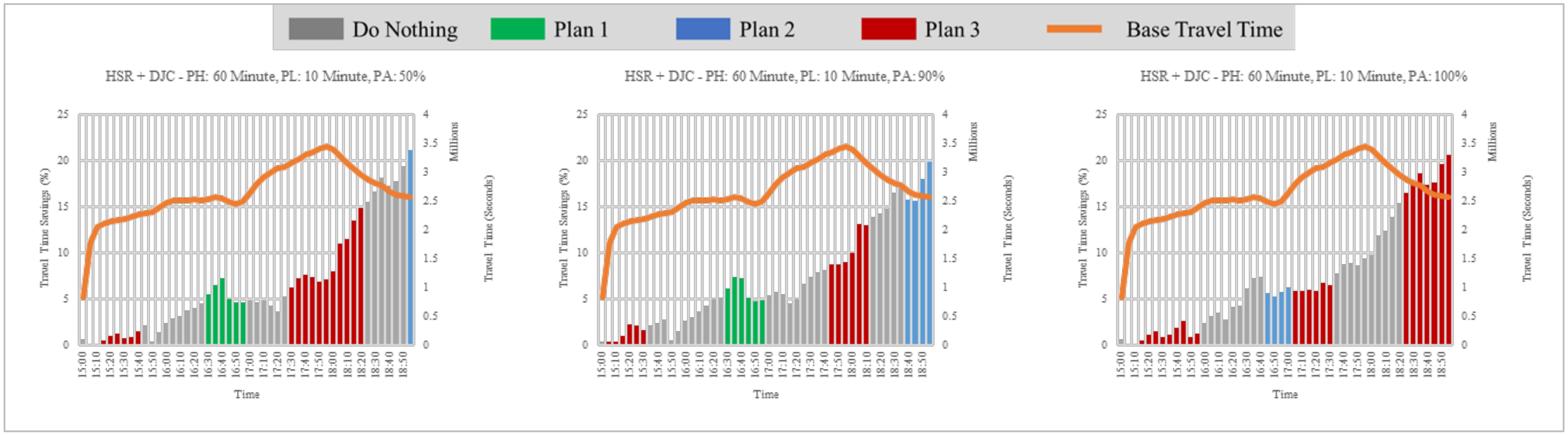


Figure 6-25: Effects of Prediction Accuracy on HSR + DJC Network Travel Time Savings [Source: Booz Allen]

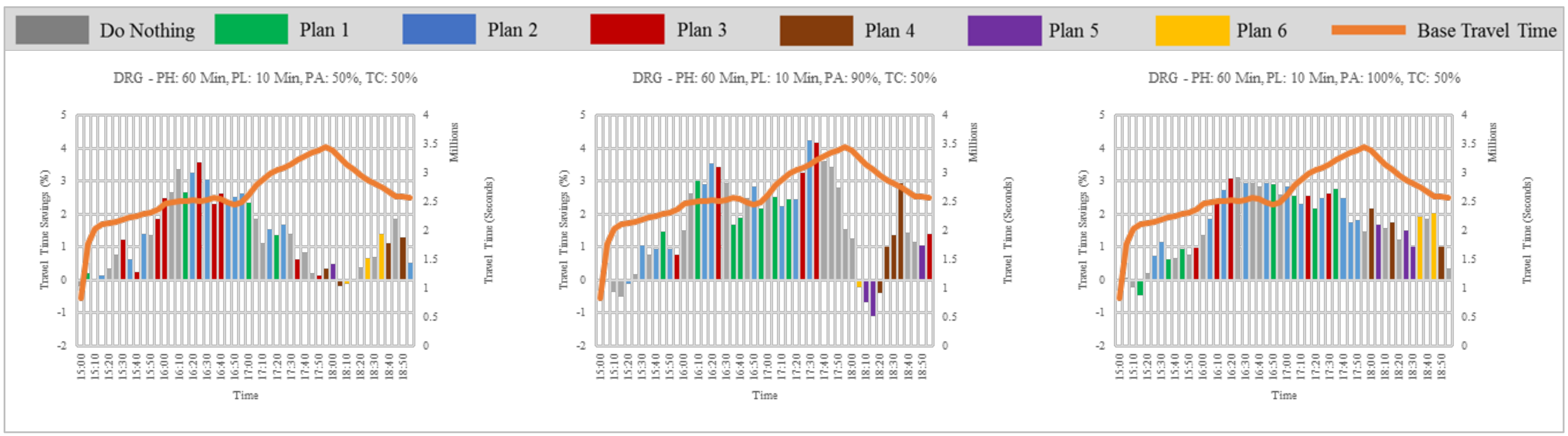


Figure 6-26: Effects of Prediction Accuracy on DRG Network Travel Time Savings [Source: Booz Allen]

6.5 Chicago Testbed Analysis

Table 6-9 shows the experimental design to test the research questions related to the prediction. Note the many factors included in the experimental design, each pertaining to a significant research question.

The main strategy bundle sensitive to prediction quality includes ADM strategies, especially dynamic routing. Also, it was assumed that the prediction accuracy is influenced by the roll period and prediction horizon. As the roll period gets shorter, the prediction state gets updated more often and becomes more accurate. As with the prediction horizon, it was assumed that the accuracy might be less for the long prediction compared to the short prediction. Therefore, two sets of tests were conducted to capture the sensitivity of the system performance to roll period and prediction horizon with the ADM strategy bundles implemented under OC1. In these tests, the latency was not taken into account.

Table 6-9: Experiment Scenarios for Research Questions of Prediction and Latency

Experiment Factor	Tests	Strategy	Net Penetration Level	Roll	Horizon	Latency
Roll Period (Prediction Accuracy)	OC1 (Clear Day)	Do nothing	0 %	-	-	-
		ADM + ATM	30%	5	30	0
		ADM + ATM	30%	15	30	0
Prediction Horizon (Prediction Accuracy)	OC1 (Clear Day)	Do nothing	0 %	-	-	-
		ADM + ATM	30%	5	15	0
		ADM + ATM	30%	5	30	0
Latency	OC1 (Clear Day)	Do nothing	0 %	-	-	-
		ADM + ATM	30%	5	15	0
		ADM + ATM	30%	5	15	3
		ADM + ATM	30%	5	15	5

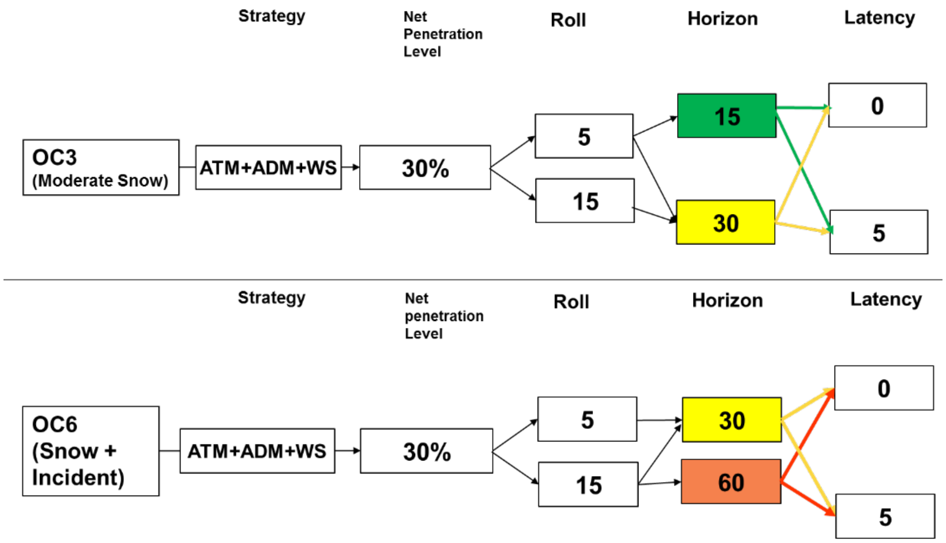
Experiment Factor	Tests
Tradeoff between Prediction Roll Period, Horizon and Latency	

Figure 6-27 shows the results related to the prediction accuracy when the roll period is varied and prediction horizon is fixed with no latency. It is observed that short roll period contributes to better prediction accuracy and leads to higher throughput compared with the simulation results with long roll period. Especially for the morning peak, the improvement from short roll period can be twice that from the long roll period. However, in the afternoon, the improvement from both scenarios are very similar, as the travel demand is not very high after morning peak and the system could maintain its stability so that vehicles may not require very often updated travel information for dynamic routing. As the simulation of the implementation of strategy with short prediction roll period requires more memory and involves more computational cost, when implementing the strategy in the real world a short roll period can be used for peak hours and moderate long roll period for off peak hours.

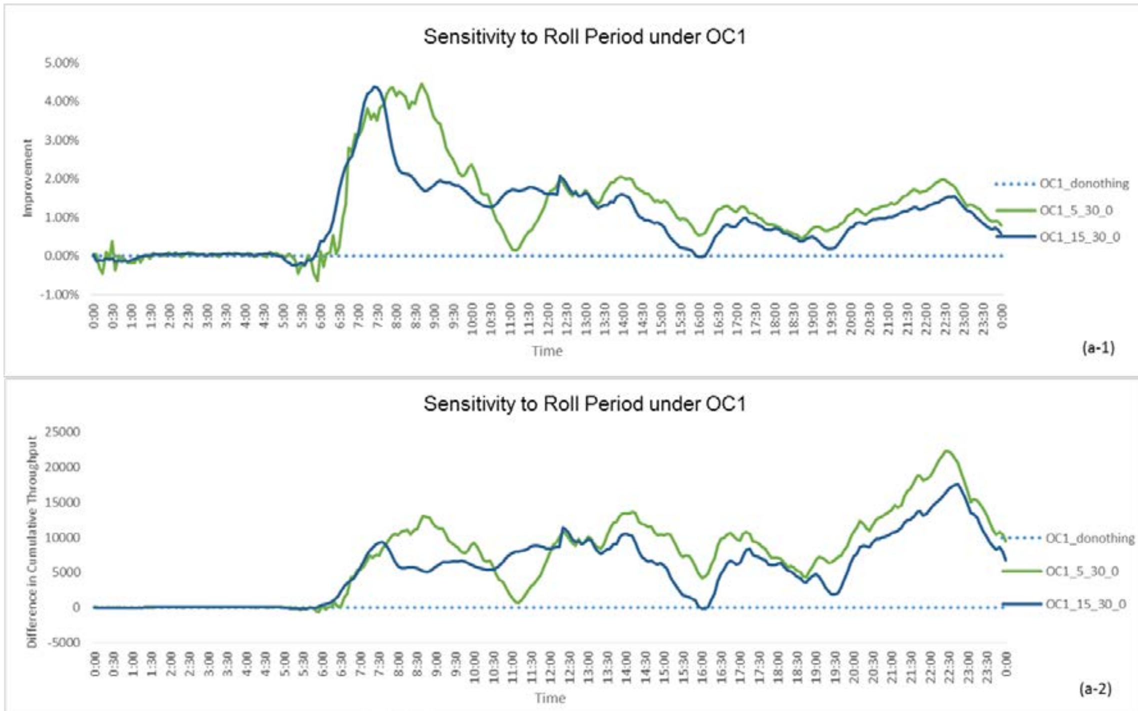


Figure 6-27: Sensitivity analysis of system performance to roll period [Source: NWU]

Figure 6-28 shows the results related to the prediction accuracy when the prediction horizon is varied and prediction horizon is fixed with no latency. When the prediction horizon is short, the prediction accuracy can be guaranteed. However, with short prediction horizon, the prediction information for dynamic routing may not be captured enough, which means that the travel time or travel cost after the prediction horizon is omitted from prediction. On the other hand, the long prediction may lead to less accuracy even though it can produce more traveler information. Therefore, it is necessary to check the time-dependent sensitivity of the system to the prediction horizon. From the test results, it is observed that during the morning peak, the system prefers shorter prediction horizon with more accuracy, but the opposite is true in the afternoon.

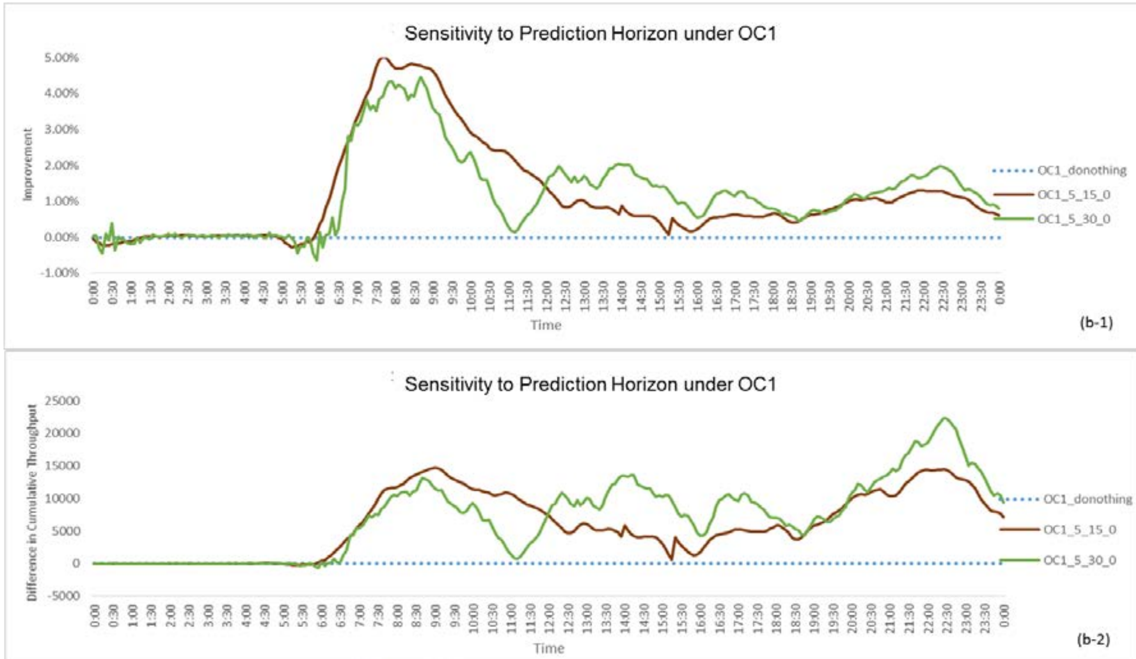


Figure 6-28: Sensitivity analysis of system performance to prediction horizon [Source: NWU]

6.6 San Diego Testbed Analysis

San Diego Testbed analysis was performed using Predictive Traveler Information framework, described in section 4.5, with response plans based on the activation of ATDM strategies. This emulates the fact that the activation of each ATDM strategy is decided based on predicted traffic conditions in a radius of 10 miles around the incident location in an anticipatory rather than reactive fashion. The ATDM strategies that are evaluated each time a prediction is made are:

- Dynamic Lane Use and Dynamic HOV/Managed Lanes
- Dynamic Speed Limits
- Dynamic Merge Control
- Combinations of two of the above strategies
- Combination of the three of them

The evaluation was performed under all four different operational conditions. The performance measures obtained in these simulations have been compared both with the baseline case and with the scenarios evaluating the activation of each ATDM strategy in isolation. The simulation framework to produce simulation-based travel time predictions was configured with response plans based on the activation of individual ATDM strategies and combinations of them. Predictions were run every 5 minutes for a horizon of 30 minutes.

Operational condition 1 (AM1)

An analysis of the speed contour on I-15 in the southbound direction shows that the Predictive Traveler Information produces no significant difference in terms of congestion (Figure 6-29).

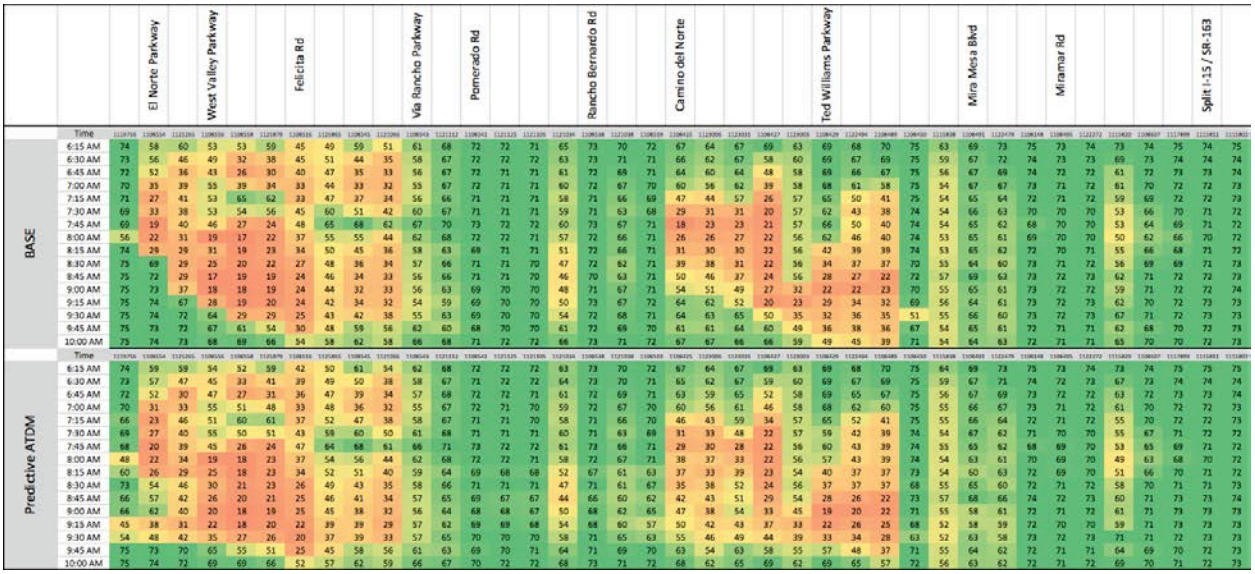


Figure 6-29: Speed contour with Predictive Traveler Information compared with the baseline case under Operational Condition 1 [Source: TSS]

If we compare network-wide traffic performance measures with Predictive Traveler Information with the baseline condition and with the activation of individual ATDM strategies (Table 6-10 and Figure 6-30) Figure 6-30 we can notice an improvement compared to the baseline, though less significant than with the constant activation of Dynamic Lane Use and Dynamic Managed Lanes alone. This is because the predictive engine in some time intervals recommended the concurrent activation of Dynamic Merge Control or Variable Speed Limit, which, as described in the previous chapter, have the effect of worsening the overall traffic performance to favor the merge from SR-78 or to reduce shockwaves.

Table 6-10: Performance measures with Predictive Traveler Information compared with the baseline case and with the activation of individual ATDM strategies under Operational Condition 1

Network Statistics	Base	Predictive ATDM	Difference	Dyn Lane Use + Dyn Managed Lanes	Difference	Dynamic Speed Limit	Difference	Dynamic Merge Control	Difference
Vehicle Miles Traveled (mi)	2,320,947	2,322,987	0.1%	2,325,470	0.2%	2,295,970	-1.1%	2,315,264	-0.2%
Total Travel Time (h)	61,946	61,362	-0.9%	60,953	-1.6%	63,713	2.9%	65,191	5.2%
Passenger Hourly Travel Time (h)	78,635	78,050	-0.7%	77,591	-1.3%	80,972	3.0%	83,511	6.2%
VMT/VHT (mi/h)	37.47	37.86	1.0%	38.15	1.8%	36.04	-3.8%	35.52	-5.2%

Figure 6-30: Performance measures with Predictive Traveler Information compared with the baseline case and with the activation of individual ATDM strategies under Operational Condition 1 [Source: TSS]

Operational condition 2 (AM2)

An analysis of the speed contour on I-15 in the southbound direction shows that the Predictive Traveler Information slightly reduces the congestion in the southern part of the corridor (Figure 6-31).

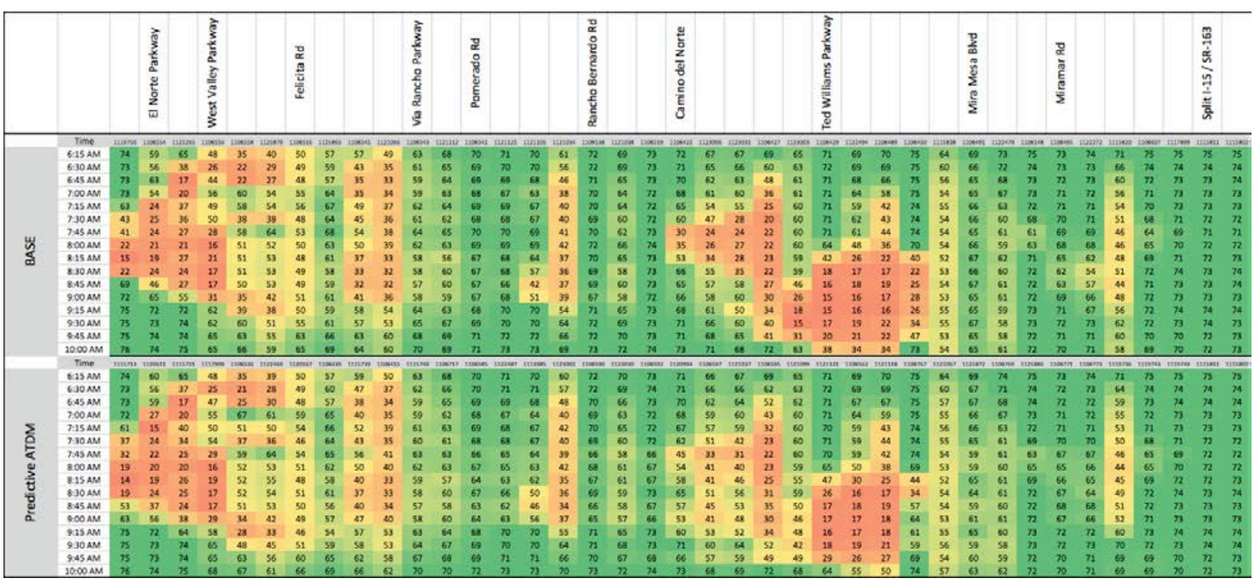
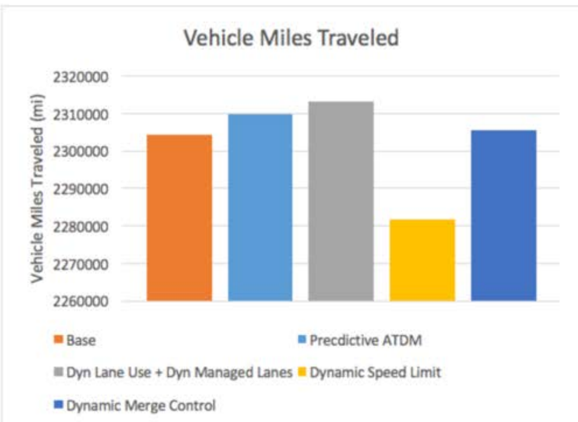


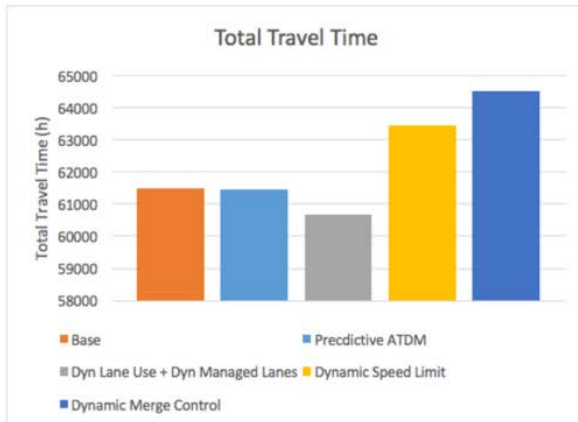
Figure 6-31: Speed Contour with Predictive Traveler Information compared with the baseline case under Operational Condition 2 [Source: TSS]

If we compare network-wide traffic performance measures with Predictive Traveler Information with the baseline condition and with the activation of individual ATDM strategies (Table 6-11 and Figure 6-32), we can notice that the difference with the baseline is negligible.

Table 6-11: Performance measures with Predictive Traveler Information compared with the baseline case and with the activation of individual ATDM strategies under Operational Condition 2

Network Statistics	Base	Predictive ATDM	Difference	Dyn Lane Use + Dyn Managed Lanes	Difference	Dynamic Speed Limit	Difference	Dynamic Merge Control	Difference
Vehicle Miles Traveled (mi)	2,304,353	2,309,786	0.2%	2,313,228	0.4%	2,281,850	-1.0%	2,305,441	0.0%
Total Travel Time (h)	61,509	61,462	-0.1%	60,683	-1.3%	63,446	3.1%	64,540	4.9%
Passenger Hourly Travel Time (h)	78,853	78,985	0.2%	77,762	-1.4%	81,278	3.1%	82,905	5.1%
VMT/VHT (mi/h)	37.46	37.58	0.3%	38.12	1.8%	35.97	-4.0%	35.72	-4.7%





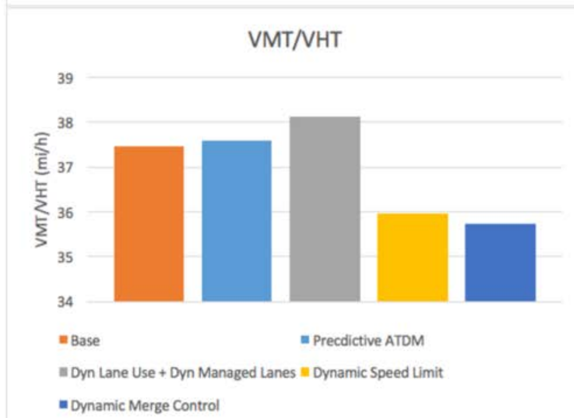


Figure 6-32: Performance measures with Predictive Traveler Information compared with the baseline case and with the activation of individual ATDM strategies under Operational Condition 2 [Source: TSS]

Operational Condition 3 (PM3)

An analysis of the speed contour on I-15 in the southbound direction shows that the Predictive Traveler Information produces no significant difference in terms of congestion (Figure 6-33).

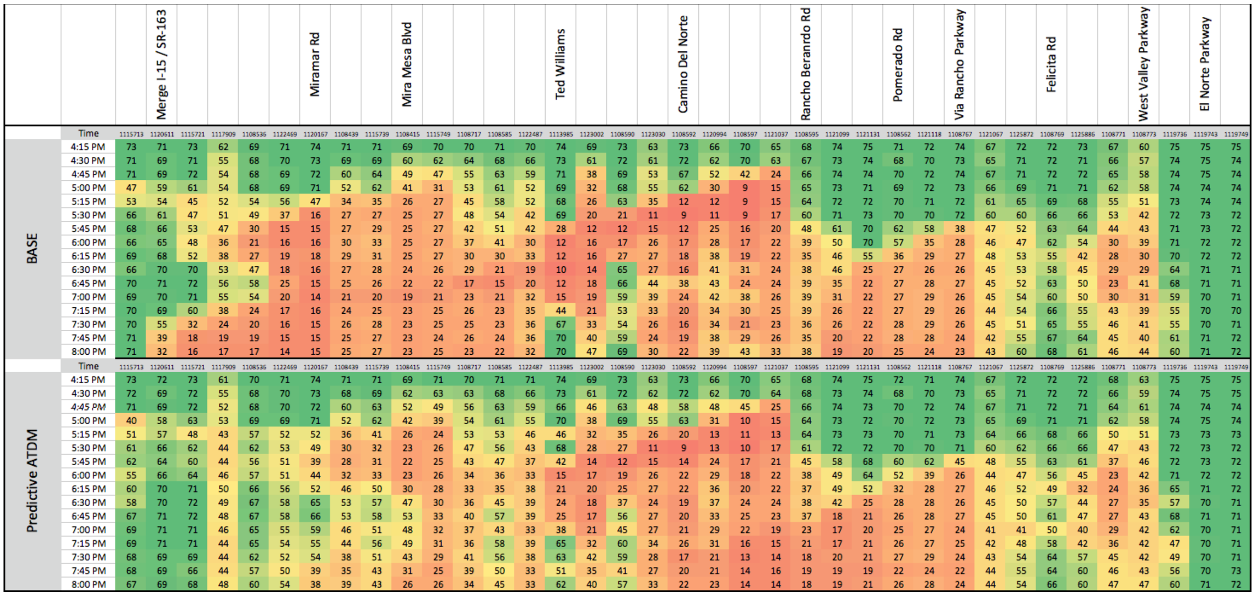


Figure 6-33: Speed contour with Predictive Traveler Information compared with the baseline case under Operational Condition 3 [Source: TSS]

If we compare network-wide traffic performance measures with Predictive Traveler Information with the baseline condition and with the activation of individual ATDM strategies (Table 6-12 and Figure 6-34), we can notice that the difference with base can only be observed in terms of travel time and the order of magnitude is approximately half of what the constant activation of Dynamic Lane Use and Dynamic Managed Lanes. The reason is that Predictive Traveler Information activates Dynamic Lane Use and Dynamic Managed Lanes sometimes in concurrence with Variable Speed Limit, which has the effect of lowering the speed, hence compensating in part the benefit of Dynamic Lane Use and Dynamic Managed Lanes.

Table 6-12: Performance measures with Predictive Traveler Information compared with the baseline case and with the activation of individual ATDM strategies under Operational Condition 3

Network Statistics	Base	Predictive ATDM	Difference	Dyn Lane Use + Dyn Managed Lanes	Difference	Dynamic Speed Limit	Difference
Vehicle Miles Traveled (mi)	2,518,604	2,520,906	0.1%	2,531,493	0.5%	2,447,851	-2.8%
Total Travel Time (h)	76,531	75,043	-1.9%	73,529	-3.9%	77,953	1.9%
Passenger Hourly Travel Time (h)	99,052	97,794	-1.3%	95,937	-3.1%	100,604	1.6%
VMT/VHT (mi/h)	32.91	33.59	2.1%	34.43	4.6%	31.40	-4.6%

Figure 6-34: Performance measures with Predictive Traveler Information compared with the baseline case and with the activation of individual ATDM strategies under Operational Condition 3 [Source: TSS]

Operational Condition 4 (PM4)

An analysis of the speed contour on I-15 in the southbound direction shows that the Predictive Traveler Information produces no significant difference in terms of congestion (Figure 6-35).

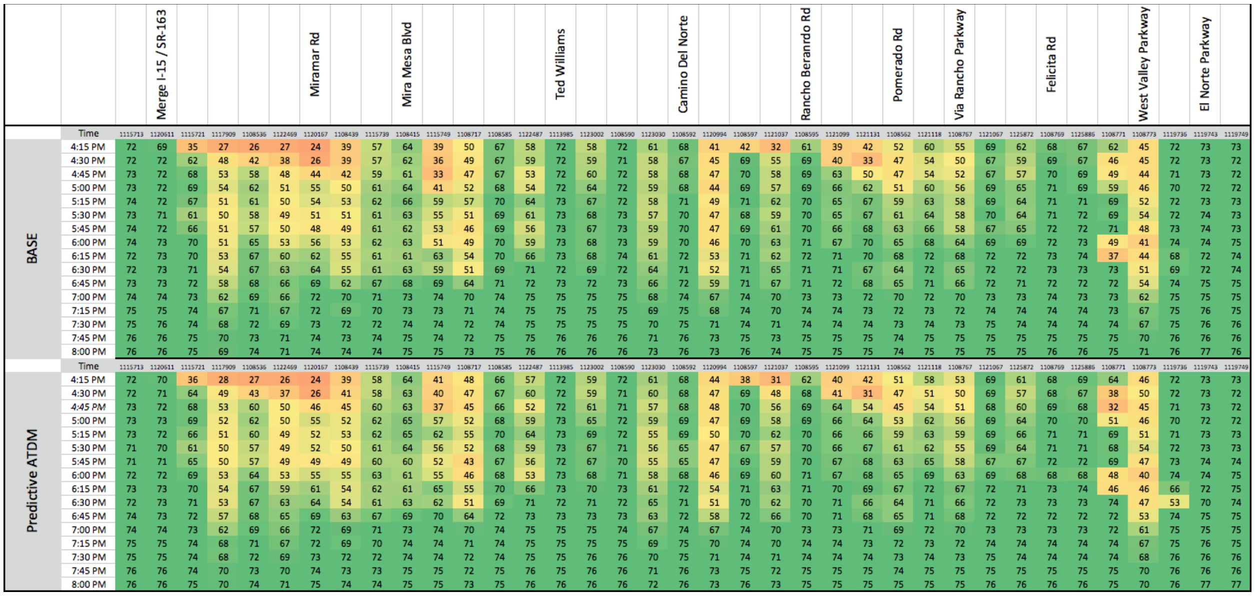


Figure 6-35: Speed contour with Predictive Traveler Information compared with the baseline case under Operational Condition 4 [Source: TSS]

If we compare network-wide traffic performance measures with Predictive Traveler Information with the baseline condition (Table 6-13 and Figure 6-36), we can notice that the difference is not significant. This is because this operational condition is characterized by almost no congestion, therefore most of the time no ATDM strategies are activated. If we compare with the activation of individual ATDM strategies, we can notice a slight improvement, which can be interpreted as follows: when there is no significant and sustained congestion, a constant and scheduled activation of an ATDM strategy may be ineffective or even counterproductive; the prediction allows a constant monitoring of the traffic condition to determine whether and when it each strategy should be activated.

Table 6-13: Performance measures with Predictive Traveler Information compared with the baseline case and with the activation of individual ATDM strategies under Operational Condition 4

Network Statistics	Base	Predictive ATDM	Difference	Dyn Lane Use + Dyn Managed Lanes	Difference	Dynamic Speed Limit	Difference
Vehicle Miles Traveled (mi)	2,302,897	2,302,802	0.0%	2,301,997	0.0%	2,302,937	0.0%
Total Travel Time (h)	57,547	57,467	-0.1%	57,589	0.1%	58,476	1.6%
Passenger Hourly Travel Time (h)	75,856	75,809	-0.1%	75,918	0.1%	76,910	1.4%
VMT/VHT (mi/h)	40.02	40.07	0.1%	39.97	-0.1%	39.38	-1.6%

Figure 6-36: Performance measures with Predictive Traveler Information compared with the baseline case and with the activation of individual ATDM strategies under Operational Condition 4 [Source: TSS]

Comparison Between Operational Conditions

If we look at the results of operational conditions with more severe incidents and sustained congestion, we see that the predictions continuously activate ATDM strategies that increase the throughput, and the result in terms of traffic performance is similar to the constant activation of those strategies; if we look at the results of operational conditions with less congestion, we see that the predictions most of the time do not activate any ATDM strategies, and the result in terms of traffic performance is better than the constant activation of those strategies.

6.7 Results Summary

This chapter analyzed the impacts of prediction attributes such as accuracy and length of prediction horizon in the effectiveness of ATDM strategies. Intuitively, it was seen that greater prediction accuracy and a longer prediction horizon resulted in better results in both Dallas and Phoenix Testbeds.

For the Dallas Testbed, a superior network performance is obtained for the case in which perfect demand prediction is assumed. The network performance gradually worsens with the increase in the level of demand prediction error. For example, savings of 7,806 and 12,341 minutes are recorded for the scenarios with 5% demand prediction error in the underestimation and overestimation cases, respectively. As the error increases to 10%, the savings are reduced to 2,252 and 3,298 minutes, respectively. The network performance generally improves as the length of the prediction horizon increases. As the horizon is increased, assuming perfect prediction accuracy, the generated schemes are more effective. Positive correlation is observed between increasing the length of prediction horizon, and total travel time savings in the network. For example, using 15-minute prediction horizon resulted in less travel time savings compared to that obtained for the scenario in which 60-minute prediction horizon is considered. For the 15-minute prediction horizon, a saving of 9,114 minutes is recorded. This saving increased to 21,586 minutes when the prediction horizon increased to 60 minutes.

For the Phoenix Testbed, freeway travel time was assessed with Adaptive Ramp Metering under different configurations. A longer prediction horizon resulted in a sub-1-percent reduction in the average travel times and the impact of communication latency on the traffic mobility was also marginal (less than 1%). Furthermore, it is found that the performance of adaptive ramp metering is very sensitive to the prediction accuracy. After certain system errors are superimposed to the prediction accuracy, the adaptive ramp metering will be under or overestimated in different scenarios. If the system errors make the mainline travel demand lower, then the ramp will allow excessive vehicles to enter the mainline. Otherwise it will unnecessarily gate some vehicles. In turn, the mainline mobility can be changed considerably, harming or not harming the traffic on adjacent roads.

This section of the analysis for the Pasadena Testbed compares the impacts of using prediction versus time of day strategy. The results shown in Table 6-5 shows consistently that all strategies implemented with prediction yield higher travel time savings compared to time of day prediction. This is primarily due to the strategy deployment prior to when the freeways form significant traffic congestion. Strategy deployment prior to peak congestion will delay the start time of significant congestions, hence delaying the facility operational breakdown. Comparing the HSR + DJC strategy that yields the highest travel time benefits between the prediction versus time-of-day plan scenario, when the HSR + DJC is activated for a total of 120 minutes (17.2% less than prediction) throughout the peak period, the network travel time savings is 2.01% which is less than one-third of the network travel time savings for the prediction scenario. This section for the Pasadena testbed also analyzes the effects of prediction horizon of network operational performance. The results show a prediction horizon of 30-minutes to 60-minutes has greater impacts on freeway focused strategies: ATM and HSR + DJC. Prediction horizon of 15-minutes to 30-minutes have greater impacts on arterial focused strategies: DSC and DRG. The analysis for prediction accuracy on the prediction recommendations demonstrate that there is very impact when selecting plan deployment for ARM. There are slightly higher effects on network travel time improvements with the increase in prediction accuracy for the HSR + DJC and DRG strategies. If the prediction accuracy falls to 50%, degradation in network travel time performance is observed from the DSC strategy.

For the Chicago Testbed, it can be concluded that the best-performing settings for predictive strategies vary under different operational conditions. To implement the strategies in the real world, it is desirable to revisit and refine these values through field deployment experience. Clear weather scenarios prefer prediction accuracy with a shorter prediction horizon and roll period for the peak hours when travel demand is high, while the snow-affected scenarios prefer a longer prediction horizon, and are sensitive to accuracy and latency. More frequent updates with shorter roll periods of the predictive strategies may lead to instabilities in system performance. As with the hypothetical scenario, i.e. the combined incident-snow scenario reaches a trade-off state between accuracy and prediction horizon, and is not particularly sensitive to latency due to incident-related delay.

For the Pasadena Testbed, it can be concluded that there were no statistically significant benefits of conducting predictions when evaluating and deploying ATDM strategies. However, the activation of ATDM strategies were reduced and only operational conditions with severe incidents and sustained congestion contributed to activation of a response plan.

Chapter 7. Operational Conditions, Modes and Facility Types

This chapter primarily addresses the research questions related to operational conditions, modes and facility types and tries to find out the most favorable conditions for each ATDM strategy or combination being tested. Additional results with respect to different hypothetical operational conditions are also provided in this chapter.

7.1 Research Questions and Hypotheses

The following research questions are answered using this analysis:

1. Which ATDM strategy or combinations of strategies will be most beneficial for certain modes and under what operational conditions?
2. Which ATDM strategy or combinations of strategies will be most beneficial for certain facility types (freeway, transit, arterial) and under what operational conditions?
3. Which ATDM strategy or combinations of strategies will have the most benefits for individual facilities versus system-wide deployment versus region-wide deployment and under what operational conditions?

In order to answer these sets of questions, the project team assumed certain research hypotheses. Certain ATDM strategies and combinations of strategies were expected to yield the highest benefits for specific modes and under certain operational conditions. Specific ATDM strategies and combinations of strategies might also yield the highest benefits for specific facility types and under certain operational conditions. Certain synergistic ATDM strategies were expected yield most benefits when deployed together on individual facilities rather than as system-wide or region-wide deployments and under certain operational conditions and vice-versa.

7.2 Dallas Testbed Evaluation

The ATDM strategies are evaluated under different operational conditions which have been described in Chapter 3. In addition, the analysis is extended to examine the effectiveness of these strategies in the major freeways in the network. The analysis in this Chapter has also been extended to examine the effectiveness of deploying ATDM strategies on two hypothetical operational conditions in Dallas testbed network; I) Adverse weather operational condition, and II) Evacuation operational conditions.

In the adverse weather operational condition, it is assumed that the drivers are more careful due to precipitation of rain or snow, which means they drive slower than normal conditions. To model these traffic conditions, the model parameters are adjusted to represent the drivers' behavior. Two scenarios are modeled for adverse weather conditions; I) reducing free-flow speed, and II) reducing free-flow speed and reducing vehicle spacing (i.e., jam density). In each scenario the traffic management system is activated to develop efficient ATDM response plans. The analysis examines the effectiveness of developed schemes under the adverse weather condition. In the evacuation scenario, it is assumed that the pattern for the given travel pattern in the network is changed as travelers evacuate towards pre-defined set of safe destinations. A set of experiments are designed to evaluate the effectiveness of different ATDM strategies under this special condition in the network.

7.2.1 Existing Operational Conditions

As described earlier in Section 3.1, there are four main operational conditions in Dallas testbed. They vary in demand and severity of occurred incidents. In all presented results in the previous chapters, we used operational condition one (MD-LI) which is characterized by medium-to-high demand level, minor severity incident, and dry weather conditions. In this section, we extend the analysis to examine the effectiveness of the ATDM strategies under different operational conditions. In addition to presenting the overall network performance, the results are presented for the US 75 freeway facility. Similar to the previous chapter, the traffic network management module generates ATDM response plans that includes the Dynamic Routing strategy and the Dynamic Signal Timing strategy. Perfect demand prediction is assumed and the prediction horizon is set at 30 minutes. The generated ATDM response plans are assumed to be deployed in the network with no latency. The moving horizon approach is used to report the different performance measures assuming a roll period of five minutes and a backward horizon of 30 minutes.

In all experiments, two scenarios are compared. In the first scenario, no ATDM response plans are deployed and all travelers are assumed to follow their habitual routes and experience the delay due to the incident (i.e., the baseline scenario). In the second scenario, the traffic management system is activated to manage the incident through deploying ATDM response plans that integrate different combinations of the strategies mentioned above. The traffic management module is activated with the start of the incident through 30 minutes after its clearance. The benefits of the traffic management system are reported in terms of saving in the total network travel time, fuel consumption and emissions as percentages of their corresponding values under the baseline scenario.

Figure 7-1 through Figure 7-6 presents the results of deploying the ATDM response plans considering the four different operational conditions on the Dallas Testbed. The travel-time results are presented for the entire network (Figure 7-1), US-75 northbound (Figure 7-2), and US-75 southbound (Figure 7-3). Similar to the previous Chapters, the percentage time-varying travel time saving are given as well as the corresponding total travel time under the baseline scenario. In addition, Figure 7-4 demonstrates the change in total fuel consumption of the network as a consequence of ATDM Traffic Management. Figure 7-5 and Figure 7-6, respectively demonstrates the change in total Carbon Dioxide emissions and Nitrogen Oxide emissions from the network. A summary of the savings in terms of mobility and environmental performance measures is provided in Table 7-1 and Table 7-2 respectively.

Two main observations can be made based on these results.

- First, the ATDM response plans generally reduce the congestion associated with the incident. However, for HD-MI, the generated schemes failed to achieve travel time saving at the network level. Please note that in this set of experiments, the schemes consist only of two strategies a) dynamic routing and b) dynamic signal timing. These strategies were effective for three out of the four operational conditions considered in this analysis. However, there is no guarantee that these are the best strategies for all operational conditions. To achieve travel time savings for the fourth operational conditions, other strategies (e.g., adaptive ramp metering, dynamic shoulder lane) could be tried and integrated as part of the schemes.
- Second, the savings in total travel time for the entire network is generally consistent with the savings in the US-75 freeway facility in both directions implying that the schemes reduce the congestion on the freeway while maintaining good level of service across the entire network.

Table 7-1: Effectiveness of ATDM Strategies under Different Operational Conditions in Mobility Terms (Dallas Testbed)

Operational Condition	Description	Total Network Travel Time Savings (minutes)	US-75 NB Travel Time Savings (minutes)	US-75 SB Travel Time Savings (minutes)
MD-LI	Medium-High Demand + Low Incident	15,125	12,492	10,179
HD-LI	High Demand + Low Incidents	39,234	10,764	2,266
HD-MI	High Demand + Medium Incidents	-20,978	-450	1,518
MD-HI	Medium Demand + High Incidents	13,161	7,767	4,681

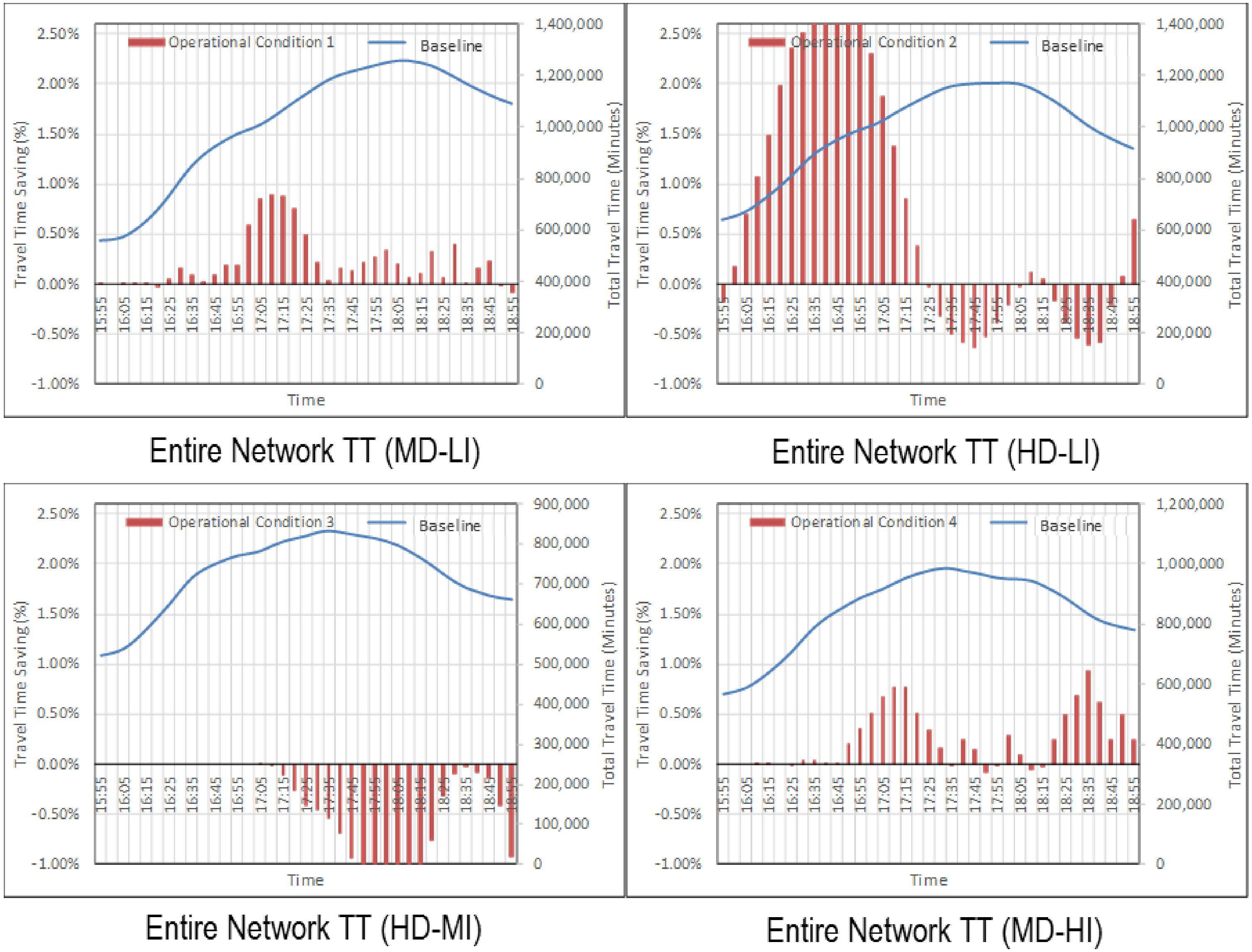


Figure 7-1: Performance of Entire Dallas Network Under Different Operational Conditions [Source: SMU]

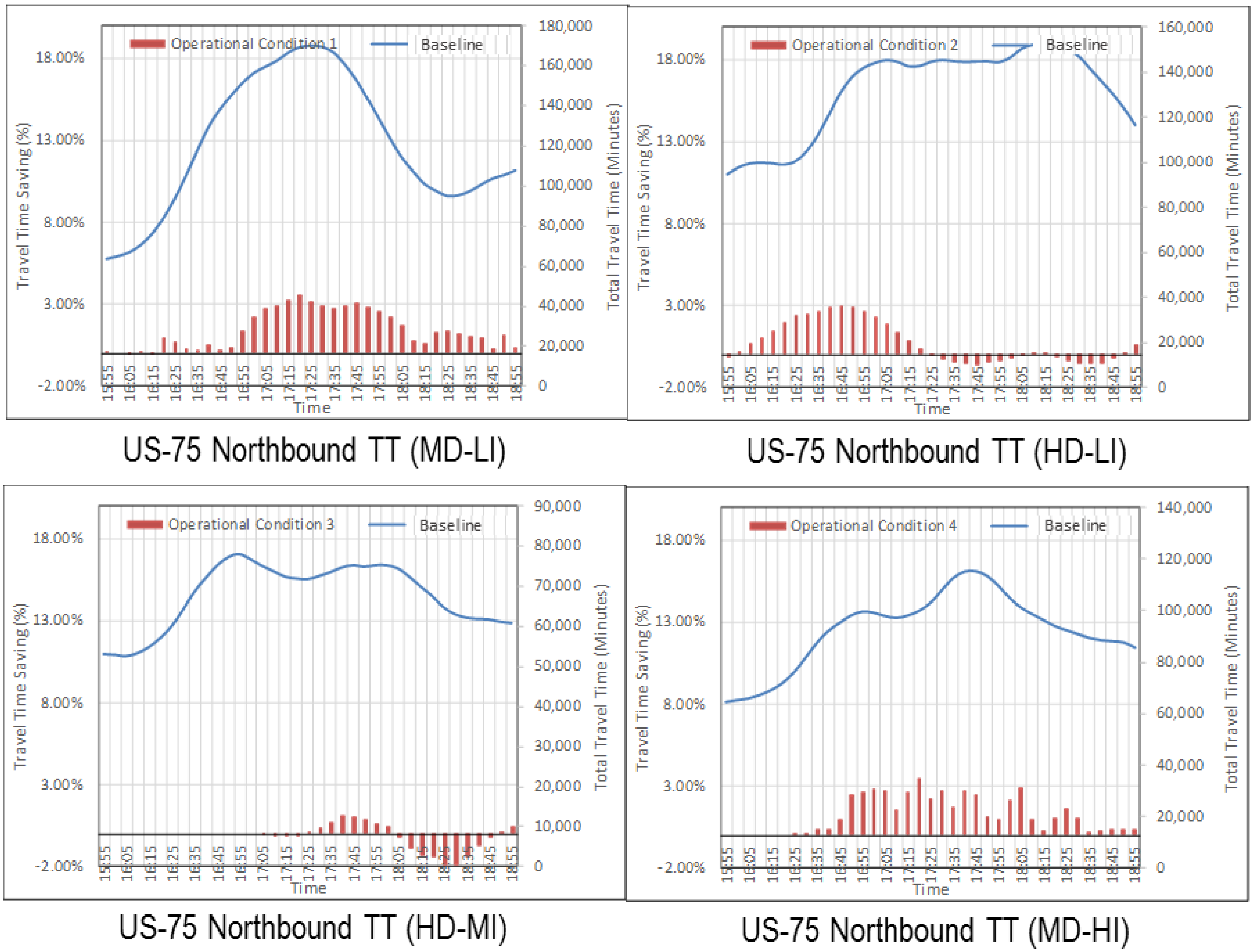


Figure 7-2: US-75 Northbound Travel Time under different Operational Conditions (Dallas Testbed) [Source: SMU]

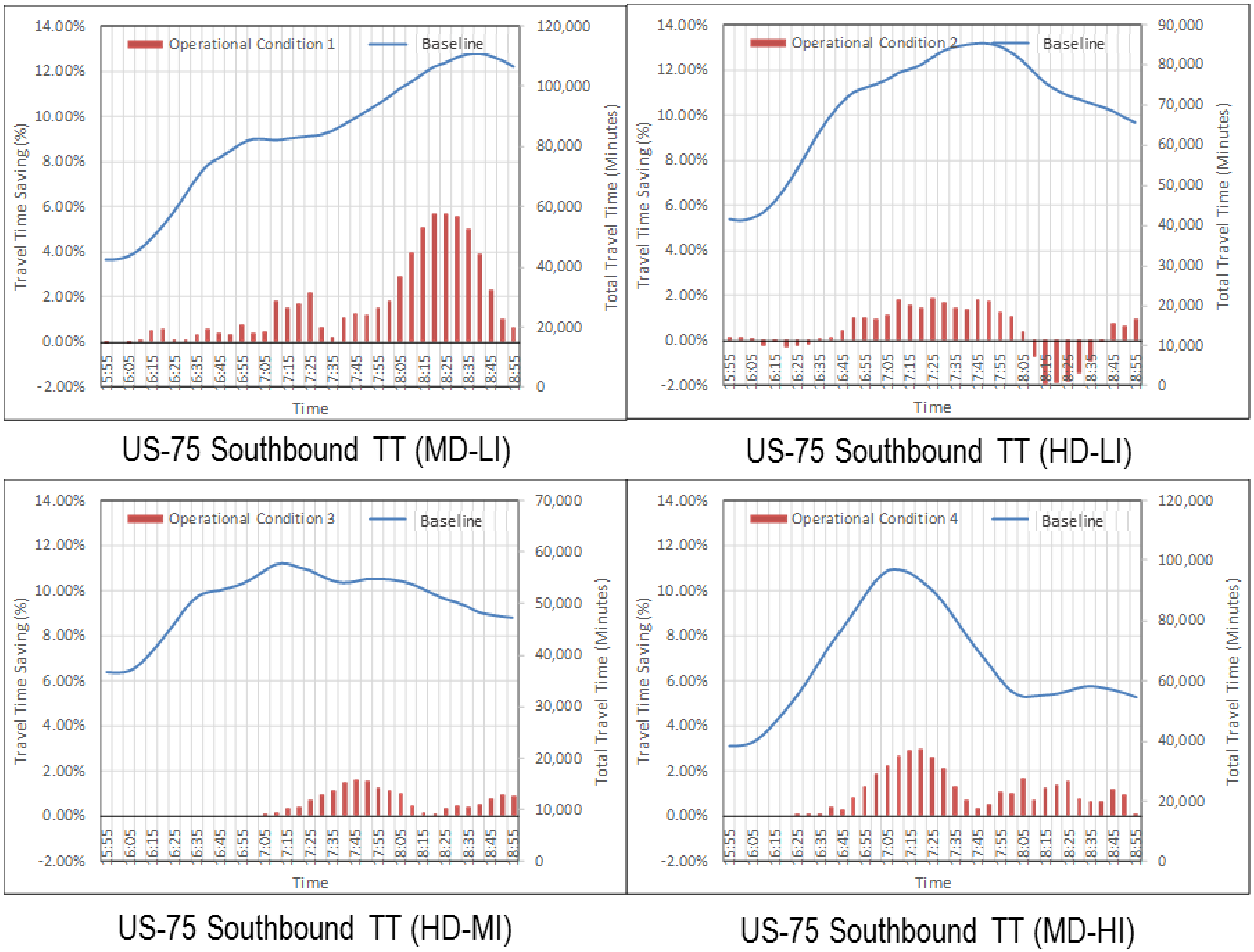


Figure 7-3: US-75 Southbound Travel Time Under Different Operational Conditions (Dallas Testbed) [Source: SMU]

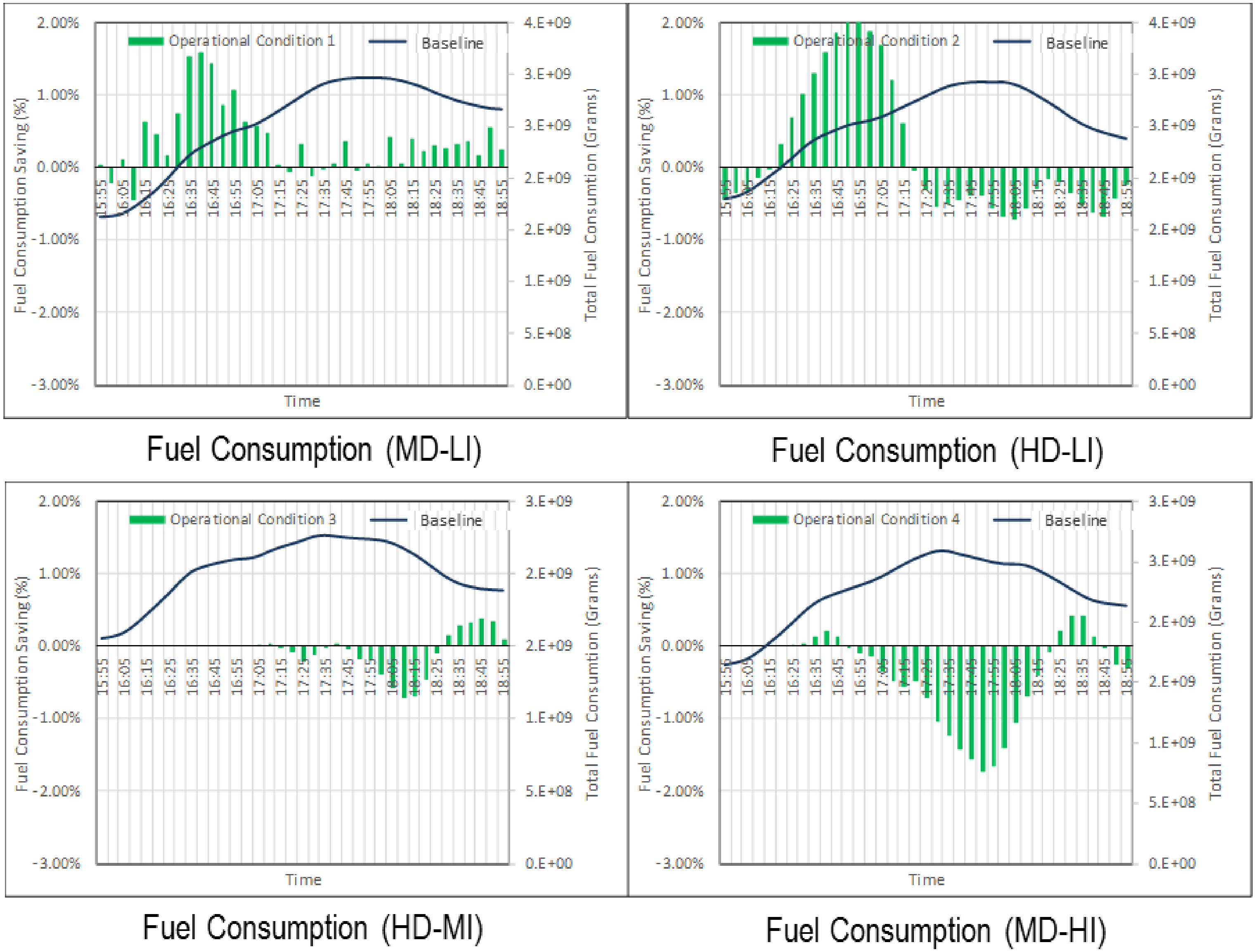


Figure 7-4: Fuel Consumption of Dallas Network Under Different Operational Conditions (Dallas Testbed) [Source: SMU]

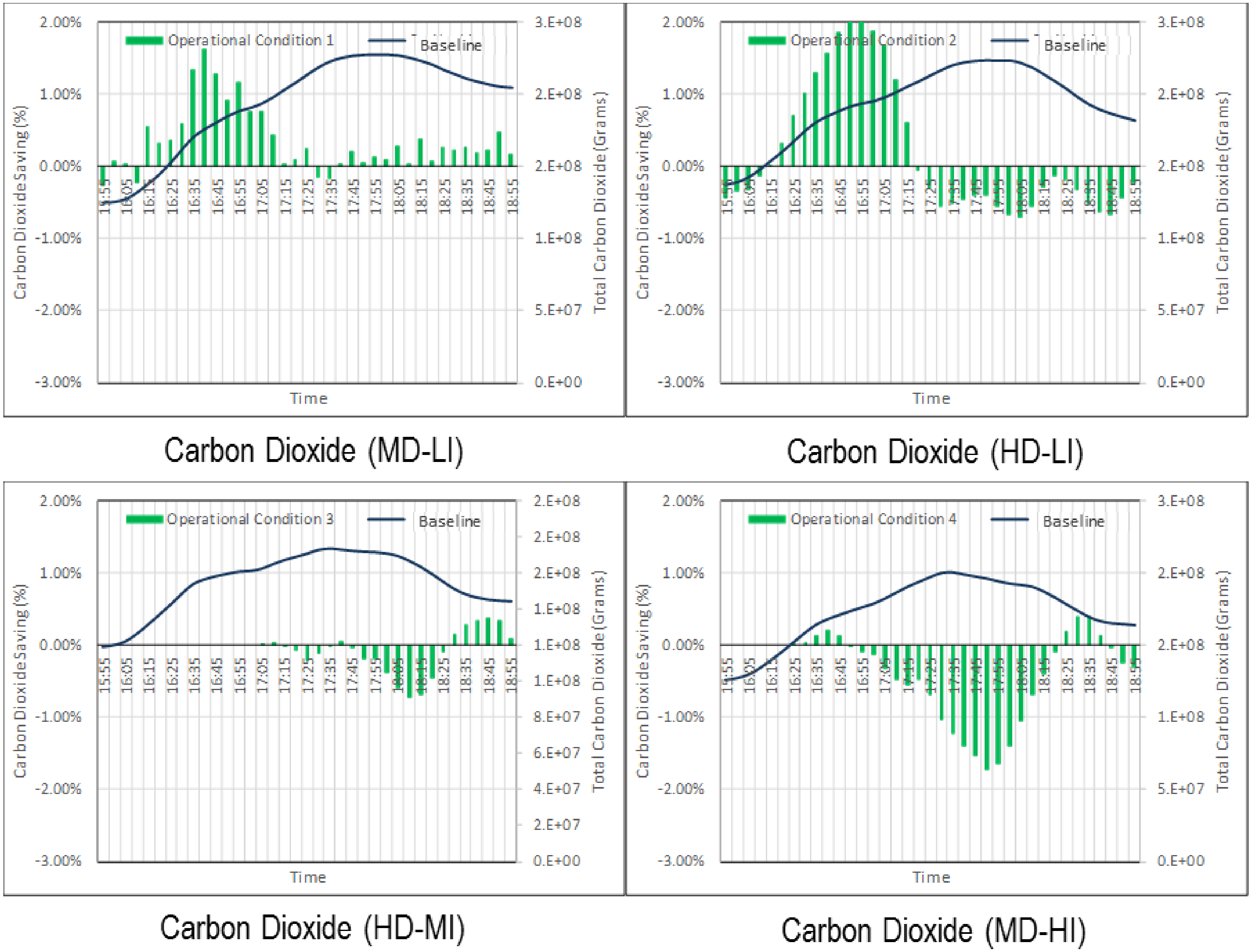


Figure 7-5: Carbon Dioxide Emissions of Dallas Network Under Different Operational Conditions (Dallas Testbed) [Source: SMU]

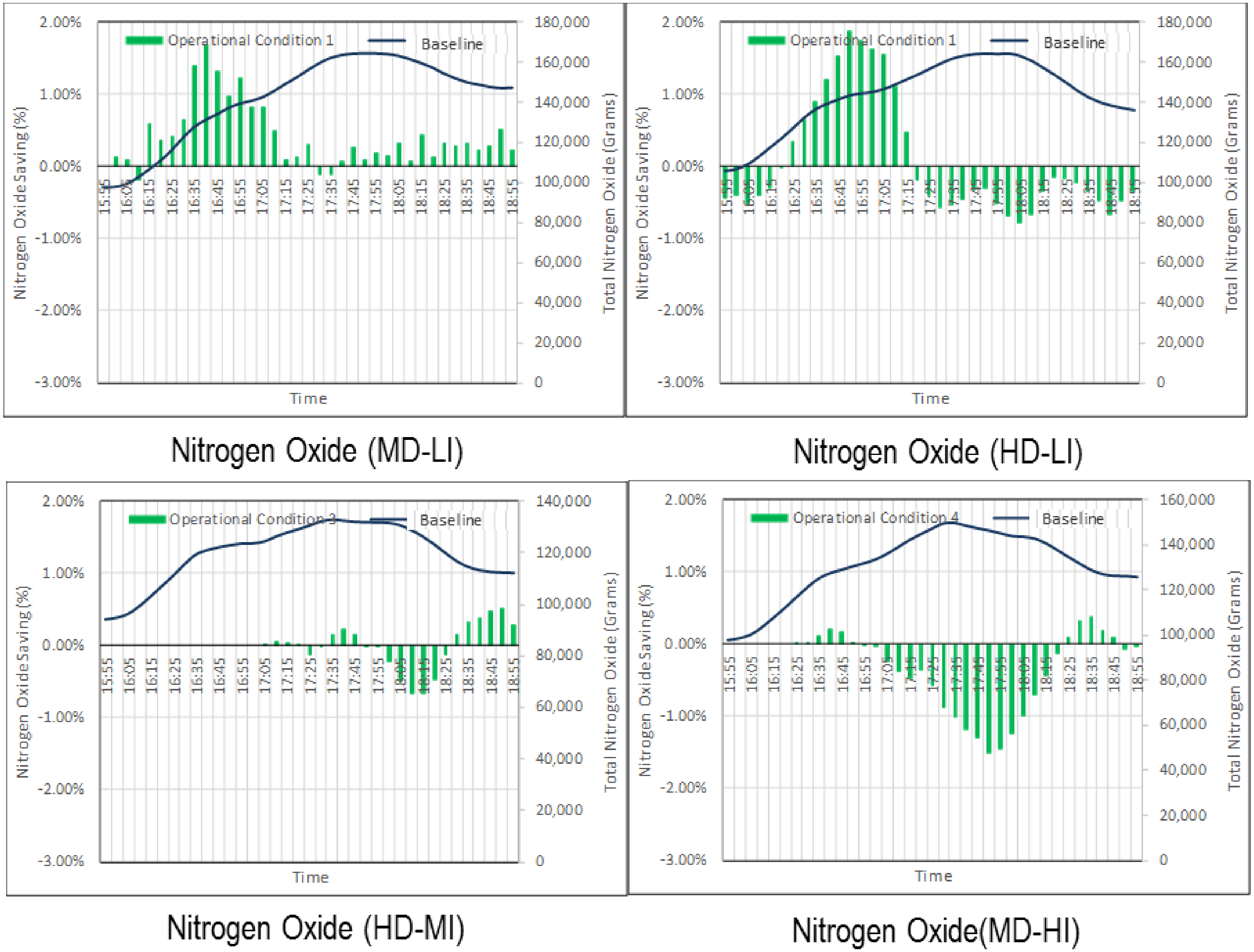


Figure 7-6: Nitrogen Oxide Emissions of Dallas Network Under Different Operational Conditions (Dallas Testbed) [Source: SMU]

Table 7-2: Environmental Effectiveness of ATDM Strategies for Different Operational Conditions on Dallas Testbed

Operational Condition	Description*	Fuel Consumption Saving (tons)	Carbon Dioxide Saving (tons)	Nitrogen Oxide Saving (kilograms)
MD-LI	Medium-High Demand + Low Incident	56.27	4.17	3.50
HD-LI	High Demand + Low Incidents	25.97	1.96	0.51
HD-MI	High Demand + Medium Incidents	-9.08	-0.70	-0.07
MD-HI	Medium Demand + High Incidents	-61.38	-4.70	-2.89

As a summary, as far as mobility measures are concerned, the condition with high-demand and low-incidents is favorable since it produced nearly 40,000 minutes of total travel time savings for the entire network, whereas for environmental savings, medium-high demand and low incident is the most favorable operational condition. Most favorable in terms of mobility and emissions are not necessarily the same since the mobility measures are measured in terms of travel time, whereas the emissions are measured in terms of number of stops, acceleration and deceleration that vehicles are subject to.

7.2.2 Adverse Weather Operational Condition

The Dallas Testbed also included a hypothetical operational condition of adverse weather, which is demonstrated in this chapter. As described in Chapter 3, the traffic network estimation model adopts a mesoscopic simulation logic in which the average traffic speed v_a^t on each lane a in each simulation interval $t \in T$ is updated as a function of the traffic density k_{at} . For that purpose, a traffic flow propagation model follows the Greenshields' model is adopted to represent traffic movement on each for each lane on the link, as illustrated in Equation 7-1.

$$v_{at} = v_{at}^{freeflow}\left[1 - \left(\frac{k_{at}}{k_{at}^{jam}}\right)\right] \qquad \forall\, a \in A \,\&\, \forall\, t \in T \qquad (7\text{-}1)$$

where $v_{at}^{freeflow}$ and k_{at}^{jam} are the free-flow speed and maximum density for lane a, respectively. To represent the impact of adverse weather on the traffic flow, two scenarios are considered. The first scenario assumes that drivers reduce their speeds. Thus, the free flow speed in the Greenshields model is reduced by a pre-defined percentage for each link is replicated this behavior. The second scenario assumes that drivers reduce their speed and also maintain longer distances with the leading vehicle. In this case, a lower free flow speed and lower jam density are adopted to model such behavior. Figure 7-7 illustrates how the Greenshields model is modified to represent the drivers' behavior under the adverse weather conditions considering these two scenarios.

Table 7-3 gives the amount of reduction in the free-flow speed for different road types. As no such data are available for the Dallas Testbed, the analysts' judgment is used to estimate these speed reduction values. In the second scenario in which both free flow speed and jam density are reduced, it the jam density is assumed to be reduced by 10 percent on the major links (freeways and major arterials). The Greenshields model is updated with the new values of free-flow speeds and jam densities to compute the speeds on the links. Figure 7-8 presents the overall network performance under these two scenarios of adverse operational conditions. The total network travel time for these two scenarios are presented and compared with that of normal operation conditions. Here, the normal operational conditions are represented by MD-LI as described in details in Chapter 3. As shown in the Figure, considering the drivers' behavior under the adverse weather conditions resulted in an increase in the overall network travel time. As expected, the scenario in which the free flow speed and jam density are reduced show more increase in the time-varying network travel time compared to that of the scenario in which only the free flow speed is reduced.

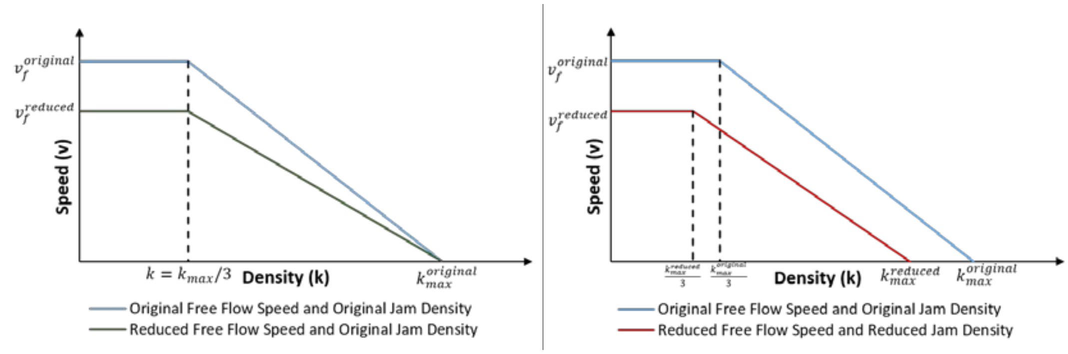


Figure 7-7: The Speed -Density Relationships Considering Adverse Weather Conditions [Source: SMU]

Table 7-2: Different Free Flow Speeds for Different Road Types

Road Type	Original Free Flow Speed (mile/hour)	Speed Reduction (mile/hour)
Freeway	Greater than 60	15
Arterial	40 to 60	10
Collector and Ramp	Less than 40	5

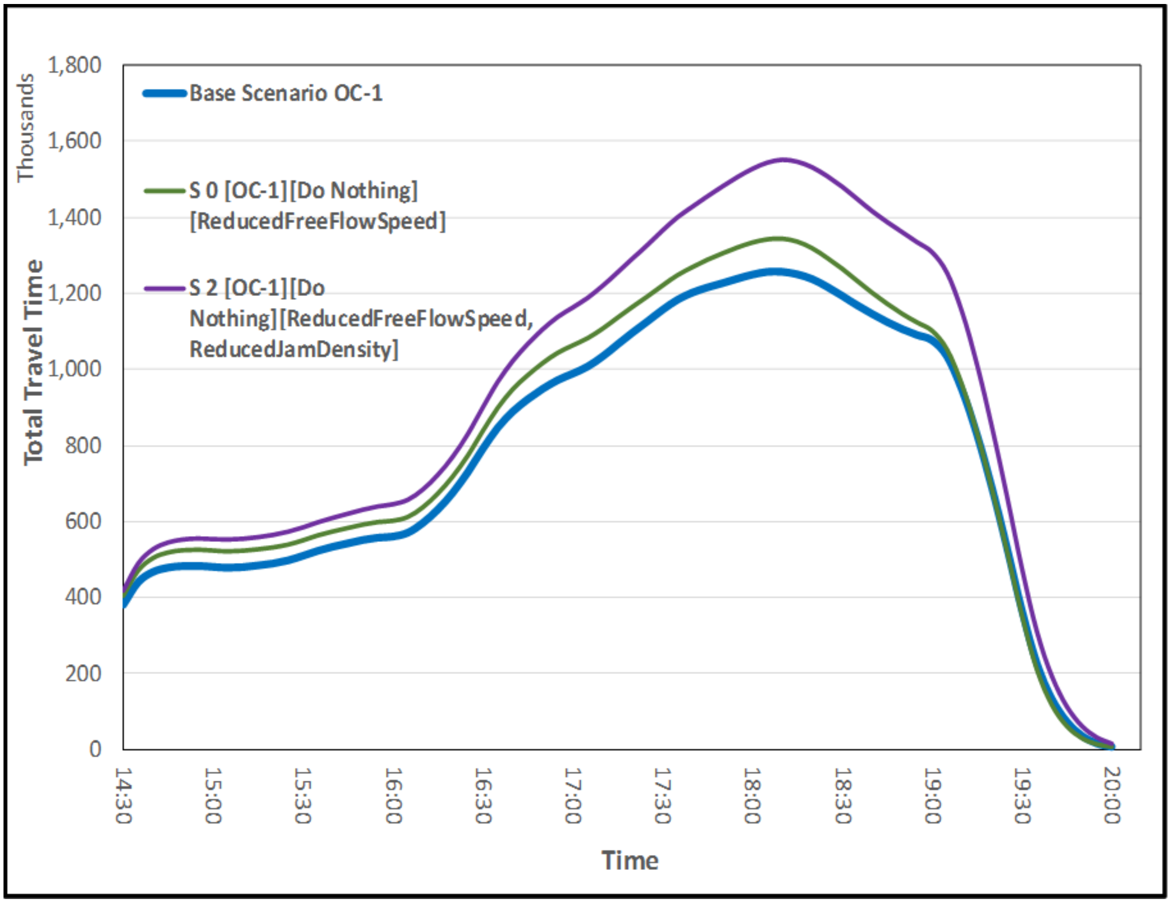


Figure 7-8: Total Network Travel Time for Hypothetical Adverse Weather Scenarios for Dallas Testbed [Source: SMU]

The traffic management system is activated to manage the traffic under the adverse weather scenarios. In this set of experiments, the generated ATDM response plans combine the dynamic routing strategy and the dynamic signal timing strategy. The results of deploying ATDM response plans for the adverse weather scenarios described above are represented in Figure 7-9. As shown in the figure, the traffic management system helps in alleviating the network congestion due to the adverse weather. Travel time saving of 163,480 minutes is recorded for the first scenario, while the saving of 84,913 minutes is recorded for the second scenario.

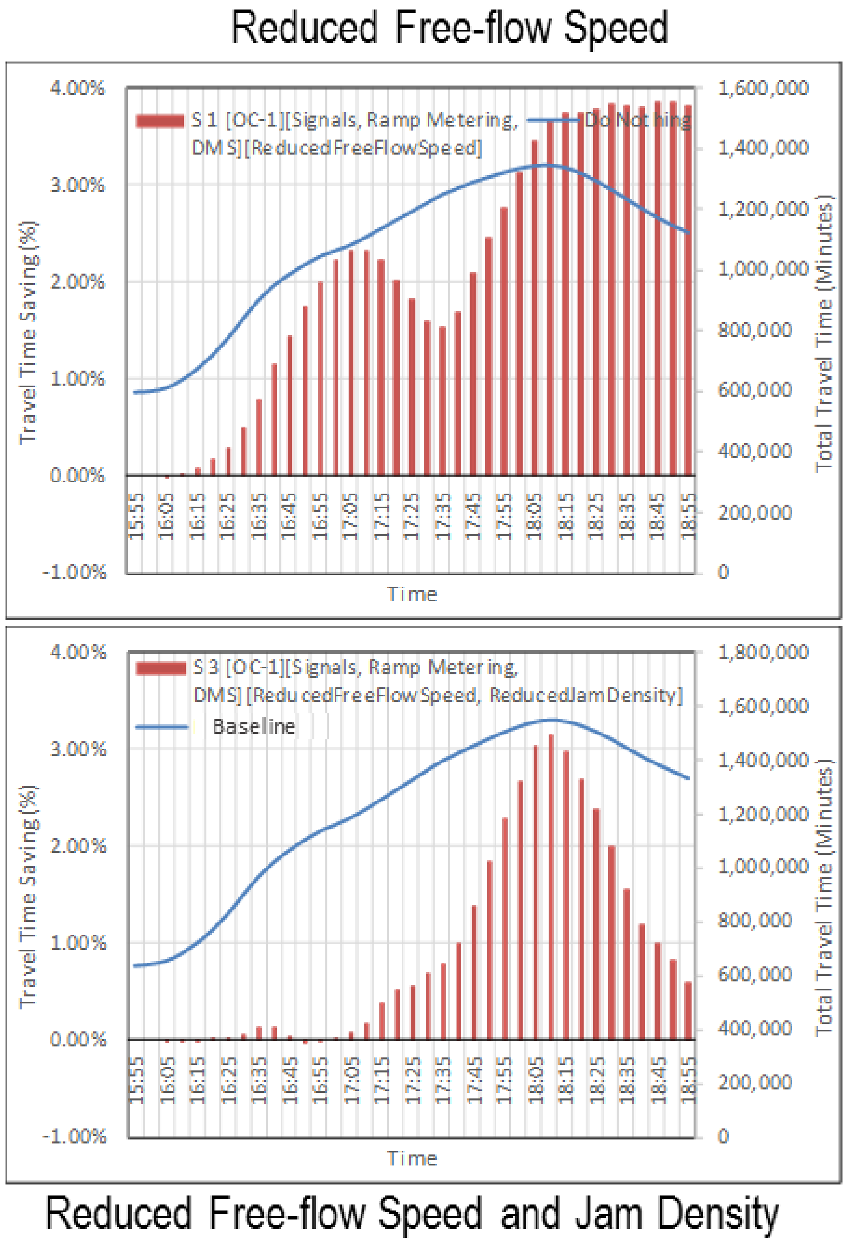


Figure 7-9: Network Travel Time Saving after Activating the Traffic Management Schemes (Dallas Testbed) [Source: SMU]

Table 7-3: Traffic Network Performance for the Scenarios of Adverse Weather Conditions (Dallas Testbed)

Scenario Description	Total Network Travel Time Savings (minutes)
Reduced Free-Flow Speed	163,480
Reduced Free-Flow Speed and Reduced Jam Density	84,913

Figure 7-10 provides the corresponding saving in the fuel consumption and the environmental measures of performance under these two scenarios. Similar to the travel time saving, savings in the fuel consumption and the amount of emission are obtained by activating the traffic management system. Table 7-4 gives a summary of fuel consumption and emission savings for these two scenarios. For example, fuel consumption saving of 160.10 tons and 99.65 tons are recorded with the activation of the traffic management system for the first and second scenarios, respectively. Figure 7-11 provides the corresponding reduction in CO2 and NOX emission. The corresponding savings in the CO2 are 12.00 tons and 7.29 tons, and the saving in the NOX are 5.62 tons and 3.87 tons.

Table 7-4: Total Environmental Performance under Adverse Weather Scenarios (Dallas Testbed)

Scenario Description	Fuel Consumption Saving (tons)	Carbon Dioxide Saving (tons)	Nitrogen Oxide Saving (kilograms)
Reduced Free-Flow Speed	160.10	12.00	5.63
Reduced Free-Flow Speed and Reduced Jam Density	99.65	7.29	3.87

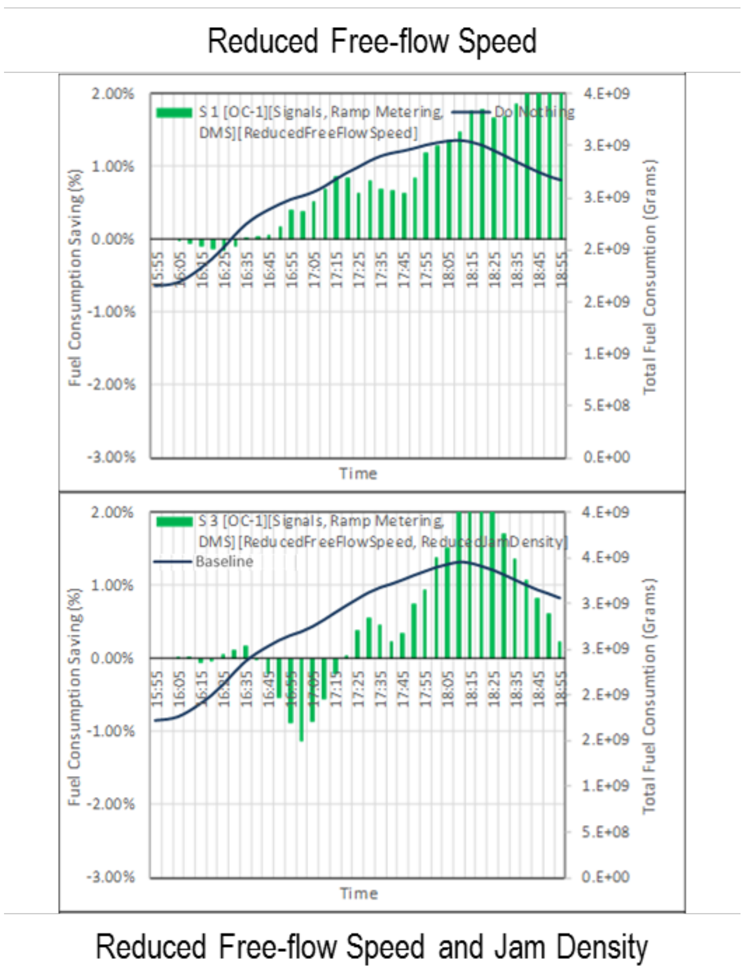


Figure 7-10: Network Fuel Consumption after Activating the Traffic Management Schemes (Dallas Testbed) [Source: SMU]

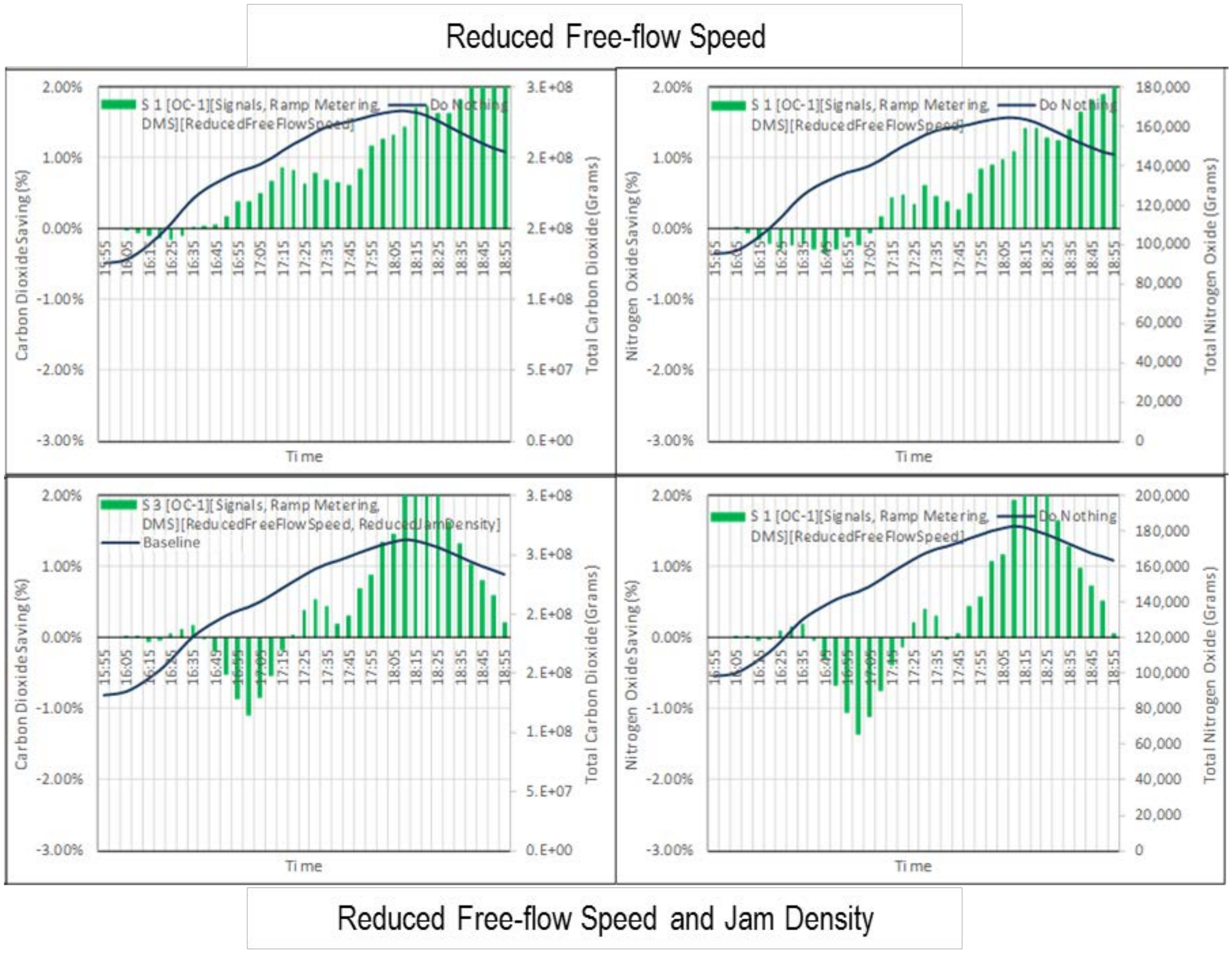


Figure 7-11: Network Carbon Dioxide and Nitrogen Oxide Emission after Activating the Traffic Management Schemes (Dallas Testbed) [Source: SMU]

7.2.3 Evacuation Operational Condition

The performance of ATDM strategies is examined considering a hypothetical evacuation scenario using the Dallas Testbed. In this scenario, 50% of the total demand representing the demand of HD-MI operational condition is considered to evacuate the network in the evening peak period. Travelers are assumed to evacuate from their work places to pre-defined safe destination zones located in the northern part of the corridor. The total generated demand for the evacuation scenario is split equally between two types of safe destination zones. Figure 7-13 illustrates the locations of the safe destination zones in the network. As shown in the figure, all these zones are selected at the northern section of the corridor. Two types of the destination zones are selected (depicted in green and orange colors). Zones in the first set are located at the terminal points of the major freeways in the network, while zones in the second set are located along the arterial roads. In addition, the time-dependent demand loading pattern is adjusted to replicate the hypothetical evacuation scenario considered in this study. Figure 7-12 shows the demand loading pattern over time which assumes that 15% of the demand is loaded in the first hour, 40% is loaded in the second hour, 20% is loaded in the third hour, 15% is loaded in the fourth hour and 10% loaded in the fifth hour.

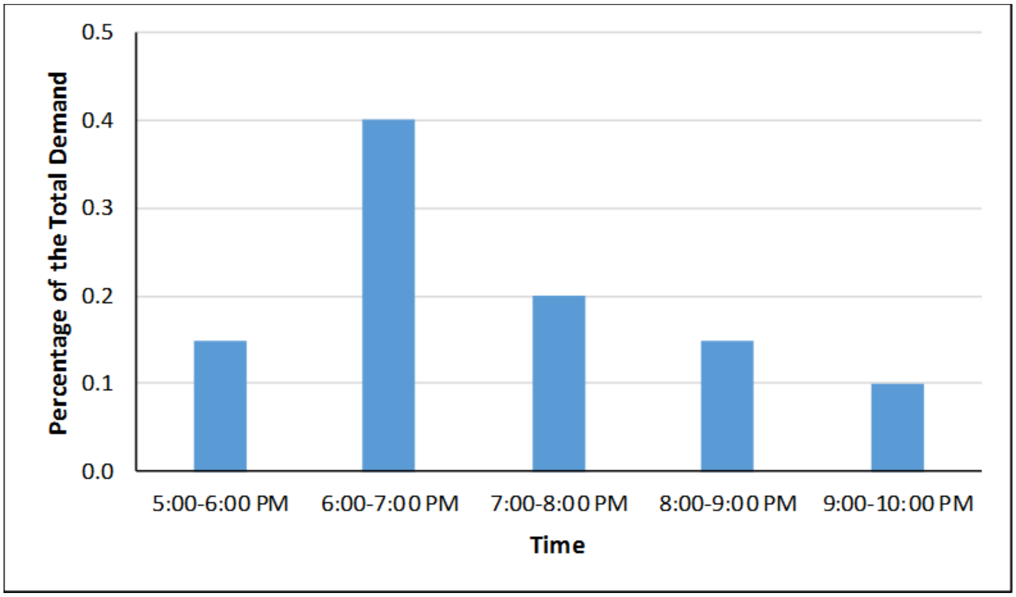


Figure 7-12: Time-Dependent Demand Loading Distribution for the Hypothetical Evacuation Scenario (Dallas Testbed) [Source: SMU]

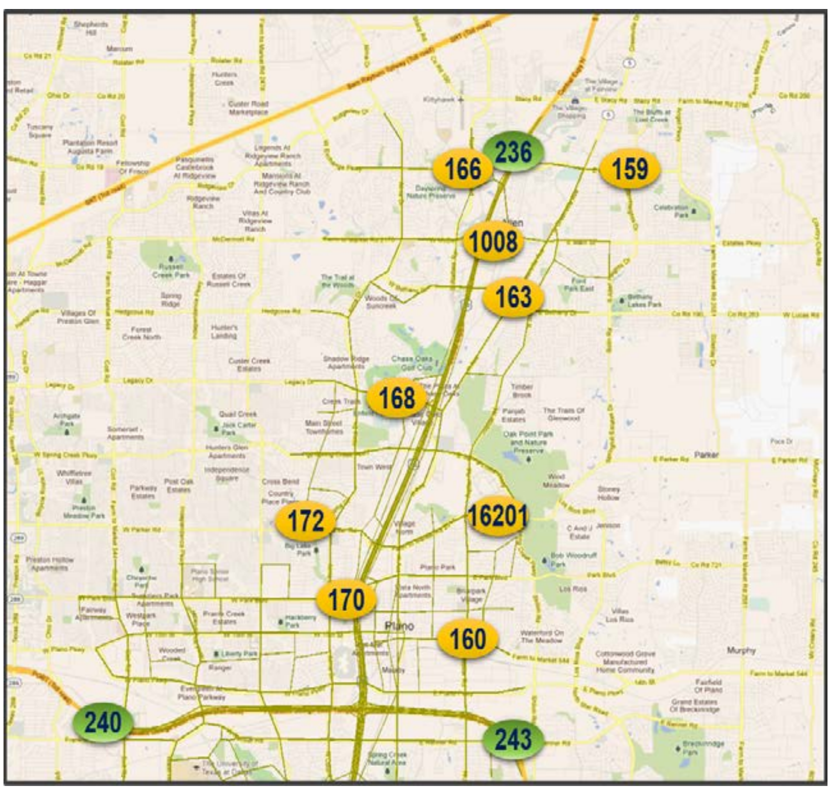


Figure 7-13: Distribution of Safe Destination Zones in the Corridor (Dallas Testbed) [Source: SMU]

Different combinations of ATDM strategies are implemented to evaluate their effectiveness in reducing the congestion associated with the evacuation scenario. These strategies include demand management, dynamic signal timing, traveler information provision, dynamic shoulder lane, and tidal flow operation. The demand management strategy explores the effect of the ability of reducing the demand level in the network through promoting telecommuting and/or carpooling. The traveler information provision strategies aim at providing travelers with pre-trip and/or en-route information on the prevailing network conditions. Travelers are assumed to use this information to better plan their trip and avoid routes with severe congestion levels. The shoulder lane strategy opens the hard shoulders as an additional lane during the evacuation which improves the freeway capacity along the evacuation direction. Tidal flow operation strategy adds one or more lanes of the opposite direction of the highway through reversing the traffic flow direction along those lanes. The logic of modeling this strategy is similar to the dynamic shoulder lane as explained earlier in Chapter 4.

A set of experiments are conducted to evaluate the effectiveness of these strategies and included 11 scenarios. Table 7-5 presents a summary of the results of these experiments. For each scenario, the table gives the total simulation time, total number of loaded travelers, and the remaining number of travelers in the network at the end of the simulation horizon. In addition, the time required to evaluate 70%, 80%, and 90% percent of the loaded travelers are given. The scenarios are ranked based on the time period required to evacuate 80% of the travelers. Based on this ranking, S3 and S10 yield the best performance. In these scenarios, the time period required to evaluate 80% of the demand is close to 5:00 hours. A common feature among these two strategies is that a demand management strategy is implemented which reduced the total demand in the network by 10%. S4 is recorded as the worst scenario which requires nine hours and 30 minutes to evacuate 80% of the demand. In this scenario, the demand management strategy failed to achieve reduction in the demand level.

Table 7-5: Different Traffic Management Strategies in Evacuation Situation (Dallas Testbed)

Scenario ID	Description	Loaded Travelers	Remianing Travelers	Simulation Time	70th Percentile	80th Percentile	90th Percentile	Rank
S 0	Base Scenario	238406	0	18:58	5:10	6:55	11:40	9
S 1	Base Scenario [80% PreTrip]	238406	0	17:46	5:15	6:20	10:05	5
S 2	10% Reduction in Demand	214467	0	11:15	4:50	5:40	7:20	3
S 3	10% Reduction in Demand, 80% Pre-Trip	214467	0	14:50	4:30	5:05	5:55	1
S 4	10% Increase in Demand	262168	25519	23:59	6:35	9:35	16:20	12
S 5	10% Increase in Demand, 80% Pre-Trip	262168	0	20:13	5:40	8:10	12:35	11
S 6	Base Demand, Shoulder Lanes, 00% Pre-Trip	238406	0	18:54	5:20	7:35	11:10	10
S 7	Base Demand, Shoulder Lanes, 80% Pre-Trip	238406	0	15:44	4:55	6:30	8:35	6
S 8	Base Demand, Tidal Flow, 80% Pre-Trip	238406	0	18:47	5:10	6:30	10:05	7
S 9	Base Demand, Shoulder Lanes, Tidal Flow, 80% Pre-Trip	238406	0	15:23	4:55	6:15	9:00	4
S 10	10% Reduction in Demand, Shoulder Lanes, Tidal Flow, 80% Pre-Trip, 00% En-Route	214467	0	15:35	4:35	5:10	6:00	2
S 11	Base Demand, Shoulder Lanes, Tidal Flow, Signals, 80% Pre-Trip	238406	0	15:11	4:55	6:35	10:15	8

7.2.4 Dynamic Parking Pricing

A set of experiments is designed to examine the effect of deploying the dynamic parking pricing strategy on the overall network performance under different operational scenarios. The Dallas Testbed was utilized for this assessment. The dynamic parking strategy is intended primarily to influence the travelers' behavior in the morning peak period. Imposing a parking cost at the trip destinations during a certain period is expected to influence the travelers' decisions regarding the trip departure and/or mode of travel. For example, a traveler might decide to change her departure time (i.e., leave earlier or later than her habitual departure time) to avoid paying a high parking rate. If the parking cost is significantly high, the traveler could decide to not use her private car and shift to transit.

However, the cluster analysis and model calibration effort were limited to developing the simulation model to represent the operational conditions only for afternoon peak periods. Therefore, for the purpose of studying the dynamic parking pricing strategy, the model calibration effort was extended to represent a morning peak period. The model was calibrated for a typical morning peak period representing the "average" conditions. This calibration effort was part of the recent Integrated Corridor Management (ICM) demonstration study for the US-75 Corridor[17]. Figure 7-14 provides a summary of the model calibration results for the morning peak period conditions considered to study the dynamic parking pricing strategy.

As described earlier, DIRECT assumes that travelers choose their route-mode travel option by evaluating their generalized cost. Following DIRECT's modeling logic, a trip could be a pure mode (i.e., transit of private car) or intermodal (park-and-ride). For the pure private car option, the cost of the trip includes the monetary value of the trip travel time, vehicle operation cost, and parking cost. For the pure transit option, the monetary value of the trip travel time and transit fare. For the park-and-ride trip, the cost includes the monetary value of the trip travel time, the vehicle operation cost for the first leg of the trip, the transit fare for the second leg of the trip and any parking cost at the transfer point. The travelers have the options to compare the travel costs over a predefined horizon. Thus, travelers could choose to depart earlier or later than their habitual departure time if saving in the overall trip cost could be achieved. As described earlier in Section 2.4.3, a hierarchal route-mode choice logic is proposed in this research to model how travelers respond to the parking cost. The logic assumes that private car users first check the option to change their departure time to avoid the high parking cost (i.e., no mode change). If a traveler decided not to change their departure time, they examine transit as an option. Travelers shift to transit only if the saving in their travel cost is less than a pre-defined threshold.

Eight hypothetical scenarios are considered in this analysis to evaluate the effectiveness of the dynamic parking pricing. These scenarios are developed to examine the sensitivity of the network performance considering the following experimental factors: a) percentage of travelers seeking parking; b) number of parking lots adopting the dynamic pricing strategy; c) the length of the time window travelers considers to modify their departure time; and d) the amount trip cost saving as percentage of the total trip cost that travelers might consider to modify their departure time or shift to transit. Figure 7-15 provides an example of time-varying pricing scheme used in the experiments. As the parking rate is designed to change with time. The highest parking value is charged during the peak value. Travelers are assumed to pay the rate applies at their arrival time at their destinations. The details of the eight scenarios considered in this analysis are provided in Table 7-6.

[17] http://www.its.dot.gov/icms/docs/icm_demo_sites.pdf

	Observed Traffic Counts				
Detector Name	6-7 AM	7-8 AM	8-9 AM	9-10 AM	Total
Park Blvd North	6705	6234	4728	3845	21512
Parker South	6582	5468	4615	3238	19903
Ruisseau	6752	5873	5104	3378	21107
Parker North	6963	6057	4960	4961	22941
Spring Creek South	6440	5998	5464	3522	21424
	33443	29630	24870	18944	106887

	Estimated Traffic Counts				
Detector Name	6-7 AM	7-8 AM	8-9 AM	9-10 AM	Total
Park Blvd North	5333	4363	5613	2291	17600
Parker South	6402	5351	5294	2720	19767
Ruisseau	6581	5640	4824	2957	20002
Parker North	6698	6415	3541	3921	20575
Spring Creek South	6829	7152	3569	4464	22014
	31843	28921	22841	16353	99958

	Percentage Error				
Detector Name	6-7 AM	7-8 AM	8-9 AM	9-10 AM	Total
Park Blvd North	-20%	-30%	19%	-40%	-18%
Parker South	-3%	-2%	15%	-16%	-1%
Ruisseau	-3%	-4%	-5%	-12%	-5%
Parker North	-4%	6%	-29%	-21%	-10%
Spring Creek South	6%	19%	-35%	27%	3%
	-5%	-2%	-8%	-14%	-6%

Figure 7-14: Traffic Counts Calibration Results for Morning Peak Period (Dallas Testbed) [Source: SMU]

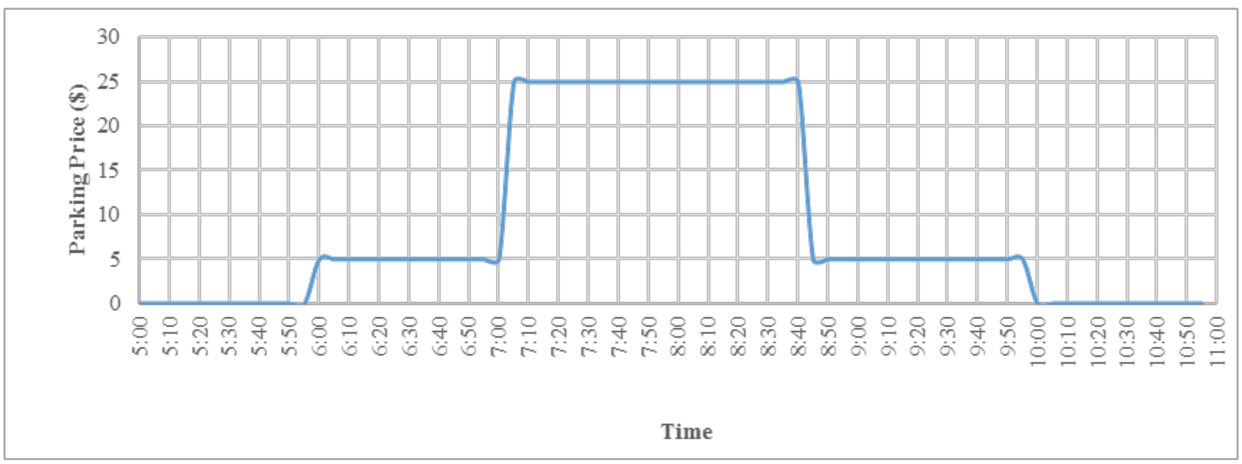


Figure 7-15: An Example of Pricing Scheme at a Parking Lot (Dallas Testbed) [Source: SMU]

Table 7-6: Scenarios for Testing Dynamically Priced Parking (Dallas Testbed)

Scenario	Description
S1	20% of the travelers are assumed to seek parking in the downtown area Travelers change their departure time only if the savings is greater than 20% Travelers consider 2-hour window for modifying their departure times 3 parking lots are assumed to adopt dynamic parking pricing strategy
S2	20% of the travelers are assumed to seek parking in the downtown area Travelers change their departure time only if the savings is greater than 20% Travelers consider 2-hour window for modifying their departure times 11 parking lots are assumed to adopt dynamic parking pricing strategy
S3	20% of the travelers are assumed to seek parking in the downtown area Travelers change their departure time only if the savings is greater than 20% Travelers consider one-hour window for modifying their departure times 11 parking lots are assumed to adopt dynamic parking pricing strategy
S4	20% of the travelers are assumed to seek parking in the downtown area Travelers change their departure time only if the savings is greater than 20% Travelers consider one-hour window for modifying their departure times 3 parking lots are assumed to adopt dynamic parking pricing strategy
S5	5% of the travelers are assumed to seek parking in the downtown area Travelers change their departure time only if the savings is greater than 20% Travelers consider one-hour window for modifying their departure times 3 parking lots are assumed to adopt dynamic parking pricing strategy
S6	5% of the travelers are assumed to seek parking in the downtown area Travelers change their departure time only if the savings is greater than 20% Travelers consider one-hour window for modifying their departure times 11 parking lots are assumed to adopt dynamic parking pricing strategy
S7	Travelers do not have the option to change their departure times 3 parking lots are assumed to adopt dynamic parking pricing strategy
S8	Travelers do not have the options to change their departure times 11 parking lots are assumed to adopt dynamic parking pricing strategy

Figure 7-16 depicts the time-dependent travel time saving as a percentage of the total network travel time under the baseline scenario for these eight operational scenarios. Also, an overall summary of the results is given in Table 7-7. The following main observations can be made based on the obtained results:

- The travel time savings obtained in scenarios S1 to S6 is due to congestion de-peaking associated with travelers modifying their departure time to avoid the high parking cost and b) travelers using transit instead of their private cars to avoid the parking cost at the destination. In Scenarios S7 and S8, travelers were limited only to the option of shifting to transit, if it reduces their overall travel cost.
- Comparing the results of S1 and S2, increasing the number of parking lots that adopt the dynamic pricing strategy has generally resulted in more travel time savings. However, despite the big difference in the number of lots considered in S1 (3 lots) and S2 (11 lots), the recorded increase in the travel time saving was relatively small. In S1, an average percentage saving of 5.07% is recorded. This percentage increased to 6.21% in S2. To explain such slight improvement, the

network demand pattern was carefully examined. The traffic demand is mostly concentrated around the three parking lots in S1. Less traffic is attracted to destinations near the other parking lots considered in the analysis. As such, the dynamic parking pricing strategy at a certain parking lot is effective only if there is high parking demand at this lot.

- Comparing the results of S1 and S3 or S2 and S4, as travelers are more constrained with respect to changing their departure times, the saving in the travel time generally decreases. For example, average travel time savings of 5.07% and 3.30% are recorded for S1 and S3, respectively. Similarly, the average travel time saving dropped from 6.21% in S2 to 4.27 in S4. Limiting the horizon considered by the travelers to modify their departure times reduces the possibility to spread the peak congestion over longer period (Scenarios S2 and S4). In other words, despite the high parking cost in the peak period, travelers do not have the flexibility to modify their departure times to avoid the high parking cost and hence spread the congestion over longer period. On the other hand, as this horizon increases as in S1 and S3, the congestion spreads over longer period resulting in more travel time savings.
- Comparing the results of S3 and S5 or S4 and S6 illustrates the effect of the demand of parking seekers on the effectiveness of the dynamic parking pricing strategy in improving the overall network performance. As shown in the figure, reducing the percentage of travelers who are seeking parking from 20% to 5% resulted in a reduction in the amount of travel time saving. As less travelers seek parking, the opportunity to influence the behavior of more travelers decrease and hence the overall improvement in the network performance also decreases.
- The effect of the dynamic parking strategy on congestion de-peaking can be illustrated using the results of S2 and S4. As shown in the figure, a slight deterioration in the network performance is recorded at the first part of the horizon (i.e., negative travel time savings). This increase in the network travel time is due to travelers who modified their travel time to earlier time in the horizon to avoid high parking cost. The departure time shift resulted in considerable travel time savings as shown in the figure.
- In scenarios S7 and S8, travelers are assumed not to change their departure times. In these two scenarios, all recorded travel time savings could be due to travelers' shift to transit. For example, in scenario S1, the average travel time saving is recorded at 5.07%. As mentioned above, this saving is due to a) congestion de-peaking associated with travelers modifying their departure time to avoid the high parking cost and b) travelers using transit instead of their private cars to avoid the parking cost at the destination. In scenario S7, travelers were limited only to the option of shifting to transit, if it reduces their overall travel cost. In this scenario, the average travel time saving is reduced to 2.75%. The difference in the travel time saving between these two scenarios could be contributed to the effect of congestion de-peaking.

The above results are consistent with the fuel consumption and emission savings as illustrated in Figure 7-18 to Figure 7-23. Figure 7-18 and Figure 7-19 gives the saving in fuel consumption, while Figure 7-20 to Figure 7-23 give the savings in carbon dioxide and nitrogen oxide, respectively. In general, more savings in the fuel consumption and emissions were obtained as a) more parking lots adopt dynamic pricing strategy; b) more travelers seek parking at their destinations; and c) travelers are more flexible to adjust their departure times. A summary of the results in these figures is given in Table 7-8.

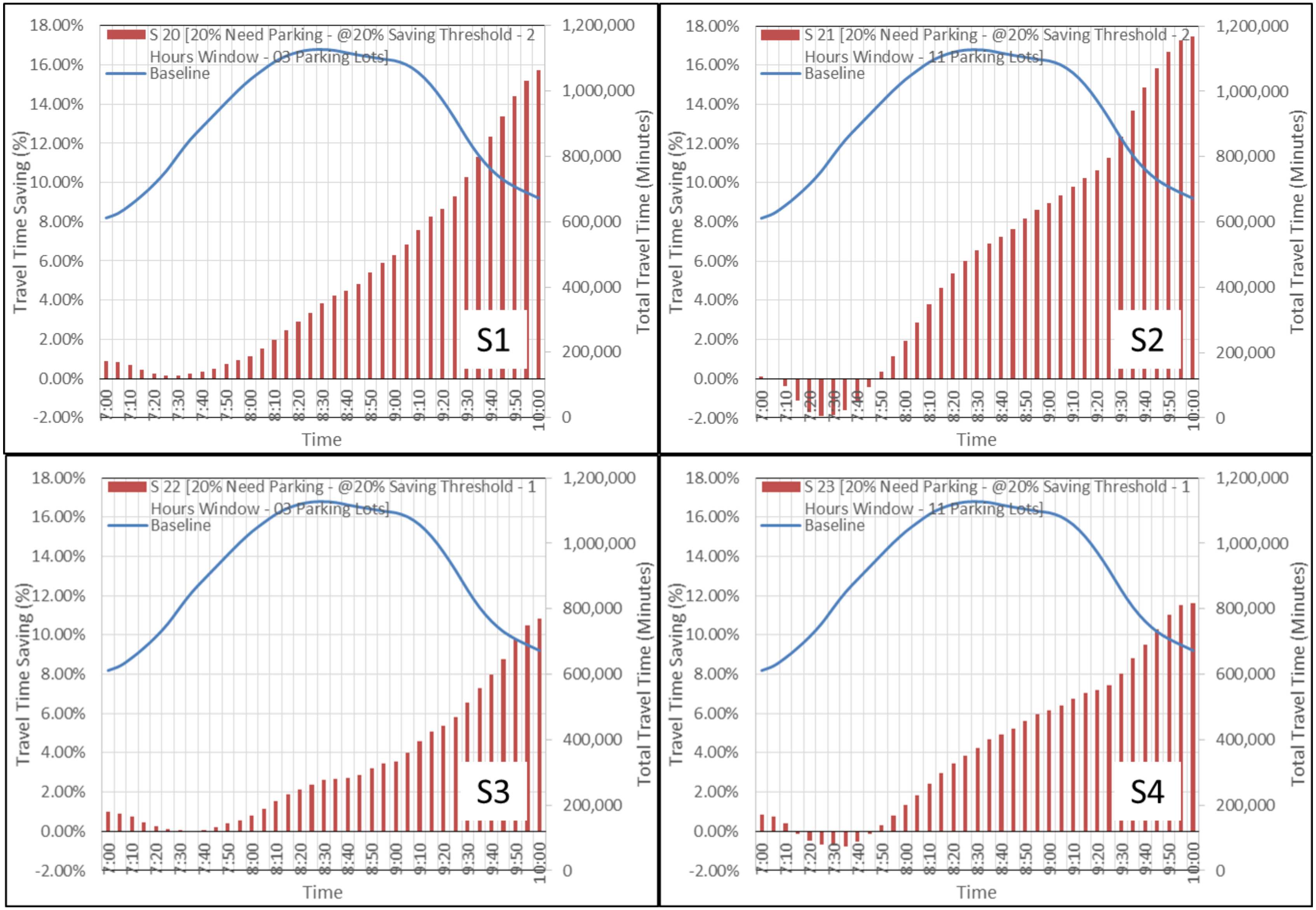


Figure 7-16: Total Network Travel Time Saving for Different Dynamic Parking Pricing Scenarios (Part 1 of 2) (Dallas Testbed) [Source: SMU]

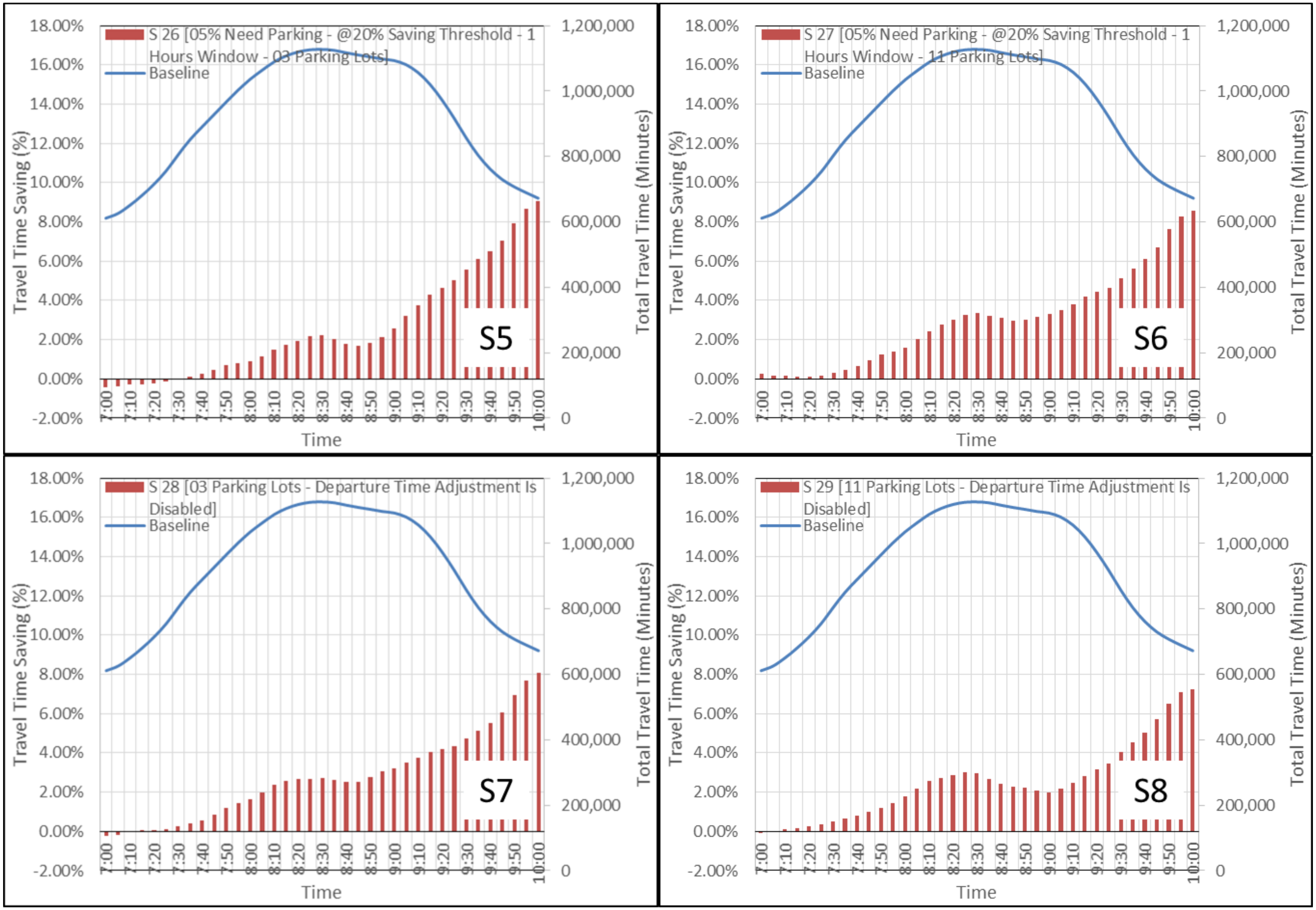


Figure 7-17: Total Network Travel Time Saving for Different Dynamic Parking Pricing Scenarios (Part 2 of 2) (Dallas Testbed) [Source: SMU]

Table 7-7: Total Travel Time Savings Considering Different Dynamic Parking Pricing Scenarios (Dallas Testbed)

Scenario *ID*	***Description of Parking Strategy***	***Total Network Travel Time Savings (minutes)***
S 1	20% Need Parking - 20% Saving Threshold - Two Hours Window - 03 Parking Lots	278,934
S 2	20% Need Parking - 20% Saving Threshold - Two Hours Window - 11 Parking Lots	353,891
S 3	20% Need Parking - 20% Saving Threshold - One Hours Window - 03 Parking Lots	179,985
S 4	20% Need Parking - 20% Saving Threshold - One Hours Window - 11 Parking Lots	242,270
S 5	5% Need Parking - 20% Saving Threshold - One Hours Window - 03 Parking Lots	142,681
S 6	5% Need Parking - 20% Saving Threshold - One Hours Window - 11 Parking Lots	170,952
S 7	3 Parking Lots - Departure Time Adjustment is Disabled	140,832
S 8	11 Parking Lots - Departure Time Adjustment is Disabled	155,779

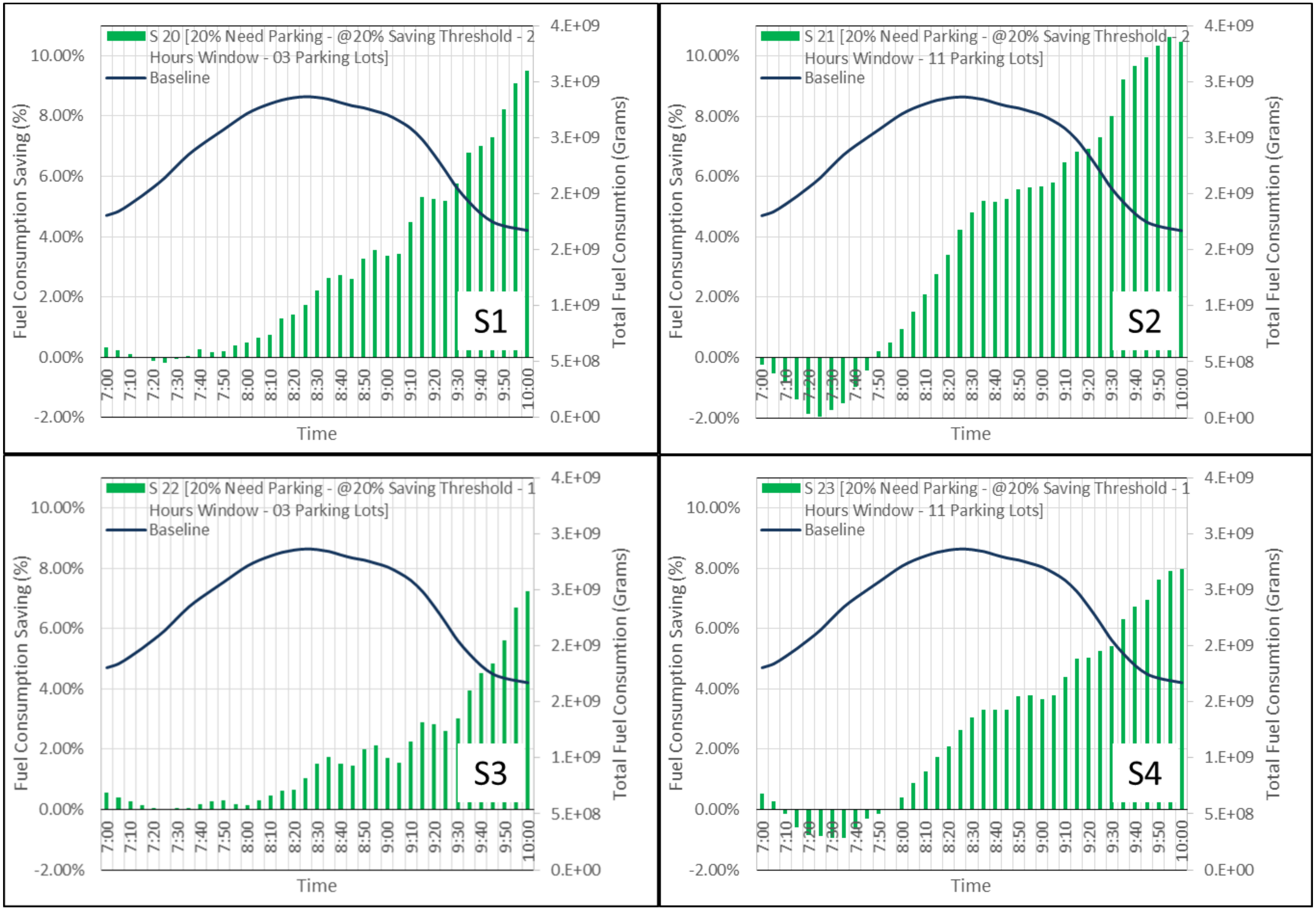


Figure 7-18: Total Fuel Consumption Saving for Different Dynamic Parking Pricing Scenarios (Part 1 of 2) (Dallas Testbed) [Source: SMU]

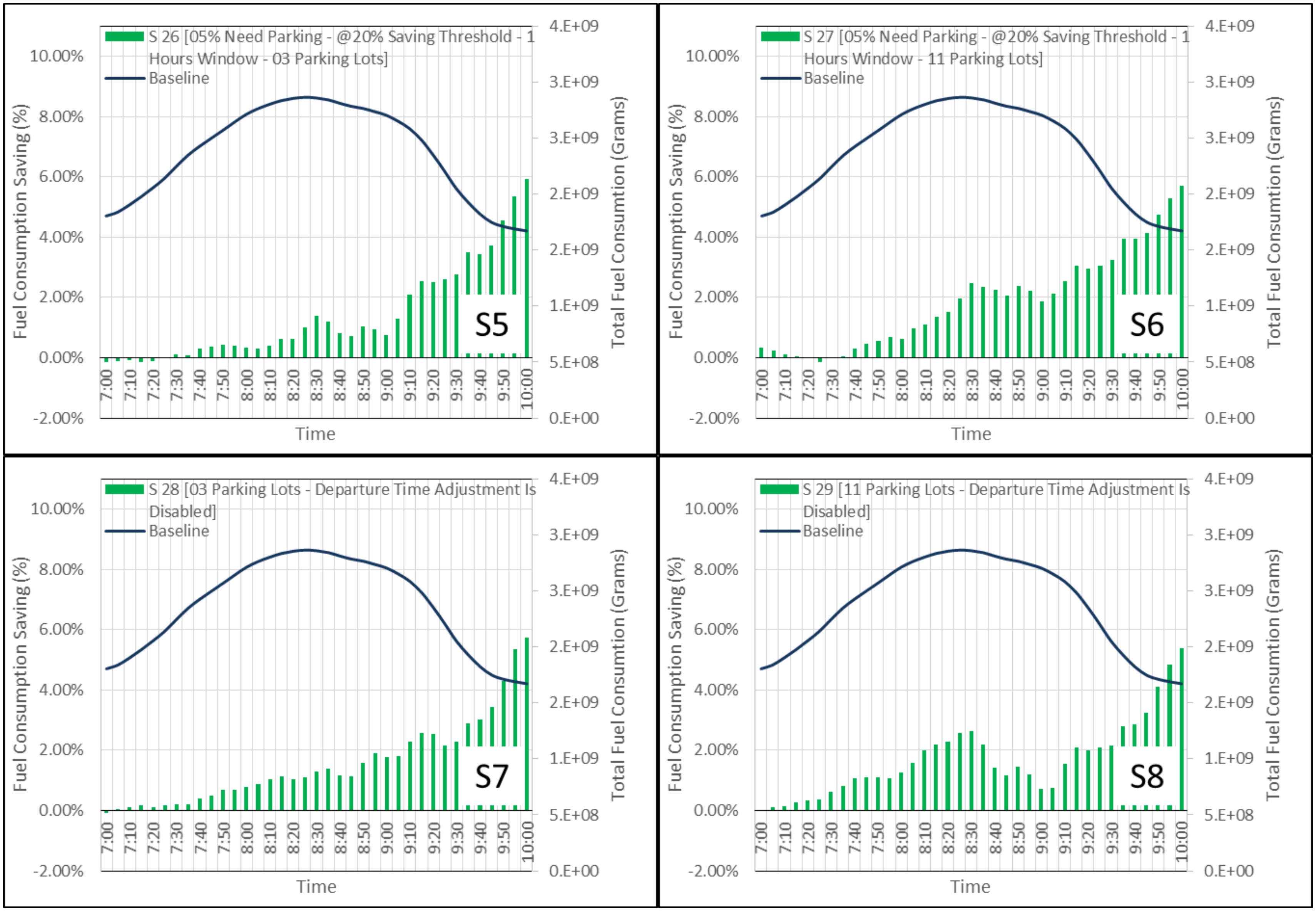


Figure 7-19: Total Fuel Consumption Saving for Different Dynamic Parking Pricing Scenarios (Part 2 of 2) (Dallas Testbed) [Source: SMU]

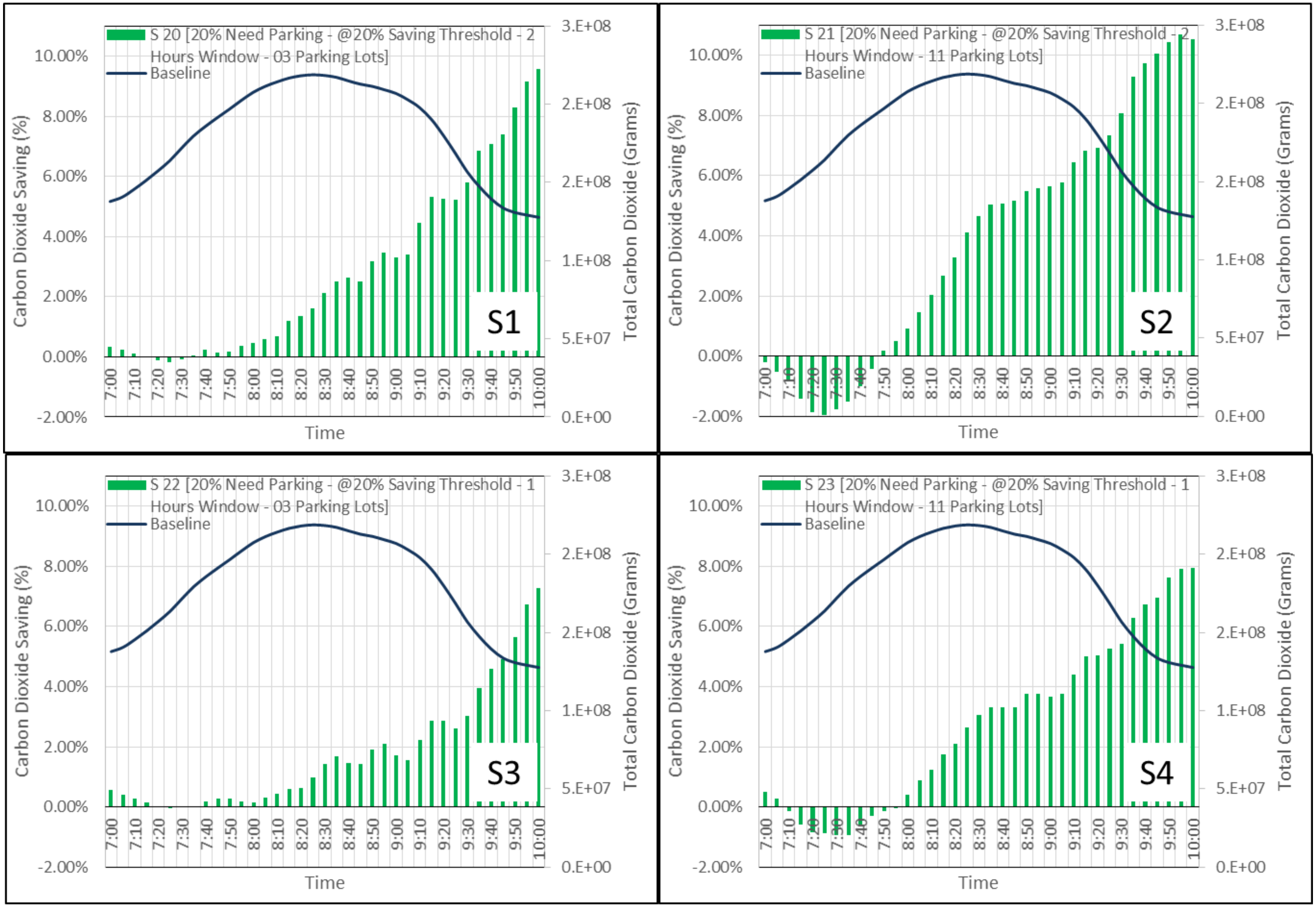


Figure 7-20: Total Carbon Dioxide Saving for Different Dynamic Parking Pricing Scenarios (Part 1 of 2) (Dallas Testbed) [Source: SMU]

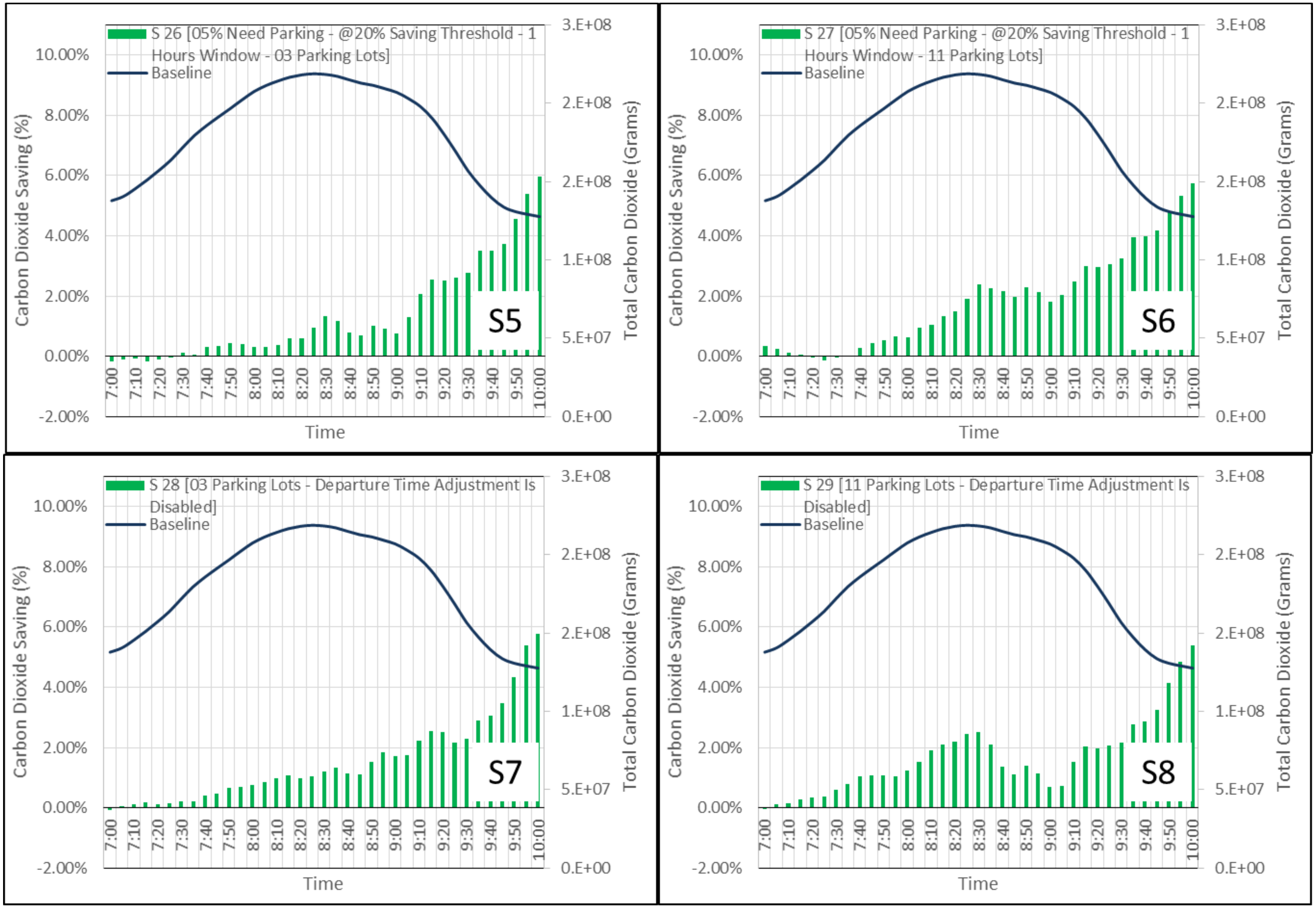


Figure 7-21: Total Carbon Dioxide Saving for Different Dynamic Parking Pricing Scenarios (Part 2 of 2) (Dallas Testbed) [Source: SMU]

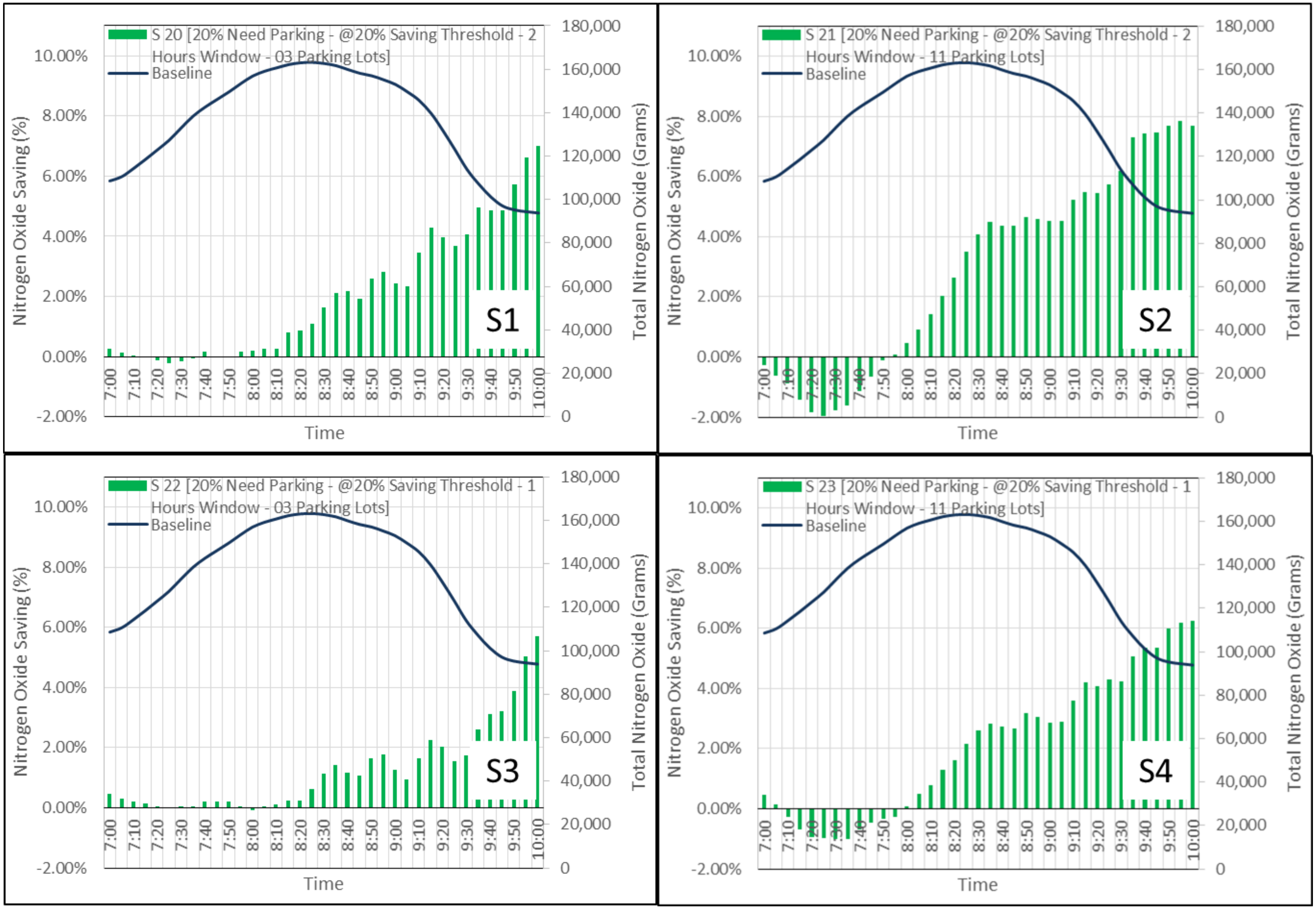


Figure 7-22: Total Nitrogen Oxide Saving for Different Dynamic Parking Pricing Scenarios (Part 1 of 2) (Dallas Testbed) [Source: SMU]

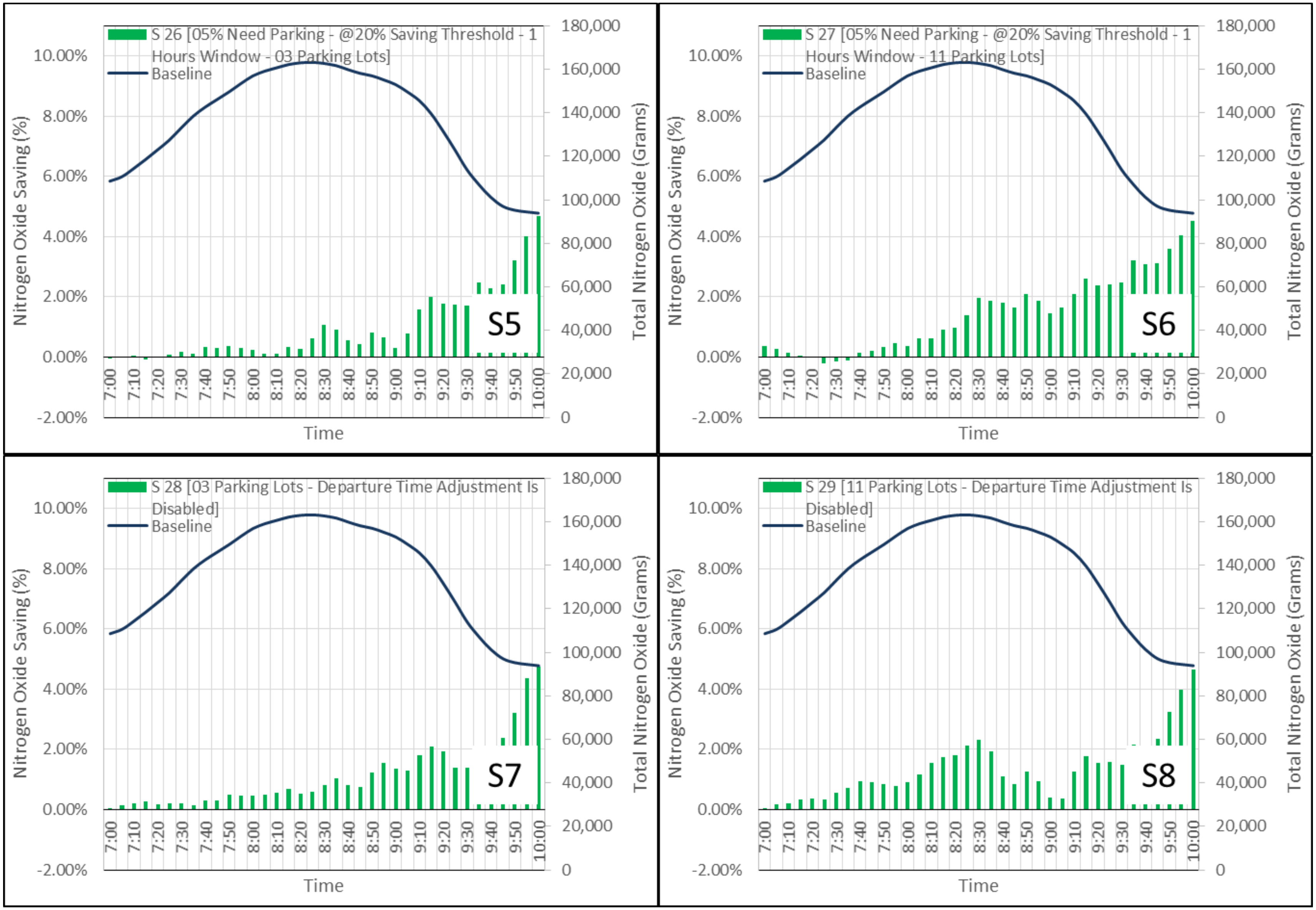


Figure 7-23: Total Nitrogen Oxide Saving for Different Dynamic Parking Pricing Scenarios (Part 2 of 2) (Dallas Testbed) [Source: SMU]

Table 7-8: Total Environmental Performance in Different Dynamic Parking Pricing Scenarios (Dallas Testbed)

Scenario ID	Description of Parking Strategy	Fuel Consumption Saving (tons)	Carbon Dioxide Savings (tons)	Nitrogen Oxide Saving (Kilograms)
S 1	20% Need Parking - 20% Saving Threshold - Two Hours Window - 03 Parking Lots	384.35	29.13	15.44
S 2	20% Need Parking - 20% Saving Threshold - Two Hours Window - 11 Parking Lots	545.17	41.36	23.14
S 3	20% Need Parking - 20% Saving Threshold - One Hours Window - 03 Parking Lots	234.50	17.80	9.21
S 4	20% Need Parking - 20% Saving Threshold - One Hours Window - 11 Parking Lots	382.18	28.94	16.32
S 5	5% Need Parking - 20% Saving Threshold - One Hours Window - 03 Parking Lots	183.52	13.94	7.27
S 6	5% Need Parking - 20% Saving Threshold - One Hours Window - 11 Parking Lots	266.41	20.06	11.52
S 7	3 Parking Lots - Departure Time Adjustment is Disabled	214.31	16.16	8.08
S 8	11 Parking Lots - Departure Time Adjustment is Disabled	243.09	18.19	11.01

7.3 Phoenix Testbed Evaluation

As described earlier in Section 3.1, there are four main operational conditions in Phoenix testbed. They vary in demand and severity of occurred incidents. Individual ATDM strategies were assessed the following four operational conditions: (1) High Demand and Low Incident Severity (HD-LI), (2) High Demand and High Incident Severity (HD-HI), (3) Low Demand and Low Incident Severity (LD-LI), and (4) High Demand, Medium Incident Severity and Wet Weather (HD-MI-WW). The four strategies and combinations of strategies assessed were (1) Adaptive Ramp Metering, (2) Adaptive Signal Control, modeled as the RHODES applications, (3) Combination of Adaptive Ramp Metering and Adaptive Signal Control, and (4) Combination of Dynamic Route Guidance and Predictive Traveler Information. Please note that the predictive traveler information is the criteria used for Dynamic Route Guidance and hence could not be assessed without each other. Figure 7-24 shows the distribution of travel time savings under each operational condition.

As per Figure 7-24, Adaptive Ramp Metering and Adaptive Signal Control (as well as their combination) works the best under High Demand, Medium Incident Severity and Wet Weather condition. Under Low Demand and Low Incident Severity, Adaptive Signal Control showed least improvement in travel time. Similarly, High Demand and Low Incident Severity showed least improvement in travel time when Dynamic Route Guidance was implemented with Predictive Traveler Information.

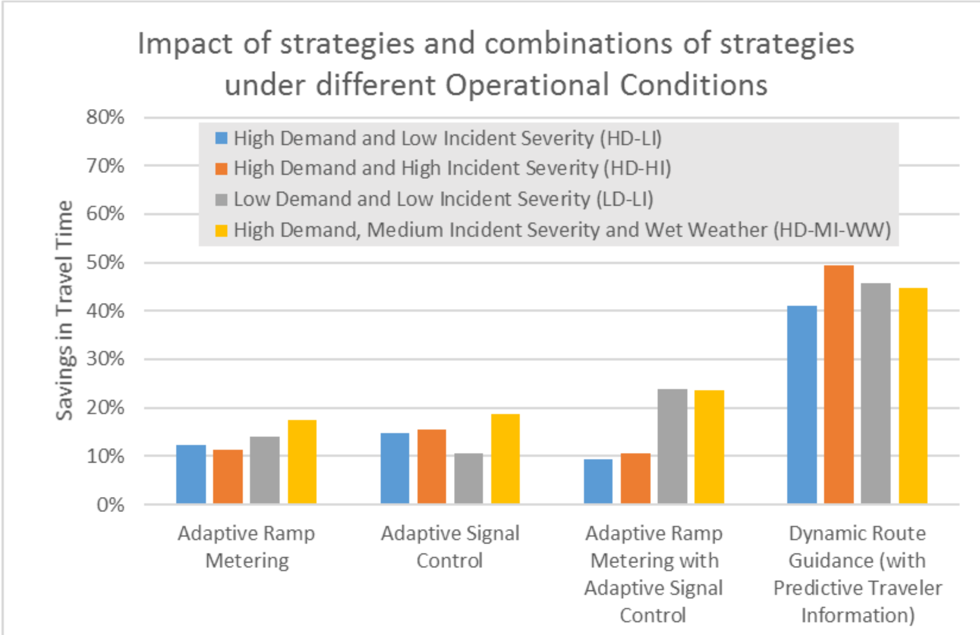


Figure 7-24: Travel Time Savings for the Phoenix Testbed under different operational conditions for different strategies and combinations of strategies. [Source: Booz Allen]

7.4 Pasadena Testbed Evaluation

Three main operational conditions were used in the Pasadena testbed for the analysis to assess each ATDM strategy performance under different traffic condition. The description of each operational condition in ascending order are as follows:

- High demand, Low to Medium incident frequency/severity, Medium corridor travel times
- Medium to high demand, High incident frequency/severity, Medium to Low corridor travel times
- High demand, Medium incident frequency/severity, High corridor travel times

The prediction scenarios chosen for OC 2 and OC 3 were chosen based on the results from OC 1 by identifying the prediction parameters that were considered sensitive for each ATDM strategy. The prediction parameters chosen for further analysis using OC 2 and OC 3 are listed in Table 7-9.

Table 7-9: Sensitive Prediction Parameters and Traveler Compliance to ATDM Strategies

ATDM Strategies	Prediction Horizon	Prediction Latency	Prediction Accuracy	Traveler Compliance
ARM	✓	✓		
DSC			✓	
HSR + DJC				
DSL + QW				✓
DRG				✓

7.4.1 Adaptive Ramp Metering

The two prediction parameters that were found as sensitive for the ARM strategy during the Pasadena testbed phase 1 analysis are prediction horizon and prediction latency. The simulation results found that the ARM strategy, which is a freeway focused active traffic management strategy had significant varying results under OC 1 with longer prediction horizon and longer prediction latency. The same test was performed using varying prediction horizon and prediction latency for OC 2 and OC 3. The results show similar trend as represented in Figure 7-25 with the detailed level results shown in Figure 7-26 and Figure 7-27. The following observations were made:

- OC 2 (Medium to Low Freeway Corridor Travel Time) and OC 3 (High Freeway Corridor Travel Time) demonstrates a sharp degradation in travel time savings when prediction horizon is reduced from 60 minutes to 30 minutes.
- The magnitude of travel time savings loss due to reduction in prediction horizon is seen to be greater at conditions when freeway traffic is heavy and lower when freeway traffic is lower. This trend is seen for OC 3 which has the highest freeway congestion with the highest travel time savings loss from 5.79% to 3.38% (difference of 2.41%), followed by OC 1 from 2.45% to 0.88% (difference of 1.57%), and finally OC 2 from 1.60% to 0.48% (difference of 1.12%).
- For the change in prediction latency, all three operational conditions show a reduction in travel time savings with the increase in prediction latency from 5 minutes to 10 minutes. OC 1 shows a reduction in travel time savings from 2.45% to 1.67%, OC 2 shows a reduction from 1.60 to 0.96%, and 5.79% to 5.50%.
- The results show the activation of ARM yields the highest travel time savings when the freeway has the highest congestion rate. OC 3 shows the highest network travel time savings at 5.79% followed by OC 1 at 2.45% and finally OC 2 at 1.60%.
- ARM shows high sensitivity to prediction horizon followed by prediction latency.

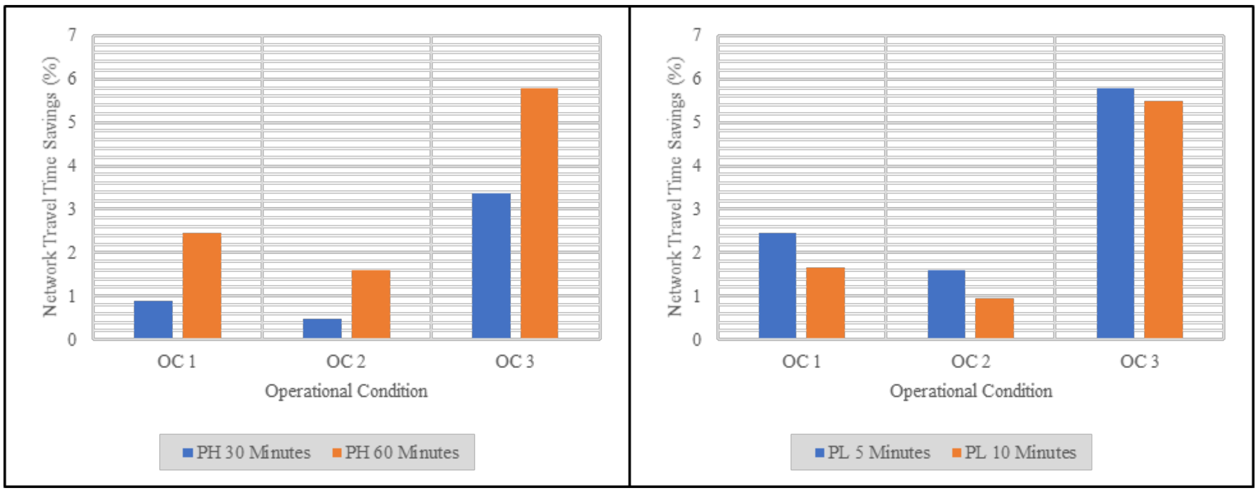


Figure 7-25: Effects of Prediction Horizon (Left) and Prediction Latency (Right) on ARM Network Travel Time Savings under Different Operational Conditions [Source: Booz Allen]

Figure 7-26: Effects of Prediction Horizon on ARM Network Travel Time Savings under Different Operational Conditions [Source: Booz Allen]

Figure 7-27: Effects of Prediction Latency on ARM Network Travel Time Savings under Different Operational Conditions [Source: Booz Allen]

7.4.2 Dynamic Signal Control

The prediction parameter that was found as sensitive for the DSC strategy during the Pasadena testbed phase 1 analysis is prediction accuracy. The simulation results found that the DSC strategy, which is an arterial focused active traffic management strategy had significant varying results under OC 1 with lower prediction accuracy. The same test was performed using varying prediction horizon and prediction latency for OC 2 and OC 3. The results show similar trend as represented in Figure 7-28 with the detailed level results shown in Figure 7-29. The following observations were made:

- All three operational conditions demonstrate a significant degradation in travel time savings when the prediction accuracy is reduced from 100% to 50%.
- Operational condition 1 and 2 shows negative travel time savings when the prediction accuracy is reduced to 50% of available data. However, the negative travel time savings is considered a very small amount (OC 1 at -0.19% and OC 2 at -0.03%)

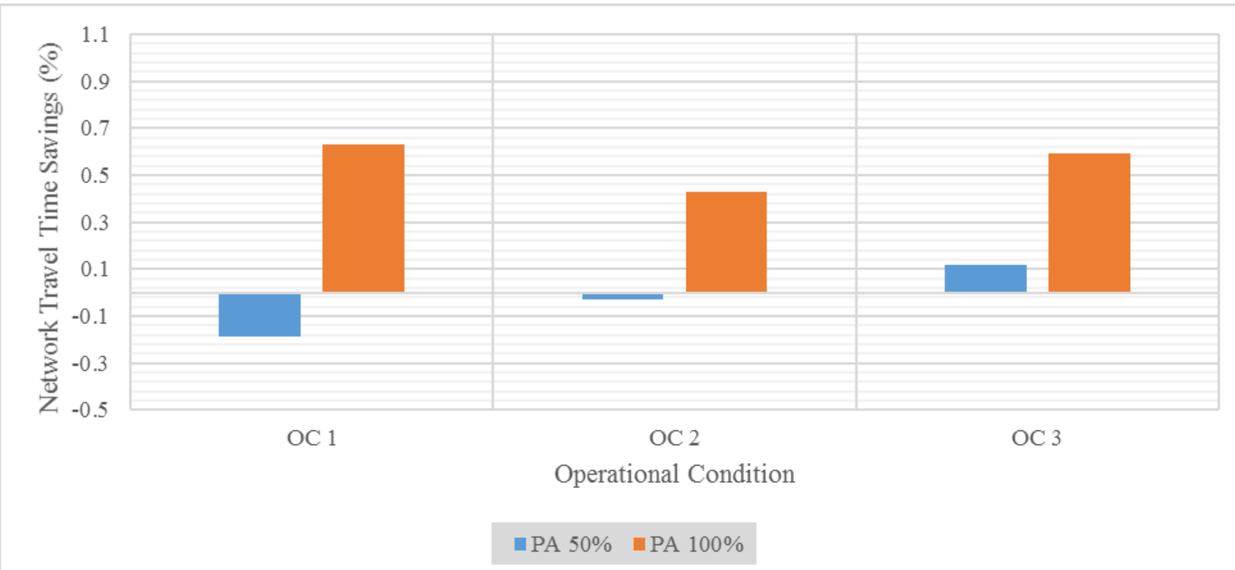


Figure 7-28: Effects of Prediction Accuracy (PA) on DSC Network Travel Time Savings under Different Operational Conditions [Source: Booz Allen]

Figure 7-29: Effects of Prediction Accuracy on DSC Network Travel Time Savings under Different Operational Conditions [Source: Booz Allen]

7.4.3 Hard Shoulder Running and Dynamic Junction Control

No prediction parameter was found as sensitive for the HSR + DJC strategy during the Pasadena testbed phase 1 analysis. The simulation results found that the HSR + DJC strategy, which is freeway focused active traffic management strategy yields the highest travel time savings compared to all other ATM strategies and is not sensitive to any specific prediction parameters that were tested. This section compares the operational benefits on HSR + DJC under different traffic conditions. The results are summarized in Figure 7-30 with the detailed level results. The following observations were made:

- HSR + DJC strategy yields the highest travel time savings when the freeway has the highest traffic congestion.

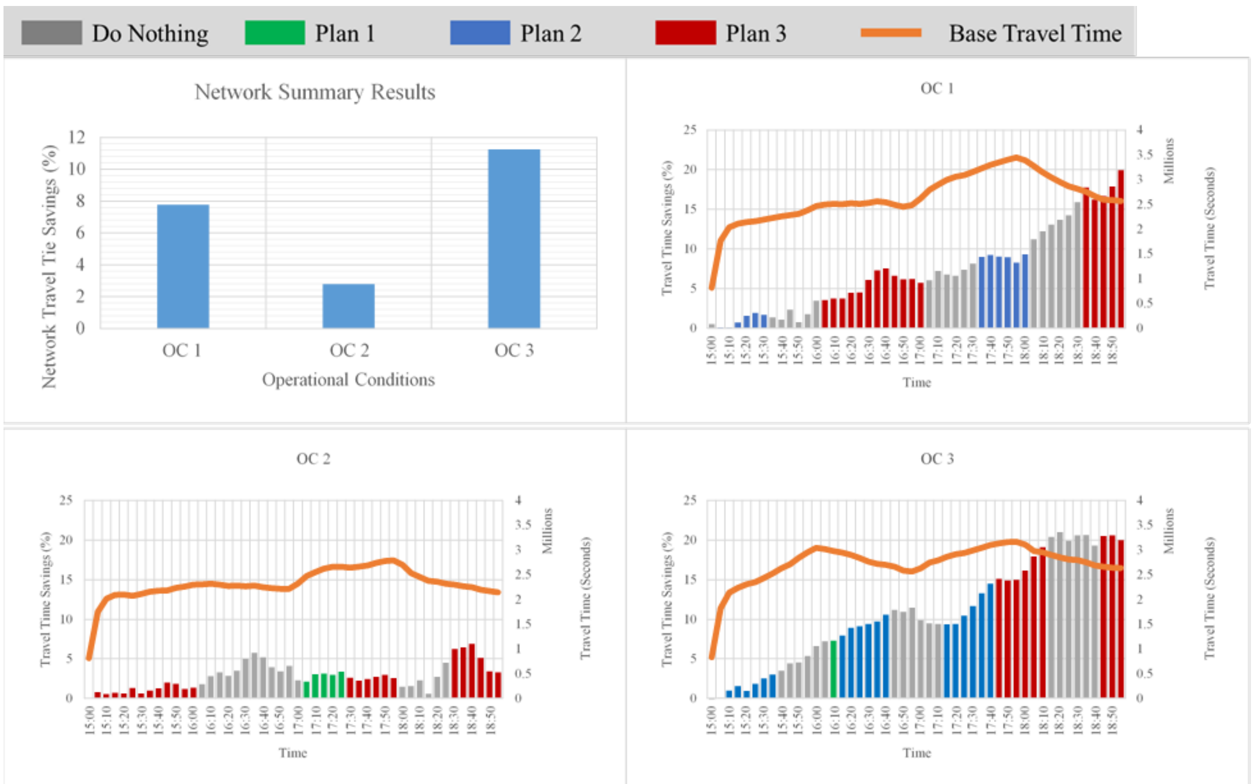


Figure 7-30: Effects of HSR + DJC under Different Operational Conditions [Source: Booz Allen]

7.4.4 Dynamic Speed Limit and Queue Warning

DSL + QW is a freeway focused ATM strategy and is the only strategy assessed that yields negative travel time savings at the freeway and network levels. The primary purpose of the DSL + QW strategy is to distribute isolated congestion over a longer segment distance to foster a gradual change in speed rather than an abrupt change. The DSL + QW strategy does not use prediction parameter, instead is a real time reactive strategy that changes the freeway VMS posted speed limit to distribute traffic congestion. The results show when traveler compliance increases, the 95th percentile spatial and temporal speed difference is reduced. The higher the traveler compliance, the lower the spatial and temporal speed difference. It is also observed that for OC 3 when the freeways are near complete saturation due to the high traffic congestion, reduction in temporal speed difference is slight. The cause of this reduction in difference is due to the inadequacy of available space to distribute the congestion caused by freeway saturation.

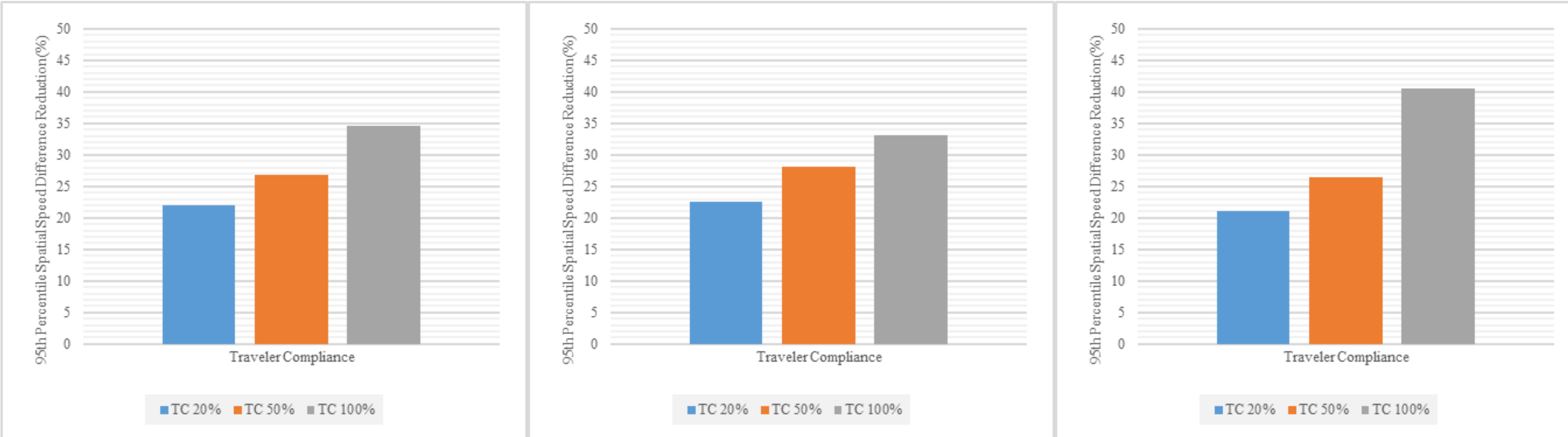


Figure 7-31: Effects of DSL + QW on 95th Percentile Spatial Speed Difference under Different Operational Condition with OC 1 (Left), OC 2 (Center), and OC 3 (Right) [Source: Booz Allen]

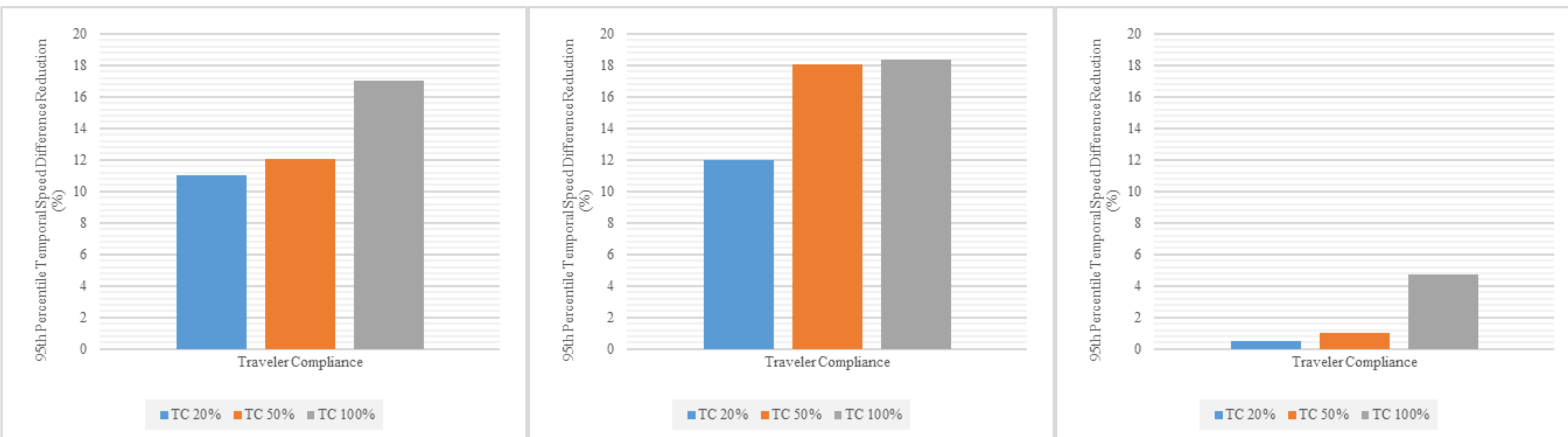


Figure 7-32: Effects of DSL + QW on 95th Percentile Temporal Speed Difference under Different Operational Condition with OC 1 (Left), OC 2 (Center), and OC 3 (Right) [Source: Booz Allen]

7.4.5 Dynamic Route Guidance

The prediction parameter that was found as sensitive for the DRG strategy during the Pasadena testbed phase 1 analysis is traveler compliance. The simulation results found that the DRG strategy, which is an arterial focused active traffic management strategy had significant varying results under OC 1 with lower traveler compliance. The same test was performed using varying traveler compliance for OC 2 and OC 3. The results show similar trend as represented in Figure 7-33 with the detailed level results shown in Figure 7-34. The following observations were made:

- The results indicate a significant decline in travel time savings for all three operational conditions when traveler compliance is reduced from 50% to 20%.
- The difference in network travel time savings for all three operational conditions at 20% can be considered negligible due to insufficient vehicles complying with the recommended strategy to make a significant change in savings. The current changes shown at 20% traveler compliance for OC 1 at -0.15%, OC 2 at 0.17%, and OC 3 at 0.08% could be considered simulation noise rather than strategy impact.
- Figure 7-34 show a mostly consistent positive network travel time impact for when traveler compliance is at 50%. The results for 20% traveler compliance on the other hand shows frequent fluctuating travel time savings which supports the argument that the changes are likely due to simulation modeling noise.

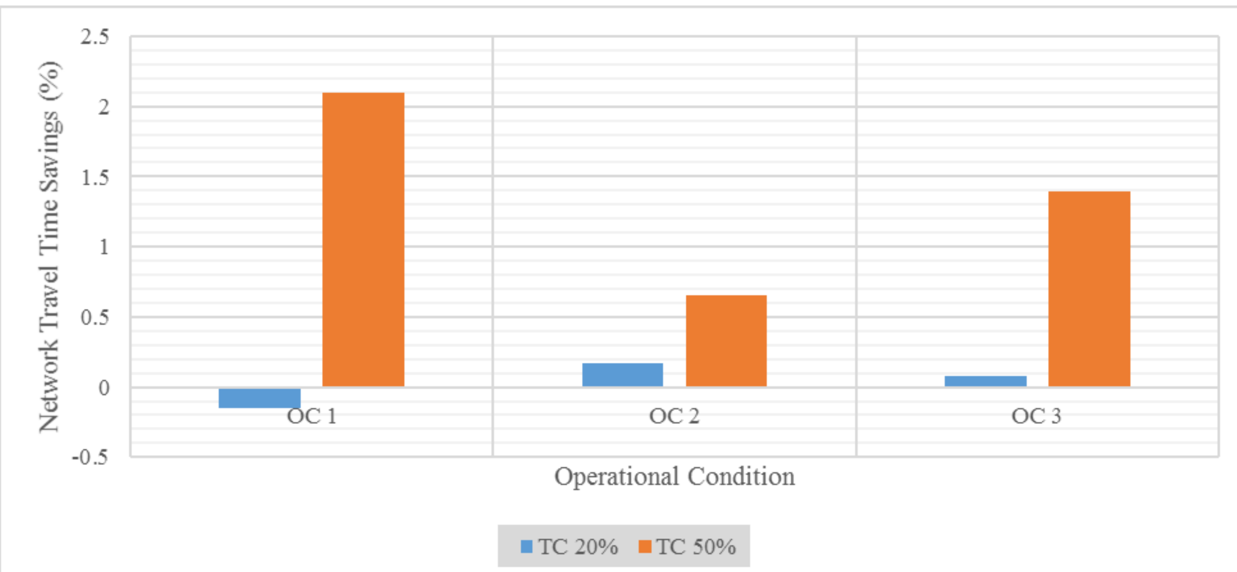


Figure 7-33: Effects of Traveler Compliance (TC) on DRG Network Travel Time Savings under Different Operational Conditions [Source: Booz Allen]

Figure 7-34: Effects of Traveler Compliance on DRG Network Travel Time Savings under Different Operational Conditions [Source: Booz Allen]

7.5 Chicago Testbed Evaluation

Table 7-10 shows the experimental design to test the research questions related to the operational conditions and facility type. To examine the best combination of strategies or strategy bundles for certain facility type, including freeway segments and arterial roads, four combinations of strategies for OC 1 and OC 2 were tested, each not taking the weather-related strategies into consideration. For the snow-affected scenarios, i.e. OC 3 to OC 6, we test the individual strategy bundle compared with the do-nothing baseline scenario to find the most effective strategy bundle.

In addition, another set of experiments were designed to test the effectiveness of different snowplow routing plans. As stated in section 7.3, the dynamic snowplow routing plan was proposed which is generated according to the predicted travel demand for each link, also referring to the link volume. The routing plan may vary by time of day and under different scenarios due to the dynamic traffic assignment. On the other hand, there is another way to generate snowplow routing, which only depends on the link travel time or link length in the network, which is called static snowplow routing plan in this study. When the static routing plan is selected, the operators do not need to update the plan according to the travel demand or the snow intensity, they only need to decide when the snowplow vehicles depart from the depot. Therefore, the question is what kind of operational conditions prefer dynamic routing plan versus static plan. In this set of tests, three snow-related operational and traffic conditions were simulated, comparing the unit travel time and travel time reliability. Both static and dynamic plans analyzed were optimized according to the objective functions.

Table 7-10: Experiment Scenarios for Research Questions of Operational Conditions and Facility Types

Experiment Factor	Tests					
		Strategy	Net Penetration Level	Roll	Horizon	Latency
Combination of strategies or Strategy bundle	OC1 (Clear Day) OC2 (Rain to Snow)	Do nothing	0 %	-	-	-
		ADM	30%	5	30	0
		ATM	0%	5	30	0
		ADM +ATM	30%	5	30	0
		Strategy	Net Penetration Level	Roll	Horizon	Latency
	OC3, 4 (Moderate Snow) OC5 (Heavy Snow) OC6 (Moderate Snow + Incident)	Do nothing	0 %	-	-	-
		ADM	30%	5	30	0
		ATM	30%	5	30	0
		WR	30%	5	30	0
		Strategy	Net Penetration Level	Roll	Horizon	Latency
Dynamic or Static Snowplow Routing	OC3 (Moderate Snow) OC4 (Moderate Snow) OC5 (Heavy Snow) OC6 (Heavy Snow)	WS (dynamic) WS (static)	0%	15	30 min 3 hours (triggered)	0

7.5.1 ATDM Strategies and Operational Conditions

In order to verify the best combination of strategies for each facility type, two representative corridors from each facility type were selected as target segments. The performance measurement for this research question category is the corridor speed profile over the entire simulation horizon on each target segment. The two corridors are displayed in Figure 7-35, where the I-90 freeway segment and the Peterson Avenue are selected.

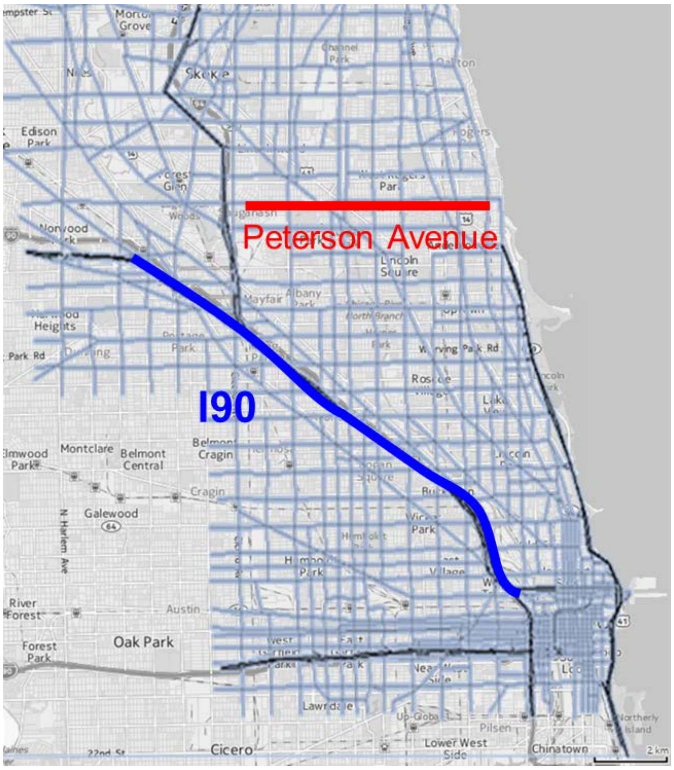


Figure 7-35: Representative corridors of freeway segments and arterial roads [Source: Booz Allen]

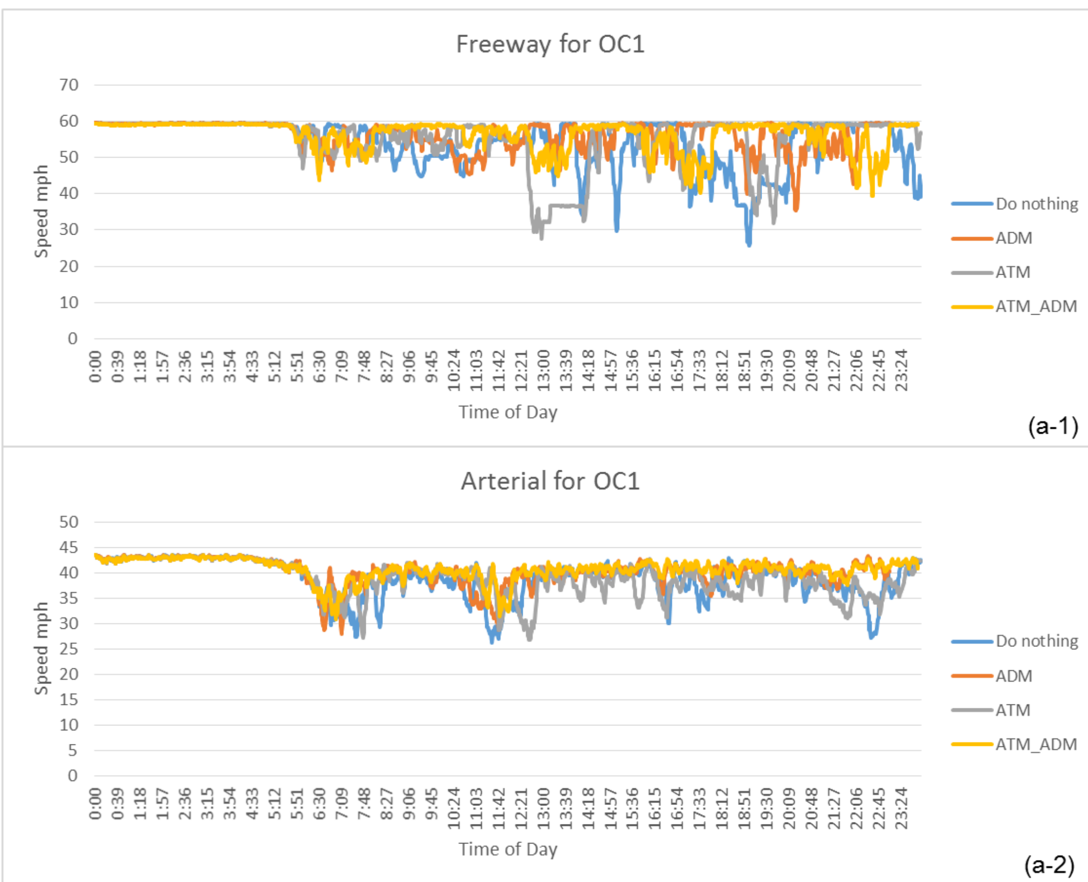
Figure 7-36 shows the speed profiles that were extracted from I-90 segment and the Peterson Avenue from different scenarios. On the I 90 segment, the dynamic shoulder lanes and dynamic speed limit were implemented, while on the Peterson Avenue the adaptive signal control was implemented on the corridor.

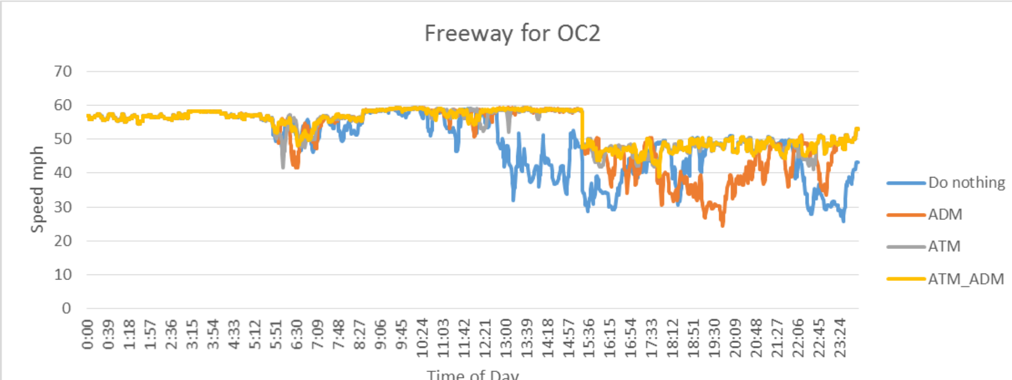
Figure 7-36 (a) shows that both ATM and ADM strategy bundles improve the corridor performance on both facility type, but if ADM strategy is implemented in conjunction with ATM, the corridor speed is increased the most over the entire horizon. Figure 7-36 (b) shows the results for the OC 2 where there was some influence from the rain and light snow. It is observed that the ATM strategies shows more effectiveness on the freeway segment than the ADM strategies, and it also generates more benefit when implemented together with the ADM strategies. But for the arterial road, the scenarios with the ATM, ADM and the combination of both strategy bundles show similar performance.

Figure 7-36 (c-f) shows the results for the snow-related scenarios with three individual strategy bundles implemented. For OC 3 where the demand is medium high and the snow intensity is moderate and uniform over the entire simulation horizon, the best strategy is the Weather-related strategy for both freeway segment and the arterial road, and the ADM strategy bundle also shows significant improvement for the corridor performance. Due to the dynamic speed limit control, one of the ATM strategies implemented on I-90 segment, the speed profile under ATM strategy, is the lowest among the test scenarios. However, as the speed limit is generated according to the speed harmonization principle, it can also be observed that speed changes within a smallest range under ATM strategies compared with the other scenarios. This phenomenon is also described in Chapter 8 where the speed harmonization helps to control the speed variance and maintain the stability of the corridor. Therefore, from the aspect of reliability, ATM strategy is also very beneficial to the I-90 freeway corridor.

For OC 4 shown in Figure 7-36 (d), the most beneficial strategy bundle is the ADM strategy instead of the Weather-related strategy. This is due to the low demand pattern under this operational condition so system may not have serious congestions even under the baseline scenario which has been confirmed in the baseline scenario performance in section 3.2. Likewise, the negative impact from the ATM strategy on both freeway segment and the arterial corridor, and from the Weather-related strategy during some period, has been also observed from the tests for Synergies and Conflicts in section 9.2. The reasons could be that: (a) dynamic shoulder lanes are not functional on weekend for OC4, producing no extra capacity, (b) speed limits may reduce the network throughput in a less congested network when demand is low, and (c) the recovered capacity from the Weather-related strategy is not effective for OC4 due to low demand, but it brings disadvantages from lane closure during implementation.

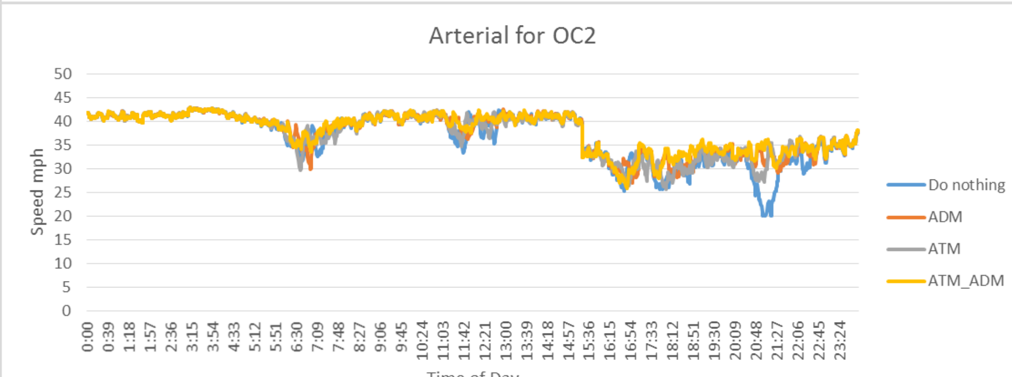
Like OC 5 in Figure 7-36 (e), for OC 3 the best strategy is the Weather-related strategy which helps to reduce the snow accumulation impact and is most beneficial especially for the heavy snow scenario. The ATM strategy helps to maintain travel speed within a small range, keeping travel time in the corridor reliable and stable. For OC 6, which shares the same demand and weather pattern as OC 3 and is an incident-snow mixed scenario, the best strategy is the ADM strategy which helps vehicle choose the best routes and avoid the impact from the incident-related delay. The ATM strategies also lead to a reliable corridor especially from 16:00 to 18:00 when the ADM strategy is less effective.





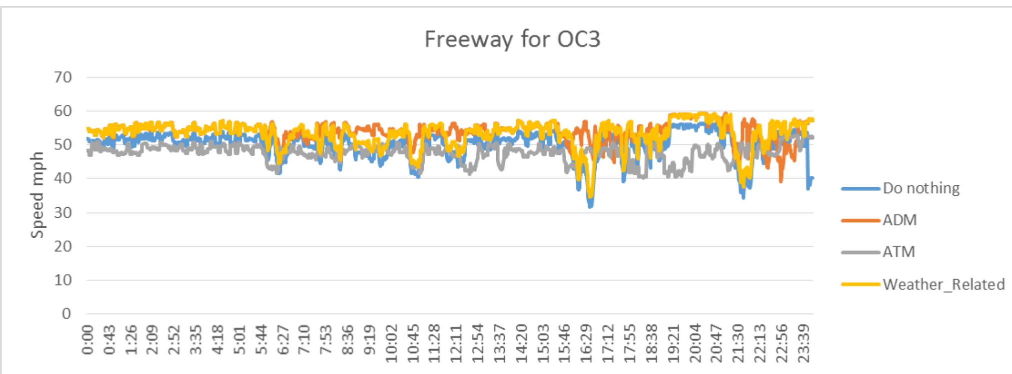
Freeway for OC2
Speed mph
70
60
50
40
30
20
10
0
0:00 0:39 1:18 1:57 2:36 3:15 3:54 4:33 5:12 5:51 6:30 7:09 7:48 8:27 9:06 9:45 10:24 11:03 11:42 12:21 13:00 13:39 14:18 14:57 15:36 16:15 16:54 17:33 18:12 18:51 19:30 20:09 20:48 21:27 22:06 22:45 23:24
Time of Day
Do nothing
ADM
ATM
ATM_ADM

(b-1)



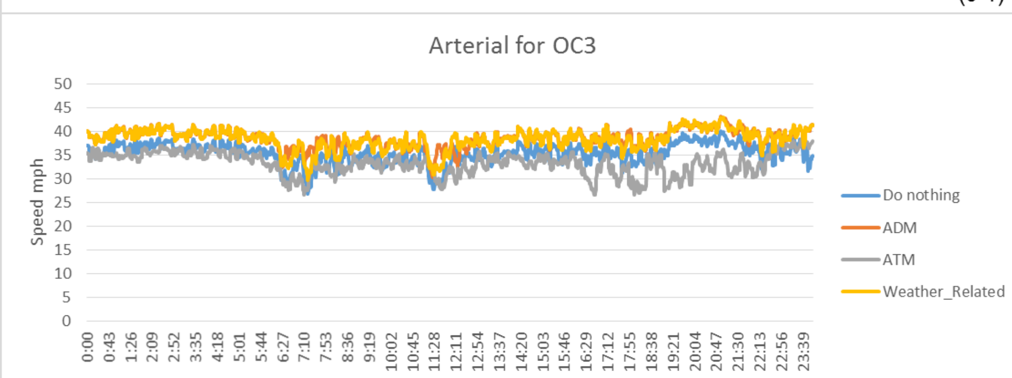
Arterial for OC2
Speed mph
50
45
40
35
30
25
20
15
10
5
0
0:00 0:39 1:18 1:57 2:36 3:15 3:54 4:33 5:12 5:51 6:30 7:09 7:48 8:27 9:06 9:45 10:24 11:03 11:42 12:21 13:00 13:39 14:18 14:57 15:36 16:15 16:54 17:33 18:12 18:51 19:30 20:09 20:48 21:27 22:06 22:45 23:24
Time of Day
Do nothing
ADM
ATM
ATM_ADM

(b-2)



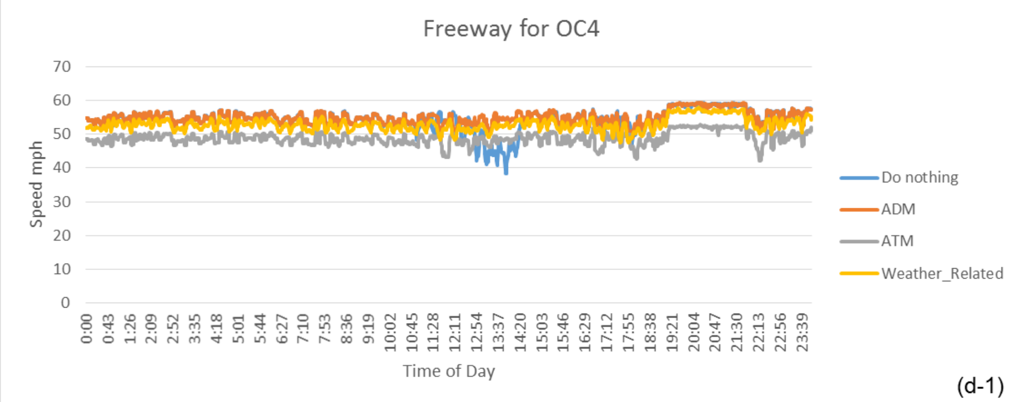
Freeway for OC3
Speed mph
70
60
50
40
30
20
10
0
0:00 0:43 1:26 2:09 2:52 3:35 4:18 5:01 5:44 6:27 7:10 7:53 8:36 9:19 10:02 10:45 11:28 12:11 12:54 13:37 14:20 15:03 15:46 16:29 17:12 17:55 18:38 19:21 20:04 20:47 21:30 22:13 22:56 23:39
Time of Day
Do nothing
ADM
ATM
Weather_Related

(c-1)

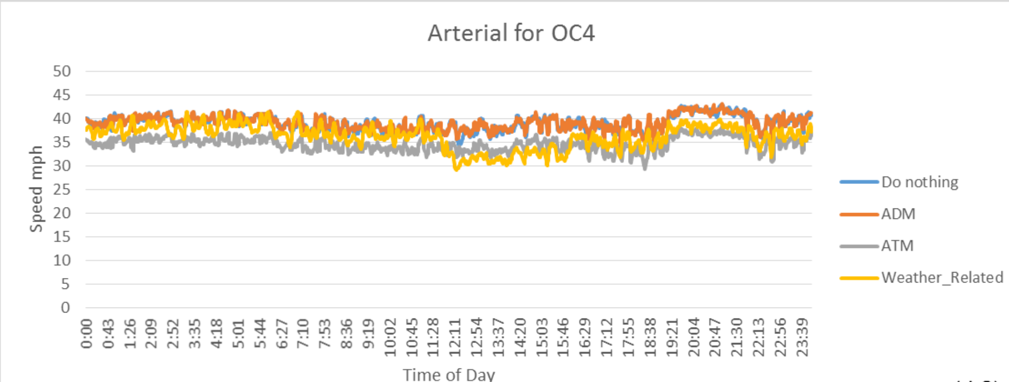


Arterial for OC3
Speed mph
50
45
40
35
30
25
20
15
10
5
0
0:00 0:43 1:26 2:09 2:52 3:35 4:18 5:01 5:44 6:27 7:10 7:53 8:36 9:19 10:02 10:45 11:28 12:11 12:54 13:37 14:20 15:03 15:46 16:29 17:12 17:55 18:38 19:21 20:04 20:47 21:30 22:13 22:56 23:39
Time of Day
Do nothing
ADM
ATM
Weather_Related

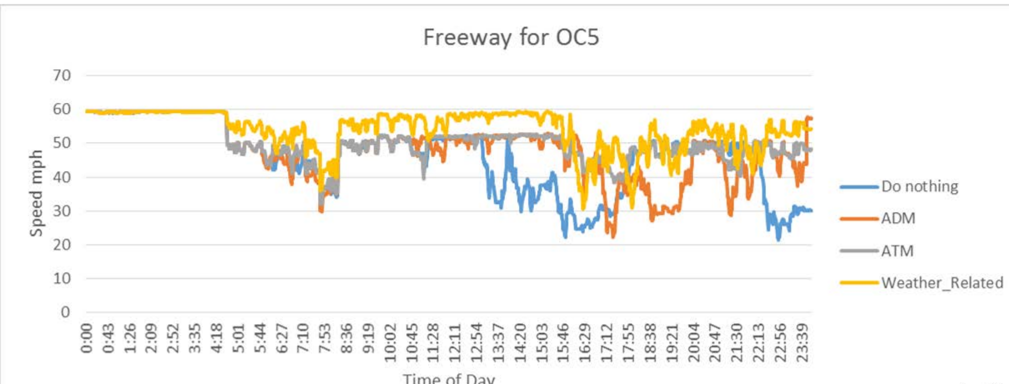
(c-2)


Freeway for OC4
Speed mph
Time of Day
Do nothing
ADM
ATM
Weather_Related

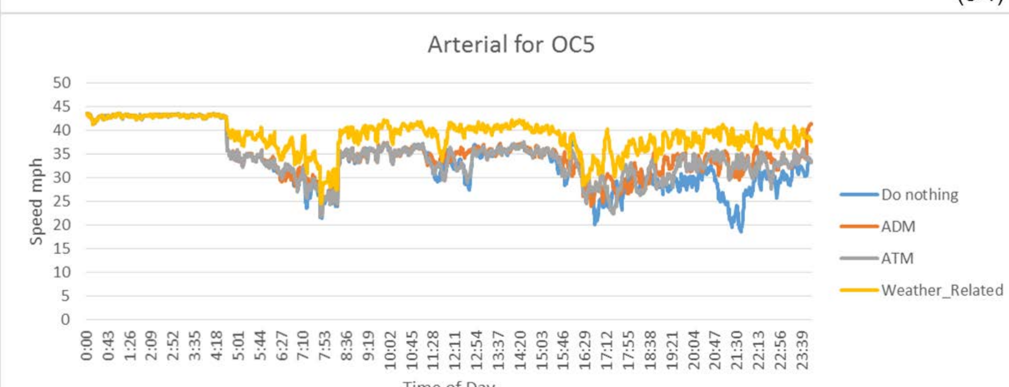
(d-1)


Arterial for OC4
Speed mph
Time of Day
Do nothing
ADM
ATM
Weather_Related

(d-2)


Freeway for OC5
Speed mph
Time of Day
Do nothing
ADM
ATM
Weather_Related

(e-1)


Arterial for OC5
Speed mph
Time of Day
Do nothing
ADM
ATM
Weather_Related

(e-2)

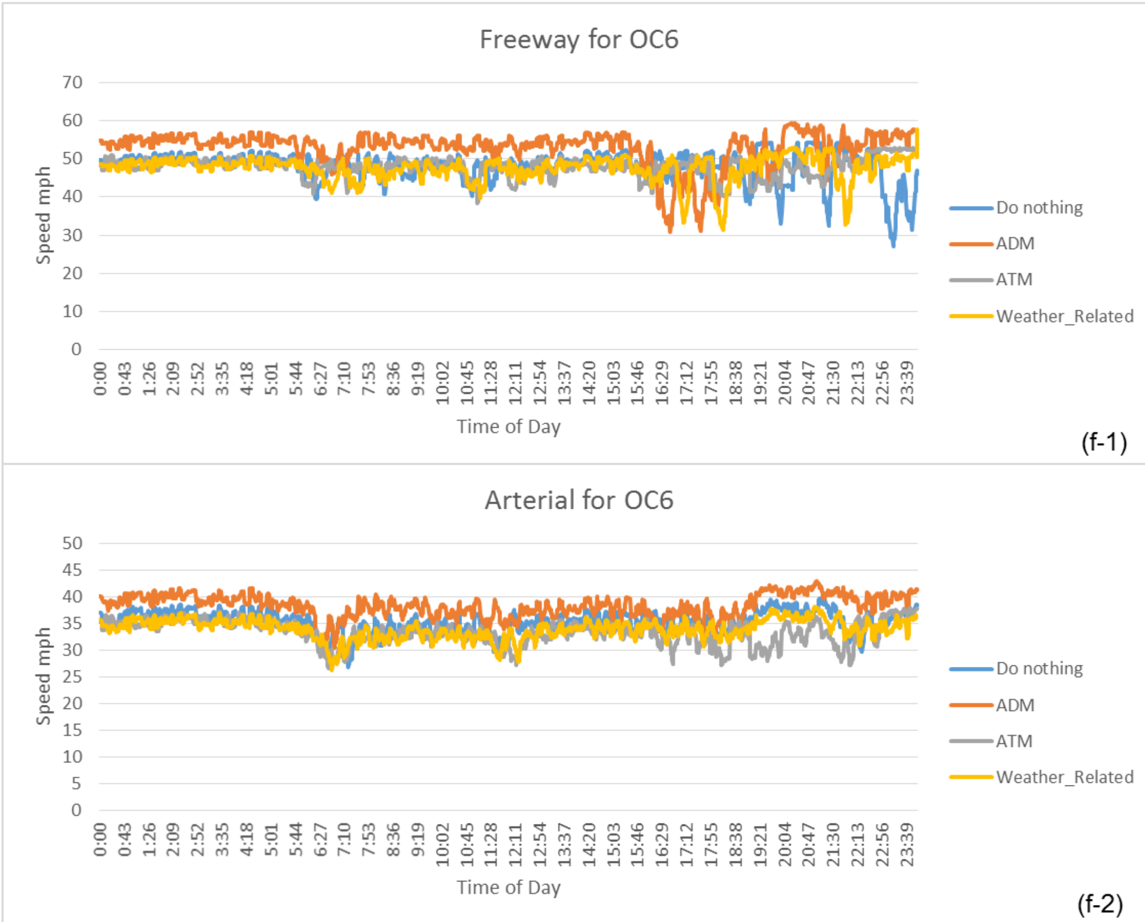


Figure 7-36: Traffic speed profiles for different facility types and operational conditions [Source: NWU]

7.5.2 Snowplow Routing Under Different Operational Condition

The snowplow routes generated by the model proposed in section 7.3 are called dynamic snowplow routes because the model uses dynamic and predictive weather and traffic information. Another set of routes, static snowplow routes, was generated by dividing the whole network into small clusters and solving the Chinese Postman Problem for each cluster. While the dynamic routing plan incorporates the benefit of plowing in the objective function, the static routing plan aims to minimize the deadheading cost. The static snowplow routes served as the benchmark against which to evaluate the performance of the dynamic snowplow routes.

We use the average travel time, average stop time, average unit travel time and 95%-unit travel time to evaluate the performance of the routing plan. The 95%-unit travel time is used as the travel time reliability measurement. The improvement of unit travel time is defined as:

$$\frac{\text{unit travel time with static routing plan} - \text{unit travel time with dynamic routing plan}}{\text{unit travel time with static routing plan}}$$

A positive improvement value indicates the dynamic routing plan has a better result, negative value indicates otherwise. Because OC1 has no snow and OC2's snow fall is too light, these two operational conditions do not have weather-related strategies. Only OC3, OC4 and OC5 results are included in this chapter.

Figure 7-37 illustrates the performance of plowing under OC3. Both routing plans, static and dynamic, have two rounds of plowing at 7:23 am and 3:58 pm respectively. Compared with the scenario using the static snowplow routes, travelers' average travel time is **3%** shorter and average stop time is **8%** less in the case of the dynamic snowplow routes. The dynamic routing plan leads to improvement in the morning and evening peak hours. Figure 7-37 (a) compares the unit average time in both scenarios and shows the dynamic snow plowing routes scenario has a lower unit travel time during most intervals of planning horizon. As shown in Figure 7-37 (b) the dynamic routing plan performed slightly better in terms of 95%-unit travel time. Figure 7-37 (c) shows the difference in terms of percentage improvement. At the beginning of each plowing operation, dynamic routing always lead to a better result as the most important links are plowed first. However, towards the end of the plowing operation, one could see the fluctuation in the improvement. Because the dynamic plow plan aims to minimize the snow's impact on traffic, it has more deadheading trips and longer routes comparing with the static plan. As discussed in section 4.4.4, the snowplow's presence on a link would reduce the link capacity and increase link density and travel time. Therefore, these extra trips cause a reduction in the performance of the dynamic plans.

Figure 7-38 shows the performance of different strategies under OC4. Because the weather under OC4 is the same as OC3, both the static and dynamic plow plan have two rounds of plowing starting at 7:23 am and 3:58 pm respectively. Compared with the scenario using the static snowplow routes, travelers' average travel time is **4.32%** shorter and average stop time is **11%** less in the case of the dynamic snowplow routes. Since OC4 has low demand during the morning peak, the dynamic routing plan has a similar performance compared to the static routing plan. However, during the PM peak, when the demand increases, the dynamic routing plan has improvement in both unit travel time and 95% unit travel time.

Figure 7-39 illustrates the OC5 scenario, with high snow intensity during the morning peak hour and moderate snow at night. It needs two rounds of plowing at 8:15 am and 10:10 pm respectively. Although OC5 is the only scenario with heavy snow in terms of intensity, and the duration of heavy snow is less than 1 hour. Therefore, the total snow accumulated on the road surface is no more than the other scenarios. Similar to OC3, Figure 7-39 (c) shows that at the beginning of each plowing session, the dynamic routing plan always has a shorter unit travel time because the most important links are plowed.

Figure 7-40 demonstrates the performance of the two plowing plans under OC6. OC6 is almost identical to the OC3, except that OC6 has four incidents. The dynamic snowplow routing is regenerated with the updated link volume and speed information. Comparing with the OC3, dynamic routing plan leads to a larger improvement in unit travel time. With the incidents, the network is more congested. The dynamic snowplow plan performance better in terms of alleviating congestion as it serves the relevant links first.

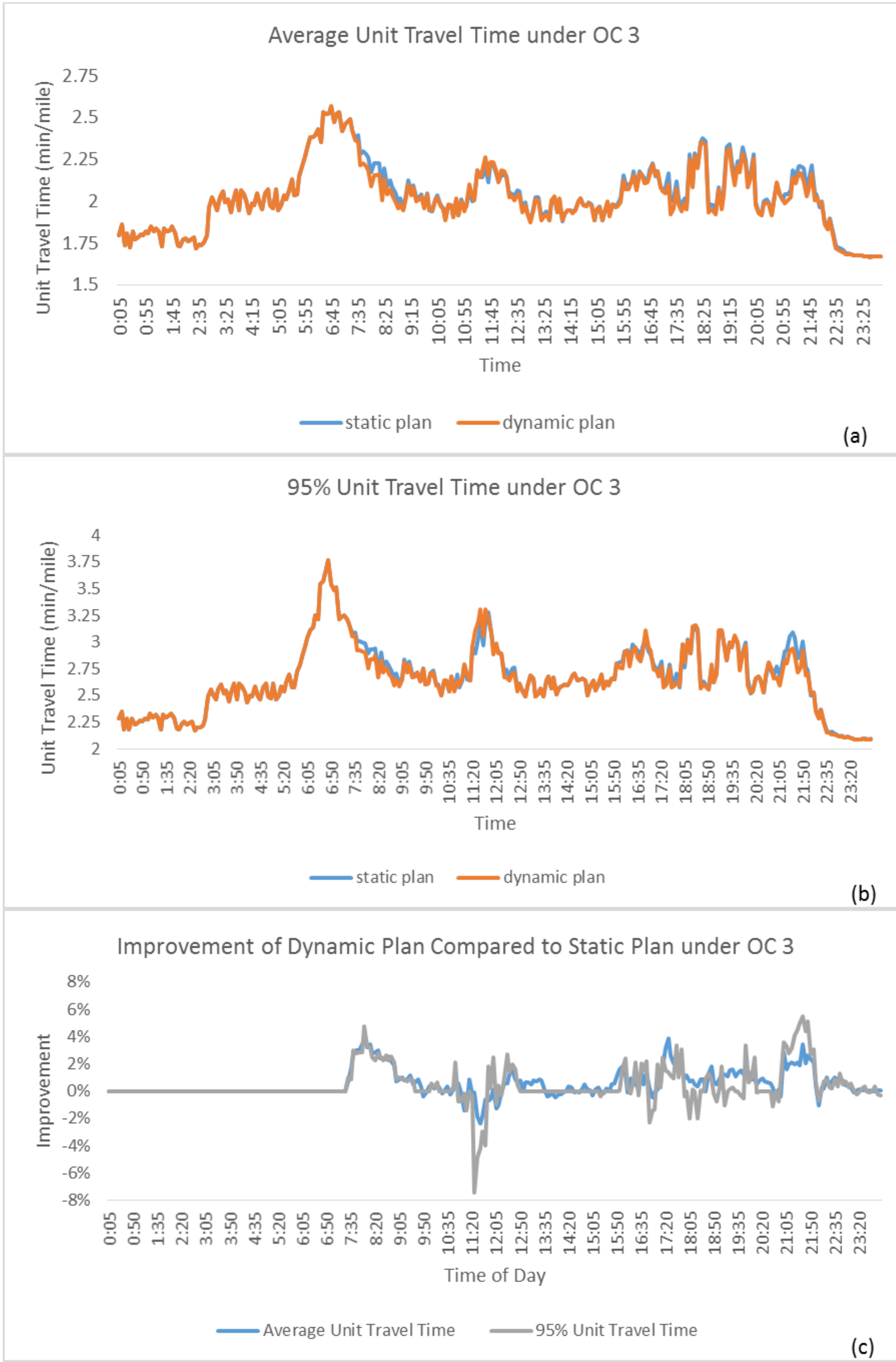


Figure 7-37: Comparison of unit travel times under different snowplow routing plans for OC 3 [Source: NWU]

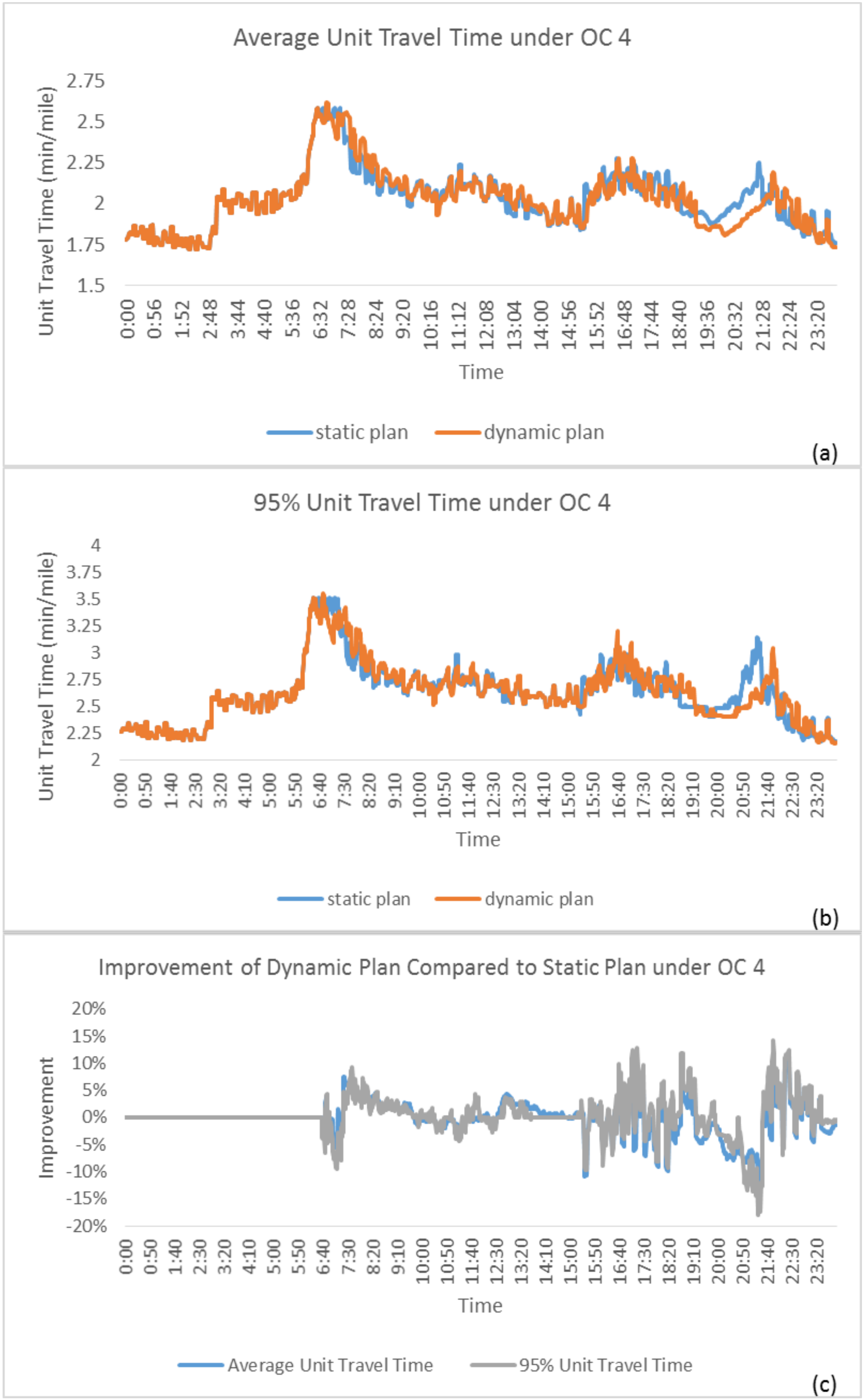


Figure 7-38: Comparison of unit travel times using different snowplow routing plans for OC 4 [Source: NWU]

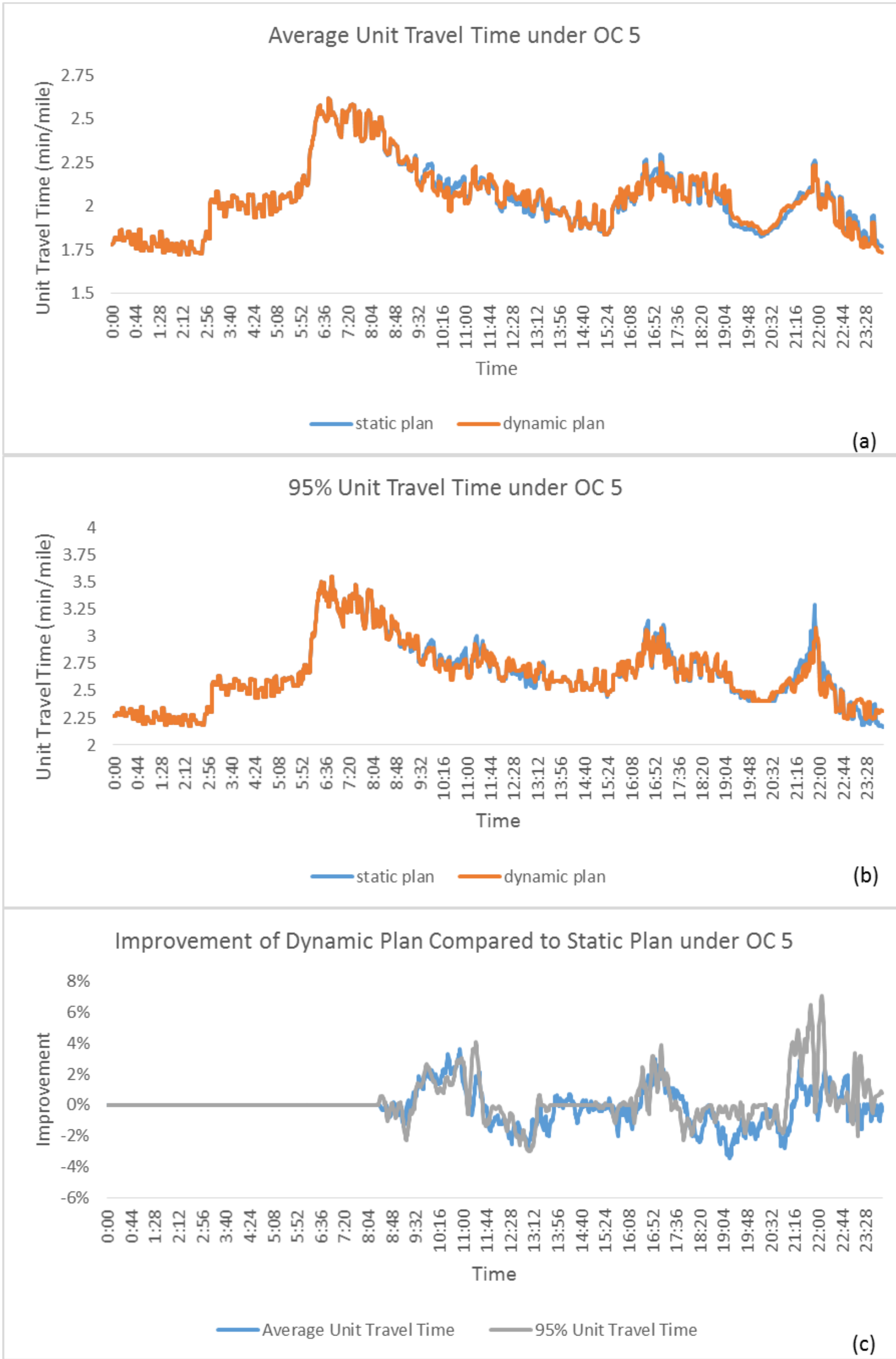


Figure 7-39: Comparison of unit travel times from different snowplow routing plans for OC 5 [Source: NWU]

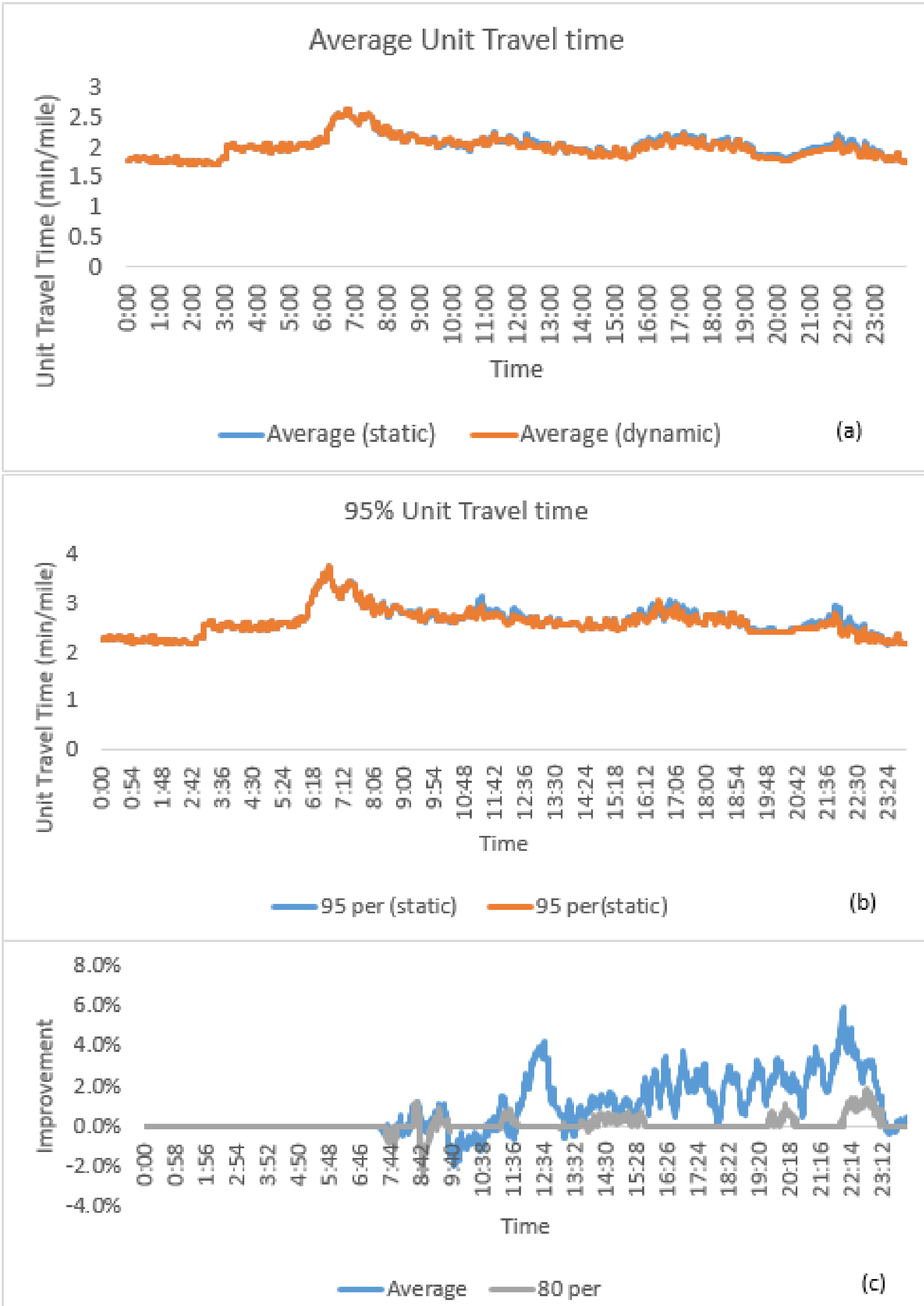


Figure 7-40: Comparison of unit travel times from different snowplow routing plans for OC 6 [Source: NWU]

7.6 San Diego Testbed Evaluation

Each ATDM strategy was evaluated in isolation under four different operational condition. The first two operational conditions (AM1 and AM2) represent a morning peak situation (i.e. higher traffic in the southbound direction) with medium demand and a medium (AM1) or high incident severity (AM2) affecting the southbound direction. The other two operational conditions (PM3 and PM4) represent an evening peak situation (i.e. higher traffic in the northbound direction) with medium demand and a medium (PM4) or high incident severity (PM3) affecting the northbound direction. The performance measures obtained in these simulations have been compared with the baseline case. The ATDM strategies that have been tested are:

- Dynamic Lane Use and Dynamic HOV/Managed Lanes
- Dynamic Speed Limits
- Dynamic Merge Control
- Predictive Traveler Information with Dynamic Routing

7.6.1 Dynamic Lane Use and Dynamic HOV/Managed Lanes

Dynamic Lane Use was modelled as a change from the standard 2 northbound and 2 southbound HOV lane configurations to 1 northbound and 3 southbound lanes for Operational Conditions 1 and 2 (AM) or 3 northbound and 1 southbound lanes for Operational Conditions 3 and 4 (PM). To promote the usage of the additional HOV lane, Dynamic HOV/Managed Lanes was concurrently modelled as the possibility for SOVs to access to the HOV lanes for free in the southbound direction for Operational Conditions 1 and 2 (AM) and in the northbound direction for Operational Conditions 3 and 4 (PM). Both strategies are activated throughout the simulation.

Operational Condition 1 (AM1)

A comparison of the speed contour on I-15 in the southbound direction with the baseline conditions shows that Dynamic Lane Use and Dynamic HOV/Managed Lanes produce overall a slight reduction of congestion along the corridor, with some localized increase of congestion where the accesses to the HOV lanes are located (Figure 7-41). This is intuitive because this strategy increases the capacity of the corridor by providing an additional lane for southbound traffic and promotes the usage of HOV lanes.

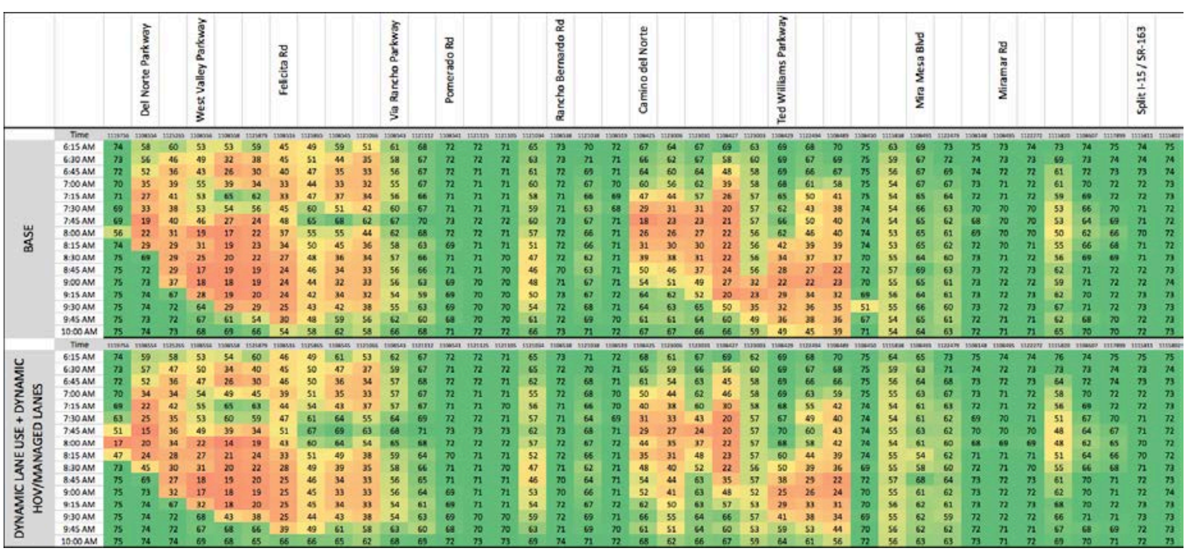


Figure 7-41: Speed contour with Dynamic Lane Use and Dynamic HOV/Managed Lanes compared with the baseline case under Operational Condition 1 [Source: TSS]

If we compare network-wide traffic performance measures with Dynamic Lane Use and Dynamic HOV/Managed Lanes with the baseline condition (Table 7-11 and Figure 7-42), we can see that there is mobility improvements in terms of average speed, total travel time and passenger travel time. In summary, the results show a slight benefit in a condition in which there are several localized bottlenecks along the corridor, as the additional lane provides a way to bypass them. However, the benefit is limited because the incident in this operational condition is located at the first entrance of the HOV lanes, so this ATDM strategy doesn't offer a way to bypass the major bottleneck.

Table 7-11: Performance measures with Dynamic Lane Use and Dynamic HOV/Managed Lanes compared with the baseline case under Operational Condition 1

Network Statistics	Base	Dyn Lane Use and Dyn HOV/Managed Lanes	Difference
Vehicles Miles Travelled (miles)	2,320,947	2,325,470	0.2%
Total Travel Time (h)	61,946	60,953	-1.6%
Passenger Hourly Travel Time (h)	78,635	77,591	-1.3%
VMT/VHT (mi/h)	37.47	38.15	1.8%

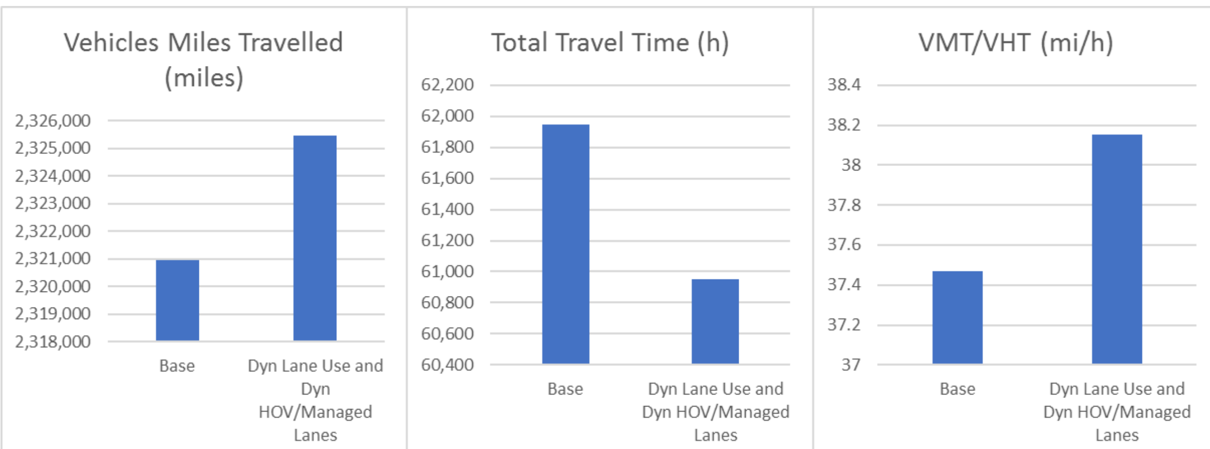


Figure 7-42: Performance measures with Dynamic Lane Use and Dynamic HOV/Managed Lanes compared with the baseline case under Operational Condition 1 [Source: TSS]

Operational condition 2 (AM2)

A comparison of the speed contour on I-15 in the southbound direction with the baseline conditions shows that Dynamic Lane Use and Dynamic HOV/Managed Lanes produce overall a slight reduction of congestion along the corridor (Figure 7-43). This is intuitive because this strategy increases the capacity of the corridor by providing an additional lane for southbound traffic and promotes the usage of HOV lanes. If we compare network-wide traffic performance measures with Dynamic Lane Use and Dynamic HOV/Managed Lanes with the baseline condition (Table 7-12 and Figure 7-44), we can notice that the throughput is practically unchanged, but the travel time improves slightly.

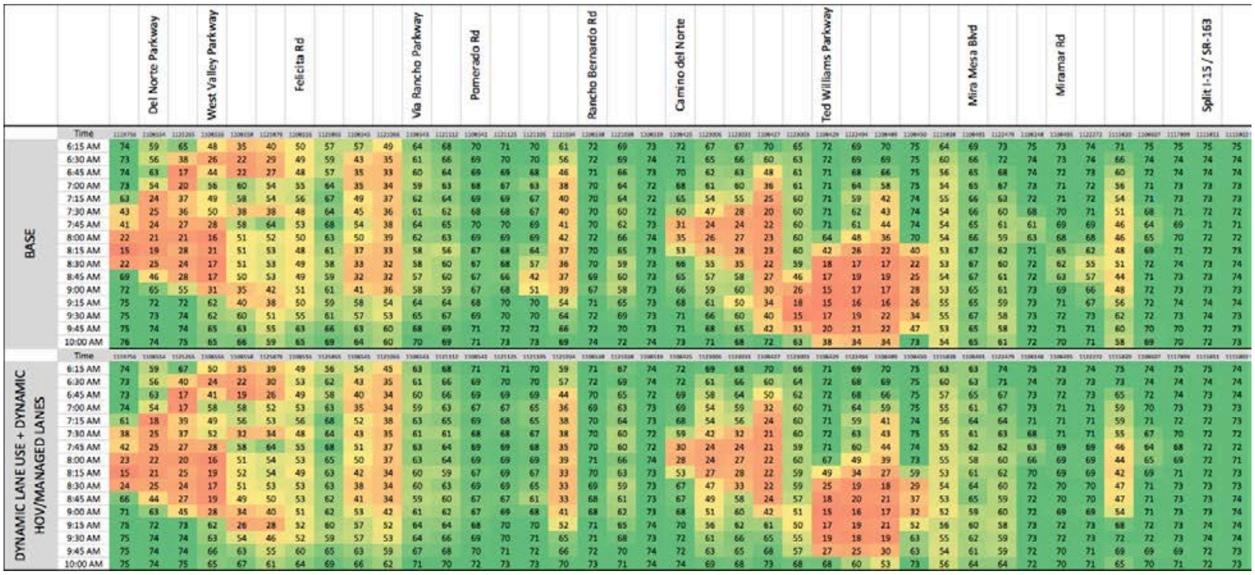


Figure 7-43: Speed contour with Dynamic Lane Use and Dynamic HOV/Managed Lanes compared with the baseline case under Operational Condition 2 [Source: TSS]

Table 7-12: Performance measures with Dynamic Lane Use and Dynamic HOV/Managed Lanes compared with the baseline case under Operational Condition 2

Network Statistics	Base	Dyn Lane Use and Dyn HOV/Managed Lanes	Difference
Vehicles Miles Travelled (miles)	2,304,353	2,313,228	0.4%
Total Travel Time (h)	61,509	60,683	-1.3%
Passenger Hourly Travel Time (h)	78,853	77,762	-1.4%
VMT/VHT (mi/h)	37.46	38.12	1.8%

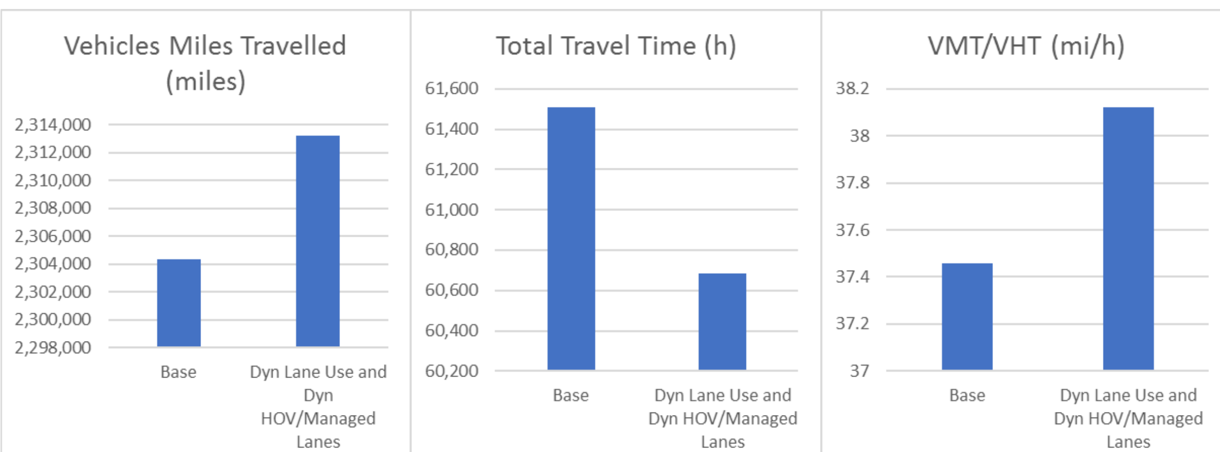


Figure 7-44: Performance measures with Dynamic Lane Use and Dynamic HOV/Managed Lanes compared with the baseline case under Operational Condition 2 [Source: TSS]

In summary, the results show a slight benefit in a condition in which there are several localized bottlenecks along the corridor, as the additional lane provides a way to bypass them. However, the benefit is limited because the incident in this operational condition is located just downstream of the first entrance of the HOV lanes, and causes a congestion that at some times spills back to the HOV entrance, so this ATDM strategy doesn't offer a way to bypass the major bottleneck.

Operational Condition 3 (PM3)

A comparison of the speed contour on I-15 in the northbound direction with the baseline conditions shows that Dynamic Lane Use and Dynamic HOV/Managed Lanes produce a reduction of congestion along the corridor (Figure 7-45). This is intuitive because this strategy increases the capacity of the corridor by providing an additional lane for northbound traffic and promotes the usage of HOV lanes.

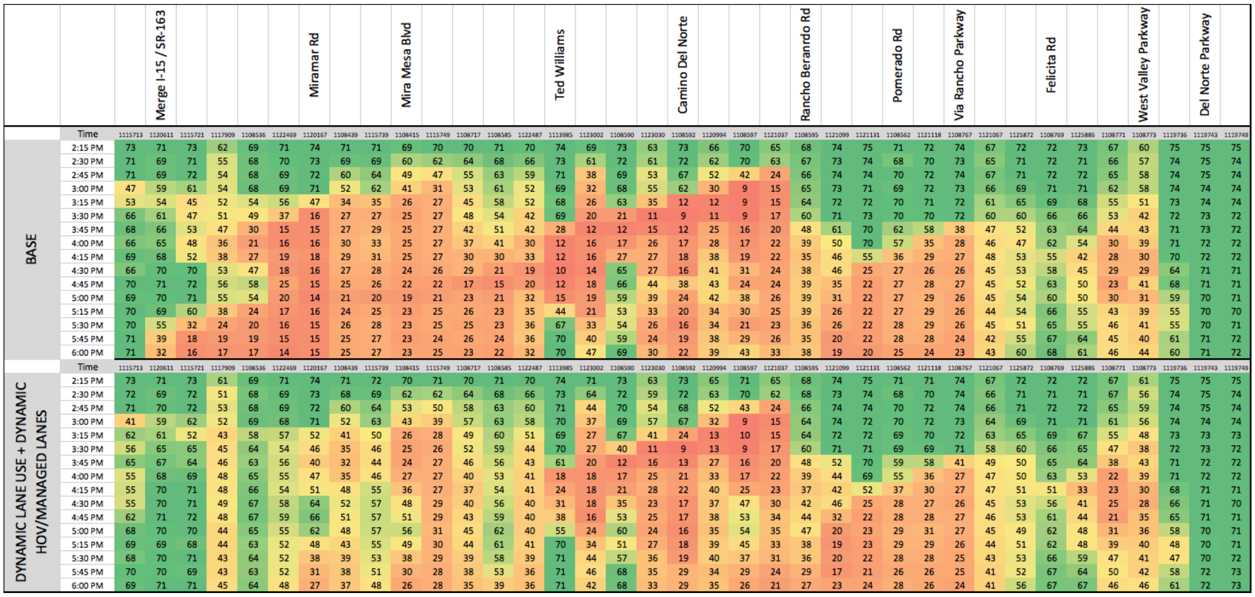


Figure 7-45: Speed contour with Dynamic Lane Use and Dynamic HOV/Managed Lanes compared with the baseline case under Operational Condition 3 [Source: TSS]

If we compare network-wide traffic performance measures with Dynamic Lane Use and Dynamic HOV/Managed Lanes with the baseline condition (Table 7-13 and Figure 7-46), we can notice that the throughput is practically unchanged, but the travel time improves slightly.

Table 7-13: Performance measures with Dynamic Lane Use and Dynamic HOV/Managed Lanes compared with the baseline case under Operational Condition 3

Network Statistics	Base	Dyn Lane Use and Dyn HOV/Managed Lanes	Difference
Vehicles Miles Travelled (miles)	2,518,604	2,531,493	0.5%
Total Travel Time (h)	76,531	73,529	-3.9%
Passenger Hourly Travel Time (h)	99,052	95,937	-3.1%
VMT/VHT (mi/h)	32.91	34.43	4.6%

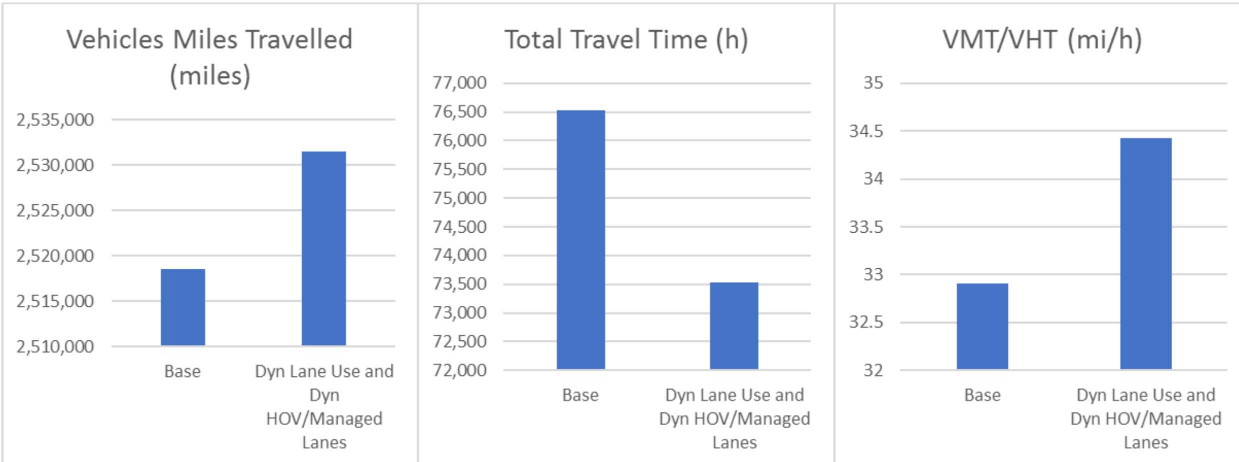


Figure 7-46: Performance measures with Dynamic Lane Use and Dynamic HOV/Managed Lanes compared with the baseline case under Operational Condition 3 [Source: TSS]

In summary, the results show a slight benefit in a condition in which there is congestion throughout the corridor, as the additional lane provides a way to bypass it. In this operational condition the benefit is more significant compared to the previous because the incident doesn't affect any entrances to the HOV lanes.

Operational Condition 4 (PM4)

A comparison of the speed contour on I-15 in the northbound direction with the baseline conditions shows that Dynamic Lane Use and Dynamic HOV/Managed Lanes produce no significant change on congestion along the corridor (Figure 7-47). This is intuitive because since under this operational condition there is no significant congestion, so the additional lane for northbound traffic doesn't provide much value. If we compare network-wide traffic performance measures with Dynamic Lane Use and Dynamic HOV/Managed Lanes with the baseline condition (Table 7-14 and Figure 7-46), we can notice that all the indicators are practically unchanged.

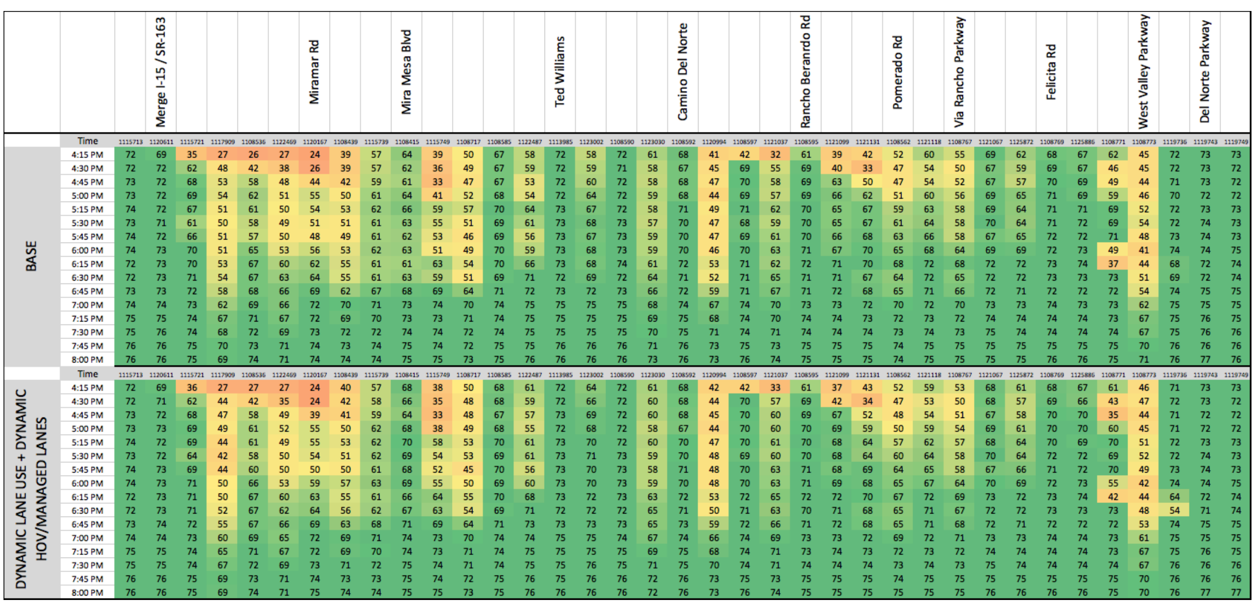


Figure 7-47: Speed contour with Dynamic Lane Use and Dynamic HOV/Managed Lanes compared with the baseline case under Operational Condition 4 [Source: TSS]

Table 7-14: Performance measures with Dynamic Lane Use and Dynamic HOV/Managed Lanes compared with the baseline case under Operational Condition 4

Network Statistics	Base	Dyn Lane Use and Dyn HOV/Managed Lanes	Difference
Vehicles Miles Travelled (miles)	2,302,897	2,301,997	0.0%
Total Travel Time (h)	57,547	57,589	0.1%
Passenger Hourly Travel Time (h)	75,856	75,918	0.1%
VMT/VHT (mi/h)	40.02	39.97	-0.1%

In summary, the results show that in a condition in which there is no congestion throughout the corridor, this ATDM strategy doesn't produce any significant benefit nor detrimental effect. However, the slight worsening of the performance indicators suggests that the additional demand using the HOV lanes may cause a slight increase of localized congestion at the access and egress points.

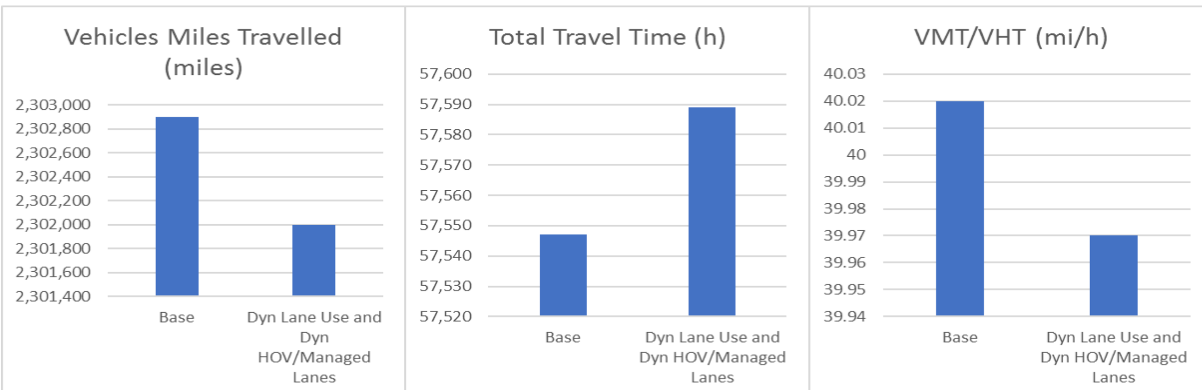


Figure 7-48: Performance measures with Dynamic Lane Use and Dynamic HOV/Managed Lanes compared with the baseline case under Operational Condition 4 [Source: TSS]

Comparison Between Operational Conditions

A comparison of the performance measures under different operational conditions shows that Dynamic Lane Use and Dynamic HOV/Managed Lanes are effective only in congested situations. Additionally, the location of incidents and bottlenecks may reduce the effectiveness of this ATDM strategy, because if the congestion caused by them affects the access points to the HOV lanes, vehicles have difficulty in reaching the additional lane that allows bypassing the bottlenecks.

7.6.2 Dynamic Speed Limits

Dynamic Speed Limits was modelled as a reduction of the speed limit of each road segment depending on congestion in the southbound direction for Operational Conditions 1 and 2 (AM) and in the northbound direction for Operational Conditions 3 and 4 (PM). See Section 0 for further details about the algorithm. The strategy is active throughout the simulation.

Operational condition 1 (AM1)

A comparison of the speed contour on I-15 in the southbound direction with the baseline conditions shows that Dynamic Speed Limits produce a "dilution" of the congestion over space and time (Figure 7-49), which corresponds to an increase of safety as the speed drop between adjacent road segments diminishes. If we compare network-wide traffic performance measures with Dynamic Speed Limits with the baseline condition (Table 7-15 and Figure 7-50), we can notice that it produces a slight decrease of throughput with some decrease of the overall speed. In summary, the results show that in a condition in which there are several localized bottlenecks along the corridor this ATDM strategy reduces the speed drops, with an increase of safety at the price of a little increase of the overall travel time.

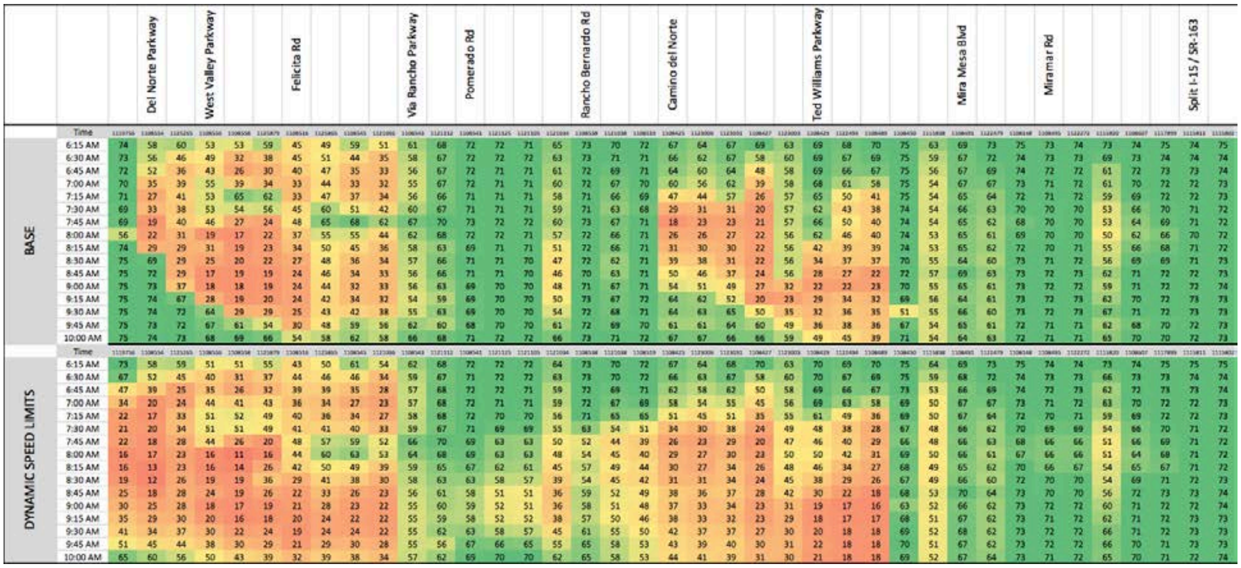


Figure 7-49: Speed contour with Dynamic Speed Limits compared with the baseline case under Operational Condition 1 [Source: TSS]

Table 7-15: Performance measures with Dynamic Speed Limits compared with the baseline case under Operational Condition 1

Network Statistics	Base	Dynamic Speed Limit	Difference
Vehicles Miles Travelled (miles)	2,320,947	2,295,970	-1.1%
Total Travel Time (h)	61,946	63,713	2.9%
Passenger Hourly Travel Time (h)	78,635	80,972	3.0%
VMT/VHT (mi/h)	37.47	36.04	-3.8%

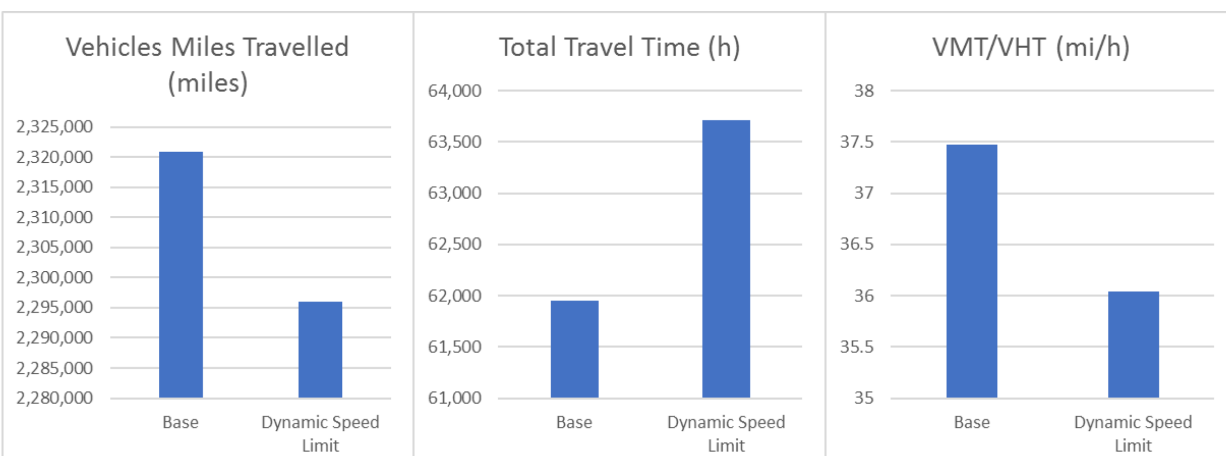


Figure 7-50: Performance measures with Dynamic Speed Limits compared with the baseline case under Operational Condition 1 [Source: TSS]

Operational condition 2 (AM2)

A comparison of the speed contour on I-15 in the southbound direction with the baseline conditions shows that Dynamic Speed Limits produce a “dilution” of the congestion over space and time (Figure 7-51), which corresponds to an increase of safety as the speed drop between adjacent road segments diminishes.

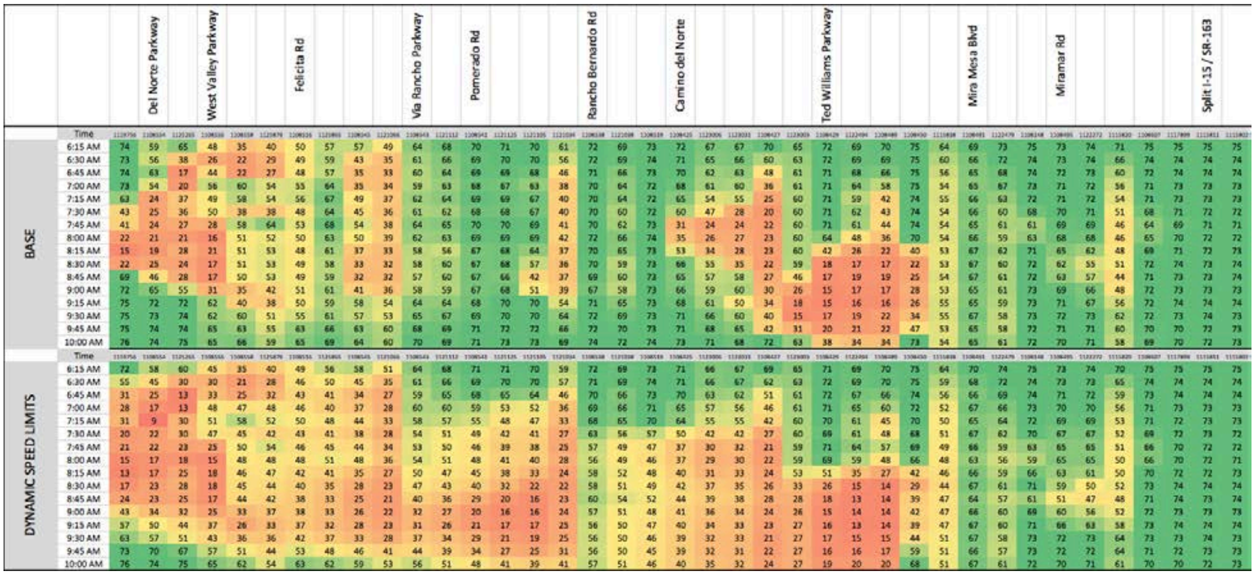


Figure 7-51: Speed contour with Dynamic Speed Limits compared with the baseline case under Operational Condition 2 [Source: TSS]

If we compare network-wide traffic performance measures with Dynamic Speed Limits with the baseline condition (Table 7-16 and Figure 7-52), we can notice that it produces a slight decrease of throughput with some decrease of the overall speed. In summary, as in the previous operational condition, the results show that in a condition in which there are several localized bottlenecks along the corridor this ATDM strategy reduces the speed drops, with an increase of safety at the price of a little increase of the overall travel time.

Table 7-16: Performance measures with Dynamic Speed Limits compared with the baseline case under Operational Condition 2

Network Statistics	Base	Dynamic Speed Limit	Difference
Vehicles Miles Travelled (miles)	2,304,353	2,281,850	-1.0%
Total Travel Time (h)	61,509	63,446	3.1%
Passenger Hourly Travel Time (h)	78,853	81,278	3.1%
VMT/VHT (mi/h)	37.46	35.97	-4.0%

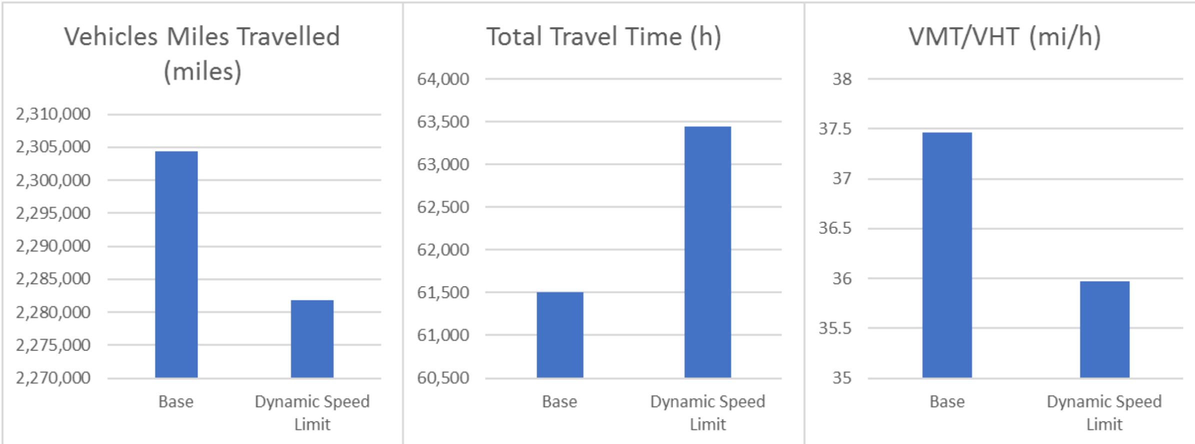


Figure 7-52: Performance measures with Dynamic Speed Limits compared with the baseline case under Operational Condition 2 [Source: TSS]

Operational condition 3 (PM3)

A comparison of the speed contour on I-15 in the northbound direction with the baseline conditions shows that Dynamic Speed Limits produce a “dilution” of the congestion over space and time (Figure 7-53), which corresponds to an increase of safety as the speed drop between adjacent road segments diminishes. If we compare network-wide traffic performance measures with Dynamic Speed Limits with the baseline condition (Table 7-17 and Figure 7-54), we can notice that it produces a little decrease of throughput with some decrease of the overall speed. In summary, the results show that in a condition in which there is high congestion throughout the corridor this ATDM strategy reduces the speed drops, with an increase of safety at the price of an increase of the overall travel time.

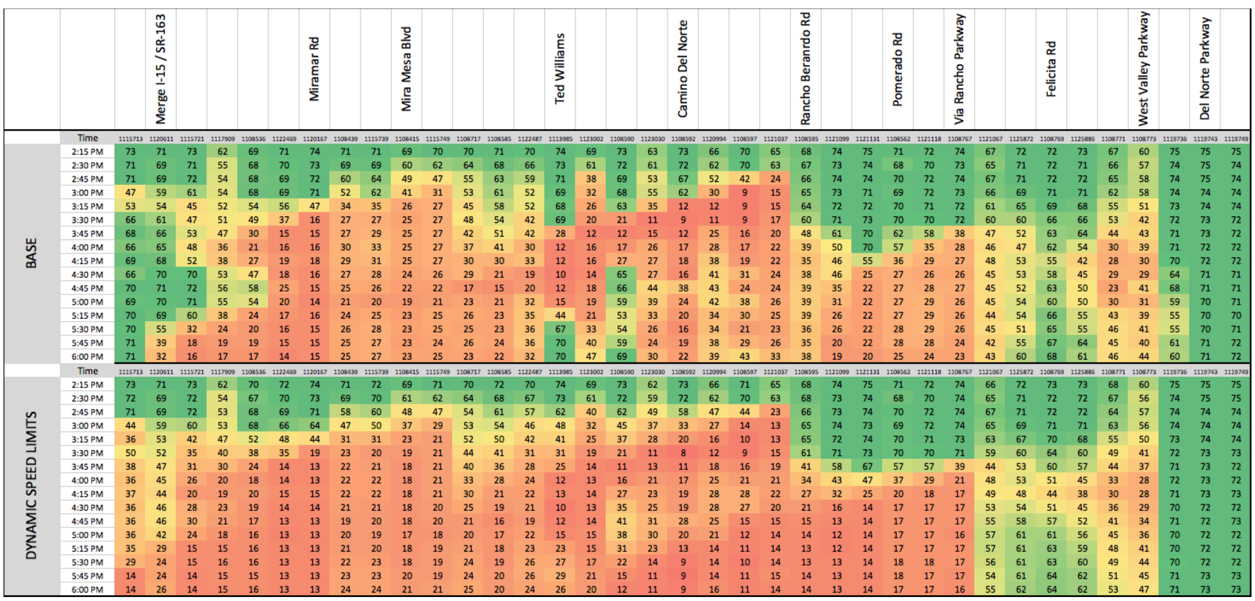


Figure 7-53: Speed contour with Dynamic Speed Limits compared with the baseline case under Operational Condition 3 [Source: TSS]

Table 7-17: Performance measures with Dynamic Speed Limits compared with the baseline case under Operational Condition 3

Network Statistics	Base	Dynamic Speed Limit	Difference
Vehicles Miles Travelled (miles)	2,518,604	2,447,851	-2.8%
Total Travel Time (h)	76,531	77,953	1.9%
Passenger Hourly Travel Time (h)	99,052	100,604	1.6%
VMT/VHT (mi/h)	32.91	31.40	-4.6%

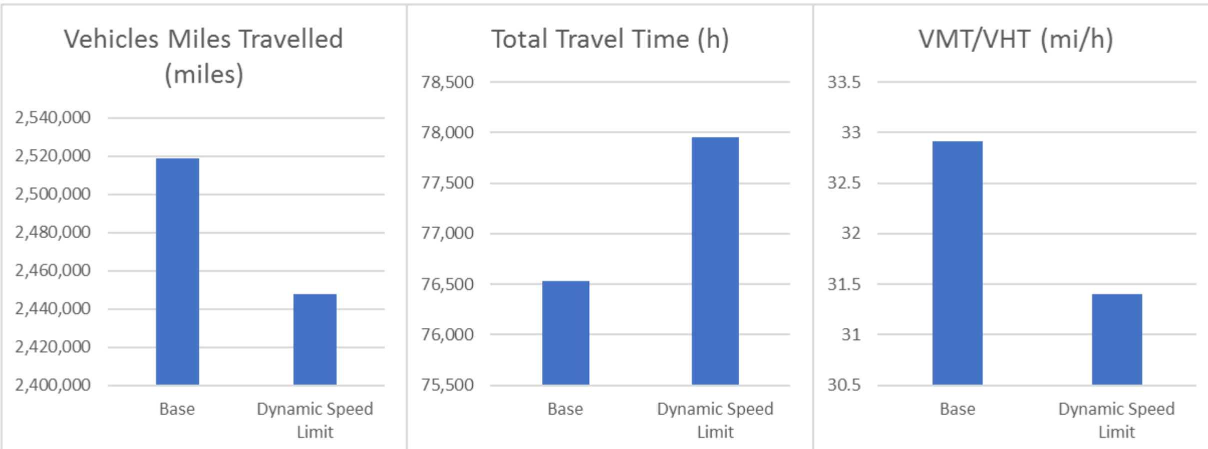


Figure 7-54: Performance measures with Dynamic Speed Limits compared with the baseline case under Operational Condition 3 [Source: TSS]

Operational condition 4 (PM4)

A comparison of the speed contour on I-15 in the northbound direction with the baseline conditions shows that Dynamic Speed Limits produce a “dilution” of the congestion over space and time (Figure 7-55), which corresponds to an increase of safety as the speed drop between adjacent road segments diminishes.

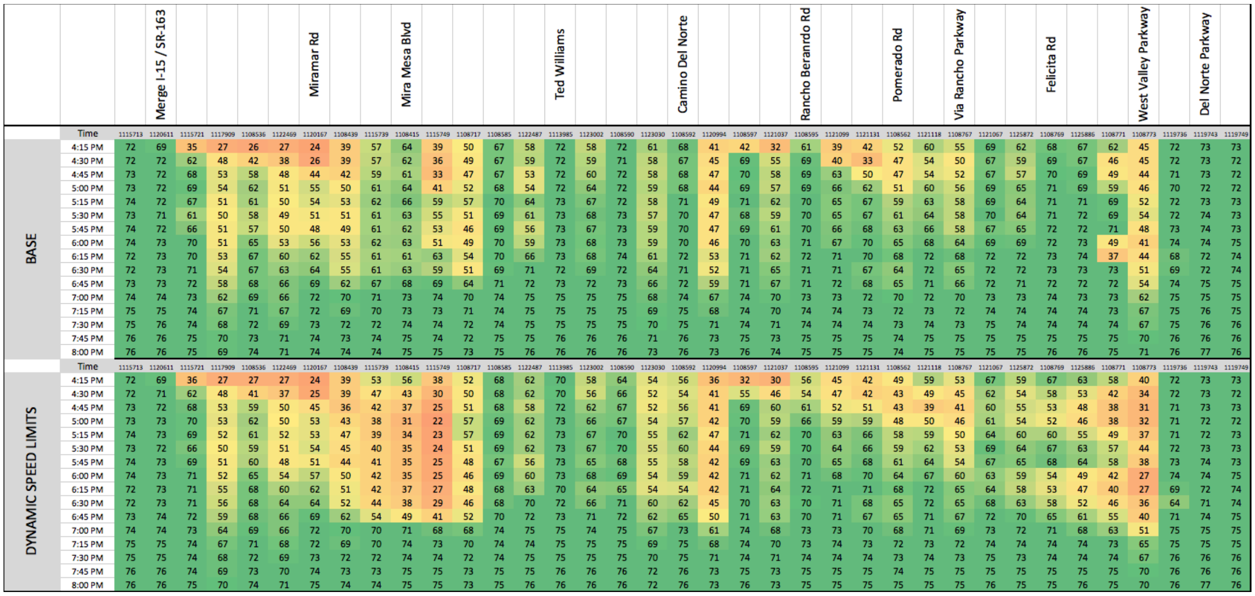


Figure 7-55: Speed contour with Dynamic Speed Limits compared with the baseline case under Operational Condition 4 [Source: TSS]

If we compare network-wide traffic performance measures with Dynamic Speed Limits with the baseline condition (Table 7-18 and Figure 7-56), we can notice that it doesn't affect the throughput but produces a slight decrease of the overall speed.

Table 7-18: Performance measures with Dynamic Speed Limits compared with the baseline case under Operational Condition 4

Network Statistics	Base	Dynamic Speed Limit	Difference
Vehicles Miles Travelled (miles)	2,302,897	2,302,937	0.0%
Total Travel Time (h)	57,547	58,476	1.6%
Passenger Hourly Travel Time (h)	75,856	76,910	1.4%
VMT/VHT (mi/h)	40.02	39.38	-1.6%

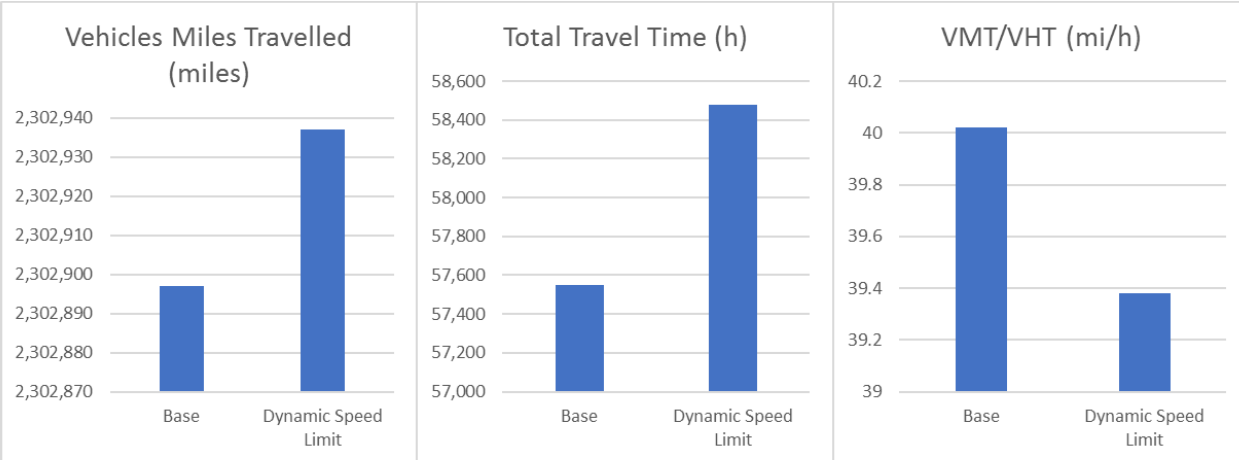


Figure 7-56: Performance measures with Dynamic Speed Limits compared with the baseline case under Operational Condition 4 [Source: TSS]

In summary, the results show that in a condition in which there is little congestion throughout the corridor this ATDM strategy reduces the speed drops, with an increase of safety at the price of a slight increase of the overall travel time.

Comparison Between Operational Conditions

Dynamic Speed Limits reduce the speed change between consecutive road segments, at the expense of reducing the overall speed along the corridor. With little congestion, the impact in terms of increase of delay is negligible, while as congestion increases the increase of delay increases, too, and is coupled with a slight decrease of throughput.

It's worth noting that the Dynamic Speed Limits algorithm that has been adopted for this evaluation is not recent nor very sophisticated. It is therefore expected that other algorithms could produce different results. However, studies available in literature show that Dynamic Speed Limits are most effective when there are heavy localized bottlenecks, in which case they can produce benefits in terms of travel time in addition to safety, while when congestion is distributed over a long segment they can produce an increase of travel time.

7.6.3 Dynamic Merge Control

Since the only location that has been selected to test Dynamic Merge Control is at the entrance into I-15 from SR-78 in the southbound direction, this ATDM strategy has been assessed only under the two operational conditions in which the prevailing traffic demand is in the southbound direction: AM1 and AM2.

The simulations were run with the rightmost lane of I-15 upstream of the ramp from SR-78 closed throughout the analysis interval (see Section 0), rather than activating the closure based on traffic conditions, because during the whole period traffic from I-15 is constantly high, so there is no simple rule to define when it should be penalized to favor the entrance from SR-78. Additionally, this setting allows assessing the maximum impact of this ATDM strategy.

Operational condition 1 (AM1)

A comparison of the speed contour on I-15 in the southbound direction with the baseline conditions shows that the Dynamic Merge Control produces an increase of congestion upstream of the location where it is applied (Figure 7-57). This is intuitive because this strategy closes one lane on I-15 at that location.

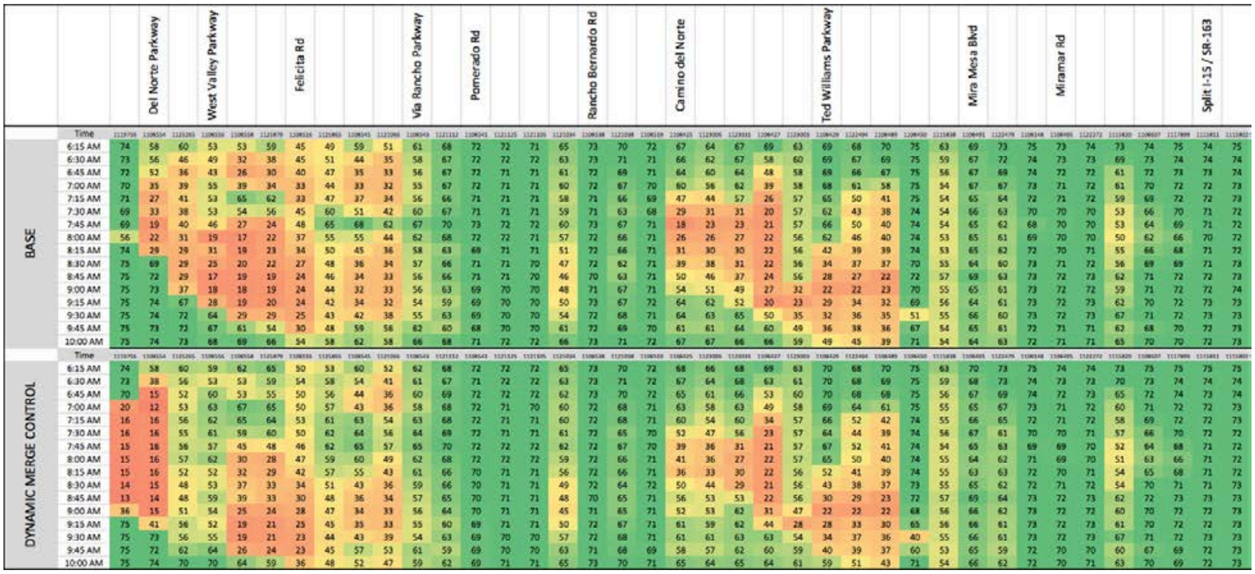


Figure 7-57: Speed contour with Dynamic Merge Control compared with the baseline case under Operational Condition 1 [Source: TSS]

If we compare network-wide traffic performance measures with Dynamic Merge Control with the baseline condition (Table 7-19 and Figure 7-58), we can notice an almost negligible decrease of throughput with a slight increase of travel time.

Table 7-19: Performance measures with Dynamic Merge Control compared with the baseline case under Operational Condition 1

Network Statistics	Base	Dynamic Merge Control	Difference
Vehicles Miles Travelled (miles)	2,320,947	2,315,264	-0.2%
Total Travel Time (h)	61,946	65,191	5.2%
Passenger Hourly Travel Time (h)	78,635	83,511	6.2%
VMT/VHT (mi/h)	37.47	35.52	-5.2%

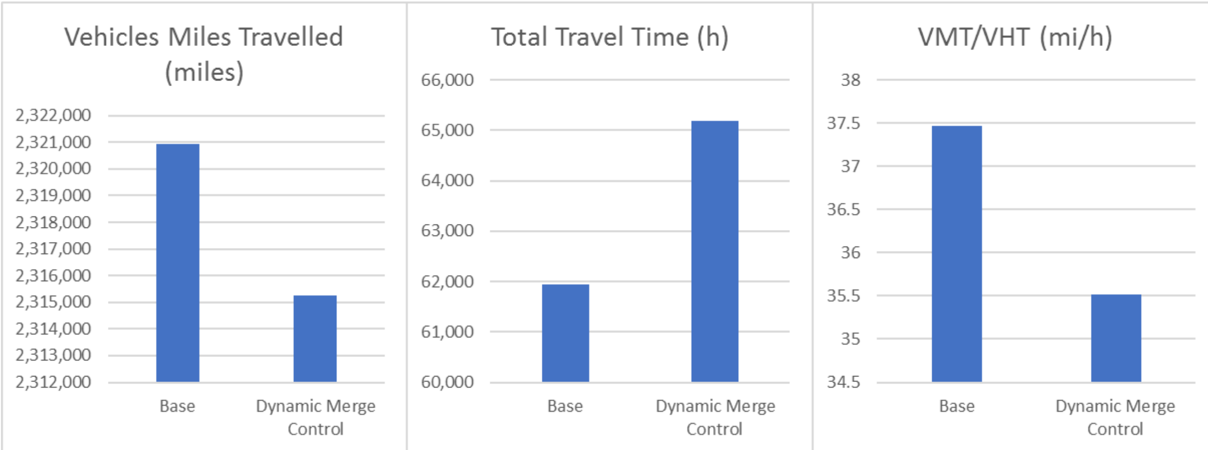


Figure 7-58: Performance measures with Dynamic Merge Control compared with the baseline case under Operational Condition 1 [Source: TSS]

If we look at the total count over the analysis period at the merge, on the upstream road section of I-15 and on the ramp coming from SR-78 (Table 7-20) we can notice that Dynamic Merge Control leaves the throughput of the merge essentially unchanged, but redistributes the inflow differently between I-15 and SR-78, promoting the entrance from the latter.

Table 7-20: Throughput at the merge with Dynamic Merge Control compared with the baseline case under Operational Condition 1

Total Count (veh)	*Base*	*Dynamic Merge Control*	*Difference*
Merging Section	35,551	34,838	-713
I-15 Upstream Section	23,669	21,981	-1688
SR-78 Ramp	11,867	12,841	974

In summary, the results show a slightly negative effect in terms of traffic performance caused by Dynamic Merge Control, which facilitates the entrance from SR-78, at the expense of penalizing traffic coming from the northern boundary of the I-15 corridor in the southbound direction.

Operational condition 2 (AM2)

A comparison of the speed contour on I-15 in the southbound direction with the baseline conditions shows that the Dynamic Merge Control produces a slight increase of congestion upstream of the location where it is applied (Figure 7-59). This is intuitive because this strategy closes one lane on I-15 at that location.

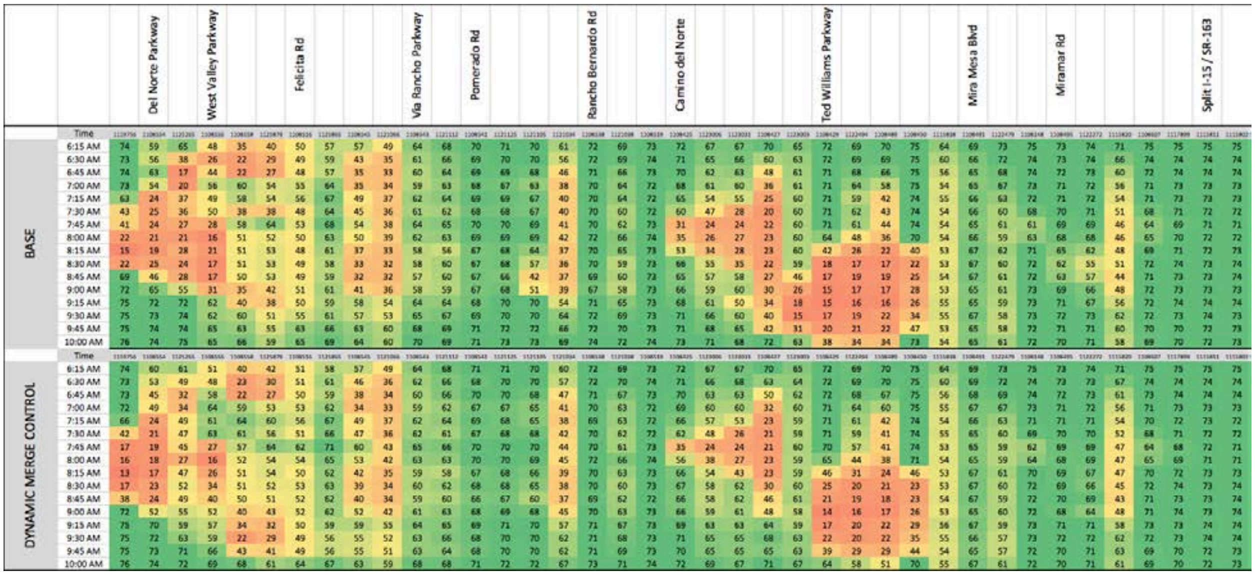


Figure 7-59: Speed contour with Dynamic Merge Control compared with the baseline case under Operational Condition 2 [Source: TSS]

If we compare network-wide traffic performance measures with Dynamic Merge Control with the baseline condition (Table 7-21 and Figure 7-60), we can notice no change of throughput with a slight increase of travel time.

Table 7-21: Performance measures with Dynamic Merge Control compared with the baseline case under Operational Condition 2

Network Statistics	Base	Dynamic Merge Control	Difference
Vehicles Miles Travelled (miles)	2,304,353	2,305,441	0.0%
Total Travel Time (h)	61,509	64,540	4.9%
Passenger Hourly Travel Time (h)	78,853	82,905	5.1%
VMT/VHT (mi/h)	37.46	35.72	-4.7%

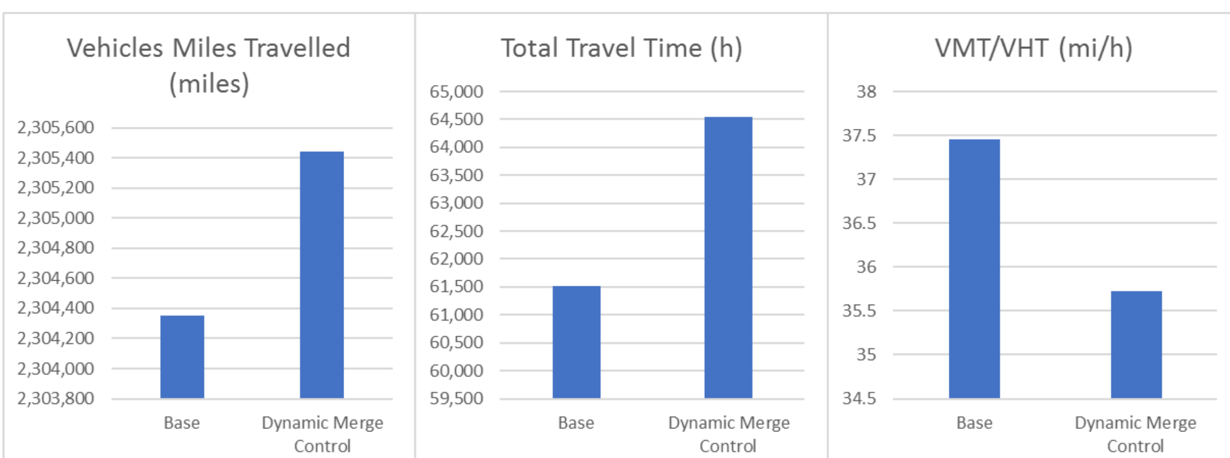


Figure 7-60: Performance measures with Dynamic Merge Control compared with the baseline case under Operational Condition 2 [Source: TSS]

If we look at the total count over the analysis period at the merge, on the upstream road section of I-15 and on the ramp coming from SR-78 (Table 7-22) we can notice that Dynamic Merge Control leaves the throughput of the merge essentially unchanged, but redistributes the inflow differently between I-15 and SR-78, promoting the entrance from the latter.

Table 7-22: Throughput at the merge with Dynamic Merge Control compared with the baseline case under Operational Condition 2

Total Count (veh)	Base	Dynamic Merge Control	Difference
Merging Section	33,899	33,813	-87
I-15 Upstream Section	22,157	21,842	-316
SR-78 Ramp	11,723	11,955	232

In summary, the results show a slightly negative effect in terms of traffic performance caused by Dynamic Merge Control, which facilitates the entrance from SR-78, at the expense of penalizing traffic coming from the northern boundary of the I-15 corridor in the southbound direction.

Comparison Between Operational Conditions

Dynamic Merge Control facilitates the entrance from SR-78, at the expense of penalizing traffic coming from the northern boundary of the I-15 corridor in the southbound direction. Under both operational conditions the traffic coming from I-15 is constantly high, and higher than that coming from SR-78, so there is no evident benefit from the activation of this ATDM strategy. It is expected however than when the southbound I-15 traffic gets lower, this strategy will have positive overall impact on the corridor, because it will reduce conflicts at the merge.

7.6.4 Predictive Traveler Information with Dynamic Routing

A simulation framework to produce simulation-based travel time predictions was built. This framework emulates the ICM capabilities provided by Aimsun Online in reality. It was used to test how vehicles would reroute if having access to predictive travel time information with two time horizons: 15 and 30 minutes. Considering that in the I-15 corridor an ICM application that predicts travel times is already in existence, and that the baseline scenario features response plans that have been activated based on it, the comparison between baseline and Predictive Traveler Information with Dynamic Routing should be considered to validate the capability of the Predictive Traveler Information testing framework of reproducing the real ICM application.

In addition to the baseline conditions, the performance of this application has been compared with the do-nothing scenario, which consists in the baseline case without any response plan applied. This comparison evaluates the effectiveness of Predictive Traveler Information with respect to a situation without any predictive capabilities.

Operational condition 1 (AM1)

An analysis of the speed contour on I-15 in the southbound direction shows that the Predictive Traveler Information produces no significant difference in terms of congestion both compared to do-nothing and to the baseline (Figure 7-61). The red row/column indicates the temporal-spatial location of congestion. If we compare network-wide (freeway + arterials) traffic performance measures with Predictive Traveler Information with the do-nothing and the baseline condition (Table 7-23), we can notice that the difference with the baseline is negligible and that, probably because of rerouting, there is a slight increase of travel time and distance travelled compared with do-nothing. The difference is higher with the longer prediction horizon.

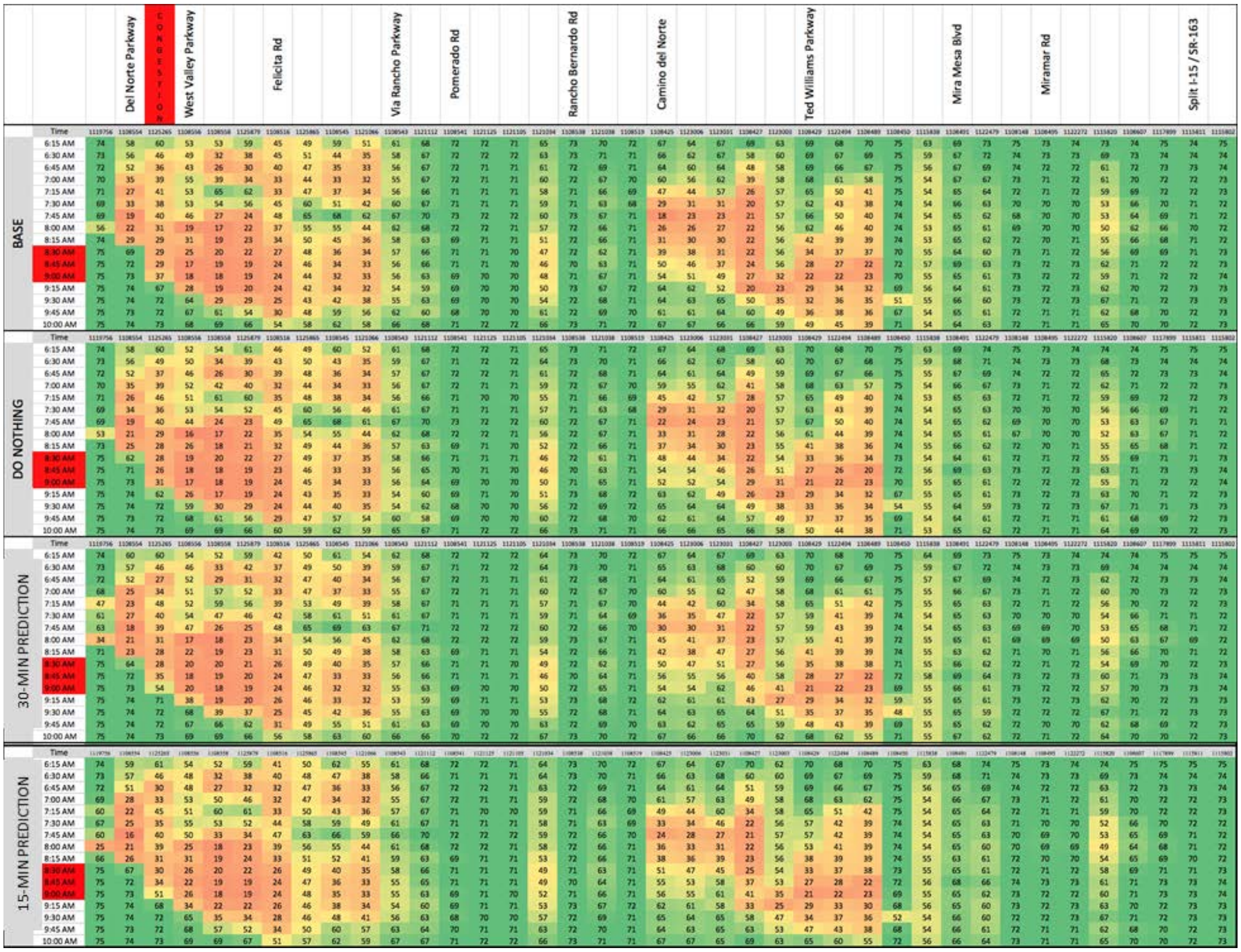


Figure 7-61: Speed contour with Predictive Traveler Information compared with the do-nothing and the baseline case under Operational Condition 1 [Source: TSS]

Table 7-23: Performance measures with Predictive Traveler Information with 30 min prediction horizon compared with the do-nothing and the baseline case under Operational Condition 1

Network Statistics	Predictive	Do Nothing	Difference	Base	Difference
Vehicles Miles Travelled (miles)	2,321,980	2,305,327	0.7%	2,320,947	0.0%
Total Travel Time (h)	62,128	60,912	2.0%	61,946	0.3%
Passenger Hourly Travel Time (h)	79,053	78,172	1.1%	78,635	0.5%
VMT/VHT (miles/h)	37.37	37.85	-1.3%	37.47	-0.2%

Table 7-24: Performance measures with Predictive Traveler Information with 15 min prediction horizon compared with the do-nothing and the baseline case under Operational Condition 1

Network Statistics	Predictive	Do Nothing	Difference	Base	Difference
Vehicles Miles Travelled (miles)	2,322,078	2,305,327	0.7%	2,320,947	0.0%
Total Travel Time (h)	61,920	60,912	1.7%	61,946	0.0%
Passenger Hourly Travel Time (h)	78,727	78,172	0.7%	78,635	0.1%
VMT/VHT (miles/h)	37.50	37.85	-0.9%	37.47	0.1%

Operational condition 2 (AM2)

An analysis of the speed contour on I-15 in the southbound direction shows that the Predictive Traveler Information produces a slight reduction of some congestion points both compared to do-nothing and to the baseline (Figure 7-62). The red row/column indicates the temporal-spatial location of incidents. The reduction is more significant with the longer prediction horizon.

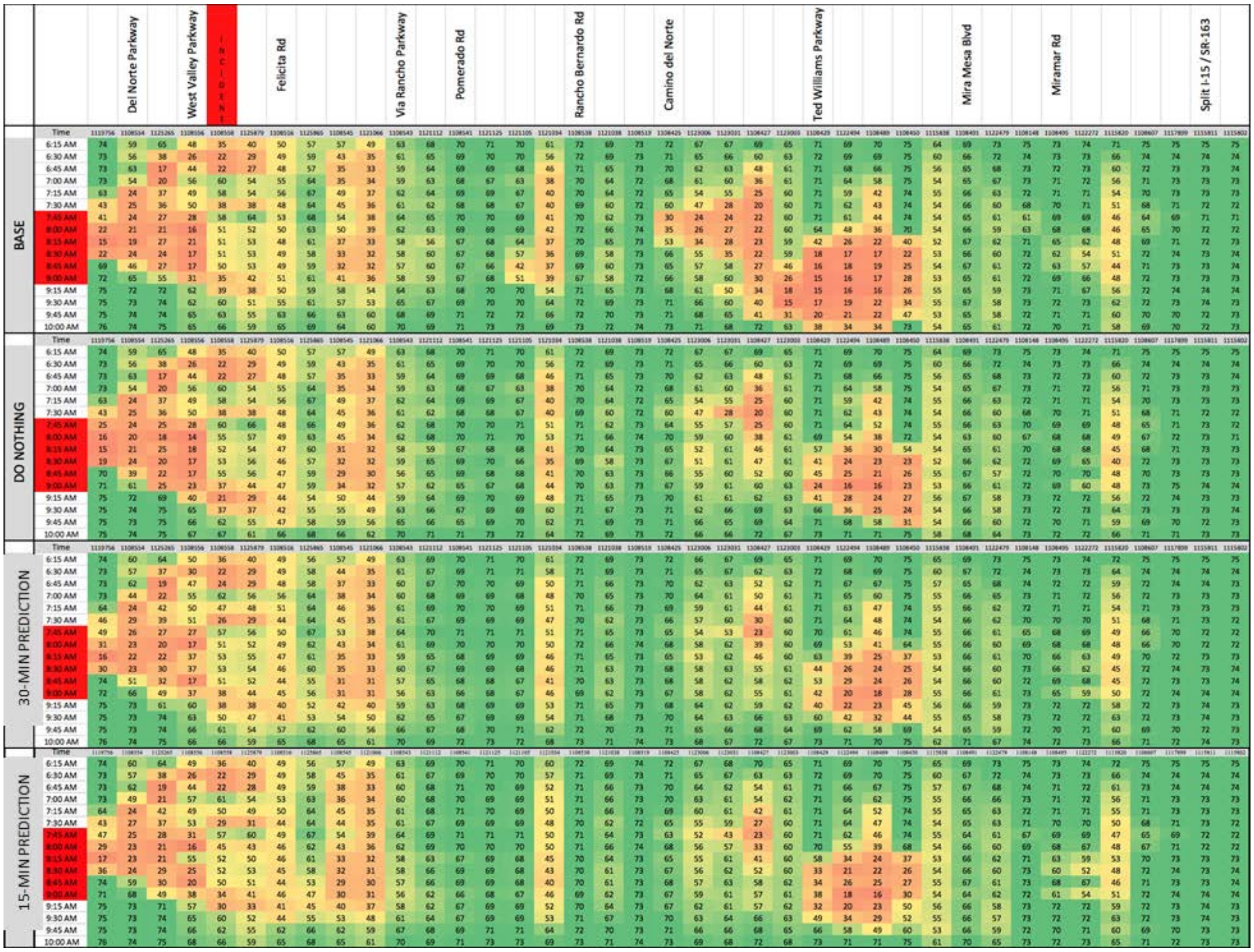


Figure 7-62: Speed contour with Predictive Traveler Information compared with the do-nothing and the baseline case under Operational Condition 2 [Source: TSS]

If we compare network-wide traffic performance measures with Predictive Traveler Information with the do-nothing and the baseline condition (Table 7-25 and Table 7-26), we can notice that the difference with the baseline is negligible and that there is a slight increase of travel time with similar distance travelled compared with do-nothing. The difference is similar with both prediction horizons.

Table 7-25: Performance measures with Predictive Traveler Information with 30 min prediction horizon compared with the do-nothing and the baseline case under Operational Condition 2

Network Statistics	Predictive	Do Nothing	Difference	Base	Difference
Vehicles Miles Travelled (miles)	2,299,074	2,305,327	-0.3%	2,304,353	-0.2%
Total Travel Time (h)	61,867	60,912	1.6%	61,509	0.6%
Passenger Hourly Travel Time (h)	79,466	78,172	1.7%	78,853	0.8%

VMT/VHT (miles/h)	37.16	37.85	-1.8%	37.46	-0.8%

Table 7-26: Performance measures with Predictive Traveler Information with 15 min prediction horizon compared with the do-nothing and the baseline case under Operational Condition 2

Network Statistics	Predictive	Do Nothing	Difference	Base	Difference
Vehicles Miles Travelled (miles)	2,300,027	2,305,327	-0.2%	2,304,353	-0.2%
Total Travel Time (h)	61,773	60,912	1.4%	61,509	0.4%
Passenger Hourly Travel Time (h)	79,267	78,172	1.4%	78,853	0.5%
VMT/VHT (miles/h)	37.23	37.85	-1.6%	37.46	-0.6%

Operational condition 3 (PM3)

An analysis of the speed contour on I-15 in the northbound direction shows that the Predictive Traveler Information produces no significant difference in terms of congestion both compared to do-nothing and to the baseline (Figure 7-63). The red row/column indicates the temporal-spatial location of incidents.

Figure 7-63: Speed contour with Predictive Traveler Information compared with the do-nothing and the baseline case under Operational Condition 3 [Source: TSS]

If we compare network-wide traffic performance measures with Predictive Traveler Information with the do-nothing and the baseline condition (Table 7-27 and Table 7-28), we can notice that the difference with the baseline is negligible and that there is a slight decrease of travel time with similar distance travelled compared with do-nothing. The difference is similar with both prediction horizons.

Table 7-27: Performance measures with Predictive Traveler Information with 30 min prediction horizon compared with the do-nothing and the baseline case under Operational Condition 3

Network Statistics	Predictive	Do Nothing	Difference	Base	Difference
Vehicles Miles Travelled (miles)	2,525,928	2,536,662	-0.4%	2,518,604	0.3%
Total Travel Time (h)	76,612	77,486	-1.1%	76,531	0.1%
Passenger Hourly Travel Time (h)	99,168	100,193	-1.0%	99,052	0.1%
VMT/VHT (miles/h)	32.97	32.74	0.7%	32.91	0.2%

Table 7-28: Performance measures with Predictive Traveler Information with 15 min prediction horizon compared with the do-nothing and the baseline case under Operational Condition 3

Network Statistics	Predictive	Do Nothing	Difference	Base	Difference
Vehicles Miles Travelled (miles)	2,536,005	2,536,662	0.0%	2,518,604	0.7%
Total Travel Time (h)	76,378	77,486	-1.4%	76,531	-0.2%
Passenger Hourly Travel Time (h)	98,927	100,193	-1.3%	99,052	-0.1%
VMT/VHT (miles/h)	33.20	32.74	1.4%	32.91	0.9%

Operational condition 4 (PM4)

An analysis of the speed contour on I-15 in the northbound direction shows that the Predictive Traveler Information produces no significant difference in terms of congestion both compared to do-nothing and to the baseline (Figure 7-64).

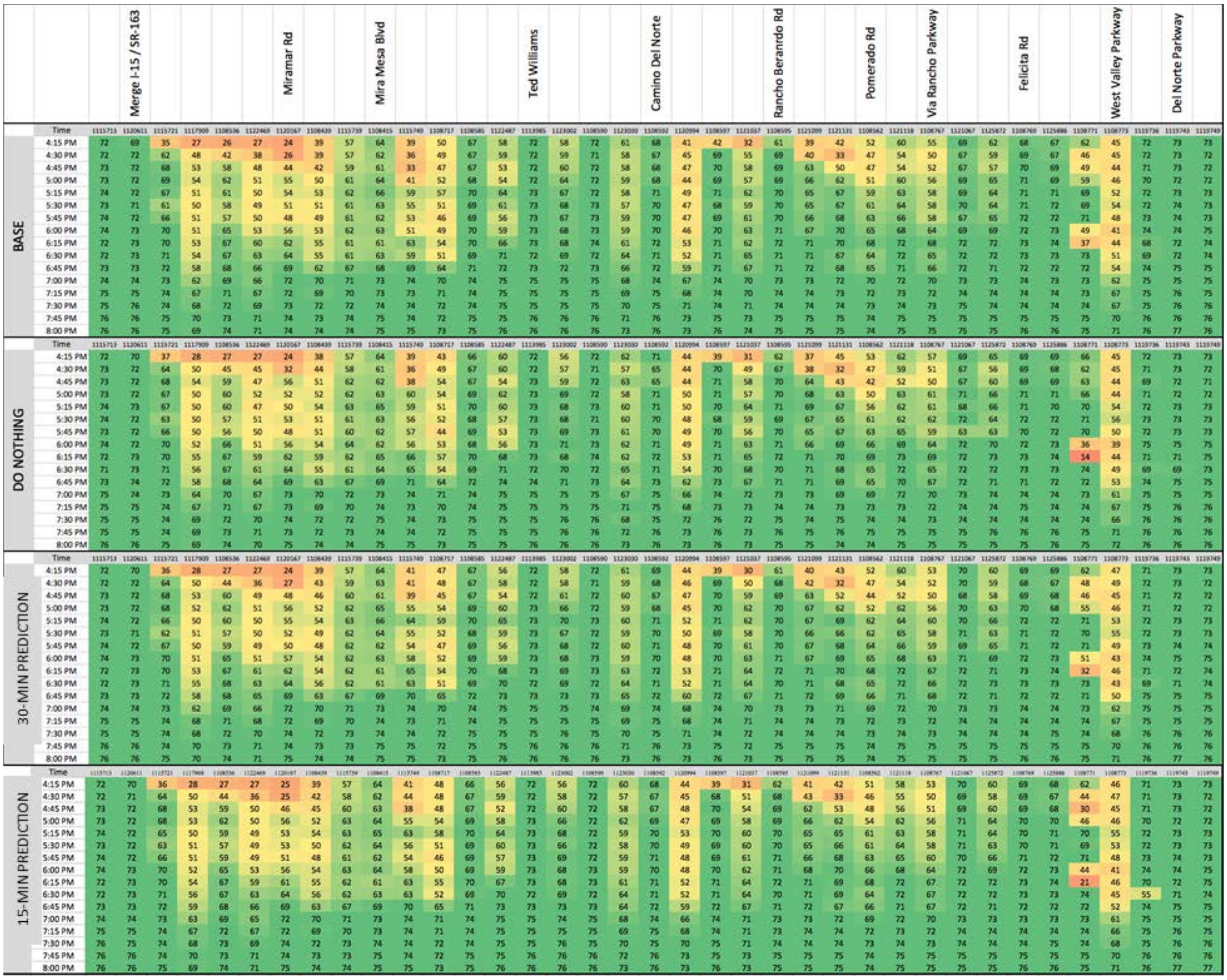


Figure 7-64: Speed contour with Predictive Traveler Information compared with the do-nothing and the baseline case under Operational Condition 4 [Source: TSS]

If we compare network-wide traffic performance measures with Predictive Traveler Information with the do-nothing and the baseline condition (Table 7-29 and Table 7-30), we can notice that the difference with both the baseline and the do-nothing case is negligible with both prediction horizons.

Table 7-29: Performance measures with Predictive Traveler Information with 30 min prediction horizon compared with the do-nothing and the baseline case under Operational Condition 4

Network Statistics	Predictive	Do Nothing	Difference	Base	Difference
Vehicles Miles Travelled (miles)	2,303,573	2,309,503	-0.3%	2,302,897	0.0%
Total Travel Time (h)	57,523	57,576	-0.1%	57,547	0.0%
Passenger Hourly Travel Time (h)	75,870	75,909	-0.1%	75,856	0.0%
VMT/VHT (miles/h)	40.05	40.11	-0.2%	40.02	0.1%

Table 7-30: Performance measures with Predictive Traveler Information with 15 min prediction horizon compared with the do-nothing and the baseline case under Operational Condition 4

Network Statistics	Predictive	Do Nothing	Difference	Base	Difference
Vehicles Miles Travelled (miles)	2,303,303	2,309,503	-0.3%	2,302,897	0.0%
Total Travel Time (h)	57,607	57,576	0.1%	57,547	0.1%
Passenger Hourly Travel Time (h)	75,987	75,909	0.1%	75,856	0.2%
VMT/VHT (miles/h)	39.98	40.11	-0.3%	40.02	-0.1%

Comparison between operational conditions

A comparison of the speed contours, which focus on the performance of the I-15 corridor, under different operational conditions and different prediction horizons shows that Predictive Traveler Information is more effective with higher demand and with more severe incidents: AM2, which has several bottlenecks scattered throughout the corridor, shows the highest reduction of congestion, even with the shorter prediction horizon; AM1, which has a similar congestion pattern but a less severe incident, shows a slightly less improvement. PM4, which has no significant congestion, shows no significant effect.

If we look at the traffic performance measures, which adopt a network-wide perspective, we can notice that in some operational condition the positive impact on the speed along the I-15 corridor is in fact counterbalanced by an overall slight increase in network-wide travel time.

7.7 Results Summary

In this Chapter, the ATDM strategies are evaluated consider the different main operational conditions identified for the Dallas Testbed. The measures of performance results are presented for the entire network, US-75 northbound, and US-75 southbound. Two main observations can be made based on these results. First, the ATDM response plans generally reduce the congestion associated with the incident most operation conditions texted. Second, the savings in total travel time for the entire network is generally consistent with the savings in the US-75 freeway facility in both directions implying that the schemes reduce the congestion on the freeway while maintaining good level of service across the entire network.

In addition, a set of experiments is designed to evaluate the network performance with deploying ATDM strategies under different operational conditions. The developed ATDM strategy is a combination of dynamic routing and dynamic signal timing. The results show the ATDM strategies is successful to improve the network performance for three operational conditions. However, in operational condition three, the developed ATDM strategy worsens the network performance. This can be explained with the fact that the mentioned strategy is not a suitable strategy for this operational condition, and the network performance might be improved with considering the other ATDM strategies. In addition, the results demonstrate the corridor performance for different operational conditions which is consistent for the results for the entire network.

The effectiveness of the ATDM strategies in reducing the network congestion associated with adverse weather conditions is also examined. Traffic management schemes that combine the dynamic routing strategy and the dynamic signal timing strategy are considered in the analysis. Based on the obtained simulation results, the traffic management system helps in alleviating the network congestion due to the adverse weather. Travel time savings of 163,480 minutes and 84,913 minutes were recorded for two different scenarios of weather impacts on the traffic flow, namely, reduced free-flow speed and a combination of reduced free-flow speed and jam density.

The performance of ATDM strategies is examined considering a hypothetical evacuation scenario. A demand scenario is created in which evacuees are traveling from their work places to a pre-defined set of safe destinations in the northern section of the corridor. Different combinations of ATDM strategies are implemented to evaluate their effectiveness in reducing the congestion associated with the evacuation scenario. These strategies include demand management, dynamic signal timing, traveler information provision, dynamic shoulder lane, and tidal flow operation. The results indicate that effective demand management and the dynamic shoulder lane could significantly reduce the congestion associated with the evacuation process.

A set of analysis was performed to evaluate dynamic parking strategies. The analysis varies in percentage of the travelers who need parking, number of parking lots, the time window of travelers for possible change in departure time, and threshold savings for the travelers. The results of analysis for dynamic parking strategies show the overall improvement on the entire network performance. Increasing the number of parking lots and extending the time window for possible change in the travelers' departure time provide more total network travel time in the network. There is significant saving in the total network travel time only with considering the change in the travelers' mode choice. The saving of 140,832 minutes is recorded for scenario S7 with three available parking lots which the travelers do not have the option to change their departure times, but they can shift to transit. This saving is increased to 155,779 minutes in scenario S8 with 11 available parking lots and similar conditions to scenario S7.

For the Phoenix Testbed, Adaptive Ramp Metering and Adaptive Signal Control (as well as their combination) works the best under High Demand, Medium Incident Severity and Wet Weather condition. Under Low Demand and Low Incident Severity, Adaptive Signal Control showed least improvement in travel time. Similarly, High Demand and Low Incident Severity showed least improvement in travel time when Dynamic Route Guidance was implemented with Predictive Traveler Information.

The Pasadena testbed was analyzed using a total of three different operational condition. The prediction parameters that were identified as sensitive for each strategy for prediction were further assessed for operational conditions 2 and 3. For ARM, prediction horizon and prediction latency were assessed as sensitive parameters. The increase in prediction horizon for ARM shows a higher rate of improvement for OC 3 which has the highest freeway congestion, followed by OC 1 which has the second highest freeway congestion, and finally OC 2 which has the lowest. Prediction horizon for ARM shows close correlation with the freeway congestion. For prediction latency, the results show consistently a network travel time savings degradation for all three operational conditions under longer prediction latency.

The best strategies for freeway segment also prove to be the most effective ones for the arterial roads under most operational conditions. OC 4, a snow-affected low demand scenario, is the only exceptional case. It is because the arterial roads have fewer lanes than the freeway. As discussed in section 7.3, it was assumed the snowplow would block one lane during service. That leads to a 50% capacity loss during plowing operation for the arterial roads with two lanes. However, the freeway segments have more lanes, and it is more resilient to the negative impact of the plowing operation. Therefore, the Weather-related strategy may bring more negative impact on the arterial road than the freeway segment. For DSC, the identified sensitive prediction parameter is prediction accuracy. The network travel time shows negative travel time savings for cases where the prediction accuracy falls to 50%. For HSR + DJC strategy, there were no prediction parameters that were identified as sensitive. Comparing the travel time savings for each operational condition, OC 3 which has the highest freeway congestion yields the highest travel time savings, followed by OC 1 which has the second highest freeway congestion, followed by OC 2. There is a strong correlation of travel time savings between freeway focused strategies with freeway level of congestion. For DSL + QW strategy, there is no prediction parameter because TRANSIMS is not used to evaluate this strategy. This strategy only differs with traveler compliance parameter. The trends show that with the increase in traveler compliance, the difference in both spatial and temporal speed difference on the freeway is reduced. The trends for the temporal speed difference for OC3 which has the highest freeway congestion shows very small reduction in temporal speed difference due to the oversaturated freeway. The reduction in spatial and temporal speed difference yields safety improvements by reducing abrupt changes in speeds by distributing them over a longer segment of the freeway. The dispersion of congestion also reduces the overall network travel time savings. Finally, the prediction parameter identified as sensitive for DRG prediction is traveler compliance. The results show very small changes from the baseline results when traveler compliance is at 20% but there is a reduction for all operational conditions compared to when traveler compliance is at 50%. The small changes when traveler compliance is at 20% can be considered negligible because only a small fraction of traffic on the arterial entering the freeway is being rerouted due to fewer vehicles complying with route guidance recommendations.

For the Chicago Testbed, it can be concluded that ADM provides the most benefits for operational conditions without snow effect, i.e. clear day and rain-to-snow day. The weather-related strategy generates the most benefits for snow-affected and high demand operational conditions. The ADM strategy yields the most improvement for the snow-affected and low demand operational conditions or the incident-mixed snow scenario. If the strategy is implemented for the entire horizon or within some specific period, like the afternoon peak hours with an incident, it provides the most benefit to the corridor.

The dynamic snowplow routing plan may be less preferred than the static routing plan under low demand (off peak hours) operational conditions when the network is less congested. In order to serve the most important links first, the dynamic plan has more deadheading trips. These deadheading trips would reduce the link capacity and impose a negative impact to the traffic. Under the low demand, less congested scenarios, the benefit generated by the dynamic plan might be offset by the negative impact associated with the extra deadheading trips. One should pay close attention to the operational conditions when select which plan to deploy.

For the San Diego Testbed, Dynamic Lane Use and Dynamic HOV/Managed Lanes are effective only in congested situations. Additionally, the location of incidents and bottlenecks may reduce the effectiveness of this ATDM strategy, because if the congestion caused by them affects the access points to the HOV lanes, vehicles have difficulty in reaching the additional lane that allows bypassing the bottlenecks. Dynamic Speed Limits reduce the speed change between consecutive road segments, at the expense of reducing the overall speed along the corridor. With little congestion the impact in terms of increase of delay is negligible, while as congestion increases the increase of delay increases, too, and is coupled with a slight decrease of throughput. Dynamic Merge Control facilitates the entrance from SR-78, at the expense of penalizing traffic coming from the northern boundary of the I-15 corridor in the southbound direction. When the I-15 traffic is lower than that entering from SR-78, this strategy has a positive overall impact on the corridor, because it reduces conflicts at the merge. Predictive Traveler Information with Dynamic Routing is more effective with higher demand and with more severe incidents. The benefit is evident if we focus on the I-15 corridor, while if we adopt a network-wide perspective, we can notice that in some operational condition the positive impact on the speed along the I-15 corridor is in fact counterbalanced by an overall slight increase of travel time because or rerouting along the arterials.

Chapter 8. Prediction Latency, Accuracy and Coverage Trade-Offs

This chapter primarily deals with the research questions that are based on prediction-based parameters such as prediction latency and geographic coverage. Specifically, the analysis provided in this chapter answers the questions that are related to whether prediction latency and geographic coverage of prediction has significant impact on the impact of ATDM strategies.

8.1 Research Questions and Hypotheses

The following research questions are answered in this chapter:

1. What is the tradeoff between improved prediction accuracy and reduced latency with existing communications for maximum benefits?
2. What is the tradeoff between prediction accuracy and geographic coverage of ATDM deployment for maximum benefits?
3. What is the tradeoff between reduced latency (with existing communications) and geographic coverage for maximum benefits?
4. What will be the impact of increased prediction accuracy, more active management, and improved robust behavioral predictions on mobility, safety, and environmental benefits?

In order to answer these, the following hypotheses were made.

1. Incremental improvements in prediction accuracy will result in higher benefits, when latency is fixed up to a certain threshold, after which marginal benefits will be reduced and vice-versa. Maximum system benefit will be obtained at an intermediate point balancing prediction accuracy and latency.
2. Incremental improvements in prediction accuracy will result in higher benefits when geographic coverage is fixed up to a certain threshold, after which marginal benefits will be reduced and vice-versa. Maximum system benefit will be obtained at an intermediate point balancing prediction accuracy and geographic coverage.
3. Incremental improvements in latency will result in higher benefits when geographic coverage is fixed up to a certain threshold, after which marginal benefits will be reduced and vice-versa. Maximum system benefit will be obtained at an intermediate point balancing latency and geographic coverage.
4. Increases in prediction accuracy, more active management, and improvements in robust behavioral predictions will result in significant mobility, safety, and environmental benefits. ATDM strategies will reduce the impact of congestion by delaying its onset, and reducing its duration and geographic extent. ATDM strategies will impact all three characteristics of congestion (onset, duration, and extent) but different strategies will impact specific congestion characteristics differently. Traveler and system mobility measures will vary inversely with respect to congestion characteristics, but not uniformly by characteristic.

8.2 Analysis Approach and Findings

ATDM-centric testbeds were utilized to study the impacts of prediction latency and geographic coverage on ATDM Strategy performance. This chapter supplements several findings made in Chapter 6 governing prediction accuracy and active management.

8.2.1 Prediction Latency

Dallas Testbed

The results in this section illustrate the effect of the decision-making latency on the effectiveness of the generated ATDM response plans using the Dallas Testbed. Several reasons might cause the latency in deploying ATDM response plans such as delay in receiving information on the incidents, the execution time needed to evaluate the ATDM response plans, and the time needed to configure the traffic control devices to deploy the different control actions. In this set of experiments, accurate demand prediction scenarios are assumed. In addition, the developed ATDM response plans consider a combination of Dynamic Routing and Dynamic Signal Timing strategies.

Figure 8-1 provides the results of this set of experiments. As shown in the figure, the latency between the incident occurrence time and the time at which the response plan is deployed in the network is incremented from zero to 20 minutes. The zero latency indicates that the response scheme is instantaneously deployed as the incident occurred. While such implementation is not feasible in real-world applications, its results is used as a benchmark for other scenarios in which latency is occurring. The zero-delay scenario is implemented in the simulation environment by pausing the simulation clock until the optimal ATDM response plan is generated. The same technique is used to model the other scenarios with latency. For instance, to represent a scenario of ten-minute latency, the simulation clock is set to advance for ten minutes. Then, the clock is paused until the plan is generated and deployed in the network. The results in the figure illustrate the impact of the latency on the effectiveness of the generated plans as indicated by the recorded network performance. In addition, Table 8-1 gives the total network travel time savings, compared to the baseline scenario, for the different latency values. As shown in the table, promptly responding to the incident (zero latency) helps in alleviating the congestion, and achieving considerable saving in total network travel time. On the other hand, as the latency increases, the system does not respond to the congestion for longer period. By the time the plan is generated, its effectiveness in alleviating the congestion reduces. For example, a saving of 15,125 minutes is recorded for the scenario with zero latency. As the latency extends to 20-minutes, an increase in the travel time, compared to the baseline scenario, is observed implying that the scheme is no longer effective because of the change in the network conditions.

Figure 8-2 also provides the corresponding saving in the fuel consumption, while Figure 8-4 gives the results for the environmental performance measures in terms of the percentage saving in the carbon dioxide, and the percentage saving the nitrogen oxide. In addition, Table 8-2 gives a summary of the saving in fuel consumption and emissions for the different latency values. As shown in the table, saving in the fuel consumption decreases as the latency in deploying the traffic management system increases. For high latency values, the schemes could have negative effect on the amount of fuel consumption. For example, in the scenario with the zero latency a fuel consumption saving of 56.27 tons is obtained. In the scenario with 20-minutes latency worsens the savings in the fuel consumption, even worse than the baseline scenario. Similar results are obtained for the carbon dioxide and nitrogen oxide emissions as given in the table.

Table 8-1: Effect of Different Traffic Management Latencies for Dallas Testbed under Medium Demand and Low Incident Severity

Scenario Description	Total Network Travel Time Savings (minutes)
Zero Latency	15,125
10-minutes Latency	-15,527
20-minutes Latency	-43,329

Table 8-2: Total Environmental Performance for Different Values of Traffic Management Latencies for Dallas Testbed under Medium Demand and Low Incident Severity

Scenario Description	Fuel Consumption Saving (tons)	Carbon Dioxide (tons)	Nitrogen Oxide (kilograms)
Zero Latency	56.27	4.17	3.50
10-minutes Latency	-40.03	-3.07	-2.29
20-minutes Latency	-102.23	-7.84	-5.58

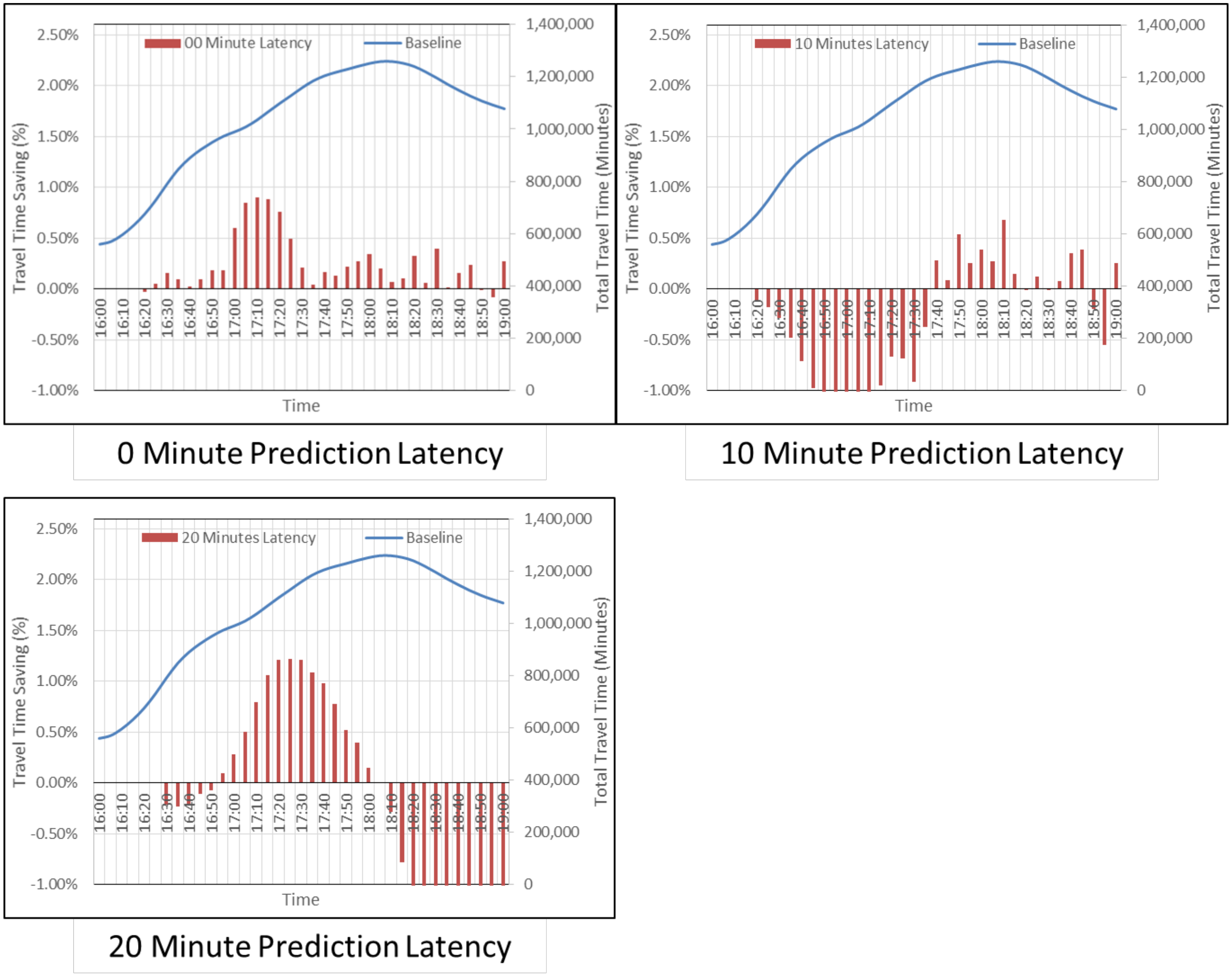


Figure 8-1: Impact of Prediction Latency on ATDM Strategy Performance Network Travel Time for Dallas Testbed under Medium Demand and Low Incident Severity [Source: SMU]

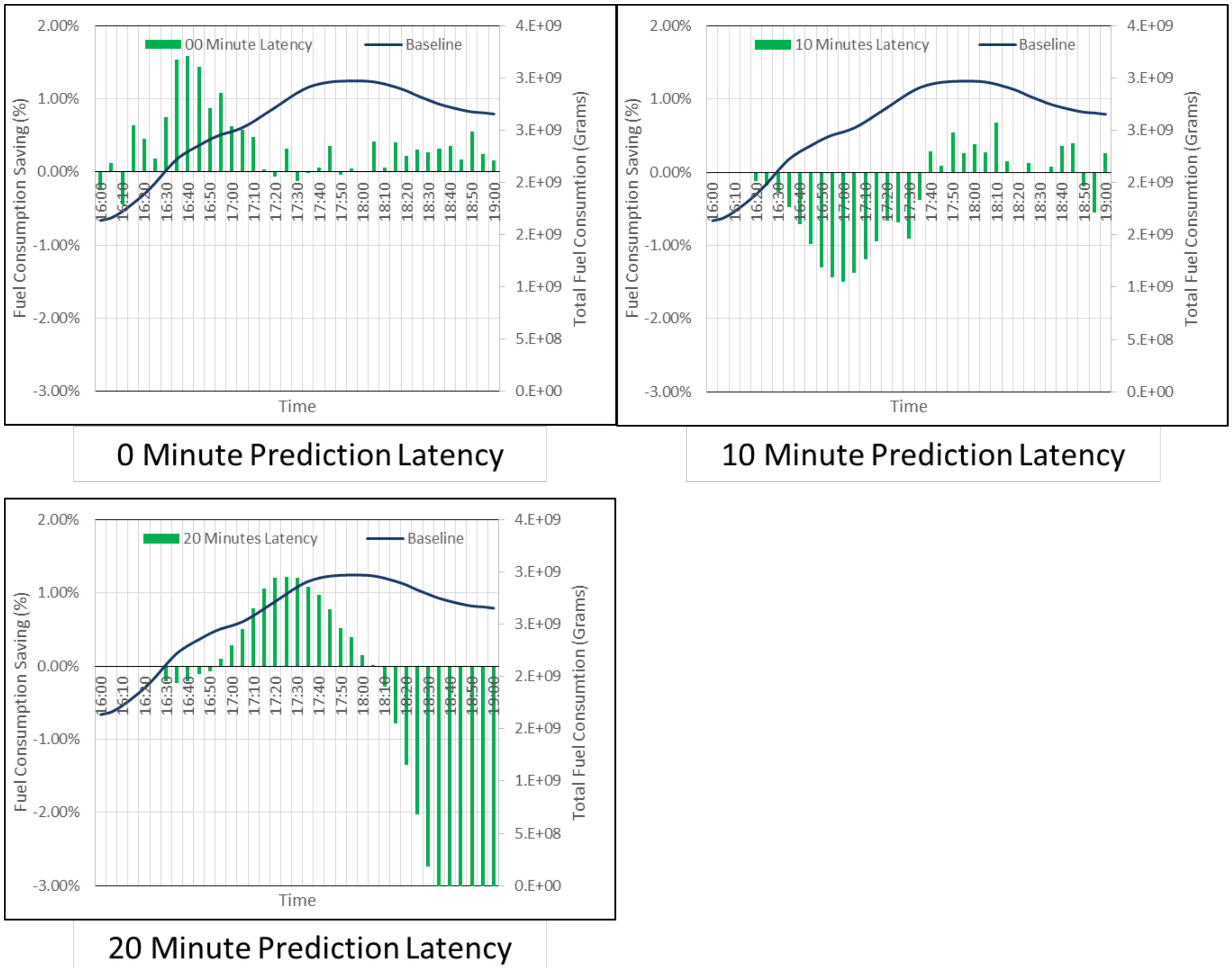


Figure 8-2: Impact of Prediction Latency on ATDM Strategy Performance Network Fuel Consumption for Dallas Testbed under Medium Demand and Low Incident Severity [Source: SMU]

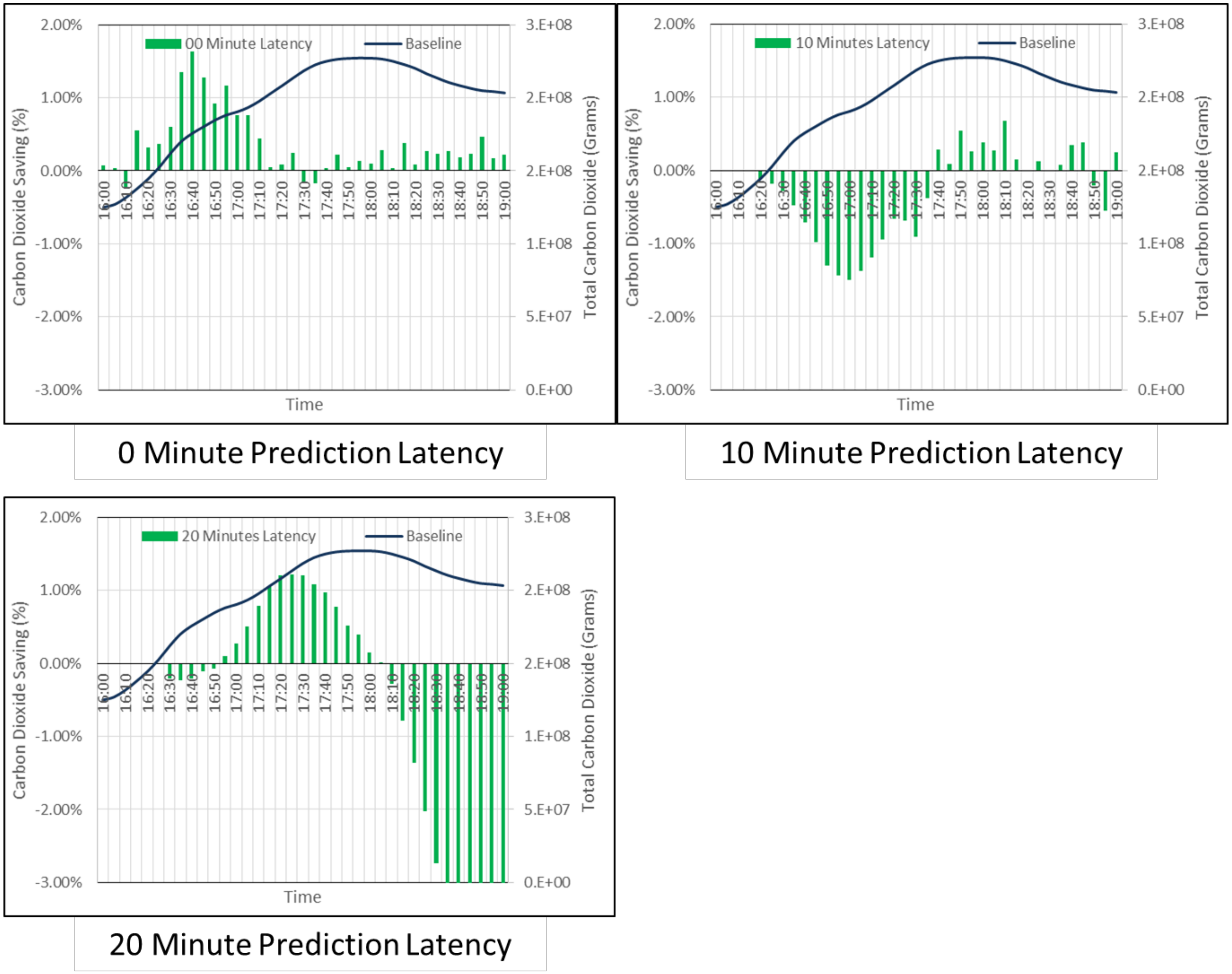


Figure 8-3: Effect of Traffic Management Latency in Total Carbon Dioxide Emission for Dallas Testbed under Medium Demand and Low Incident Severity [Source: SMU]

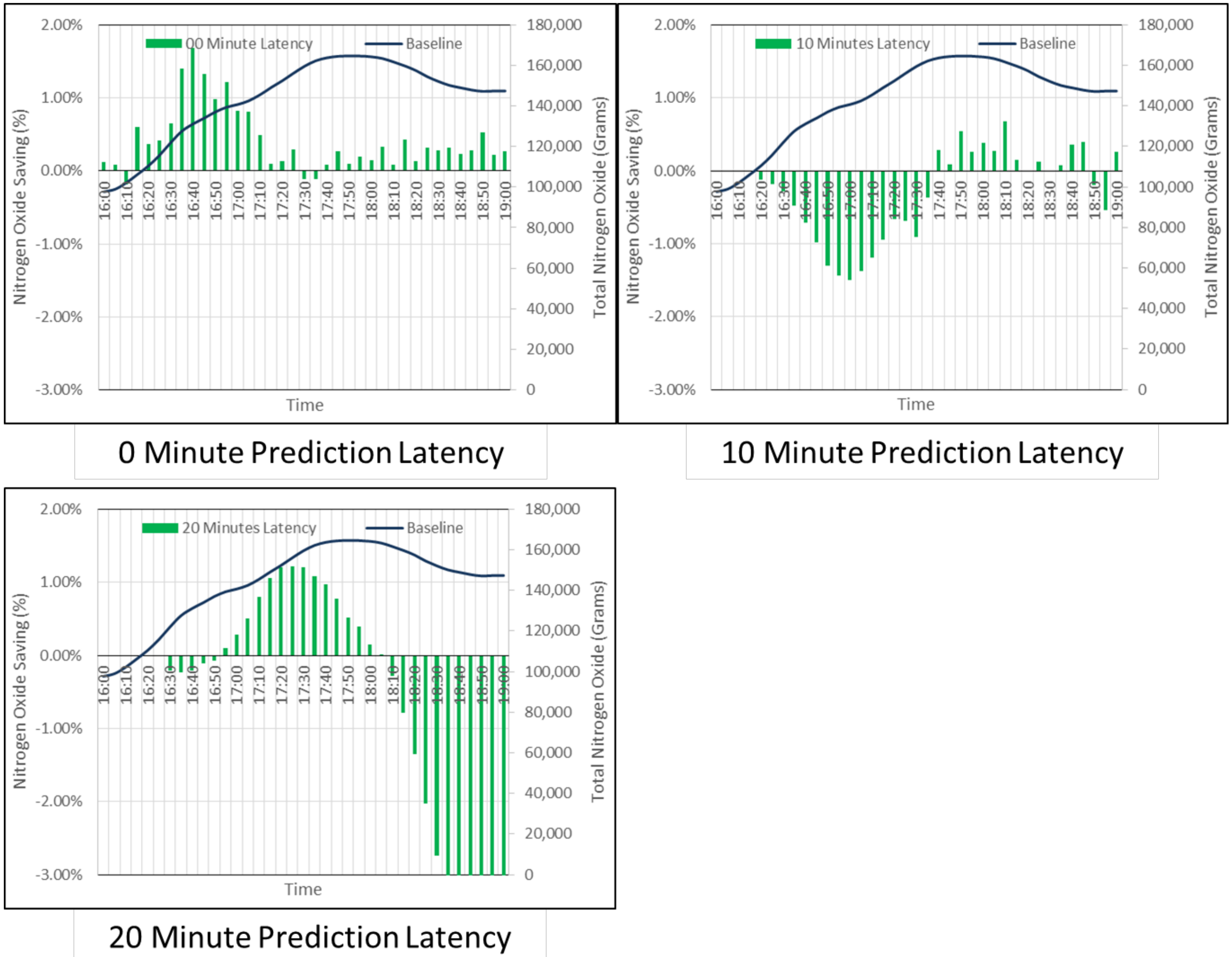


Figure 8-4: Effect of Traffic Management Latency in Total Nitrogen Oxide Emission for Dallas Testbed under Medium Demand and Low Incident Severity [Source: SMU]

Phoenix Testbed

Phoenix Testbed was also utilized to assess the impact of prediction latency on ATDM strategies, in particular, Adaptive Ramp Metering. Figure 8-5 shows the average travel time along the freeway segment under different prediction latencies (5 min vs. 10 min) for two operational conditions Low Demand + Low Incident and High Demand + High Incident. It also shows how this compares to the baseline travel time as well as the travel time under zero latency. The Figure shows a consistent reduction of travel time if the communication latency is reduced from 10 minutes to 5 minutes. Given the increase of network scope will definitely increase the communication latency and it is expected the latency issue may become more outstanding if the adaptive ramp metering strategies are applied to large areas.

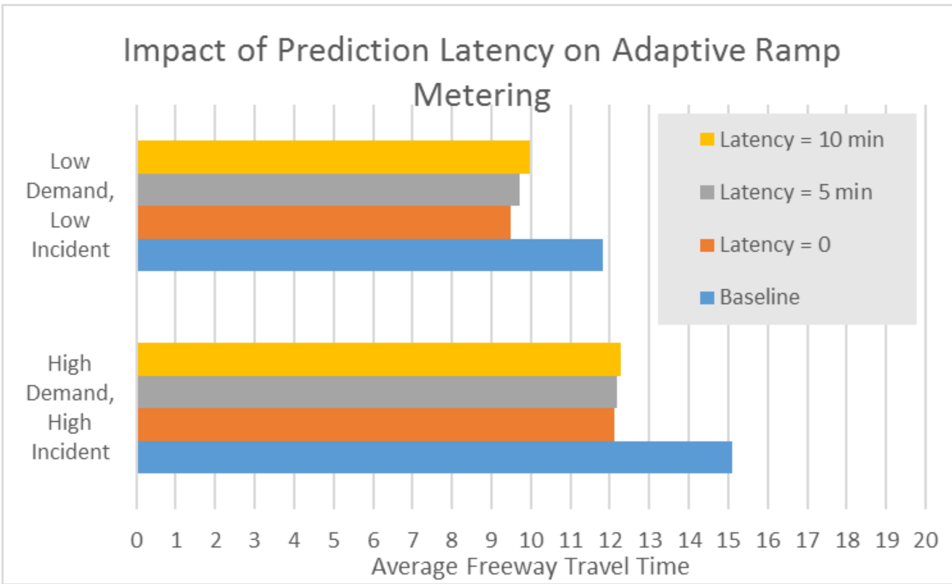


Figure 8-5: Impact of Prediction Latency on Adaptive Ramp Metering on Phoenix Testbed [Source: Booz Allen]

Pasadena Testbed

The analysis was performed on each isolated ATDM strategy to compare the effects of different prediction latency on operational performance using the following prediction latency values: 5 Minutes and 10 Minutes. The results from the comparative analysis are summarized in Table 8-3 and Figure 8-6. A more detailed demonstration of travel time savings for each strategy with different prediction horizon are shown in Figure 8-7 to Figure 8-10. The following are the observations from the network operations results:

- All strategies demonstrate a decrease in operational benefits with the increase in prediction latency.
- ARM shows a significant loss in operational benefit, from 2.45% to 1.67%, when prediction latency is increased from 5 minutes to 10 minutes.
- DSC shows a significant loss in operational benefit, from 1.36% to 0.63%, when prediction latency is increased from 5 minutes to 10 minutes.
- HSR + DJC strategy shows minor changes with a slight decrease in operational benefit, from 7.77% to 7.75% when prediction latency is increased from 5 minutes to 10 minutes.
- DRG shows a moderate decrease in operational condition benefit, from 2.10% to 1.72%, when prediction latency is increased from 5 minutes to 10 minutes.

Table 8-3: Traffic Management Strategies Network Travel Time Savings with Different Prediction Latency

Strategies	***Prediction Latency***	
	5 Minutes	**10 Minutes**
ARM	2.45%	1.67%
DSC	1.36%	0.63%
HSR + DJC	7.77%	7.75%
DRG	2.10%	1.72%

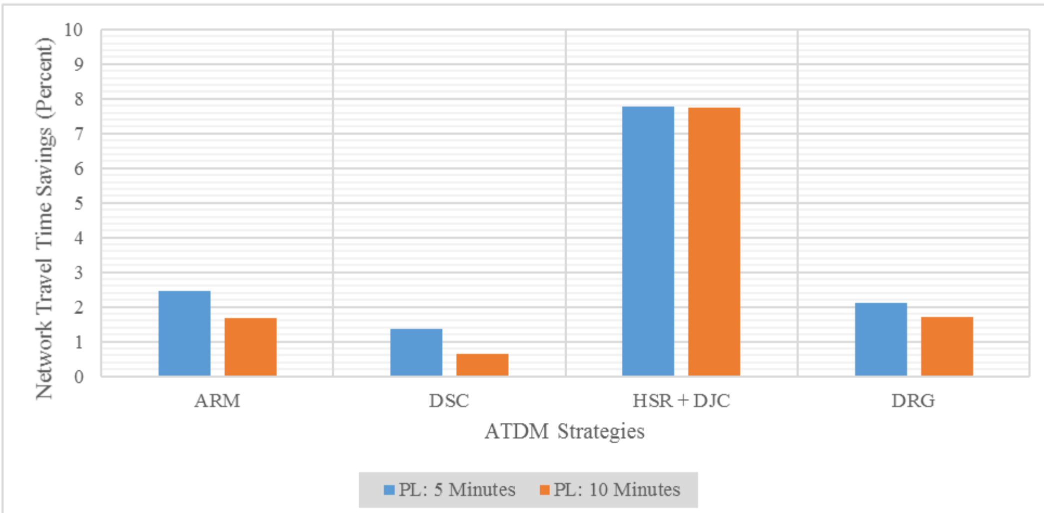


Figure 8-6: Effects of Prediction Latency on ATDM Strategies Network Travel Time Savings [Source: Booz Allen]

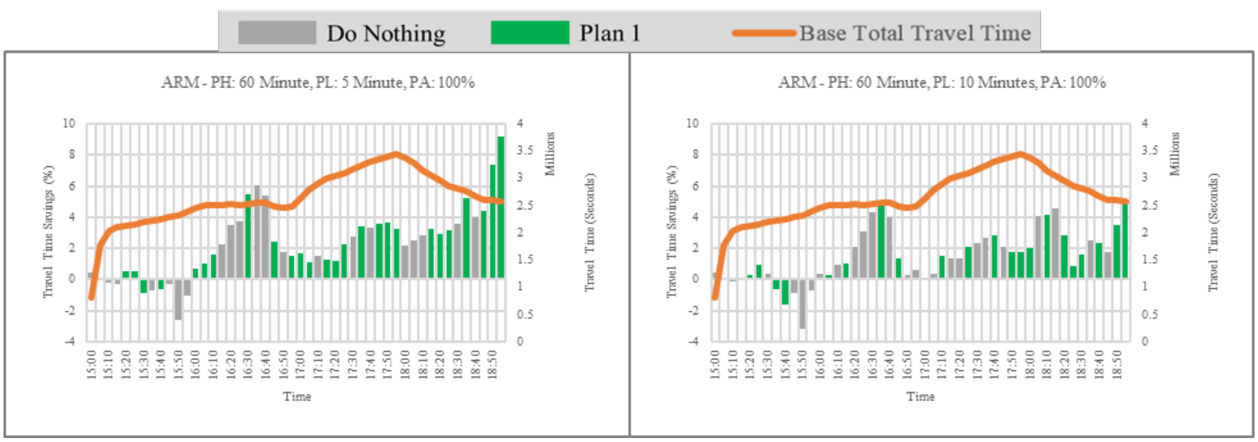


Figure 8-7: Effects of Prediction Latency on ARM Network Travel Time Savings [Source: Booz Allen]

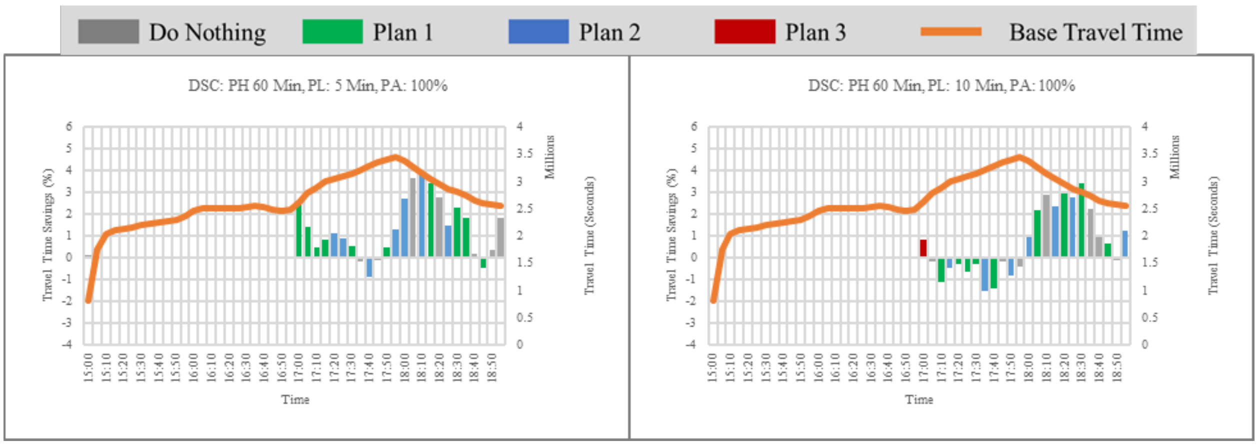


Figure 8-8: Effects of Prediction Latency on DSC Network Travel Time Savings [Source: Booz Allen]

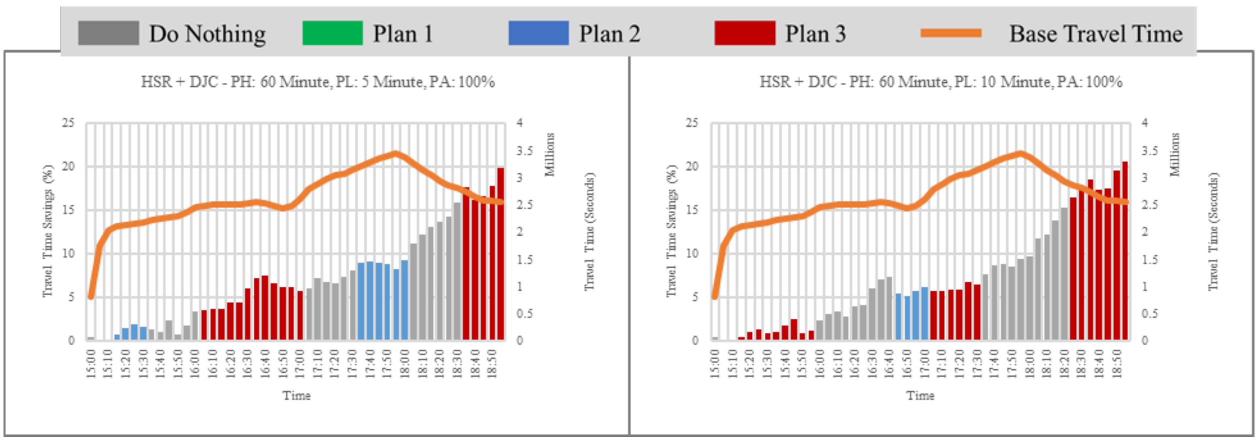


Figure 8-9: Effects of Prediction Latency on HSR + DJC Network Travel Time Savings [Source: Booz Allen]

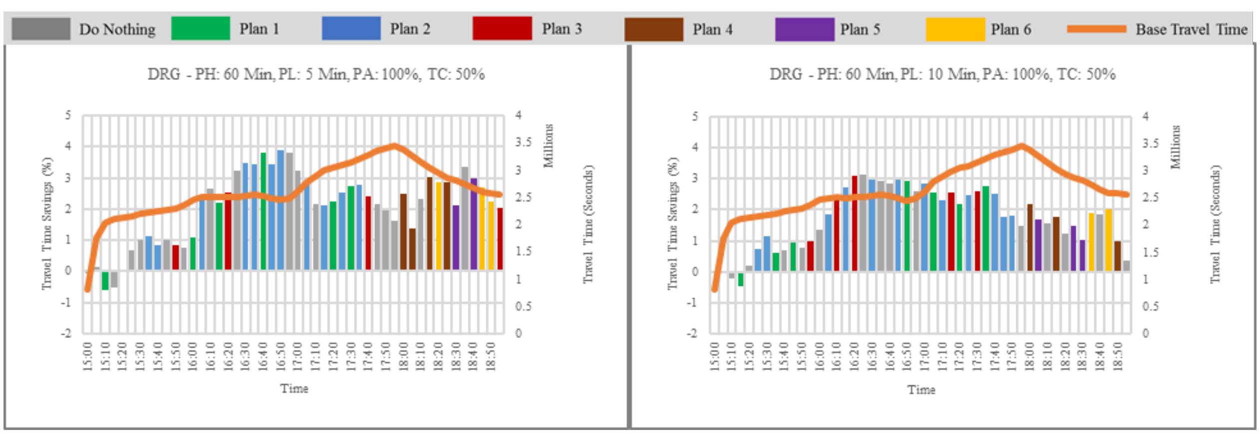


Figure 8-10: Effects of Prediction Latency on DRG Network Travel Time Savings [Source: Booz Allen]

Chicago Testbed

For this analysis, the roll period and prediction horizon were fixed while the communication latency was varied in three levels, i.e. no latency (0 minute), moderate latency (3 minutes), and large latency (5 minutes). According to the overall framework, latency determines when the predictive information is received by the simulation system (as input to the decision or control logic to be applied). Prior to that time, the latest received prediction remains in effect. The experiments to examine the tradeoff between prediction and latency are designed to test sensitivity of the system performance to the changes of prediction quality when the combination of strategies yielding to the most benefits are implemented. Since the focus of this study is weather-affected conditions, OC 3 and OC 6 were tested. As OC 6 is an incident-related scenario, it is tested with a longer prediction horizon than OC 3, because the incident is expected to lead to longer travel time.

Figure 8-11 shows the results related to the latency when the prediction roll period and horizon are fixed. The results show that the system prefers no latency, especially during peak hours. If there exists a little latency which is much less than the prediction roll period, the system under off peak can still perform well. However, if the latency is no less than the roll period, which means that the system always get some predictive traveler information from the previous prediction stage, it will bring some negative effect to the system performance. Figure 8-12 shows the test results for the tradeoff analysis of the entire network performance with the prediction quality and the communication latency under the selected weather-related scenarios, i.e. OC 3. Only the best combination of strategies identified from the analyses of Synergies and Conflicts were tested.

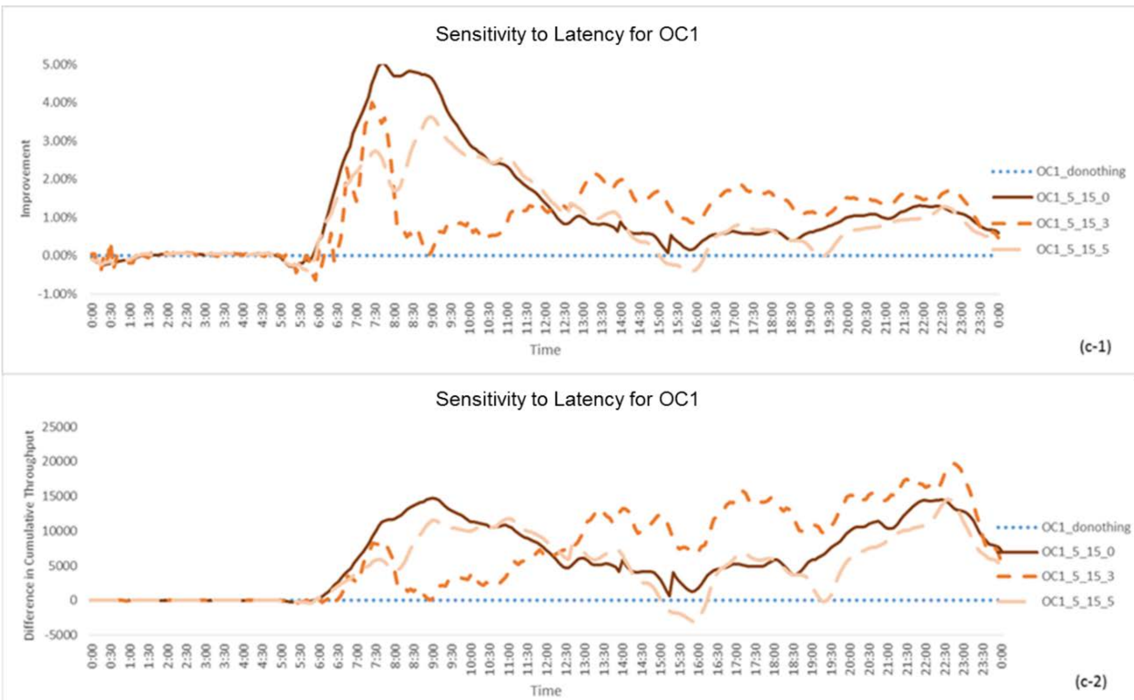


Figure 8-11: Sensitivity analysis of system performance to communication latency [Source: NWU]

Prediction Parameters Trade-off

The sensitivity of system performance to the specific operational settings implemented depends on the particular operational conditions experienced on a given day. In other words, the best settings are one operational condition are not necessarily best under all operational conditions. Different from OC1, OC3 prefers longer prediction horizon and roll period, and is only sensitive to latency for the evening peak hours. Though the predictive information is updated more frequently with a short roll period, it may still lead to an unstable system as vehicles may change routes very often. OC6 reaches a trade-off state between short roll period and long prediction horizon., and it is not sensitive to latency due to incident-related delay. By and large, the use of the predictive approach ensures that the deployed strategies result in improved overall network performance. The improvements resulting from application of a particular strategy, or bundle of strategies, depend on selecting appropriate operational settings. The operational settings include net penetration rate and prediction/latency features, and the combination of strategies.

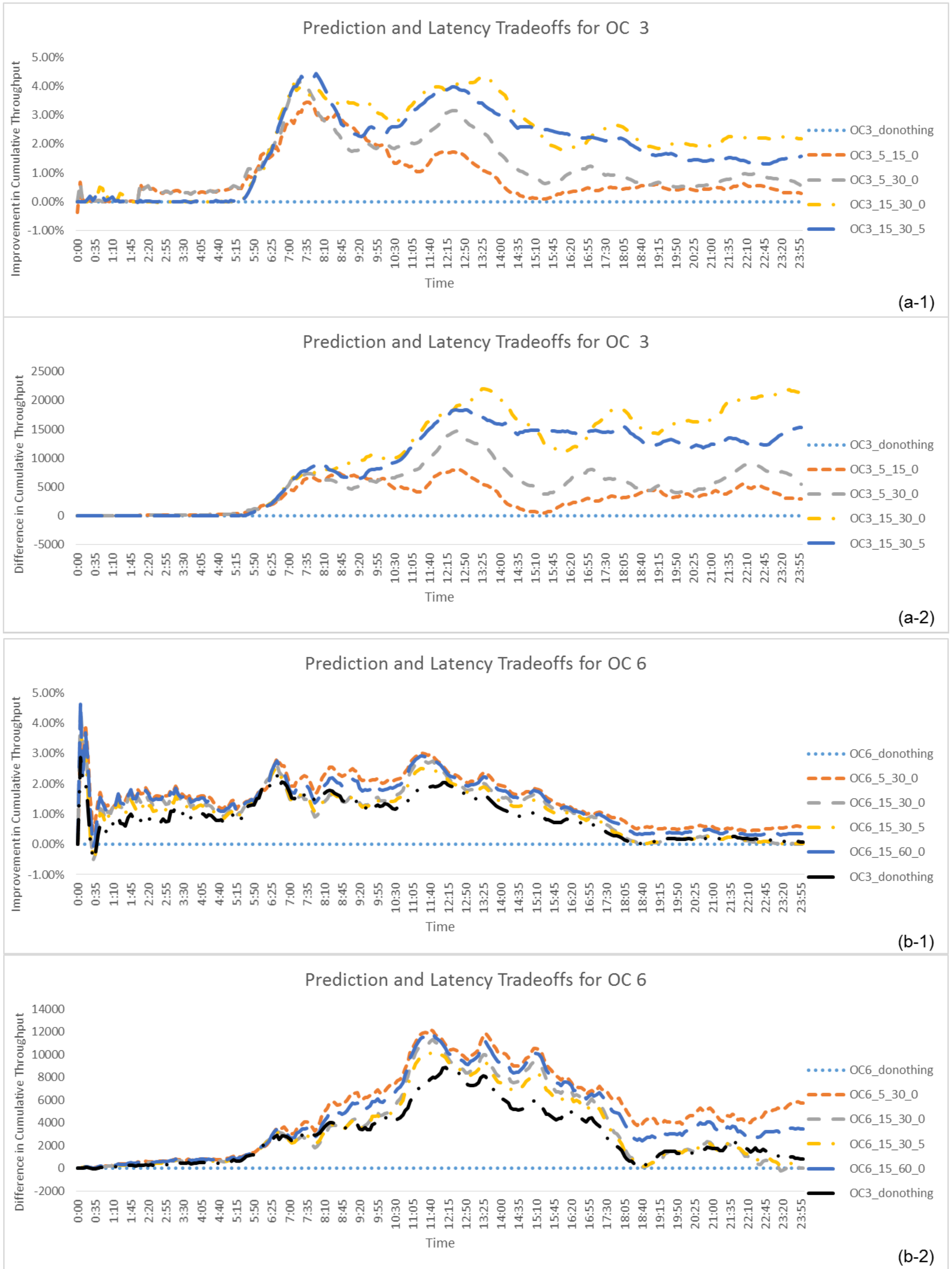
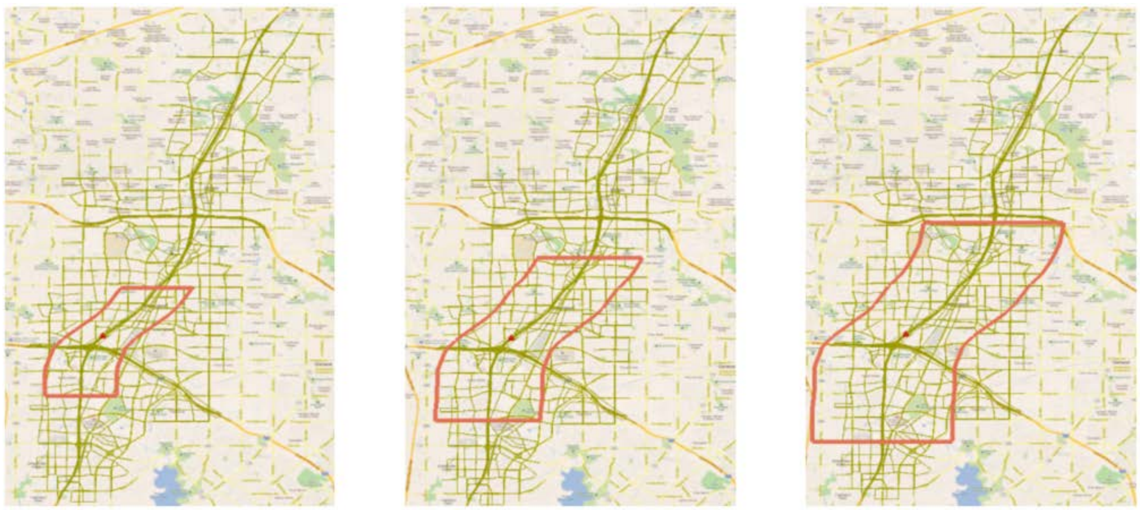


Figure 8-12: Tradeoff analysis of system performance to prediction quality and communication latency [Source: NWU]

8.2.2 Spatial Coverage

This set of experiments examines the effect of coverage extension of the generated ATDM response plans on the overall network performance. Three different levels of spatial coverage extensions (2-mile, 3-mile and 4-mile coverage) are considered as illustrated in Figure 8-13. For instance, in the 4-mile coverage case, a rectangular area that extends four miles around the incident location such that the incident is located at the center of the rectangle.



Small Coverage 2 miles | **Medium Coverage 3 miles** | **Large Coverage 4 miles**

Figure 8-13: Different Levels of Spatial Coverage Extension on Dallas Testbed [Source: SMU]

Similar to the previous analysis, the developed ATDM response plans consider the combination of dynamic routing and dynamic signal timing control. Also, the demand pattern is assumed to be predicted perfectly, and the traffic management module is activated with zero latency. The prediction horizon is assumed at 30 minutes. The time-varying travel time savings as a percentage of the baseline scenario is presented in Figure 8-15. Table 8-4 summarizes the results by providing the total travel time savings for the entire network. For limited area coverage, the generated ATDM response plans fail to significantly achieve significant travel time savings. On the other hand, as the coverage expands, more information on the congestion pattern in the area is obtained and also more traffic control devices could be included (traffic signals and DMSs) to developing the generated schemes. Thus, more significant improvement in the network performance can be achieved. As shown in the table, extending the covered area provides more total network travel time saving. For example, travel time saving of 9,930 minutes is obtained for the spatial coverage of two miles. The saving is increased to 16,460 minutes as the coverage is extended to four miles.

Figure 8-15 also provides the corresponding saving in the fuel consumption associated with developing ATDM response plans considering the different spatial coverage extensions. Also, Figure 8-16 and Figure 8-17 give the results for environmental measures of performance for deploying traffic management strategies considering different spatial coverage extensions in terms of the percentage saving in the carbon dioxide and the percentage saving the nitrogen oxide. Table 8-5 gives the total saving in fuel consumption and emissions for the different coverage extension scenarios. As shown in the table, fuel consumption savings of 32.98 tons and emission savings of 2.25 tons and 2.95 tons of CO and NOX, respectively, are recorded for the two-mile converge scenario. As the coverage scenario is extended to four miles, the fuel consumption saving increased to 65.61 tons. The savings in CO and NOX are 5.54 tons and 4.98 tons, respectively.

Table 8-4: Effect of Spatial Coverage in Total Network Travel Time Saving for Dallas Testbed under Medium Demand and Low Incident Severity

Scenario Description	Total Network Travel Time Savings (minutes)
2 miles Extension	9,930
3 miles Extension	15,125
4 miles Extension	16,460

Table 8-5: Total Environmental Performance for Different Spatial Coverages for Dallas Testbed under Medium Demand and Low Incident Severity

Scenario Description	Fuel Consumption Saving (tons)	Carbon Dioxide (tons)	Nitrogen Oxide (kilograms)
2 miles Extension	32.98	2.95	2.25
3 miles Extension	56.27	4.17	3.50
4 miles Extension	65.61	5.54	4.98

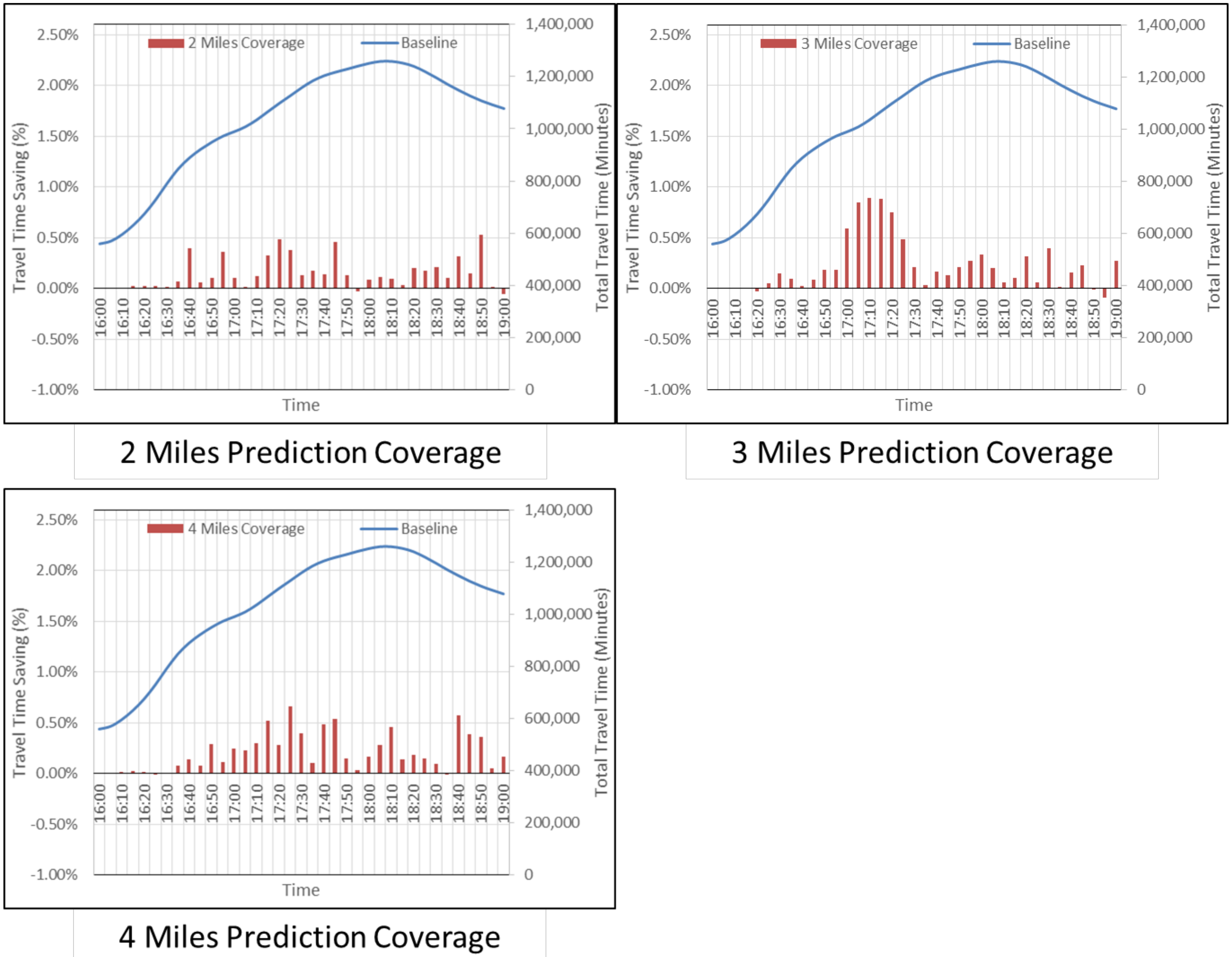


Figure 8-14: Network Travel Time Savings Under Various Prediction Coverage for Dallas Testbed under Medium Demand and Low Incident Severity [Source: SMU]

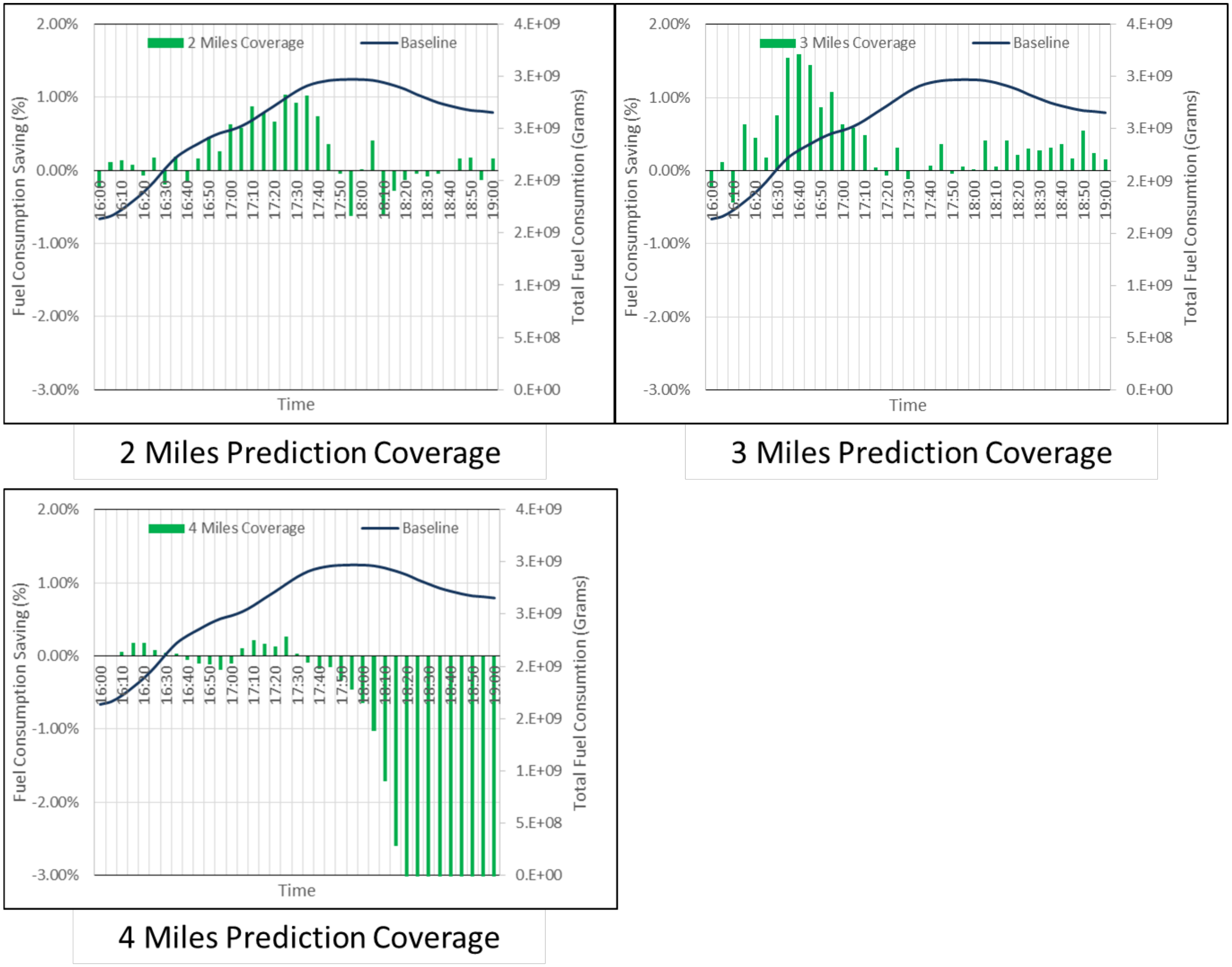


Figure 8-15: Network Fuel Consumption Under Various Prediction Coverage for Dallas Testbed under Medium Demand and Low Incident Severity [Source: SMU]

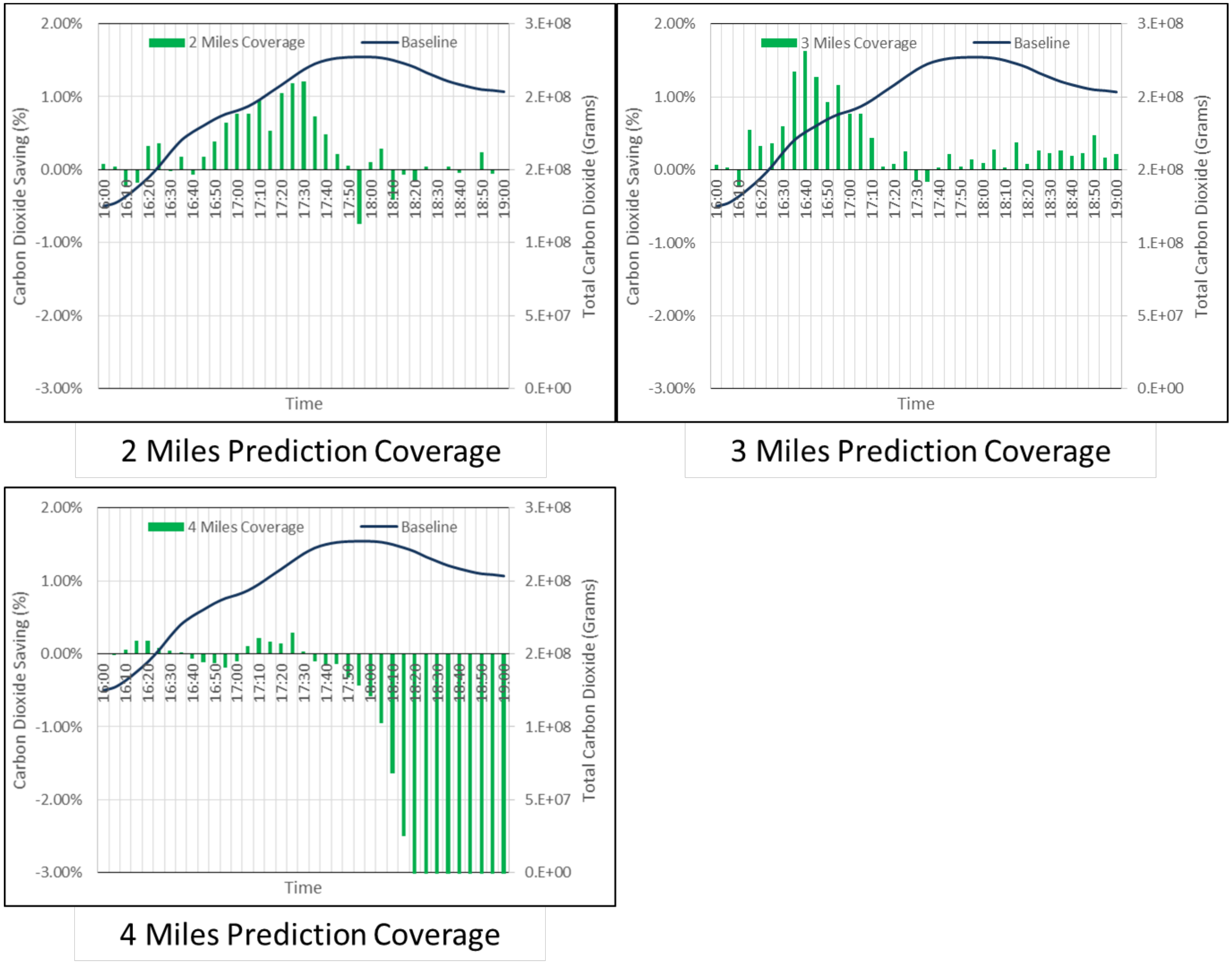
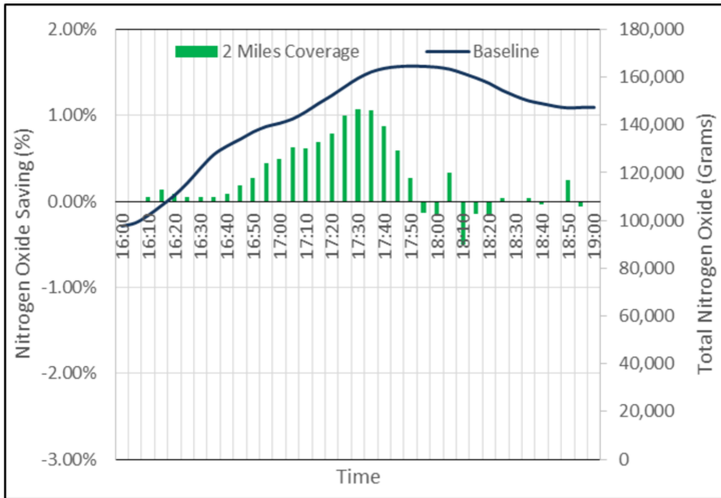
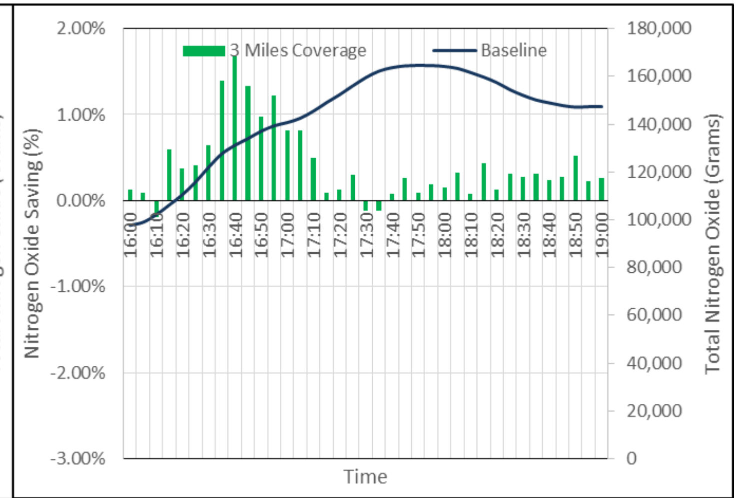


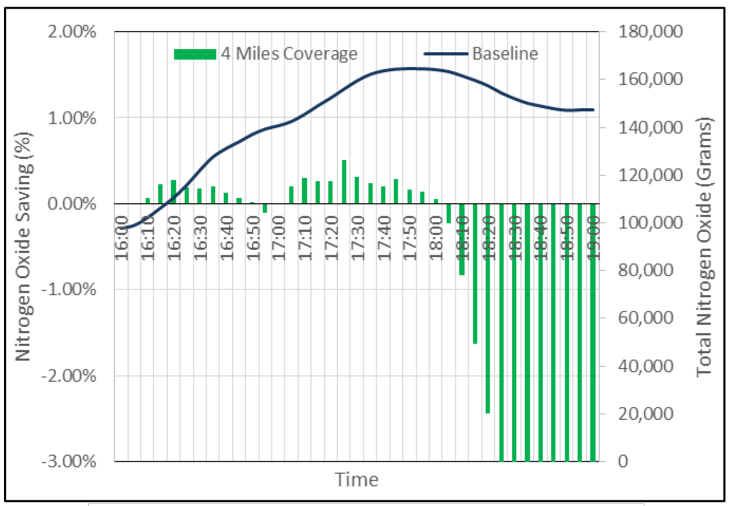
Figure 8-16: Network Carbon Dioxide Emission Under Various Prediction Coverage for Dallas Testbed under Medium Demand and Low Incident Severity [Source: SMU]



2 Miles Prediction Coverage



3 Miles Prediction Coverage



4 Miles Prediction Coverage

Figure 8-17: Environmental Performance Measures Under Various Prediction Coverage for Dallas Testbed under Medium Demand and Low Incident Severity [Source: SMU]

8.3 Results Summary

This chapter assessed the impact of prediction latency and extent of prediction coverage on the effectiveness of ATDM Strategies using both Dallas and Phoenix Testbed.

For the Dallas Testbed, promptly responding to the incident (zero latency) helps in alleviating the congestion, and achieving considerable saving in total network travel time. On the other hand, as the latency increases, the system does not respond to the congestion for longer period. By the time the plan is generated, its effectiveness in alleviating the congestion reduces. For example, a saving of 15,125 minutes is recorded for the scenario with zero latency. As the latency extends to 20-minutes, an increase in the travel time, compared to the baseline scenario, is observed implying that the scheme is no longer effective because of the change in the network conditions. For limited area coverage, the generated ATDM response plans fail to significantly achieve significant travel time savings. On the other hand, as the coverage expands, more information on the congestion pattern in the area is obtained and also more traffic control devices could be included (traffic signals and DMSs) to developing the generated schemes. Thus, more significant improvement in the network performance can be achieved. Based on the obtained simulation results, extending the covered area provides more total network travel time saving. For example, travel time saving of 9,930 minutes is obtained for the spatial coverage of two miles. The saving is increased to 16,460 minutes as the coverage is extended to four miles. Similar analysis with Phoenix Testbed with variable prediction latencies showed that as latencies go up, effectiveness of ATDM Strategies go down.

The Pasadena testbed has demonstrated that prediction latency has a significant effect on arterial strategies compared to freeway strategies. Though ARM is typically considered a freeway focused strategy, it is also the transition from aterial collector roads to and from the freeway. The ARM does show degradation with increase in prediction latency from 5-minutes to 10-minutes. This degradation is likely due to vehicles metered at a rate that was recommended for a traffic state 10-minutes before. HSR + DJC strategy shows negligeble changes between 5-minute to 10-minute prediction latency.

As far as the Chicago Testbed was concerned, the sensitivity of system performance to the specific operational settings implemented depends on the particular operational conditions experienced on a given day. In other words, the best settings are one operational condition are not necessarily best under all operational conditions. Different from OC1, OC3 prefers longer prediction horizon and roll period, and is only sensitive to latency for the evening peak hours. Though the predictive information is updated more frequently with a short roll period, it may still lead to an unstable system as vehicles may change routes very often. OC6 reaches a trade-off state between short roll period and long prediction horizon., and it is not sensitive to latency due to incident-related delay. By and large, the use of the predictive approach ensures that the deployed strategies result in improved overall network performance. The improvements resulting from application of a particular strategy, or bundle of strategies, depend on selecting appropriate operational settings. The operational settings include net penetration rate and prediction/latency features, and the combination of strategies.

Chapter 9. Summary of Results

In this project, different ATDM strategies were assessed using Dallas and Phoenix Testbed to help answer a multitude of research questions that were put forth by the US Department of Transportation. These questions are categorized and the results are summarized in this chapter in the following sub-sections.

9.1 Synergies and Conflicts

The project team analyzed the impact of combining different strategies and implementing them together in an active traffic management context and to find out synergistic and conflicting strategies. In order to assess the impact of combination of different ATDM strategies, the proposed strategies were assessed in isolation and in combination. It was found that these strategies are synergistic in nature, with combination of strategies showing better performance measures than isolation.

The results from the Dallas Testbed shows that all of the ATDM strategies improve the overall network performance during non-recurrent congestion scenario. Integrated ATDM strategies such as Dynamic Signal Timing, Dynamic Routing, Adaptive Ramp Metering and Dynamic Shoulder Lane could have significant benefits in terms of congestion reduction. As mentioned earlier, the system periodically reports the performance of the network in terms of travel time savings for 30 minutes rolling horizon. Careful examination of the entire results reveals that travel time savings of over 1,250 hours have been reached at some instances. For example, when multiple strategies are integrated in one scheme, more than 75,000 minutes' savings in travel time was seen at the most congested time in the network. The results of environmental network performance show the ATDM strategies has positive impact on the fuel consumption and other pollution measures in the network. Among all the strategies, dynamic shoulder lanes strategy has significant impact on reducing the fuel consumption, and pollution in the entire network. However, the adaptive ramp metering strategy usually increases the fuel consumption and pollution in the total network. The integrated ATDM strategies such as dynamic signal timing, dynamic routing, and dynamic shoulder lane was the most successful scenario in terms of reducing the fuel consumption, carbon dioxide emission, and nitrogen oxide emission. According to Table 9-1, Dynamic Shoulder Lanes strategy contributed to the highest benefits, in isolation and in combination. Most of the strategies were synergistic.

Table 9-1: Deploying Different ATDM Traffic Management Strategies on the Dallas Testbed under Medium Demand and Low Incident Severity Condition

Scenario	ATDM Strategy Implemented				Total Network
	Dynamic Signal Timing	Dynamic Shoulder Lanes	Dynamic Ramp Metering	Dynamic Routing	Travel Time Savings (minutes)
S1	✓				223
S2		✓			48,630
S3			✓		10,923

S4		✓		✓	44,210
S5	✓			✓	15,125
S6	✓	✓		✓	53,871
S7	✓		✓	✓	22,926
S8	✓	✓	✓	✓	75,304

Based on the Phoenix Testbed analysis, it was seen that Adaptive Ramp Metering system was beneficial in all congested conditions, especially when there are incidents on the mainline and the mainline travel demand becomes higher than remaining road capacities. Adaptive Signal Control was also beneficial to improve the traffic mobility along the arterials in terms of travel time reductions. When Adaptive Ramp Metering and Adaptive Signal Control in a road network composed of both urban freeways and arterials are deployed together, it is more likely that they will be jointly beneficial rather than harmful to the overall traffic mobility. Dynamic Routing/Predictive Traveler Information System was shown to help travelers avoid bottlenecks and therefore considerably reduce their overall travel delays.

Based on the results from the Pasadena Testbed, it can be seen that the freeway facility focused strategies yield significantly more benefits than the arterial focused strategies. The addition of an additional lane on the freeway and flow management by the HSR and DJC strategies yield the highest operational benefits at the network level. Looking at the combination scenarios, the initial observation for travel time savings shown in Table 5-10 indicates that HSR + DJC strategy implemented in isolation yields the highest travel time savings at 7.77%. A closer investigation into the total duration when the HSR strategy was deployed for the for this isolated strategy was a total of 195 minutes. Comparing the travel time savings for the isolated strategy with the combination scenario, the ARM + HSR + DJC combination scenario has a HSR activation duration of 110 minutes (43.6% less than isolated) but yields a network travel time savings of 6.64%. The final combination strategy of ARM + HSR + DJC + DSC + DRG combination scenario has a HSR activation duration of 50 minutes (74.4% less than isolated) but yields a network travel time savings of 6.68%. The result comparison suggests there are synergies when combining freeway focused strategies, HSR + DJC with ARM, and even higher synergies when combining additionally with arterial focused strategies, DSC and DRG. The combination yields high network travel time savings with the lower needs to frequently activating an additional shoulder lane for freeway traffic. Freeway traffic represents a significant portion of traffic for the Pasadena testbed as demonstrated by the travel time savings impact by HSR + DJC and DSL + QW. The DSL + QW strategy implemented in isolation and combination yields negative travel time savings but shows patterns of traffic safety improvements as discussed in Chapter 7.

Table 9-2: ATDM Strategies Network Travel Time Savings Summary (Pasadena)

Scenario	ATDM Strategy Implementation					Network Travel Time Savings (Seconds)	Network Travel Time Savings (Percent)
	ARM	DSC	HSR + DJC	DSL + QW	DRG		
S1	✓					64,663	2.45
S2		✓				20,322	0.77
S3			✓			205,075	7.77
S4				✓		-187,920	-7.12
S5					✓	55,425	2.10

S6		✓			✓	55,689	2.11
S7	✓		✓			175,251	6.64
S8	✓	✓	✓		✓	176,370	6.68
S9	✓		✓	✓		-118,769	-4.50
S10	✓	✓	✓	✓	✓	-105,573	-4.00

From the Chicago Testbed results, we can conclude that the low-medium penetration rate yields the most benefits for system performance, while the high penetration rate requires coordination in vehicle routing to achieve benefits. Therefore, for the ADM involved scenarios, we recommend the net penetration level could be set with the low-medium penetration rate. In terms of synergies and conflicts, it is observed that (1) the ATM, ADM and the Weather-related strategies are synergistic for clear day and rain-to snow day scenarios; (2) the ATM, ADM and the Weather-related strategies are synergistic for high demand snow day scenarios and (3) the ATM and the Weather-related strategy may not be effective when applied jointly for the low demand, snow day scenario considered. The analyses showed the most beneficial strategy or combination of strategies.

In the San Diego Testbed, Dynamic Lane Use, Dynamic HOV/Managed Lanes and Dynamic Speed Limits show neither a significant conflict nor a significant synergy. The increase of congestion at the entrances and exits of the HOV lanes due to the increase of demand triggered by Dynamic Lane Use, Dynamic HOV/Managed Lanes is sensed by Dynamic Speed Limits, which extends the congestion over a larger space and longer time in order to avoid abrupt speed changes. This increase of safety is obtained at the expense of throughput and travel time. Dynamic Lane Use and Dynamic HOV/Managed Lanes alone would produce better traffic performance, at the expense of safety. Dynamic Speed Limits alone would produce an increase of safety, but with a more pronounced reduction of throughput. The combined effect of having an increase of safety with less reduction of throughput can be interpreted as a good compromise, which can be considered a synergy. Dynamic Merge Control and Dynamic HOV/Managed Lanes show a synergy: Dynamic HOV/Managed Lanes compensate the slightly negative effect in terms of traffic performance caused by Dynamic Merge Control, which facilitates the entrance from SR-78, at the expense of penalizing traffic coming from the northern boundary of the I-15 corridor in the southbound direction. In other words, the decision to activate Dynamic Merge Control or not should be dictated purely by the need to reduce queueing on the ramp coming from SR-78 rather than by overall traffic performance benefits, and if Dynamic Merge Control is activated, Dynamic HOV/Managed Lanes would compensate its slightly negative impact on throughput. Dynamic Merge Control, Dynamic HOV/Managed Lanes and Dynamic Routing show also a synergy: Dynamic HOV/Managed Lanes and Dynamic Routing compensate the slightly negative effect in terms of traffic performance caused by Dynamic Merge Control, which facilitates the entrance from SR-78, at the expense of penalizing traffic coming from the northern boundary of the I-15 corridor in the southbound direction. Again, the decision to activate Dynamic Merge Control or not should be dictated purely by the need to reduce queueing on the ramp coming from SR-78 rather than by overall traffic performance benefits, and if Dynamic Merge Control is activated, Dynamic HOV/Managed Lanes and Dynamic Routing would compensate its slightly negative impact on throughput.

9.2 Prediction and Active Management

The team also analyzed the impacts of prediction attributes such as accuracy and length of prediction horizon in the effectiveness of ATDM strategies. Intuitively, it was seen that greater prediction accuracy and a longer prediction horizon resulted in better results in both Dallas and Phoenix Testbeds.

For the Dallas Testbed, a superior network performance is obtained for the case in which perfect demand prediction is assumed. The network performance gradually worsens with the increase in the level of demand prediction error. For example, savings of 7,806 and 12,341 minutes are recorded for the scenarios with 5% demand prediction error in the underestimation and overestimation cases, respectively. As the error increases to 10%, the savings are reduced to 2,252 and 3,298 minutes, respectively. The network performance generally improves as the length of the prediction horizon increases. As the horizon is increased, assuming perfect prediction accuracy, the generated schemes are more effective. Positive correlation is observed between increasing the length of prediction horizon, and total travel time savings in the network. For example, using 15-minute prediction horizon resulted in less travel time savings compared to that obtained for the scenario in which 60-minute prediction horizon is considered. For the 15-minute prediction horizon, a saving of 9,114 minutes is recorded. This saving increased to 21,586 minutes when the prediction horizon increased to 60 minutes.

For the Phoenix Testbed, freeway travel time was assessed with Adaptive Ramp Metering under different configurations. A longer prediction horizon resulted in a slight reduction in the average travel times and the impact of communication latency on the traffic mobility was also marginal (less than 1%). Furthermore, it is found that the performance of adaptive ramp metering is very sensitive to the prediction accuracy. After certain system errors are superimposed to the prediction accuracy, the adaptive ramp metering will be under or overestimated in different scenarios. If the system errors make the mainline travel demand lower, then the ramp will allow excessive vehicles to enter the mainline. Otherwise it will unnecessarily gate some vehicles. In turn, the mainline mobility can be changed considerably, harming or not harming the traffic on adjacent roads.

For the Pasadena Testbed, the impact of prediction was assessed by comparing the network performance for a case where ATDM strategies were deployed based on congestion response. It was found that predictive traffic managed had better network performance than responsive traffic management. This is primarily due to the strategy deployment prior to when the freeways form significant traffic congestion. Strategy deployment prior to peak congestion will delay the start time of significant congestions, hence delaying the facility operational breakdown. Comparing the HSR + DJC strategy that yields the highest travel time benefits between the prediction versus time-of-day plan scenario, when the HSR + DJC is activated for a total of 120 minutes (17.2% less than prediction) throughout the peak period, the network travel time savings is 2.01% which is less than one-third of the network travel time savings for the prediction scenario. This section for the Pasadena testbed also analyzes the effects of prediction horizon of network operational performance. The results show a prediction horizon of 30-minutes to 60-minutes has greater impacts on freeway focused strategies: ATM and HSR + DJC. Prediction horizon of 15-minutes to 30-minutes have greater impacts on arterial focused strategies: DSC and DRG. The analysis for prediction accuracy on the prediction recommendations demonstrate that there is very impact when selecting plan deployment for ARM. There are slightly higher effects on network travel time improvements with the increase in prediction accuracy for the HSR + DJC and DRG strategies. If the prediction accuracy falls to 50%, degradation in network travel time performance is observed from the DSC strategy.

For the Chicago Testbed, it can be concluded that the best-performing settings for predictive strategies vary under different operational conditions. To implement the strategies in the real world, it is desirable to revisit and refine these values through field deployment experience. Clear weather scenarios prefer prediction accuracy with a shorter prediction horizon and roll period for the peak hours when travel demand is high, while the snow-affected scenarios prefer a longer prediction horizon, and are sensitive to accuracy and latency. More frequent updates with shorter roll periods of the predictive strategies may lead to instabilities in system performance. As with the hypothetical scenario, i.e. the combined incident-snow scenario reaches a trade-off state between accuracy and prediction horizon, and is not particularly sensitive to latency due to incident-related delay.

For the Pasadena Testbed, it can be concluded that there were no statistically significant benefits of conducting predictions when evaluating and deploying ATDM strategies. However, the activation of

ATDM strategies were reduced and only operational conditions with severe incidents and sustained congestion contributed to activation of a response plan.

9.3 Operational Conditions, Modes and Facility Types

The different ATDM strategies were also evaluated under the different operational conditions identified for the Dallas Testbed. The measures of performance results are presented for the entire network, US-75 northbound, and US-75 southbound. Two main observations can be made based on these results. First, the ATDM response plans generally reduce the congestion associated with the incident most operation conditions texted. Second, the savings in total travel time for the entire network is generally consistent with the savings in the US-75 freeway facility in both directions implying that the schemes reduce the congestion on the freeway while maintaining good level of service across the entire network.

In addition, a set of experiments is designed to evaluate the network performance with deploying ATDM strategies under different operational conditions. The developed ATDM strategy is a combination of dynamic routing and dynamic signal timing. The results show the ATDM strategies is successful to improve the network performance for three operational conditions. However, in operational condition three, the developed ATDM strategy worsens the network performance. This can be explained with the fact that the mentioned strategy is not a suitable strategy for this operational condition, and the network performance might be improved with considering the other ATDM strategies. In addition, the results demonstrate the corridor performance for different operational conditions which is consistent for the results for the entire network.

The effectiveness of the ATDM strategies in reducing the network congestion associated with adverse weather conditions is also examined. Traffic management schemes that combine the dynamic routing strategy and the dynamic signal timing strategy are considered in the analysis. Based on the obtained simulation results, the traffic management system helps in alleviating the network congestion due to the adverse weather. Travel time savings of 163,480 minutes and 84,913 minutes were recorded for two different scenarios of weather impacts on the traffic flow, namely, reduced free-flow speed and a combination of reduced free-flow speed and jam density.

The performance of ATDM strategies is examined considering a hypothetical evacuation scenario. A demand scenario is created in which evacuees are traveling from their work places to a pre-defined set of safe destinations in the northern section of the corridor. Different combinations of ATDM strategies are implemented to evaluate their effectiveness in reducing the congestion associated with the evacuation scenario. These strategies include demand management, dynamic signal timing, traveler information provision, dynamic shoulder lane, and tidal flow operation. The results indicate that effective demand management and the dynamic shoulder lane could significantly reduce the congestion associated with the evacuation process.

A set of analysis was performed to evaluate dynamic parking strategies. The analysis varies in percentage of the travelers who need parking, number of parking lots, the time window of travelers for possible change in departure time, and threshold savings for the travelers. The results of analysis for dynamic parking strategies show the overall improvement on the entire network performance. Increasing the number of parking lots and extending the time window for possible change in the travelers' departure time provide more total network travel time in the network. There is significant saving in the total network travel time only with considering the change in the travelers' mode choice. The saving of 140,832 minutes is recorded for scenario S7 with three available parking lots which the travelers do not have the option to change their departure times, but they can shift to transit. This saving is increased to 155,779 minutes in scenario S8 with 11 available parking lots and similar conditions to scenario S7.

For the Phoenix Testbed, Adaptive Ramp Metering and Adaptive Signal Control (as well as their combination) works the best under High Demand, Medium Incident Severity and Wet Weather condition. Under Low Demand and Low Incident Severity, Adaptive Signal Control showed least improvement in travel time. Similarly, High Demand and Low Incident Severity showed least improvement in travel time when Dynamic Route Guidance was implemented with Predictive Traveler Information.

The Pasadena testbed was analyzed using a total of three different operational condition. The prediction parameters that were identified as sensitive for each strategy for prediction were further assessed for operational conditions 2 and 3. For ARM, prediction horizon and prediction latency were assessed as sensitive parameters. The increase in prediction horizon for ARM shows a higher rate of improvement for OC 3 which has the highest freeway congestion, followed by OC 1 which has the second highest freeway congestion, and finally OC 2 which has the lowest. Prediction horizon for ARM shows close correlation with the freeway congestion. For prediction latency, the results show consistently a network travel time savings degradation for all three operational conditions under longer prediction latency.

The best strategies for freeway segment also prove to be the most effective ones for the arterial roads under most operational conditions. OC 4, a snow-affected low demand scenario, is the only exceptional case. It is because the arterial roads have fewer lanes than the freeway. As discussed in section 7.3, it was assumed the snowplow would block one lane during service. That leads to a 50% capacity loss during plowing operation for the arterial roads with two lanes. However, the freeway segments have more lanes, and it is more resilient to the negative impact of the plowing operation. Therefore, the Weather-related strategy may bring more negative impact on the arterial road than the freeway segment. For DSC, the identified sensitive prediction parameter is prediction accuracy. The network travel time shows negative travel time savings for cases where the prediction accuracy falls to 50%. For HSR + DJC strategy, there were no prediction parameters that were identified as sensitive. Comparing the travel time savings for each operational condition, OC 3 which has the highest freeway congestion yields the highest travel time savings, followed by OC 1 which has the second highest freeway congestion, followed by OC 2. There is a strong correlation of travel time savings between freeway focused strategies with freeway level of congestion. For DSL + QW strategy, there is no prediction parameter because TRANSIMS is not used to evaluate this strategy. This strategy only differs with traveler compliance parameter. The trends show that with the increase in traveler compliance, the difference in both spatial and temporal speed difference on the freeway is reduced. The trends for the temporal speed difference for OC3 which has the highest freeway congestion shows very small reduction in temporal speed difference due to the oversaturated freeway. The reduction in spatial and temporal speed difference yields safety improvements by reducing abrupt changes in speeds by distributing them over a longer segment of the freeway. The dispersion of congestion also reduces the overall network travel time savings. Finally, the prediction parameter identified as sensitive for DRG prediction is traveler compliance. The results show very small changes from the baseline results when traveler compliance is at 20% but there is a reduction for all operational conditions compared to when traveler compliance is at 50%. The small changes when traveler compliance is at 20% can be considered negligible because only a small fraction of traffic on the arterial entering the freeway is being rerouted due to fewer vehicles complying with route guidance recommendations.

For the Chicago Testbed, it can be concluded that ADM provides the most benefits for operational conditions without snow effect, i.e. clear day and rain-to-snow day. The weather-related strategy generates the most benefits for snow-affected and high demand operational conditions. The ADM strategy yields the most improvement for the snow-affected and low demand operational conditions or the incident-mixed snow scenario. If the strategy is implemented for the entire horizon or within some specific period, like the afternoon peak hours with an incident, it provides the most benefit to the corridor.

The dynamic snowplow routing plan may be less preferred than the static routing plan under low demand (off peak hours) operational conditions when the network is less congested. In order to serve the most important links first, the dynamic plan has more deadheading trips. These deadheading trips would reduce the link capacity and impose a negative impact to the traffic. Under the low demand, less congested scenarios, the benefit generated by the dynamic plan might be offset by the negative impact associated with the extra deadheading trips. One should pay close attention to the operational conditions when select which plan to deploy.

For the San Diego Testbed, Dynamic Lane Use and Dynamic HOV/Managed Lanes are effective only in congested situations. Additionally, the location of incidents and bottlenecks may reduce the effectiveness of this ATDM strategy, because if the congestion caused by them affects the access points to the HOV lanes, vehicles have difficulty in reaching the additional lane that allows bypassing the bottlenecks. Dynamic Speed Limits reduce the speed change between consecutive road segments, at the expense of reducing the overall speed along the corridor. With little congestion the impact in terms of increase of delay is negligible, while as congestion increases the increase of delay increases, too, and is coupled with a slight decrease of throughput. Dynamic Merge Control facilitates the entrance from SR-78, at the expense of penalizing traffic coming from the northern boundary of the I-15 corridor in the southbound direction. When the I-15 traffic is lower than that entering from SR-78, this strategy has a positive overall impact on the corridor, because it reduces conflicts at the merge. Predictive Traveler Information with Dynamic Routing is more effective with higher demand and with more severe incidents. The benefit is evident if we focus on the I-15 corridor, while if we adopt a network-wide perspective, we can notice that in some operational condition the positive impact on the speed along the I-15 corridor is in fact counterbalanced by an overall slight increase of travel time because or rerouting along the arterials.

9.4 Predication Latency, Accuracy and Coverage Trade-Offs

The impact of prediction latency and extent of prediction coverage on the effectiveness of ATDM Strategies was assessed using both Dallas and Phoenix Testbed.

For the Dallas Testbed, promptly responding to the incident (zero latency) helps in alleviating the congestion, and achieving considerable saving in total network travel time. On the other hand, as the latency increases, the system does not respond to the congestion for longer period. By the time the plan is generated, its effectiveness in alleviating the congestion reduces. For example, a saving of 15,125 minutes is recorded for the scenario with zero latency. As the latency extends to 20-minutes, an increase in the travel time, compared to the baseline scenario, is observed implying that the scheme is no longer effective because of the change in the network conditions. For limited area coverage, the generated ATDM response plans fail to significantly achieve significant travel time savings. On the other hand, as the covered expands, more information on the congestion pattern in the area is obtained and also more traffic control devices could be included (traffic signals and DMSs) to developing the generated schemes. Thus, more significant improvement in the network performance can be achieved. Based on the obtained simulation results, extending the covered area provides more total network travel time saving. For example, travel time saving of 9,930 minutes is obtained for the spatial coverage of two miles. The saving is increased to 16,460 minutes as the coverage is extended to four miles. Similar analysis with Phoenix Testbed with variable prediction latencies showed that as latencies go up, effectiveness of ATDM Strategies go down.

The Pasadena testbed has demonstrated that prediction latency has a significant effect on arterial strategies compared to freeway strategies. Though ARM is typically considered a freeway focused strategy, it is also the transition from aterial collector roads to and from the freeway. The ARM does show degradation with increase in prediction latency from 5-minutes to 10-minutes. This degradation is likely due to vehicles metered at a rate that was recommended for a traffic state 10-minutes before. HSR + DJC strategy shows negligeble changes between 5-minute to 10-minute prediction latency.

As far as the Chicago Testbed was concerned, the sensitivity of system performance to the specific operational settings implemented depends on the particular operational conditions experienced on a given day. In other words, the best settings are one operational condition are not necessarily best under all operational conditions. Different from OC1, OC3 prefers longer prediction horizon and roll period, and is only sensitive to latency for the evening peak hours. Though the predictive information is updated more frequently with a short roll period, it may still lead to an unstable system as vehicles may change routes very often. OC6 reaches a trade-off state between short roll period and long prediction horizon., and it is not sensitive to latency due to incident-related delay. By and large, the use of the predictive approach ensures that the deployed strategies result in improved overall network performance. The improvements resulting from application of a particular strategy, or bundle of strategies, depend on selecting appropriate operational settings. The operational settings include net penetration rate and prediction/latency features, and the combination of strategies.

APPENDIX A. Acronyms Used

The following table provides a comprehensive listing of acronyms used in this report.

Acronyms	Expansion
ADM	Active Demand Management
AMS	Analysis, Modeling and Simulation
API	Application Programming Interface
APM	Active Parking Management
ARM	Adaptive Ramp Metering
ASC	Adaptive Signal Control
ASC/3	Adaptive Signal Control Version 3
ASU	Arizona State University
ATDM	Active Transportation and Demand Management
ATM	Active Traffic Management
DIRECT	Dynamic Intermodal Routing Environment for Control and Telematics
DMA	Dynamic Mobility Applications
DMS	Dynamic Message Signs
DTA	Dynamic Traffic Assignment
FHWA	Federal Highway Administration
GA	Genetic Algorithm
HD-DTA	High Definition Dynamic Traffic Assignment Tool
HOV	High Occupancy Vehicles
HSR	Hard Shoulder Running
ICM	Integrated Corridor Management
ITS	Intelligent Transportation Systems
MAG	Maricopa Association of Governments
MRSP	Multi-Resolution Simulation Platform
NEXTA	Network EXplorer for Traffic Analysis
NTCIP	National Transportation Communications for ITS Protocol
OC	Operational Condition
OD	Origin-Destination
RHODES	Real-time Hierarchical Optimizing Distributed Effective System
SMU	Southern Methodist University
SOV	Single Occupacny Vehicles
TT	Travel Time
UE	User Equilibrium
USDOT	United States Department of Transportation
VMT	Vehicle Miles Traveled

APPENDIX B. AMS Project Publications List

A list of all the publications from the AMS Project is provided below:

No.	Document Title	JPO Publication #
1	ATDM-DMA AMS Testbed Project: Detailed AMS Requirements	FHWA-JPO-16-369
2	ATDM-DMA AMS Testbed Project: AMS Testbed Selection Report	FHWA-JPO-16-355
3	ATDM-DMA AMS Testbed Project: Analysis Plan for San Mateo Testbed	FHWA-JPO-16-370
4	ATDM-DMA AMS Testbed Project: Analysis Plan for Pasadena Testbed	FHWA-JPO-16-371
5	ATDM-DMA AMS Testbed Project: Analysis Plan for Phoenix Testbed	FHWA-JPO-16-372
6	ATDM-DMA AMS Testbed Project: Analysis Plan for Dallas Testbed	FHWA-JPO-16-373
7	ATDM-DMA AMS Testbed Project: Analysis Plan for Chicago Testbed	FHWA-JPO-16-374
8	ATDM-DMA AMS Testbed Project: Analysis Plan for San Diego Testbed	FHWA-JPO-16-375
9	ATDM-DMA AMS Testbed Project: AMS Evaluation Plan	FHWA-JPO-16-376
10	ATDM-DMA AMS Testbed Project: Calibration Report for San Mateo Testbed	FHWA-JPO-16-377
11	ATDM-DMA AMS Testbed Project: Calibration Report for Pasadena Testbed	FHWA-JPO-16-378
12	ATDM-DMA AMS Testbed Project: Calibration Report for Phoenix Testbed	FHWA-JPO-16-379
13	ATDM-DMA AMS Testbed Project: Calibration Report for Dallas Testbed	FHWA-JPO-16-380
14	ATDM-DMA AMS Testbed Project: Calibration Report for Chicago Testbed	FHWA-JPO-16-381
15	ATDM-DMA AMS Testbed Project: Calibration Report for San Diego Testbed	FHWA-JPO-16-382
16	ATDM-DMA AMS Testbed Project: Evaluation Report for DMA Program	FHWA-JPO-16-383
17	ATDM-DMA AMS Testbed Project: Evaluation Summary for DMA Program	FHWA-JPO-16-384
18	ATDM-DMA AMS Testbed Project: Evaluation Report for ATDM Program	FHWA-JPO-16-385
19	ATDM-DMA AMS Testbed Project: Evaluation Summary for ATDM Program	FHWA-JPO-16-386

No.	Document Title	JPO Publication #
20	ATDM-DMA AMS Testbed Project: Evaluation Report for Chicago Testbed	FHWA-JPO-16-387
21	ATDM-DMA AMS Testbed Project: Evaluation Summary for Chicago Testbed	FHWA-JPO-16-388
22	ATDM-DMA AMS Testbed Project: Evaluation Report for San Diego Testbed	FHWA-JPO-16-389
23	ATDM-DMA AMS Testbed Project: Evaluation Summary for San Diego Testbed	FHWA-JPO-16-390
24	ATDM-DMA AMS Testbed Project: White Paper on AMS Gaps, Challenges, and Future Research	FHWA-JPO-16-391

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