BSM (+BMM) Data Emulator

Dynamic Interrogative Data Capture (DIDC) Assessment Report: Proof of Concept

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16. Abstract
The report documents the study conducted as part of the BSM+BMM Data Emulator project, to examine the DIDC concept and determine the best set of DIDC parameters that provide the most support to the performance measure estimation process with the least amount of data load on communications. The four key transportation performance measures studied include:

- Travel Time
- Queues
- Turning Movements
- Slippery Conditions

This study used a genetic algorithm process to evaluate a set of possible DIDC alternatives which were then evolved into better solutions through repetitive application of mutation and recombination. The study made use of Trajectory Conversion Algorithm-DIDC (TCA-DIDC) Version 2.4, the DIDC offline version of the software tool developed in the BSM Emulator project. The TCA-DIDC Version 2.4 generated connected vehicle messages from simulated trajectories for a single hypothetical network called Philosopher's Corner which were analyzed using measures estimation algorithm code developed in Task 4: Performance Measures.

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Executive Summary

The objective of the DIDC algorithms and software is to optimize the capture and transmission of vehicle-based data under a range of dynamically configurable messaging strategies. The DIDC software is used to reduce the capture and transmission of redundant or otherwise unnecessary data and to enhance the capture and transmission of high-value data depending on current needs of transportation system managers. DIDC software systematically conducts a heuristic optimization routine to identify the smallest set of captured and transmitted data capable of supporting system manager needs for system-wide situational awareness as well as system control for a target prediction horizon (e.g., next 30 minutes). These situational awareness needs are described as a set of desired measures of system and sub-system performance (e.g., predicted travel times along a specific path or shockwave location and speed along a specific roadway link). In short, the DIDC attempts to optimize the data collection process by minimizing the amount of data captured and transmitted (reducing data-related costs), while also upholding the accuracy in predicting measures of performance (maximizing the value of the data).

As part of the BSM Data Emulator project, Noblis experimented with the ranges of DIDC parameters to determine what helps to best estimate key transportation measures under various scenarios while keeping data communication costs low. These scenarios included various connected vehicle market penetrations, traffic demand, incidents, and slippery condition regions.

To conduct the assessment, Noblis made use of TCA 2.4, the offline TCA-DIDC version of the BSM Emulator and measures estimation algorithms developed in Task 4.

Purpose

The purpose of this report is to document the study conducted to:

- Explore the DIDC concept further by implementing and testing DIDC within the TCA software
- Assess the effectiveness of DIDC in estimating key transportation measures
- Assess the data load on communications of the DIDC concept
- Assess the impact of the DIDC Controller on measures estimation results

Technical Approach

Two factors were considered for measuring the usefulness and efficiency of each DIDC alternative: key performance measurement estimation ability and data communication costs. The effectiveness of DIDC was measured by its ability to provide vehicle data that produced accurate performance measure estimation of four key measures: travel time, queues, slippery conditions, and turning movements. These four key measures were chosen because they cover significant aspects of the DIDC concept such as the DIDC Controller's regional and global adjustment on data yield. Another important variable for each test scenario was the data communication cost calculated by how much vehicle data is transmitted during the simulation.

Analysis Scenarios

Noblis developed a test network in VISSIM called Philosopher's Corner to test the DIDC concept. Figure ES- 1 shows the key features of the network which include eighteen origin and destination points spread out amongst two towns, Platoville and Spinoza Oaks, with a shopping center in the middle.

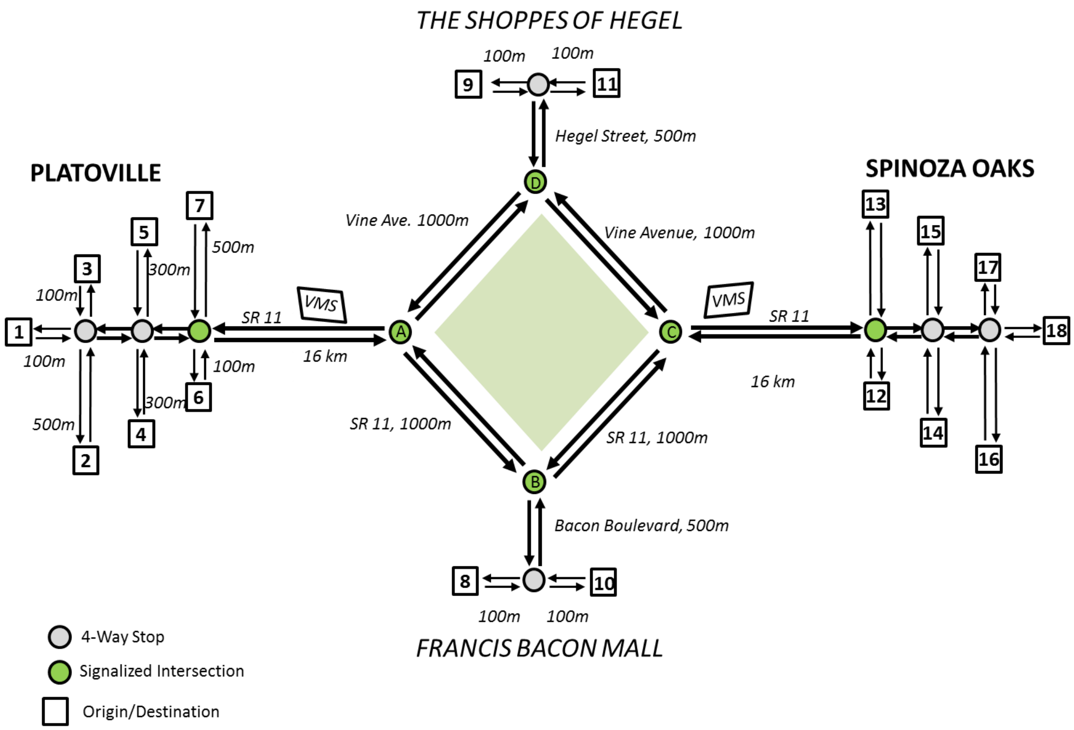

Figure ES- 1. Philosopher's corner VISSIM test network

There were many possible test combinations of parameters in the DIDC concept. To keep this testing effort manageable, a genetic algorithm testing process was used to limit the amount of combinations to evaluate but still produce an acceptable solution. A generation of the genetic algorithm included 80 combinations of network operational conditions and DIDC alternatives. The fitness of each combination was measured by its effectiveness in estimating performance measures and the data load on communication. The total ranking score consisted of 60% based on accuracy in estimating performance measures and 40% on communications load. The genetic algorithm process continued until one DIDC alternative consistently ranked in the top four over the first three consecutive rounds

Key Findings

- **The winning DIDC Alternative had consistently good measures estimation results compared to the other DIDC alternatives**: Although the winning DIDC alternative did not often have the best measures estimation results, it was consistently near the top across all market penetrations.
- **The winning DIDC alternative generated far less data than most DIDC alternatives**: This was most likely due to the conservative initial generation mean times (lambda values) of

message generation frequency which allowed the DIDC Controller to ramp message generation up or down depending on the data yield.

- **The winning DIDC alternative initial generation mean times (lambda values) were best suited for the 20 to 55% market penetration range**: The winning DIDC alternative consistently scored in the top 5 out of 16 in the 20-60% market penetration range. This is most likely due to the initial mean times of the triggered BMMs being best suited to conditions with this percentage of connected vehicles on the Philosopher's Corner Network.
- **The DIDC Controller effectively adjusted message generation rates (lambdas) to match target values**: The DIDC Controller correctly increases and decreases the lambda value based on the comparison of actual data yield to defined targets.
- **Queue and travel time measures estimation results improve or are preserved as message generation rates are adjusted to meet target amounts**: Depending on market penetration, the measures estimation results improved on average towards the end of each simulation. This is due to the DIDC Controller adjusting message frequencies to match defined target rates. Simulations with market penetration greater than 20% showed the most improvement.

1 Introduction

The objective of the DIDC algorithms and software is to optimize the capture and transmission of vehicle-based data under a range of dynamically configurable messaging strategies. The DIDC software is used to reduce the capture and transmission of redundant or otherwise unnecessary data and to enhance the capture and transmission of high-value data depending on current needs of transportation system managers. DIDC software systematically conducts a heuristic optimization routine to identify the smallest set of captured and transmitted data capable of supporting system manager needs for system-wide situational awareness as well as system control for a target prediction horizon (e.g., next 30 minutes). These situational awareness needs are described as a set of desired measures of system and sub-system performance (e.g., predicted travel times along a specific path or shockwave location and speed along a specific roadway link). In short, the DIDC attempts to optimize the data collection process by minimizing the amount of data captured and transmitted (reducing data-related costs), while also upholding the accuracy in predicting measures of performance (maximizing the value of the data).

As part of the BSM Data Emulator project, we will experiment with the ranges of DIDC parameters to determine what helps to best estimate key transportation measures under various scenarios while keeping data communication costs low. These scenarios include various connected vehicle market penetrations, traffic demand, incidents, and slippery condition regions.

To conduct the assessment, we will make use of TCA 2.4, the offline TCA-DIDC version of the BSM Emulator and measures estimation algorithms developed in Task 4.

1.1 Purpose

The purpose of Task 7 is to explore the DIDC concept further by implementing and testing DIDC within the TCA Version 2 software. The purpose of this report is to describe the testing method and results for determining the best set of DIDC parameters that provide the best estimation of key transportation performance measures with the least amount of data load on communications.

2 Assumptions

It is critical to document assumptions to caveat findings from the analyses so that there are no false expectations of the benefits that may be realized in the field. The assumptions of this study were the following:

1. Vehicles transmit data via cellular only with no loss or latency.
2. Cost of cellular coverage is not part of the assessment.
3. Equipment failure rates are not part of the assessment.

3 Technical Approach

This section identifies the key transportation measures and variables that were examined. Two factors were considered for measuring the usefulness and efficiency of each DIDC alternative: key performance measurement estimation ability and data communication costs. Each of these two variables are explained below.

3.1 Performance Measures

The effectiveness of DIDC was measured by its ability to provide vehicle data that produced accurate performance measure estimation of four key measures: travel time, queues, slippery conditions, and turning movements. These four key measures were chosen because they cover all of the significant aspects of the DIDC concept. Significant aspects of the DIDC Concept include dynamic capabilities to react regionally or globally to data yield and adjust BMM generation parameters using the DIDC Controller.

3.1.1 Definitions of Measures

These measures and their descriptions are as follows:

Queues

- A vehicle is in queue when it is either stopped or is traveling at a speed less than 10 ft./s (3 m/s) and is approaching another queued vehicle at headway of less than 20 ft. (6 m).

Travel time

- This is defined as the average travel time on route segments experienced by all vehicles that begin travel in a specific time interval.

Slippery Conditions

- The use of traction control suggests a possible occurrence of slippery conditions.

Turning Movements

This is defined as a percentage of vehicles turning left or right at a given intersection.

3.1.2 System Description

Figure 3-1 illustrates the overall process of the offline TCA-DIDC Version 2.4 software to model the DIDC concept and estimate the performance measures. In this approach, vehicle trajectory files are input to the TCA which then produces vehicle-based BMMs. The offline analytic loop shows the optimization interval process where the DIDC Controller adjusts message generation parameters based on the current transmitted vehicle message data flow.

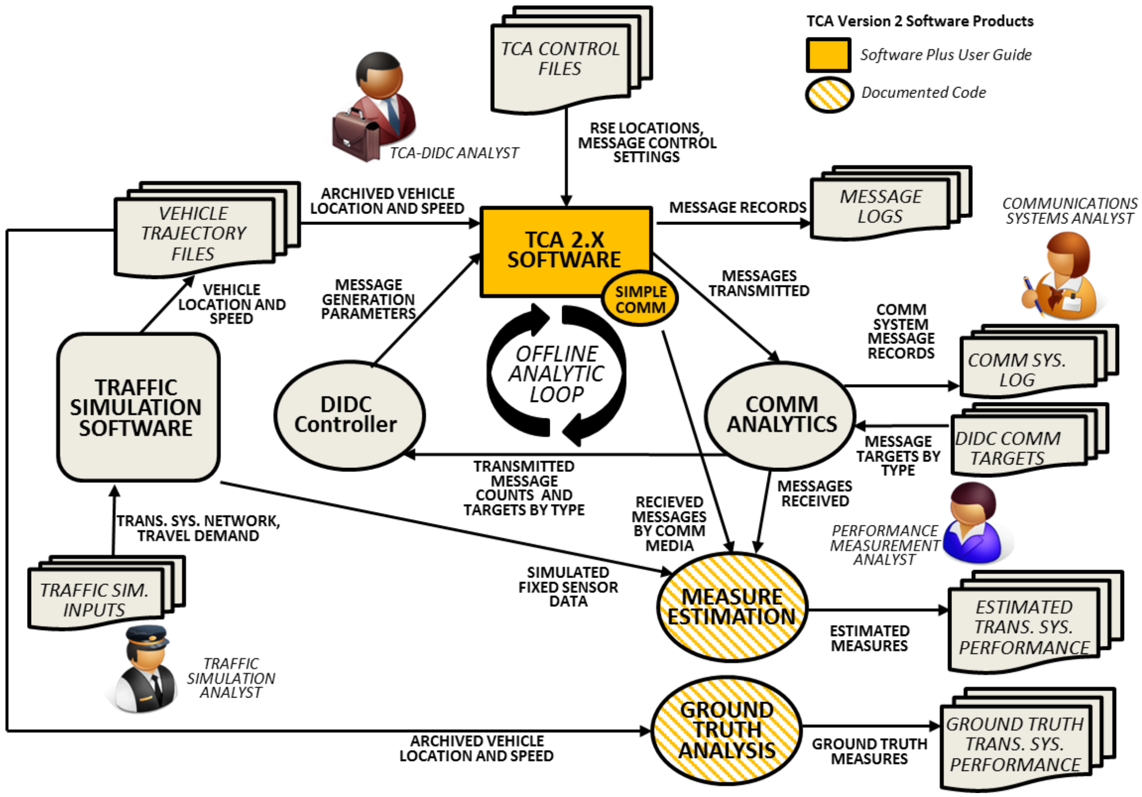

Figure 3-1: TCA-DIDC Version 2 Software System Description

TCA vehicle message output is ultimately used for measures estimation. The measures estimation success is determined by comparing to ground truth. Ground truth represents reality, i.e., what happened on the ground [1]. Therefore, ground truth measures are calculated based on the original vehicle trajectory data instead of the TCA vehicle-based messages.

3.2 Data Communication Cost

Another important variable for each test scenario was the data communication cost calculated by how much vehicle data is transmitted during the simulation. One of the assumptions in the Phase 1 test scenarios is that all communication is unlimited by loss, latency, or bandwidth. However, the amount of vehicle data was a factor in ranking the efficiency of each DIDC alternative against each other.

4 Analysis Scenarios

This section presents the network and process for producing analysis scenarios used in the Phase 1 DIDC testing.

4.1 Roadway Network

Using the requirements for the DIDC test network, Noblis developed Philosopher's Corner as depicted in Figure 4-1. This VISSIM network was designed to meet the requirements outlined in the DIDC Network Requirements and Design Report [2]. Key features include eighteen origin and destination points spread out amongst two towns, Platoville and Spinoza Oaks, with a shopping center in the middle.

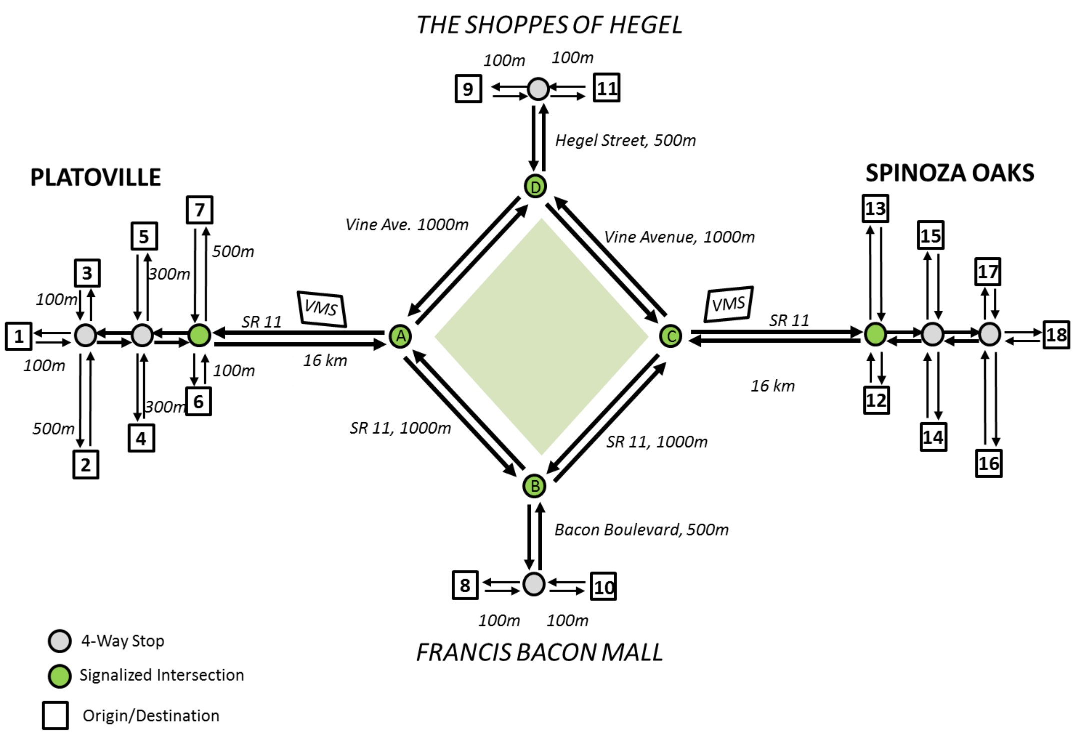

Figure 4-1: Philosopher's corner VISSIM test network

Three traffic condition levels were modeled on the Philosopher's Corner Network: Static Normal, Static High, and Dynamic High. The Static High Demand scenario was modeled by increasing the demand by 20% over the entire simulation period (of 1.5 hours). The Dynamic High Demand scenario was modeled by increasing the demand by 20% over the first hour of simulation and returning to normal demand levels for the last 30 minutes.

For the Philosopher's Corner network, incidents were modeled as a speed reduction over all lanes for the incident duration and incident area. For the scenarios with a single incident, a reduced speed area affecting all lanes was modeled on the Northeast-bound Vine Avenue between points A and D over a 150 foot stretch of roadway. The incident lasted for 30 minutes, starting at 2900 simulation seconds and ending at 4700 simulation seconds. The second incident affected all lanes traveling Eastbound on SR11 between points 1 and A over a 250 foot stretch of roadway. The incident lasted for 20 minutes, starting at 2700 simulation seconds and ending at 3900 simulation seconds. For both incidents, speeds were reduced to between 2.5 and 3.7 mph.

4.2 Genetic Algorithm

There were many possible combinations of parameters in the DIDC concept. To keep this testing effort manageable, a genetic algorithm testing process was used to limit the amount of combinations to evaluate but still produce an acceptable solution. A genetic algorithm process is commonly used when there are many possible solutions to an optimization problem. A set of possible solutions are evaluated using a fitness test and then evolved into better solutions through repetitive application of mutation and recombination. Figure 4-2 illustrates how this type of approach was used to determine the best set of DIDC properties. Each phase of this process is described in more detail below.

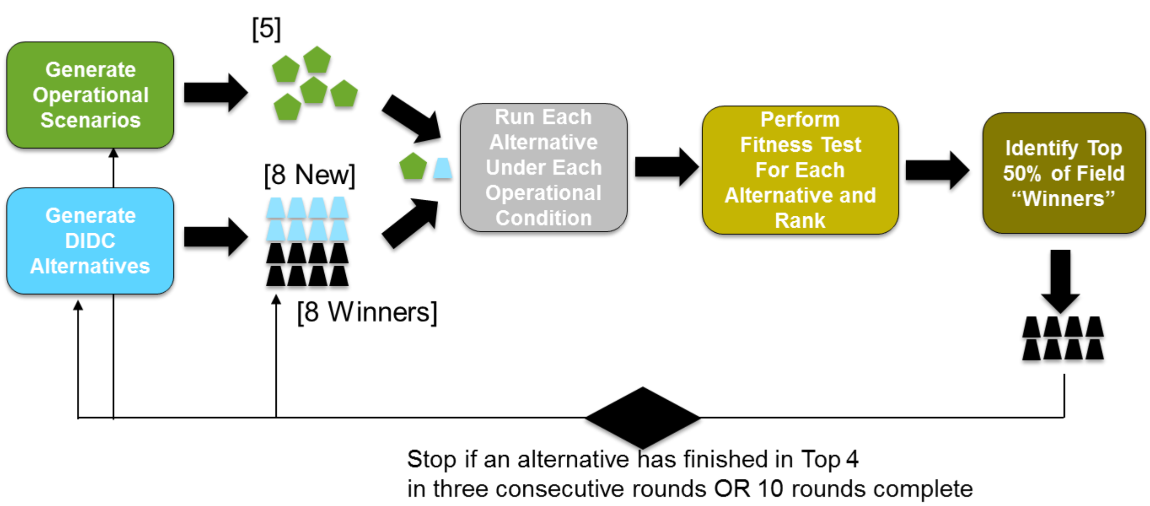

Figure 4-2: Genetic algorithm process

4.2.1 Generate Alternatives and Scenarios

The first step of the DIDC genetic algorithm approach was to generate the DIDC alternatives. The attributes of the alternatives were the parameters of the DIDC Controller. Key parameters included: the optimization time interval, message targets, lambda values, transmission threshold, trigger thresholds, and burst mode properties. Table 4-1 describes these parameters and the range of possible values.

In the initial round of testing, 16 possible combinations of alternatives were generated. Up to four of those combinations were determined by human best guess and the remaining were generated at random. Of these 16 alternatives, 8 were the "winners" of the previous round of simulation and 8 were new combinations.

Table 4-1: DIDC Alternative Parameters

DIDC Alternative Scenario Parameter	Range
1. Travel Time Periodic Trigger Inputs	1. Optimization Interval: 2-10 minutes
	2. Generation Mean Time (lambda): 30-210 seconds
	3. Message Target per 1000 ft.: 5-150 messages
2. Queue Trigger Inputs	1. Optimization Interval: 1-5 minutes
	2. Generation Mean Time (lambda): 1-10 seconds
	3, Message Target per 100 ft.: 50-1000 messages
	4. Median Post Trigger Reports: 3-8 messages
3. Turning Movement Trigger Inputs	1. Optimization Interval: 1.5-5 minutes
	2. Generational Mean Time (lambda): 15-100 seconds
	3. Message Target per intersection approach: 50-500 messages
4. Slippery Condition Trigger Inputs	1. Optimization Interval: 5-30 seconds
	2. Generation Mean Time (lambda): 1-10 seconds
	3. Message Target per region: 100-250
	4. Burst Time Length: 60-180 seconds
	5. Burst Range: 150-300 feet
	6. Burst Generation Mean Time: 5-30 seconds
	7. Burst Time Extension: 5-30 seconds
5. Transmission Threshold	1-32 Messages per Transmission

4.2.2 Generate Testing Scenarios

The second phase of the genetic algorithm approach for testing DIDC was to generate the operational inputs for each VISSIM scenario. These are the circumstantial inputs as described in Table 4-2 and include: market penetration, traffic incidents, traffic demand, origin-destination inputs, and the existence of slippery conditions.

There was one random combination of operational inputs for each market penetration value making a total of five operational scenarios. Each of the five operational scenarios were run with each of the 16 DIDC alternatives meaning each generation of the genetic algorithm produced results from 80 simulations.

Table 4-2: VISSIM operational input parameters

Operational Input	Values	Description
Market Penetration of connected vehicles	2-7%, 20-30%, 45-55%, 70-80%, 95-100%	DIDC is designed to adapt vehicle message frequency depending on market penetration. However, market penetration is unknown at the beginning of a simulation. Varying the market penetration will test how well DIDC adapts to the abundance or lack of vehicle messages. The values listed are ranges from which the market penetration will be selected at random.
Traffic Incidents	None, one incident, two incidents	An incident causes an increase of travel times and alters the normal flow of traffic.
Traffic Conditions	Static Normal, Static High, Dynamic High	Similar to market penetration, DIDC should adapt to the congestion levels of the network.
Origin-Destination (O-D) Inputs	Various implementations of vehicle routes	Various O-D inputs affects the turning movements at each intersection.
Slippery Condition Regions	None, one, two	Traction Control triggered messages are triggered by events such as slippery conditions. The presence of one or multiple slippery condition regions will be tested to determine the accuracy of DIDC in identifying their locations.

4.2.3 Run Simulation

A single simulation was modeled by the cycle of events shown in Figure 4-3. The operational attributes of the scenarios were simulated by VISSIM and the trajectory output fed into the TCA-DIDC software. The attributes of the DIDC alternatives were parameters of the TCA-DIDC which produced the resulting vehicle messages. These messages were analyzed by measures estimation algorithms to determine their accuracy compared to the ground truth results.

In order to best capture the ability of DIDC to adapt to the demands of the network, the TCA-DIDC was run for 30 minutes of seeding time on the vehicle trajectory data. Only the vehicle messages transmitted after this seeding period were used to estimate performance measures.

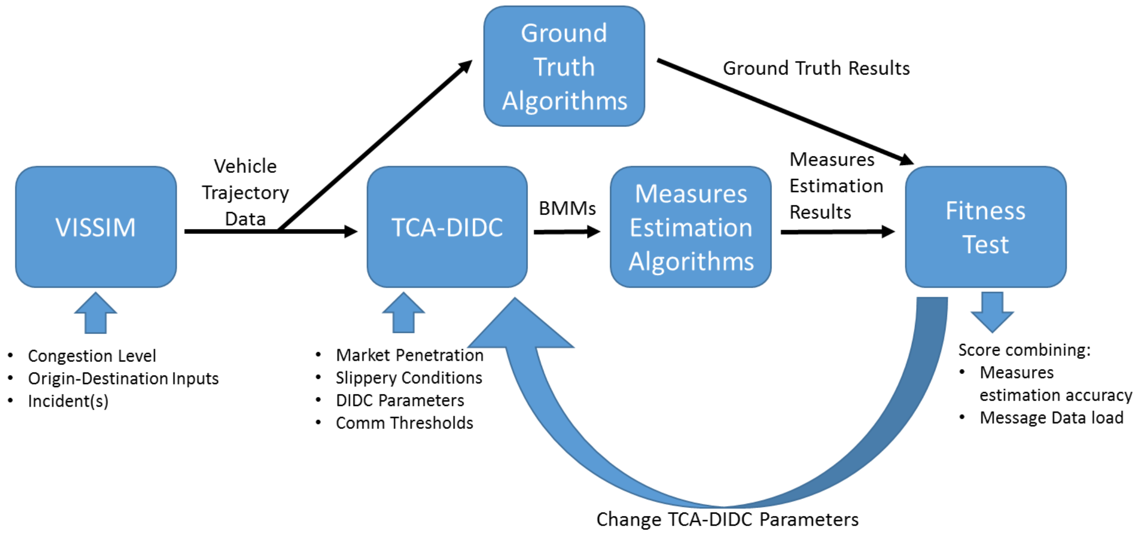

Figure 4-3: Scenario Workflow

4.2.4 Conduct Fitness Test and Rank

The fitness of each simulation was measured by its effectiveness in estimating performance measures and the data load on communication. The total ranking score consisted of 60% based on accuracy in estimating performance measures and 40% on communications load. Performance measures estimation accuracy was measured by running the measures algorithms on the vehicle message output from the TCA and comparing to ground truth. Since there were four performance measures, the accuracy of each measure counted towards 15% of the total ranking score. Data load was measured by the total number of transmitted messages and size of the message data.

Each of the 16 DIDC Alternatives combined their scores for each VISSIM operational scenario into a total combined score. After ranking these combined scores, the top eight DIDC alternatives returned in the next round of testing.

4.2.5 Termination Conditions

The genetic algorithm process illustrated in Figure 4-2 continued until a maximum of ten rounds was reached or when a single DIDC alternative consistently ranked in the top four over three consecutive rounds. Each round consisted of 16 DIDC alternatives each run with five various operational scenarios. Unless a DIDC alternative ranked in the top four over three consecutive rounds, a maximum number of 800 simulations would have been completed over ten rounds of the genetic algorithm process. In this case, one DIDC alternative consistently ranked in the top four over the first three consecutive rounds.

5 Results

This section discusses the winning DIDC alternative and describes the characteristics that made it consistently in the top four over three consecutive rounds. Also discussed are key observations of how well the DIDC concept worked to regulate data flow in the Philosopher's Corner Network to meet targets set by the user.

5.1 The Winning DIDC Alternative

The termination conditions of the genetic algorithm process were met when a single DIDC alternative placed first, third and fourth respectively across three consecutive rounds of testing. The parameter values of the winning DIDC alternative are shown in Figure 5-1. The average rank results per market penetration range for the winning DIDC alternative in Table 5-1 show that this set of DIDC parameters ranked particularly well in the 20-55% market penetration range. While not always the highest ranked DIDC alternative in measures estimation, the winning set of DIDC parameters was consistently in the top five for all but one instance in round 2 at the 2-5% market penetration condition where it was eighth.

BMM Type	Parameter	Value
Periodic (Travel Time estimation)	Optimization Interval	270 seconds
	Periodic Mean Time	210 deciseconds
	Target (1000 ft)	25 messages
Queue	Optimization Interval	180 seconds
	Target (100 ft)	80 messages
	Mean Time	20 deciseconds
Slippery Conditions	Optimization Interval	15 seconds
	Mean Time	22 deciseconds
	Burst Time Length	2 seconds
	Burst Time Extension	11 seconds
	Burst Range	100 feet
	Burst Mean Time	8 deciseconds
Turning Movements	Optimization Interval	300 seconds
	Mean Time	40 deciseconds
	Target	343 messages

Figure 5-1: DIDC parameters of the winner

Table 5-1: Rank of the winning DIDC alternative across three rounds and market penetrations

Round Number	Market Penetration 2-5%	Market Penetration 20-30%	Market Penetration 45-55%	Market Penetration 70-80%	Market Penetration 95-100%	Overall Rank
1	1	1	3	1	2	**1**
2	8	2	1	3	4	**3**
3	5	3	4	4	4	**4**
Average Rank	4.67	2.00	2.67	2.67	3.33	

Also contributing to the high ranking of this alternative was the relatively low amount of data as noted in Table 5-2. The winning DIDC alternative consistently had less data than most of its competitors. The score added for data was consistently between approximately 2-6 percentage points and contributed significantly to the better overall ranking. As a result, the winning DIDC alternative scored better than some alternatives with better measures estimation results. The average measures estimation results for the winning DIDC alternative are also listed in Table 5-2. The following sections will walk through each performance measure and analyze the measures estimation capability of the winning DIDC alternative.

Table 5-2: Measures estimation and data cost results for DIDC winner

	~5% Market Penetration	~25% Market Penetration	~50% Market Penetration	~75% Market Penetration	~97% Market Penetration
Travel Time Estimation Average Error	7%	8%	7%	7%	9%
Queue Estimation Average Error	71%	54%	44%	34%	36%
Turning Movements Estimation Average Error	46%	28%	27%	18%	20%
Slippery Conditions Estimation Average Error	75%	39%	5%	20%	3%
Average Number of Messages	44,942	296,849	464,775	719,557	966,776

	~5% Market Penetration	~25% Market Penetration	~50% Market Penetration	~75% Market Penetration	~97% Market Penetration
Average Data Score (out of 40)	6.85	2.29	2.59	3.56	3.75

5.2 Measures Estimation Results

This section describes and provides graphical illustrations of the measures estimation results of the winning DIDC alternative. The effectiveness of the DIDC Controller in improving or preserving measures estimation accuracy is also discussed in each section.

5.2.1 Travel Time

Travel time estimation results had a less than 15% average mean percentage error rate across every DIDC alternative tested. Increasing the target number of messages per roadway did not significantly increase travel time accuracy as shown by an example in Figure 5-2. The winning DIDC alternative had a target of 25 Periodic BMMs per 1000 feet of roadway and an initial lambda (periodic mean frequency time) of 21 seconds. In contrast, the other DIDC alternative whose results are also depicted in Figure 5-2 had a higher target of 94 Periodic BMMs per 1000 feet and a more frequent initial periodic mean time of 18 seconds. As the figure shows, the additional frequency only improved Travel Time average error rates by less than 1% in three of the five market penetrations and slightly decreased accuracy in the remaining two.

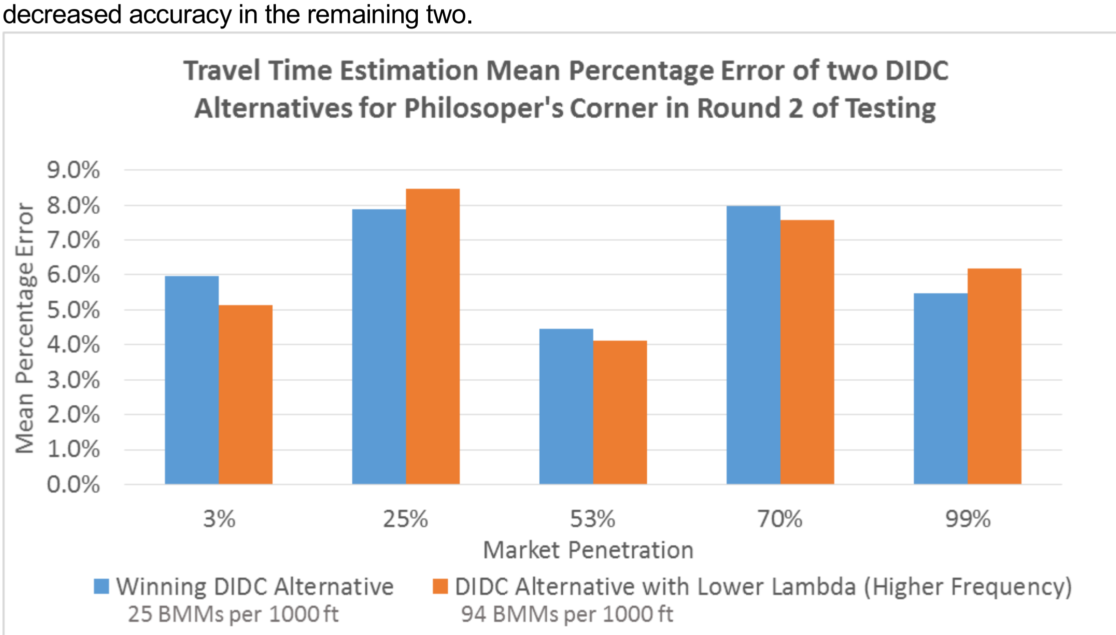

Figure 5-2: Travel Time Estimation Mean Percentage Error

5.2.1.1 Effectiveness of the DIDC Controller Adjustment of Periodic BMMs

In DIDC Phase 1 testing, the DIDC Controller dynamically adjusted the Periodic BMM frequency regionally. That is, the DIDC Controller used each separate link of the VISSIM Philosopher's Corner network to compare realized data yield to expected targets and adjusted each link separately as needed.

Figure 5-3 models the periodic BMM frequency rate along a 4 mile roadway compared to data yield of the Philosopher's Corner Network under the dynamic high traffic demand operational condition. This figure shows that when the data yield of periodic BMMs is below the user-defined target at the beginning of the congestion period, the DIDC Controller increased the frequency of periodic BMMs by lowering the lambda value. As the number of BMMs nears the target amount, the periodic BMM lambda value levels off. Later in the simulation, as traffic builds on the network and the data yield exceeds the target, the DIDC Controller increases the lambda value so that the frequency of BMMs is decreased. This, in turn, reduces the amount of periodic BMM data being generated. This is an example of the DIDC Controller effectively adjusting the data yield of a roadway on the Philosopher's Corner network by adjusting message generation rates in that region.

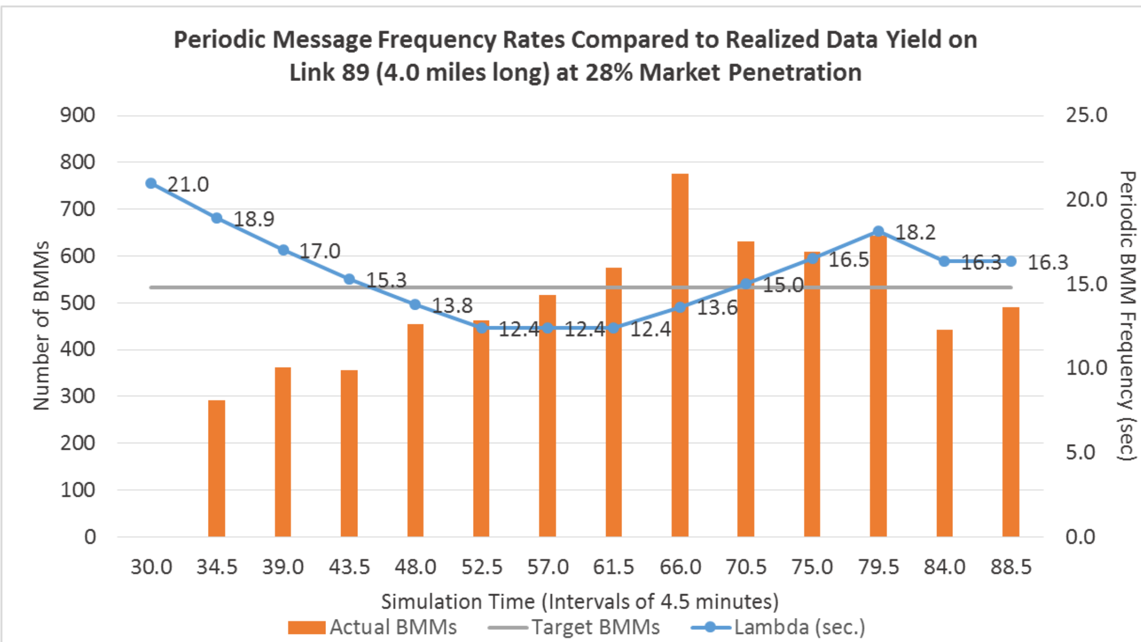

Figure 5-3: Example DIDC Controller Adjustment of Periodic BMMs (Travel Time) Frequency on a Roadway with Limited Congestion

The roadway showed in Figure 5-3 was Eastbound SR 11 (see Figure 4-1) which consisted of mainly free-flowing traffic exiting the more congested shopping mall traffic of the diamond and entering the town of Spinoza Oaks. In contrast, Figure 5-4 shows congestion within the shopping mall diamond on a roadway that also contained an incident. This example shows that the amount of data yielded on this roadway was as much as 35 times the target amount of data set by the user even at just 28% market penetration of connected vehicles. And while the DIDC Controller successfully decreased the frequency of the Periodic BMM to bring the data yield closer to the target, the lambda value was not changed fast enough to cause much impact in data yield. However, if the simulation were longer we would expect the data yield to eventually meet the target number of messages.

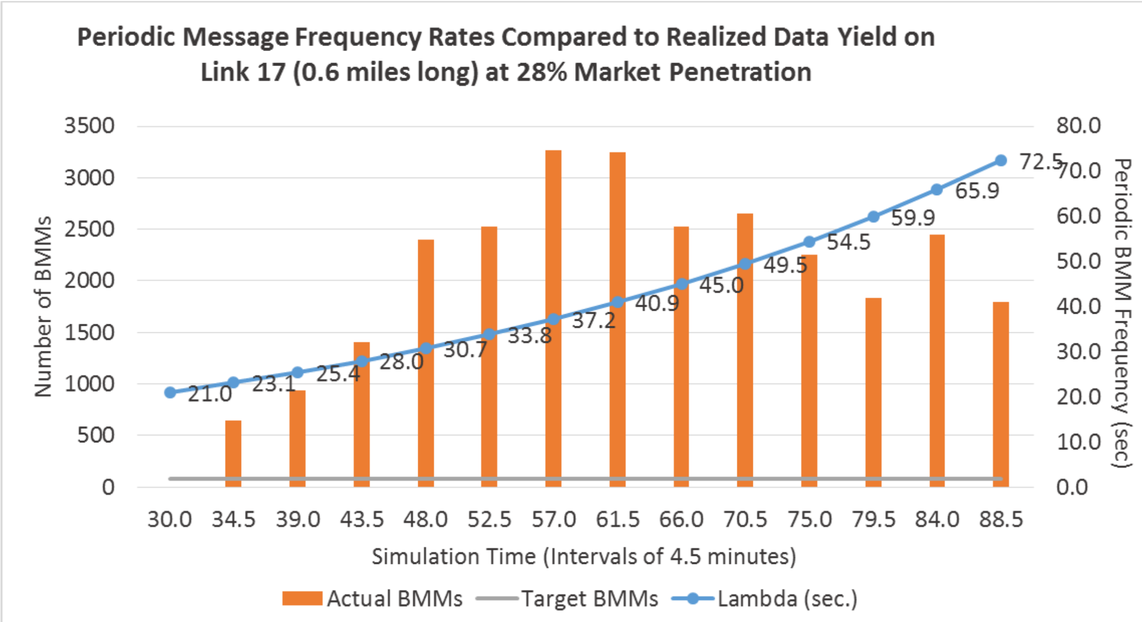

Figure 5-4: Example DIDC Controller Adjustment of Periodic BMM (Travel Time) Frequency on a Roadway with Significant Congestion

Overall, the DIDC Controller appeared to effectively increase and decrease the data yield of the network by increasing and decreasing the generation frequency of periodic BMMs.

5.2.2 Queue Length

Average queue length estimation errors of the winning DIDC alternative ranged from 70% at low market penetrations to 30% at higher market penetration. The target number of queue BMMs per 100 feet was 80 messages for the winning DIDC alternative. The initial lambda was 20 deciseconds meaning the frequency of queue-triggered BMMs followed a Poisson distribution with an input lambda of 0.2 seconds. In Round 3 of the genetic algorithm testing, an effort was made to increase the accuracy of queue measurement by testing a DIDC alternative with a higher queue BMM target of 500 BMMs per 100 feet of roadway. The average error percentage rates for these two DIDC Alternatives is compared in Figure 5-5.

The increased queue message frequency only improved the queue length estimation in three of the five operational conditions and only when market penetration was over 50%. This is most likely due to the mechanics of the queue length estimation algorithm. For known bottleneck location queues, a vehicle starts off a queue if it is traveling at a speed of less than 10 fps and is within 100 feet of the known bottleneck. Additional length is added to the queue if a BMM is discovered with a recorded speed of less than 10 fps and a location within 100 feet of the existing queue. When market penetration is less than 100%, not all vehicles will generate messages resulting in gaps between messages received. The higher message frequency helps prevent these gaps at higher market penetrations. But overall, the high data communication cost of the additional data from these DIDC alternatives prevented them from scoring well in the genetic algorithm.

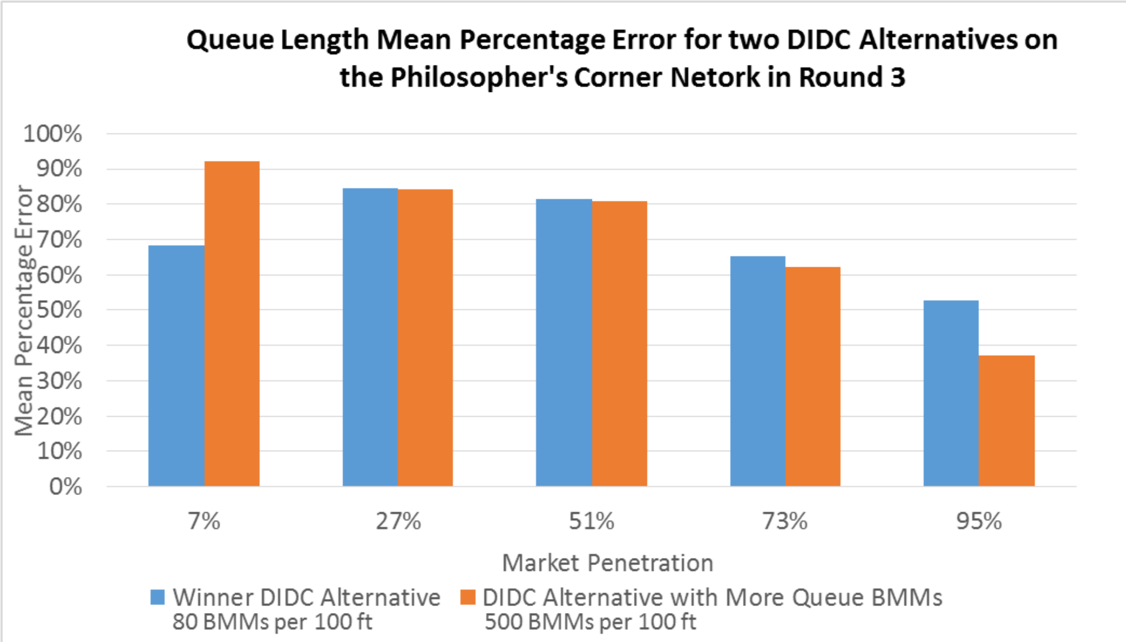

Figure 5-5: Queue Length Estimation Errors of Two DIDC Alternatives on the Philosopher's Corner Network in Round 3

5.2.2.1 Effectiveness of the DIDC Controller Adjustment of Queue BMMs

During the TCA simulations, the DIDC Controller tracked the length of the queue in order to determine if the user-defined target rate of 80 queue BMMs per 100 feet was met. The DIDC Controller compared the actual data yield to the target rate at an optimization interval of every 3 minutes (180 seconds). The adjusted frequency of queue BMMs is represented in Figure 5-6 with the actual data yield compared to the targeted amount of data. The target amount of BMMs changed as the length of the detected queue changed. Figure 5-6 shows that the DIDC Controller successfully decreased the frequency of queue BMMs early in the simulation run when actual data yield was greater than the target amount. The target and actual data yield are noticeably more similar after 69 minutes of simulation time except for one anomaly at 75 minutes. This large sudden difference between actual data yield and target rate was most likely due to an abnormally large queue with an increased level of congestion on the roadway.

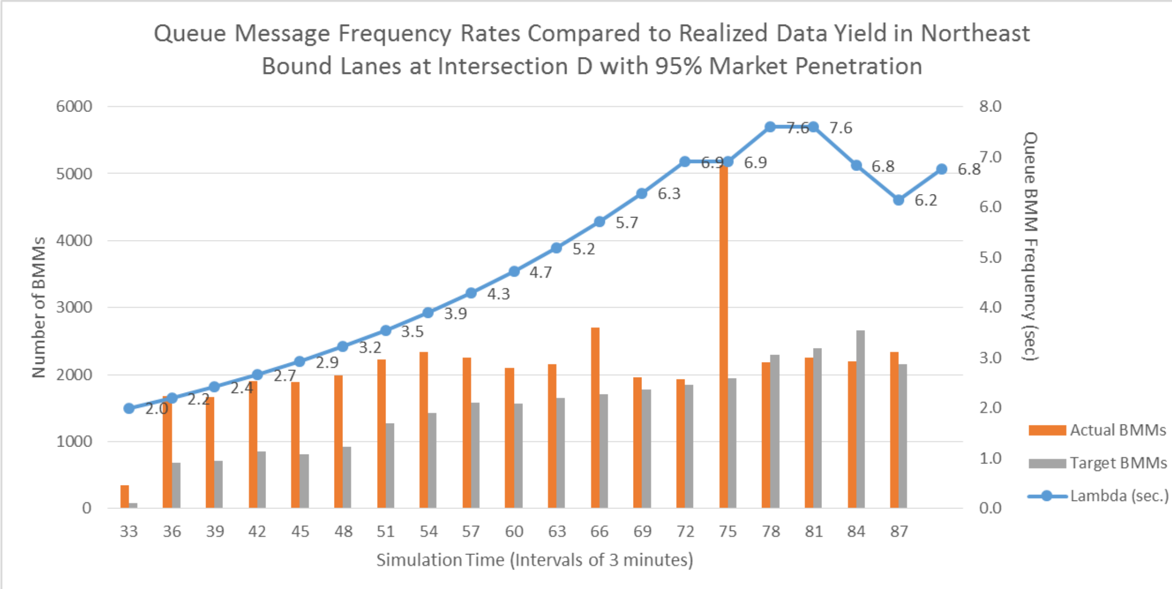

Figure 5-6: Queue Message Frequency Over Simulation Time of the Philosopher's Corner Network in Round 3 with 95% Market Penetration

Also examined is the DIDC Controller's ability to improve the queue length estimation over the duration of the simulation. The hypothesis is that measures estimation results improve as the DIDC Controller adjusts message generation rates to meet the target set by the user. Figure 5-7 shows an example from Round 3 of the genetic algorithm where the queue length estimation errors slightly improved over the duration of the simulation as noted by the dotted trend line.

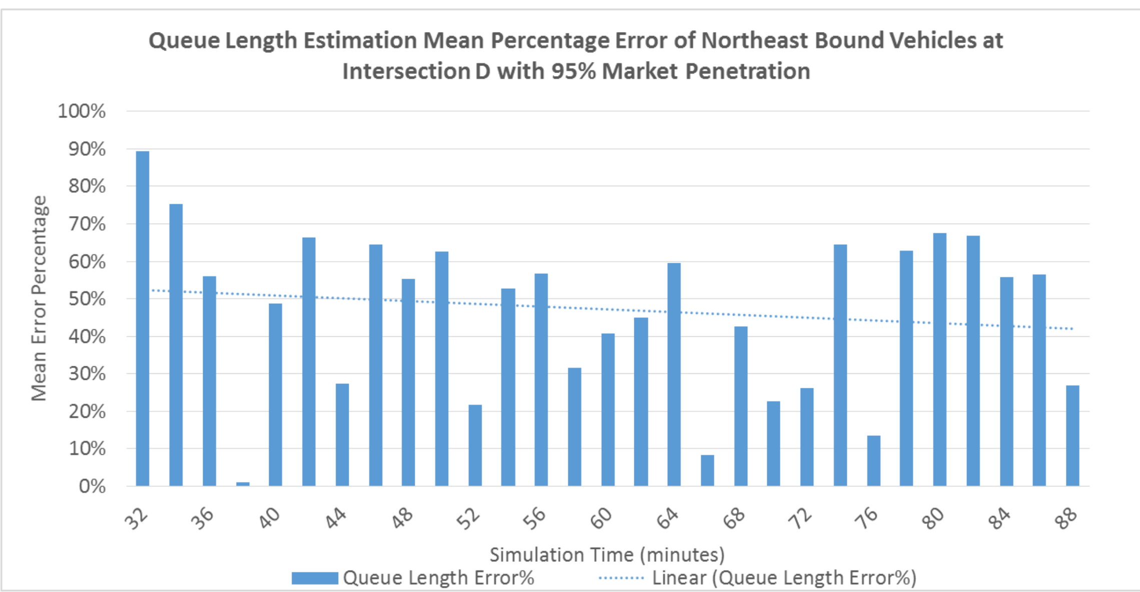

Figure 5-7: Variability of the Queue Length Estimation Mean Percentage Error on the Philosopher's Corner network with 95% Market Penetration of Connected Vehicles

5.2.3 Turning Movements

Average turning movement estimation errors of the winning DIDC alternative ranged from 90% errors at low market penetrations to 15% errors at high market penetration. The target number of turning BMMs at Intersection A for the winning alternative was 343 BMMs, a relatively average target compared to other DIDC alternatives tested on the Philosopher's Corner network. For comparison, the results from a DIDC alternative with a higher target value of 500 BMMs per intersection is shown in Figure 5-8.

Figure 5-8 shows that increasing the target number of turning movement BMMs at Intersection A improved turning movement estimation errors by approximately 2-10%. However, this would also lead to higher amounts of BMM data yield, while the winning DIDC alternative was able to achieve similar measures estimation success with less data.

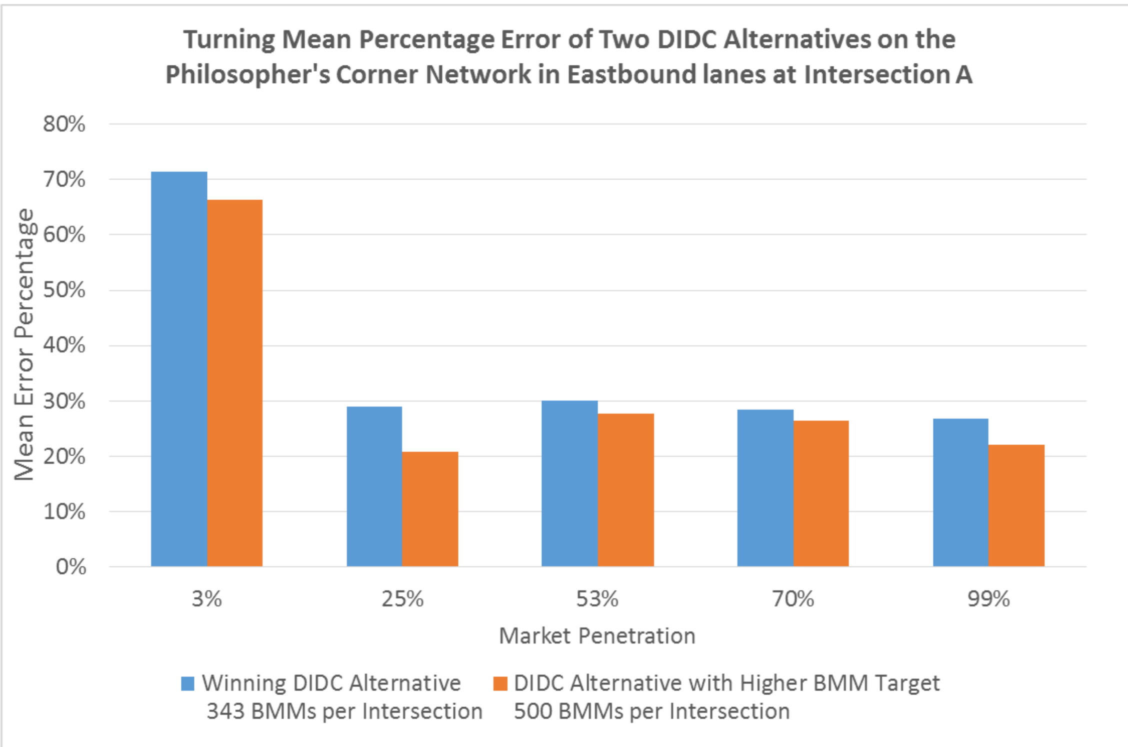

Figure 5-8: Turning Movements Estimation Errors of Two DIDC Alternatives on the Philosopher's Corner Network in Round 1

5.2.3.1 *Effectiveness of the DIDC Controller's Adjustment of Turning Movement Messages*

The DIDC Controller counts the number of transmitted BMMs within the intersection region and compares to user-defined targets every optimization interval. The winning DIDC alternative had a turning optimization interval of 5 minutes. Figure 5-9 and Figure 5-10 show the DIDC Controller's adjustment of the turning BMM frequency and the comparison of data yield to targeted amounts at each optimization interval. In Figure 5-9 with 6% connected vehicle market penetration, the simulation began with a data yield that was below the target. The DIDC Controller effectively decreased the lambda value to cause turning movement BMMs to be generated more frequently. After 70 minutes of simulation time, the data yield went above the defined target and the DIDC Controller responded by increasing the lambda value so that turning BMMs were less frequent. However, this example had such a low market penetration, a low data yield could also signify that there were less connected vehicles in the intersection region.

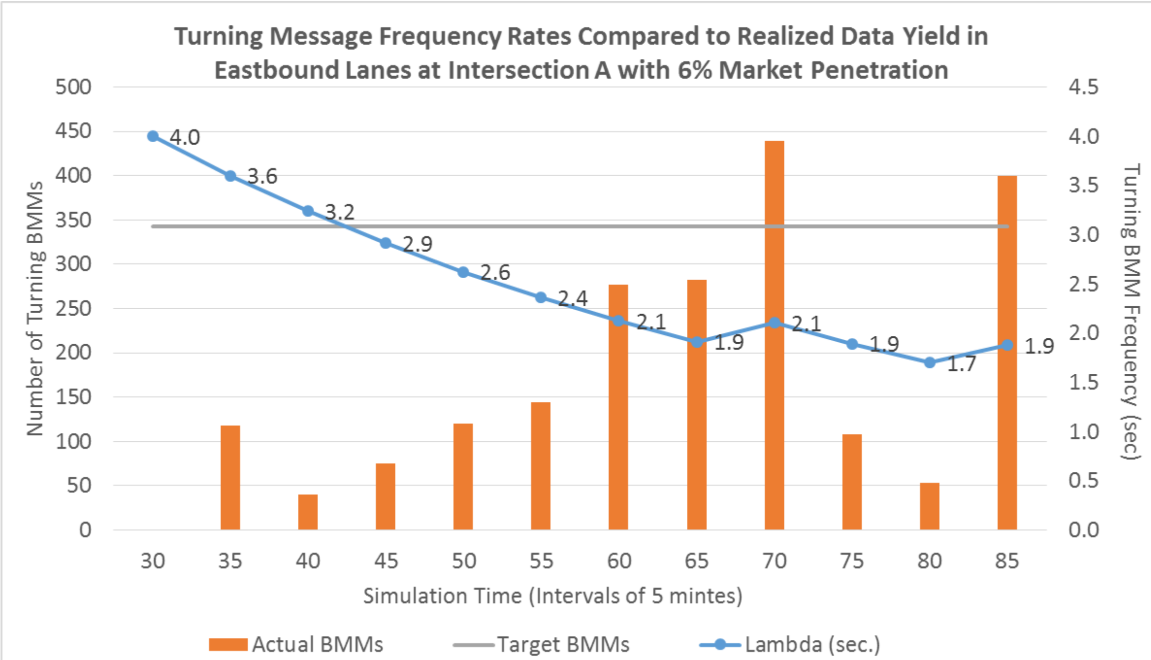

Figure 5-9: Turning Movement Message Frequency over Simulation Time of the Philosopher's Corner Network in Round 1 with 6% Market Penetration

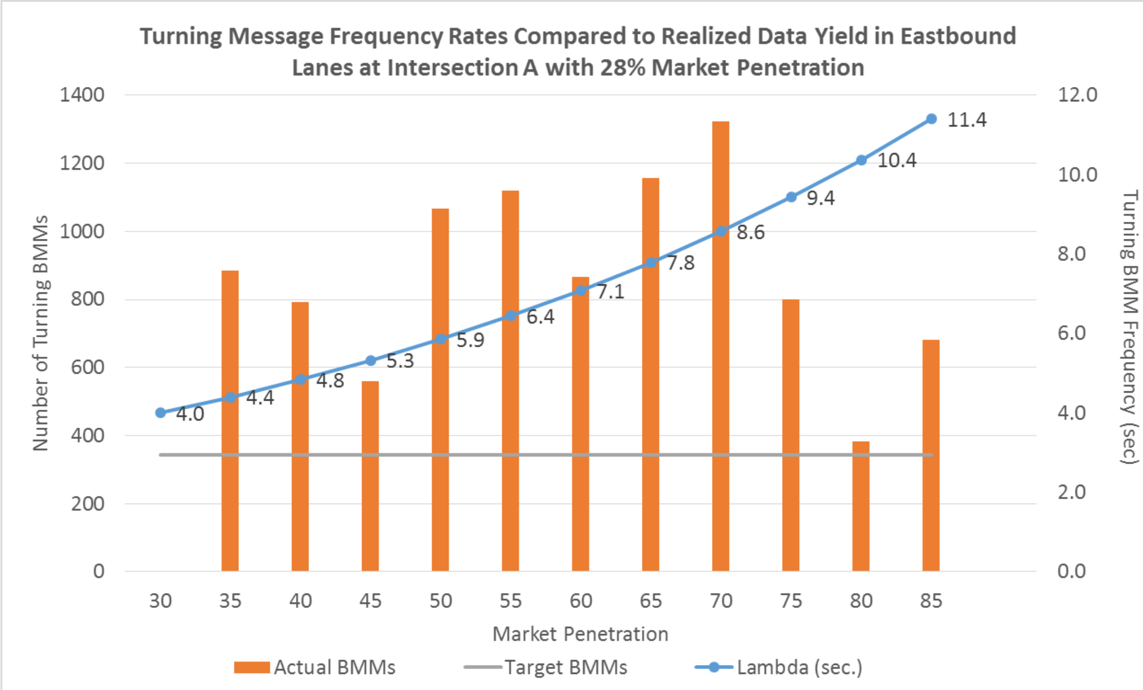

Figure 5-10: Turning Movement Message Frequency over Simulation Time of the Philosopher's Corner Network in Round 1 with 28% Market Penetration

Although the previous two figures show that the DIDC Controller effectively increased and decreased the actual data yield, Figure 5-11 shows that there was no improvement in turning measures estimation accuracy. This is most likely due to the mechanics of the turning movements estimation algorithm. The algorithm used the data yield and length of turn to provide results as a ratio of left to right turns. Since the output is a ratio, the increase or decrease in data yield as a result from the DIDC Controller's adjustment of generation frequencies did not affect the turning movement estimation results. Most likely, the accuracy of turning movements depends on how many connected vehicles turn right or left. If the majority of connected vehicles turn right, then the measures estimation results will be skewed to show most traffic turning right, or vice versa.

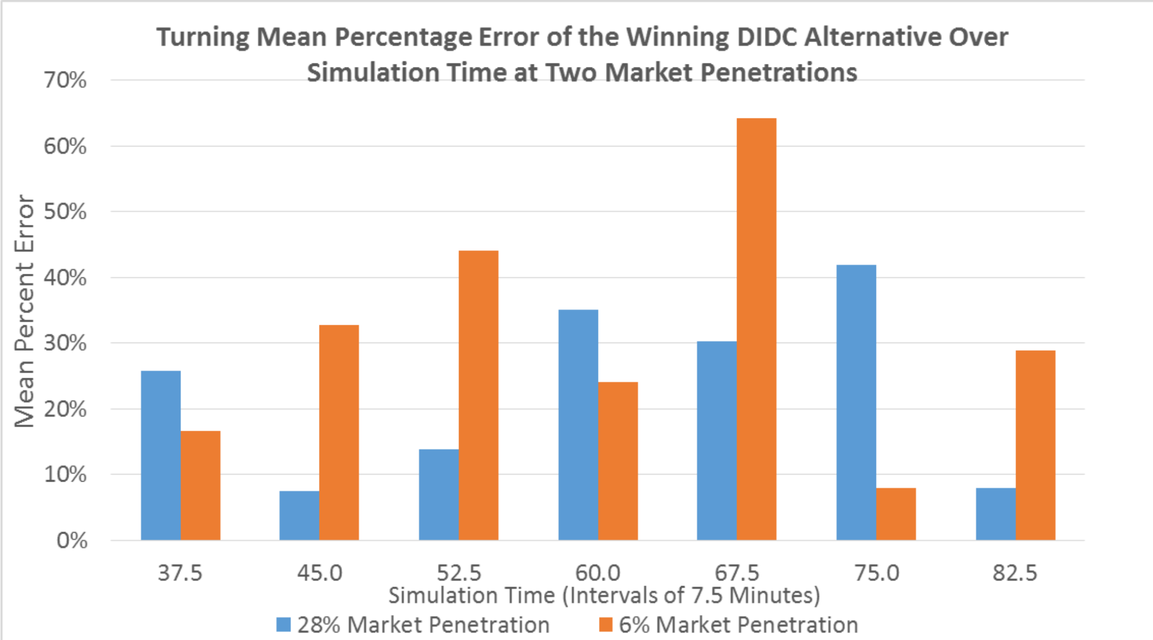

Figure 5-11: Turning Movements Mean Percentage Error of the Philosopher's Corner Network of Two Market Penetrations

5.2.4 Slippery Conditions

A slippery condition region is detected successfully if the start and end time of the predicted region are within 60 seconds of ground truth and the coordinates are within 500 feet of the ground truth slippery condition position. Overall, slippery condition predictions were fairly successful when market penetrations were above 25%. Most likely because at lower market penetrations there were not enough connected vehicles reporting traction control events for the measures estimation algorithm to detect a slippery region. Other than the two ground truth slippery regions on the Philosopher's Corner network, there was also a global probability of 3% that a vehicle's traction control would turn on. This was both to mimic real world circumstances when traction control may turn on when a vehicle brakes or turns suddenly and to make slippery region prediction more difficult.

At market penetrations of approximately 25% and above, all DIDC alternatives consistently predicted true positive regions with similar accuracy of times and coordinates. Table 5-3 compares the coordinate and time errors for three DIDC alternatives at 53% market penetration: the winner, Alternative A, and Alternative B. Noticeably, all three predicted the start and end time almost perfectly. The coordinate errors were also noticeably similar even though all three alternatives had different lambda values for traction control triggered BMM generation. The winning DIDC alternative had the lowest lambda value of 8 deciseconds and consequently had slightly more accurate coordinate estimation results. The similar coordinate errors of these three alternatives is due to each simulation equipping the same connected vehicles, albeit with slightly different traction control triggered BMM generation criteria.

Table 5-3: Slippery Condition Estimation Errors of Three DIDC Alternatives with 53% Market Penetration on the Philosopher's Corner Network

	Winning DIDC Alternative Region 1	Winning DIDC Alternative Region 2	Alternative A Region 1	Alternative A Region 2	Alternative B Region 1	Alternative B Region 2
Start Time Error (sec)	0	0	0	0	0	0
End Time Error (sec)	0	1	0	0.7	0.8	0.6
Left Coordinate Error (ft.)	9.111906	325.2099	21.0597	325.2099	20.30079	367.2122
Right Coordinate Error (ft.)	9.096463	21.21328	9.096463	21.21328	9.096463	21.21328

5.2.4.1 Effectiveness of the DIDC Controller for Improving Slippery Condition Region Detection Results

Unlike the other event triggered BMMs, the traction control BMMs do not have a user-defined target data amount. Instead, the traction control trigger uses a unique method of regional DIDC where the DIDC Controller may request traction control BMMs from all connected vehicles in an area containing an active traction control event. This is called burst mode messaging. The effectiveness of this messaging mode will be evaluated in Phase 2 when DIDC is compared to other message types.

6 Conclusions and Future Research

6.1 Key Findings

- **The winning DIDC Alternative had consistently good measures estimation results compared to the other DIDC alternatives**: Although the winning DIDC alternative did not often have the best measures estimation results, it was consistently near the top across all market penetrations.
- **The winning DIDC alternative generated far less data than most DIDC alternatives**: This was most likely due to the conservative initial generation mean times (lambda values) of message generation frequency which allowed the DIDC Controller to ramp message generation up or down depending on the data yield.
- **The winning DIDC alternative initial generation mean times (lambda values) were best suited for the 20 to 55% market penetration range**: The winning DIDC alternative consistently scored in the top 5 out of 16 in the 20-60% market penetration range. This is most likely due to the initial mean times of the triggered BMMs being best suited to conditions with this percentage of connected vehicles on the Philosopher's Corner Network.
- **The DIDC Controller effectively adjusted message generation rates to match target values**: The DIDC Controller correctly increases and decreases the lambda value based on the comparison of actual data yield to defined targets.
- **Queue and travel time measures estimation results improve or are preserved as message generation rates are adjusted to meet target amounts**: Depending on market penetration, the measures estimation results improved on average towards the end of each simulation. This is due to the DIDC Controller adjusting message frequencies to match defined target rates. Simulations with market penetration greater than 20% showed the most improvement.

6.2 Future Research

Future research during Phase 2 of DIDC testing should investigate if measures estimation accuracy improves towards the end of the simulation for other message types as it does for BMMs. If only BMMs show measures estimation accuracy increasing over simulation time, it can be concluded that the DIDC Controller's adjustment of message generation frequency effectively improves measures estimation results over time. Comparison of slippery conditions will also be especially valuable in Phase 2 to determine the effectiveness of the DIDC region burst mode messaging.

References

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2. Deurbrouck, T., Wunderlich, K. BSM (+BMM) Data Emulator: Network Requirements and Design Description. Prepared by Noblis for U.S.DOT, November 2015.

APPENDIX A. List of Acronyms

Acronym	Meaning
BMM	Basic Mobility Message
BSM	Basic Safety Message
CAM	Cooperative Awareness Message
DIDC	Dynamic Interrogative Data Capture
DOT	Department of Transportation
FHWA	Federal Highway Administration
ITS	Intelligent Transportation Systems
JPO	Joint Program Office
PDM	Probe Data Message
O-D	Origin-destination
TCA	Trajectory Conversion Algorithm

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