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Journal details:

- ISSN: 2644-2388
- Publisher: Mason Publishing (George Mason University)
- Distribution: On-line only
- Publication Frequency: Immediately after acceptance. Archival is currently done annually.
- Indexing: Currently indexed by CrossRef and Google Scholar. Will be indexed in DOAJ and other premier indexing avenues as soon as the eligibility criteria are met.
- Article processing fee: Currently there is no fee to publish in JMMS

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Editors' Note

The overarching goal of Journal of Modern Mobility Systems (JMMS) is to provide a high-quality venue to display time-critical research on a public venue that can positively impact society. Because technology and its impact on transportation systems are evolving at a faster pace in the recent years, the primary objective of (JMMS) is to facilitate the publication of cutting-edge, peer-reviewed research works in a timely manner. Specifically, JMMS strives to obviate the need for researchers to await a six- to twelve-month turn around time for presentation at a major conference or publication in a leading journal. From our perspective, it is also important to assure that authors retain the rights to their work while parts of their research results are disseminated quickly through JMMS.

We launched JMMS in 2020, which will forever be known for the outbreak of the COVID-19 pandemic. The core theme of this journal is to disseminate early the research findings related to the disruptive forces in transportation that are reshaping travel, travel modes and travel demand worldwide.

In 2021 the challenges due to the pandemic continued to prevail. Despite these challenges, we are pleased to release Volume 02 (2021) of JMMS with three high quality research briefs.

We sincerely thank the Dean of College of Computing and Engineering, the Dean of Libraries, the Provost and the President of George Mason University for their support and encouragement in launching JMMS. We also thank our sponsor ATPIO (http://ATPIO.org) for helping us deliver a highly professional product.

We are anticipating and looking forward to a robust year ahead for JMMS.

Mohan Venigalla
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Journal of Modern Mobility Systems (JMMS), Vol. 02 (2021), 101-107
Document: https://doi.org/10.13021/jmms.2021.2932

Evaluating the Effectiveness of a Connected Vehicle Environment on an Arterial Road Using the Trajectory Data

Raunak Mishra, M.Tech.[a], Srinivas S. Pulugurtha, Ph.D., P.E., F.ASCE[a,*]

[a] *The University of North Carolina at Charlotte, 9201 University City Blvd, Charlotte, NC 28223; *Corresponding Author: sspulugu@uncc.edu*

Received: 24 Dec. 2020 ● **Revised** 26 April. 2021 ● **Accepted**: 10 May. 2021 ● **Published**: 17 May. 2021

ABSTRACT

The transportation system is a complex interaction between the infrastructure, vehicles, and users. Over time, many innovations have come through in the field of transportation. The connected vehicle technology is one such innovation with potential to improve mobility, reduce congestion, and enhance safety of the transportation system. However, the successful deployment of connected vehicle technology depends on improved system-level performance and user experiences. In order to understand and assess the real-world behavior of this technology, the United States Department of Transportation (USDOT) has built several testbeds across the United States. The focus of this research is to evaluate the effectiveness of a connected vehicle environment using the trajectory data of test vehicles collected from the Arizona testbed, United States, an arterial corridor with a series of signalized intersections. Vehicle to infrastructure communication using the dedicated short range communication (DSRC) technology was tested along this corridor. The test vehicle trajectories were captured after processing data points obtained from a Global Positioning System (GPS) device. The trends in built trajectories in the connected vehicle environment and base condition were compared by time of the day. The results show a statistically significant increase in the average speed of the test vehicles along the arterial corridor in the connected environment compared to the base condition.

Keywords: Vehicle to infrastructure communication, Connected vehicle testbed, Vehicle trajectory.

INTRODUCTION

The connected vehicle technology could help solve many existing transportation problems such as congestion, ineffective utilization of road capacity, and safety. The connected vehicles can communicate with each other as well as with the infrastructure using advanced information and communication technology. They can contribute by enhancing complex decision-making processes such as prioritization and maintaining a minimum safe distance between two vehicles. The successful deployment of connected vehicle technology mainly depends on improved system-level performance and user experiences. In order to understand and assess the real-world behavior of this technology, the United States Department of Transportation (USDOT) has built several testbeds across the United States. The focus of this research is to evaluate the effectiveness of a connected vehicle environment on an arterial corridor using trajectory data of test vehicles collected from a testbed in Arizona, United States.

Over the past decade, several researchers have explored the connected vehicle technology from different disciplinary perspectives, e.g., transportation engineering, electrical engineering, computer science, and mechanical engineering. Trajectory data of vehicles are typically captured using Global Positioning System (GPS)-enabled devices, cell phones, radio frequency identification (RFID) tags, and Bluetooth devices.

The vehicle trajectory data was successfully used in car-following model calibration [*1*], signal optimization [*2*], and the calibration of the network-wide fundamental diagram [*3*]. Guo et al. [*4*] proposed a graph-based approach for vehicle trajectory analysis. They collected and analyzed the truck trajectories using the regional-level dataset of Athens, Greece. Liu et al. [*5*] studied the one-year GPS trajectories of over 5,000 taxis in China. They proposed a weighting-based map matching algorithm and a trajectory interpolation-information (WI-matching) algorithm to improve the accuracy of GPS trajectories. Jin et al. [*6*] addressed the error accumulation issue in calibrating the car-following models using the vehicle trajectory dataset collected in Los Angeles, California, United States. Five car-following models were checked using the proposed error dynamic model. They concluded that the weighted location mean absolute error (MAE) and the location MAE with crash rate penalty can achieve the best overall error accumulation performance for the five car-following models.

Feng et al. [*7*] modeled signalized intersections using VISSIM traffic simulation software. They developed a two-phase algorithm and tested the real-time adaptive signal control in a connected environment. Their results indicate a 16.33% reduction in delay at 100% connected vehicle penetration. Kim et al. [*3*] proposed a framework to characterize the spatial and temporal travel patterns in a traffic network using vehicle trajectories. The trajectories data from New York City, New York, United States, was used to demonstrate the network-level traffic flow patterns and travel time reliability. Goli et al. [*8*] addressed the vehicle trajectory prediction for collision avoidance using the Gaussian Process Regression method. The results showed improved prediction accuracy when compared from the connected vehicle trajectory dataset collected in Los Angeles, California, United States.

Overall, vehicle trajectory data applications such as studying the headway distribution, car-following model, acceleration-deceleration behavior, safe gap, etc. were documented in the literature [1, *6, 8, 9*]. Most of the past studies on evaluating the effectiveness of a connected environment used a simulation-based approach assuming a fully connected and automated environment. However, the penetration rate of connected vehicles is minimal at this time and is expected to grow over a period of time. It is likely that what is observed in the real-world could differ from what is predicted using a simulation-based approach due to differences in the penetration rate. Furthermore, studies focusing on evaluating using real-world data in a connected vehicle environment and comparing with the base condition are very limited. While the effectiveness of any transportation system could vary by the time of the day, the procedures adopted to process the data (for example, vehicle trajectories) could have a bearing on the results. This research contributes by focusing on the aforementioned areas and gaps.

In order to deploy connected and automated vehicle technology efficiently in a real-world environment, the United States Department of Transportation has constructed several connected vehicle testbeds in Arizona, California, Florida, Michigan, New York, Tennessee and Virginia. The trajectory data of test vehicles from the Arizona testbed connected environment to improve progression over an arterial corridor passing through a series of signalized intersections was considered for evaluation and analysis in this research.

METHODOLOGY

The methodology adopted includes gathering testbed details, data processing, and comparison of test vehicle trajectories in a connected vehicle environment with the base condition. Each step is discussed next in detail.

2.1 Testbed Details

The testbed located in Anthem, Maricopa County, Arizona, United States was selected for this research. The testbed consists of six signalized intersections along N Daisy Mountain Dr, an arterial road (Figure 1). It starts prior to N Gavilan Peak Pkwy in the west and extends past W Anthem Way in the east. While these two intersections are ~1.9 mi apart, the overall study corridor is ~2.5 mi long. It is a six-lane divided road (three lanes in each direction) with a posted speed limit of 40 mph. An interstate highway (I-17) is closely located (within 0.5 mi) to N Daisy Mountain Dr & N Gavilan Peak Pkwy intersection. The annual daily traffic volume is 10,142 in the eastbound (EB) direction and 11,411 in the westbound (WB) direction on N Daisy Mountain Dr [*10, 11*].

2.2 Data Processing and Analysis

The data was gathered from the United States Department of Transportation's (USDOT) Intelligent Transportation Systems (ITS) Joint Program Office (JPO) opensource website. The data gathered was collected on March 3rd and March 4th of 2015. Test vehicles capable of communicating with roadside infrastructure were used to collect the data.

Selected drivers were asked to drive the test vehicles as per a scheduled departure plan (say, at 2-min intervals to minimize being in close proximity) and maintain the traffic stream conditions. However, the purpose of the study and information about the connected vehicle technology was not disclosed to the drivers to obtain naturalistic driving data [*10, 11*].

Dedicated Short Range Communication (DSRC) technology (5.9 GHz) was used for communication between the test vehicles and the road-side infrastructure. A Multi-Modal Intelligent Traffic Signal System (MMITSS) prototype in the connected environment was tested along the testbed [*10, 11*]. The connected environment technology enabled two-way wireless communication between the test vehicles with an on-board equipment (OBE) and the road-side infrastructure (signalized intersections) with DSRC equipment (typically installed on one of the traffic signal heads). The signalized intersections equipped with the DSRC equipment along the testbed recognized the approaching DSRC equipped test vehicles. The algorithms in the MMITSS prototype optimized the phase sequence and signal timings and made the decision to serve the test vehicles (give priority, green signal). Other than the two-way wireless communication between the test vehicles and the road-side infrastructure for prioritization in the case of the connected environment, no notable changes in signal timing and phasing details are known between the two data collection dates that would influence the research results.

The trajectory data was collected using GPS-enabled devices in the connected environment on March 3, 2015, while the base condition data was collected on March 4, 2015. Both the connected environment and base condition tests were conducted on weekdays (Tuesday and Wednesday) to minimize the variations due to traffic condition [*12*]. The variation due to driver behavior, age, and gender was minimized by having the same selected pool of drivers drive several trips in both the connected environment and the base condition.

The gathered GPS-enabled data was processed using R and ESRIs' ArcGIS Pro software, unlike using a MATLAB code by defining the coordinates of the study corridor boundary sections *[11]*. It is envisioned that using geospatial software like ArcGIS Pro provides flexibility to visualize the datapoints and exclude outliers that could influence the analytical results. This approach might be more beneficial when the study corridor is not a straight section and comprises horizontal curves.

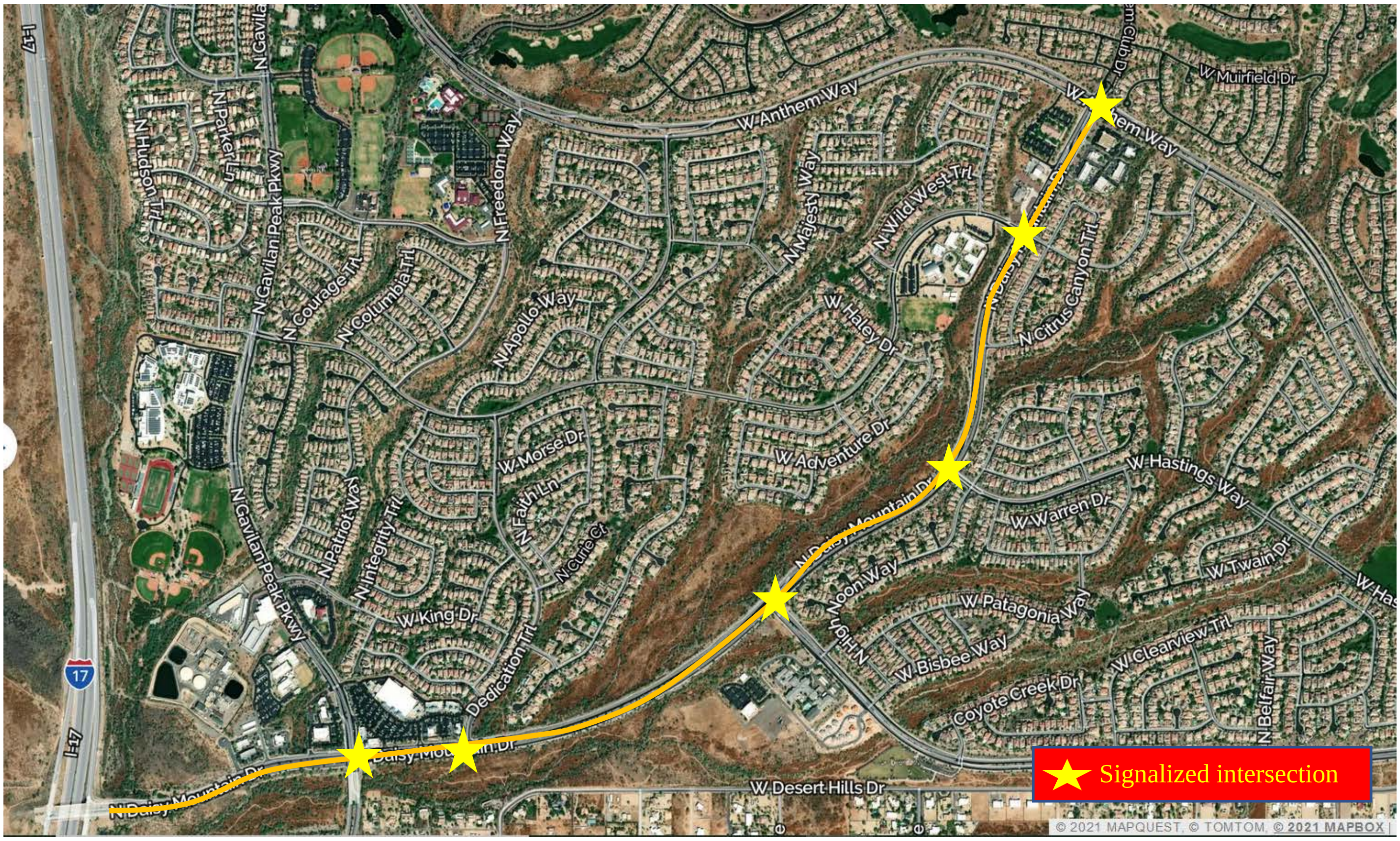


Figure 1. Study corridor

The raw dataset included some outliers (datapoints) located outside the testbed. These data points represent the incoming and outgoing of test vehicles from the nearby parking lot/rest areas and increase the data processing and analysis complexity. The plotted trajectory data points were, therefore, examined and such outliers were manually excluded from the raw dataset.

Data for eight to ten trips were gathered and processed for each test vehicle. The data from three test vehicles comprising of 113 trips were analyzed in this research. The raw dataset included timestamp, latitude, longitude, speed, altitude, heading, and GPS source information. The moving direction of vehicles (EB/WB), and start and end time of each trip was noted after manually verifying the data. The data points with turning movements from EB/WB, and vice versa were excluded in this research.

The performance was evaluated using distance-time plots, average trip travel time, and the average speed. The distance-time plots were used to assess progression along the study corridor, number of times each test vehicle stopped along the corridor, and delay during such stops. For distance-time plots (example, Figure 2), the distance between consecutive points were computed using speed and time data. The travel time data for the three test vehicles was averaged to compute the average trip travel time and the average speed.

RESULTS

Figure 2 (a-d) shows the trajectories of a selected test vehicle in the base condition and in the connected environment for EB and WB directions (starting trip at 16:40 in the EB direction and at 16:45 in the WB direction). Each trajectory represents a single trip in EB or WB direction. The trajectories slope is steeper and relatively stable (consistent) in the connected vehicle environment than in the base condition. The spacing between the trajectories is also lower in the connected vehicle environment than in the base condition. The test vehicle was able to complete eight trips in ~30% lesser time in the connected vehicle environment than in the base condition.

In addition to variations in the trajectories, differences in travel times and the number of stops per vehicle were observed in the connected environment compared to the base condition. In addition to an increase in delay, the number of stops were two to three times more for the test vehicles in the base condition than in the connected environment. For example, trip travel time in the connected environment was 32 sec to 257 sec less in the EB direction and 93 sec to 255 sec less in the WB direction for a test vehicle when compared to the base condition (Table 1). Hence, it can be inferred that the test vehicle travels faster and with a relatively fewer number of stops, resulting in a reduction in delay, along the considered arterial corridor in a connected environment. Differences were observed when trajectories are compared by the direction of travel.

The distance-time plots and trajectories were also used to assess the performance at signalized intersections (for example, Figure 3). It can be observed from Figure 3 that the number of stops per test vehicle at the selected intersection was higher in the base condition than in the connected environment. Three out of five times during the 20-min observation period, a test vehicle had to stop and wait for two signal cycles to cross the signalized intersection in the base condition. On the other hand, a test vehicle received priority and did not have to stop five out of nine times in the connected environment. As was observed previously, the delay and number of stops differed by the direction of travel.

Analysis was also conducted to compare the connected environment and the base condition by the time of the day (evening peak and evening off-peak). Table 2 shows the speed variation of test vehicles in the base condition and in the connected environment at selected times of the day, by the direction of travel. The average speed of the three test vehicles at selected times of the day is presented in Figure 4. The increase in the average speed was observed to be varying between 7.62% and 20.95% in the EB direction, and between 6.03% and 28.27% in the WB direction at selected times of the day (Figure 4). Considering the entire time period, the results show a 17.36% (base condition - 25.76 mph; connected environment - 30.24 mph) increase in the average speed in the EB direction and a 12.06% (base condition - 27.24 mph; connected environment - 30.53 mph) increase in the average speed in the WB direction along the arterial corridor.

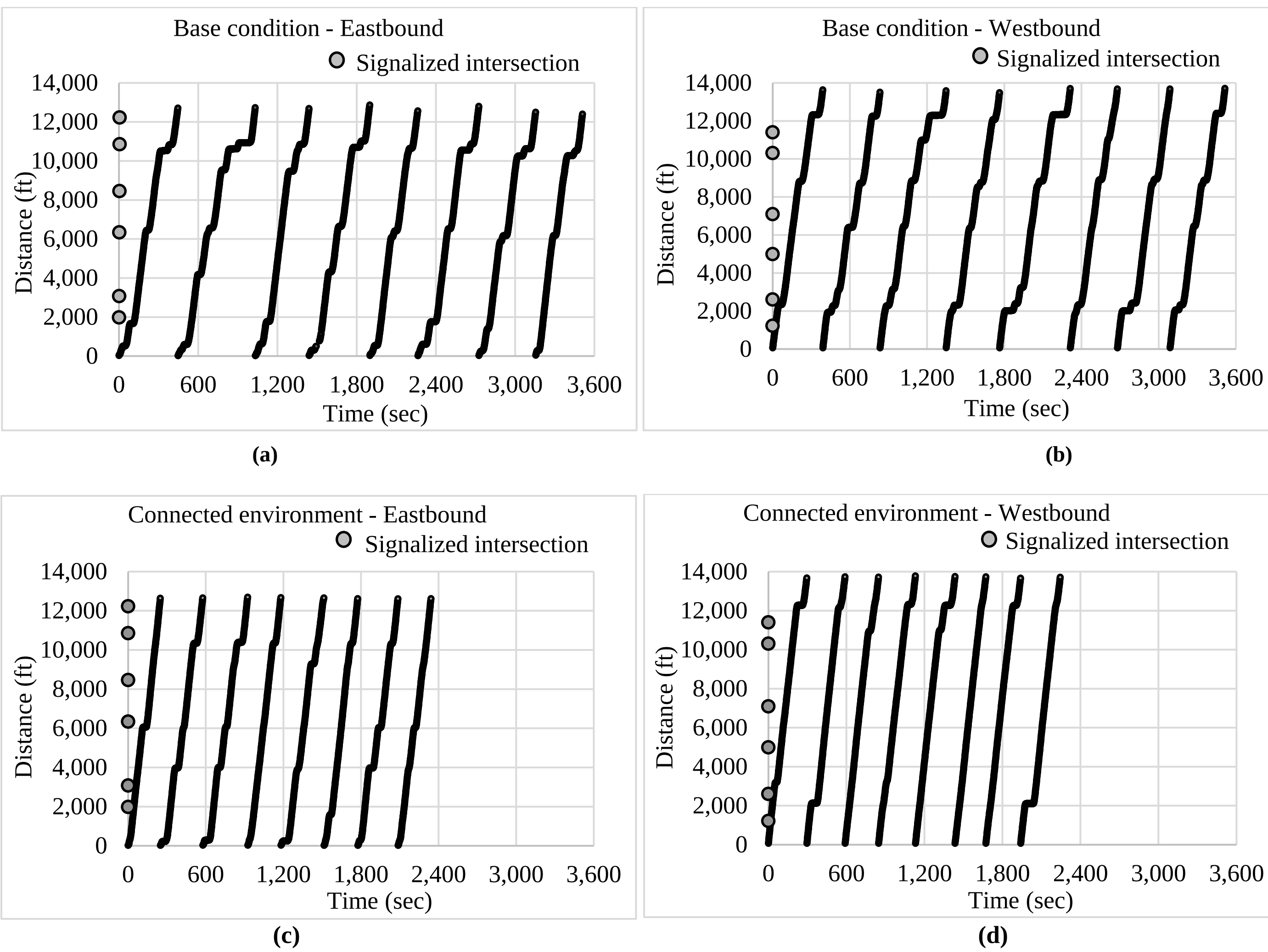
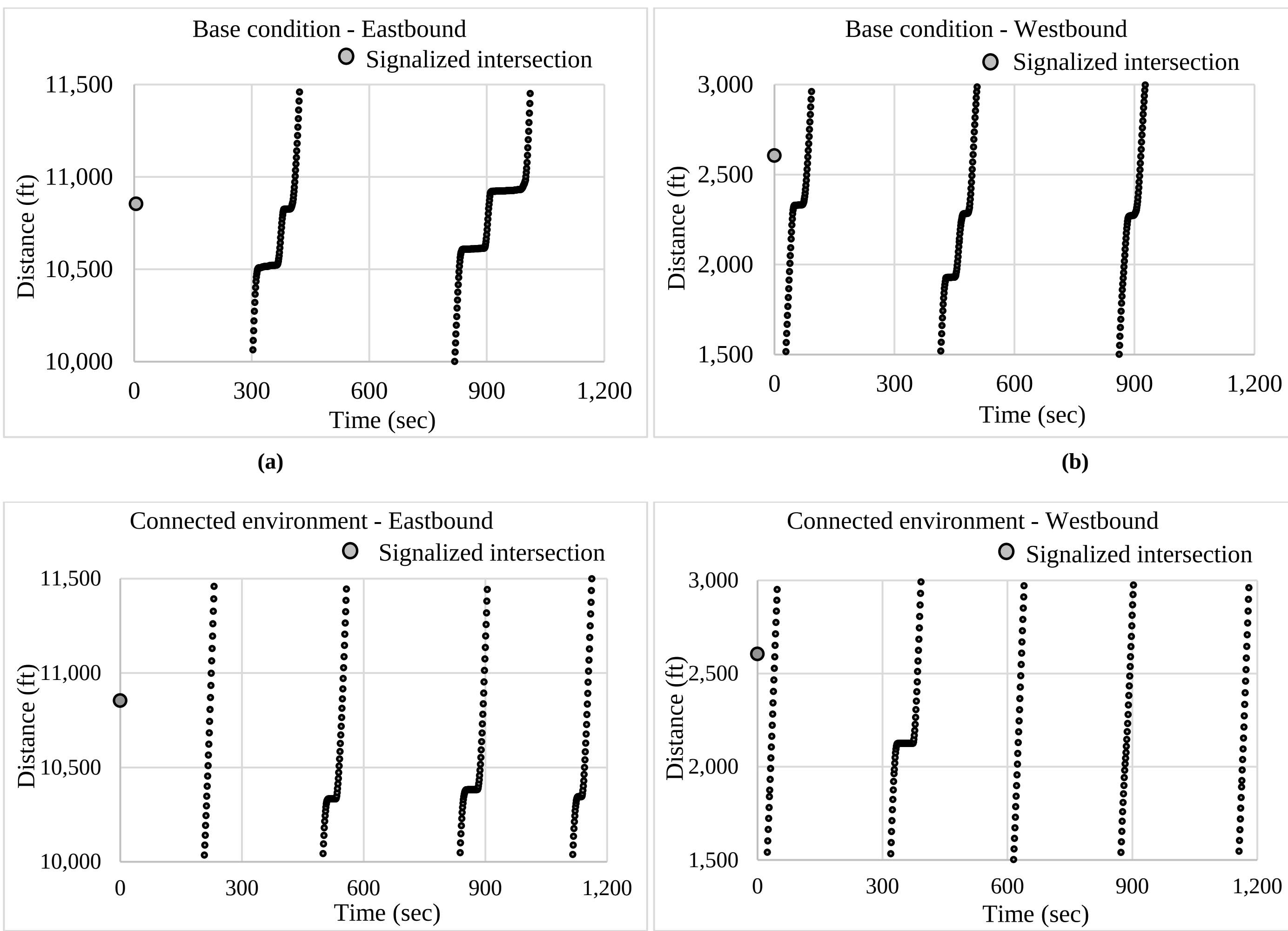


Figure 2. Distance-time plots for a test vehicle in the base condition and the connected environment along the study corridor

Table 1. Travel time and delay for the test vehicle shown in Figure 2

	Direction	Trip 1	Trip 2	Trip 3	Trip 4	Trip 5	Trip 6	Trip 7	Trip 8	Average
Travel time (sec) - base condition	EB	447	585	408	459	365	461	431	354	439
	WB	390	445	514	415	549	367	409	427	440
Travel time (sec) - connected environment	EB	250	328	348	256	333	262	311	254	293
	WB	297	293	259	283	304	238	267	304	281
Difference in travel time (sec)	EB	-197	-257	-60	-203	-32	-199	-120	-100	-146
	WB	-93	-152	-255	-132	-245	-129	-142	-123	-159
% difference	EB	-44	-44	-15	-44	-9	-43	-28	-28	-32
	WB	-24	-34	-50	-32	-45	-35	-35	-29	-35

Note: Difference in travel time (an indicator of delay) is travel time in the connected environment minus travel time in the base condition. % difference is the difference in travel time divided by travel time in the base condition multiplied by 100.

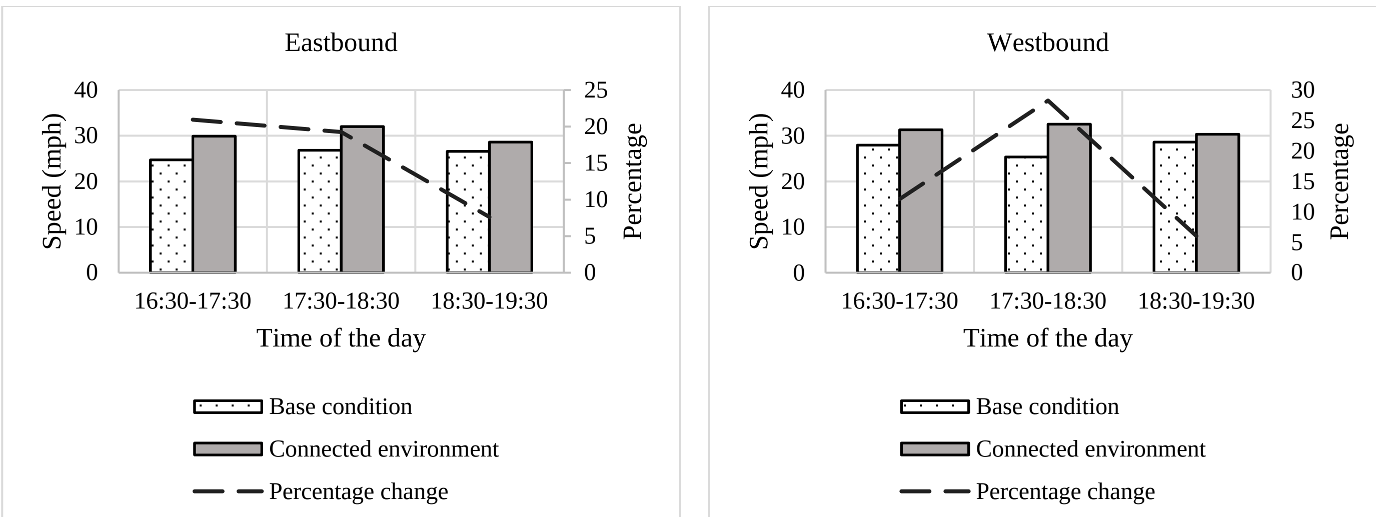


(a) **(b)** **(c)** **(d)**

Figure 3. Distance-time plots for a test vehicle in the base condition and the connected environment at a signalized intersection

Table 2. Summary of speed (mph) - base condition and the connected environment

Vehicle	Direction	Time of the day 16:30-17:30		Time of the day 17:30-18:30		Time of the day 18:30-19:30	
		Base condition	Connected env.	Base condition	Connected env.	Base condition	Connected env.
Vehicle 1	EB	28.86	30.69	29.36	36.11	29.65	26.94
Vehicle 2	EB	18.49	28.63	20.72	30.84	21.18	30.67
Vehicle 3	EB	26.79	30.36	30.41	29.03	28.94	28.24
Vehicle 1	WB	26.89	33.46	28.98	34.73	27.89	31.80
Vehicle 2	WB	20.85	33.29	21.58	34.49	24.19	32.79
Vehicle 3	WB	36.08	27.20	25.51	28.35	33.76	26.42
Average	EB	24.71	29.89	26.83	31.99	26.59	28.61
	WB	27.94	31.32	25.36	32.53	28.61	30.34



(a) **(b)**

Figure 4. Average speed and percentage change in the speed - base condition compared to the connected environment

A one-tailed t-test was conducted to examine the statistical significance of an increase in the average speed in the connected environment. The null hypothesis is defined as the average speed in the base condition is greater than or equal to the average speed in the connected environment while the alternate hypothesis is defined as the average speed in the base condition is less than the average speed in the connected environment. The computed hourly average speeds in the base condition and the connected environment (irrespective of the direction of travel or time of the day) are 26.7 mph and 30.8 mph, respectively. The computed p-value is 0.007 (t-statistic = -2.73), indicating a significant increase in the average speed in the connected environment compared to the base condition. A similar analysis of speeds comparing trips that were departing within ±2-min also indicate a significant increase in the speed in the connected environment compared to the base condition.

CONCLUSION

In this research, the effectiveness of the connected vehicle environment was evaluated using real-world test vehicle data gathered from a connected vehicle testbed, MMITSS, located in Arizona, United States. DSRC technology (5.9 GHz) was used to communicate between roadside equipment and the test vehicles. The data stored in the server was used to optimize the signal phase/time.

The vehicle trajectories in the connected environment and base condition were plotted and analyzed. Lower variation in travel speeds and relatively fewer number of stops were observed in the connected environment compared to the base condition. The results show a 12% to 18% increase in the average speed of the test vehicles along the considered arterial corridor with six signalized intersections in the connected environment compared to the base condition. The increase in speeds or decrease in travel time from the trajectory data differed by the direction of travel and time of the day.

The underlying factors that influence the effectiveness of a connected vehicle environment should be further explored in the future. Further, the effectiveness by vehicle type and priority scenario like emergency vehicle, transit vehicle, or truck compared to a passenger car by time of the day and different traffic conditions should be explored using larger datasets in the future.

Also, the influence of the connected and automated environment on the operational performance at each individual intersection, along the corridor, and on the cross-streets merits an investigation. The data from other testbeds and technologies should also be compared to check how the effectiveness varies with the facility type, built environment, and technology.

ACKNOWLEDGMENTS

The trajectory dataset used in this research was gathered from the opensource website of the United States Department of Transportation's (USDOT) Intelligent Transportation Systems (ITS) Joint Program Office (JPO).

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Journal of Modern Mobility Systems (JMMS), Vol. 02(2021), 108-113
Document: https://doi.org/10.13021/jmms.2021.3172

Application of Pareto Front to Evaluate Adaptive Traffic Signal Timing for Multiple Objectives

Yifan Yang[a], Andalib Shams[a], Christopher M. Day[a,*]

[a] *Department of Civil, Construction, and Environmental Engineering, Iowa State University, Ames, IA 50011; *Corresponding Author*

Received: 28 Dec. 2021 ● **Revised**: [29 Dec 2021] ● **Accepted**: [30 Dec 2021] ● **Published**: [30 Dec 2021]

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ABSTRACT

This paper examines the effects of policies on coordinated traffic signal control using a multi-objective framework inspired by the Pareto front concept. The Pareto front describes the set of optimal outcomes in a space defined by multiple objectives. This concept is applied to a nine-intersection signalized corridor in a microsimulation study comparing performance from an array of conventional signal control policies that represent a spectrum of options with performance tradeoffs between locally optimal and system optimal control. This is used to identify a Pareto front using delays for coordinated and non-coordinated movements, which offers a frame of reference for comparing the performance of adaptive control algorithms. Two different real-time adaptive control algorithms, a self-organizing algorithm and a schedule-based algorithm, are examined and their performance compared to the Pareto front of conventional controls. The self-organizing algorithm was found to extend the region of feasible performance beyond the capabilities of the conventional methods in different directions relative to the Pareto front.

Keywords: Traffic signal timing, Adaptive control, Performance Measures

1. INTRODUCTION

Operational objectives are important to the development of a traffic signal control plan. Often, multiple objectives are in tension with one another. An example that often arises in coordinated traffic signals is the tradeoff between locally optimal control at local intersections (e.g., balancing delays among movements) versus system operation that seeks other objectives (e.g., smooth traffic flow) and imposes constraints on the local control. The importance of identifying objectives has been emphasized in recent FHWA guidance on traffic signal timing [*1*].

Recent research has applied the concept of Pareto efficiency to explore such tradeoffs [*2, 3, 4*]. The Pareto front allows the identification of tradeoffs in performance that result from alternative control policies. Figure 1 shows an example Pareto front for two objectives. In this example, each objective represents an undesirable quantity (for example, delay), so minimization is desirable. A "feasible region" of possible performance is located above and to the right of the curve. The Pareto front can be identified from various observations (points A, B, C) optimized with alternative objectives having different degrees of priority. The curve represents a set of solutions where one objective cannot be improved without worsening the other. A change to the control policy may cause movement along the front (e.g. from A to C) or into the front (e.g. to G). Finally, new technology might yield performance that is infeasible for conventional controls (points D, E, F).

The general location of the Pareto front could be found by testing several ideally optimal or near-optimal control options that favor one objective or the other to differing degrees. This study accomplishes this by using common variants of conventional signal control forming a spectrum of options favoring either local or system control. After finding the Pareto front, adaptive signal control methods are compared to determine whether they extend the envelope of performance beyond the conventionally feasible range. This study investigates whether a Pareto front can be readily found by testing a series of conventional control methods in a simulation model of a corridor and compares these against three different adaptive control methods to demonstrate use of the Pareto front as an evaluative tool.

2. METHODOLOGY

1.1 Simulation Model

A nine-intersection network of two intersecting signalized corridors in Ames, Iowa was modeled (Figure 2). Traffic volumes were obtained from the Iowa DOT. A scenario reflecting the PM peak hour volumes was developed. Signal timing plans for the network were obtained using Synchro [*5*]. The network was modeled in VISSIM using the Econolite ASC/3 virtual controller to implement signal control. Phase assignments were made according to the standard eight-phase layout. Further details are provided elsewhere [*6*].

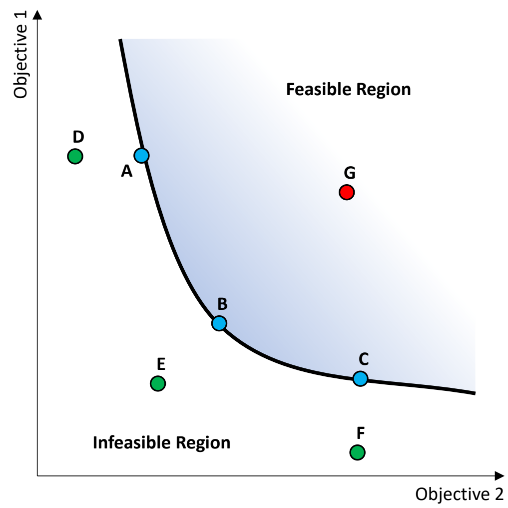

Figure 1. Pareto front diagram

1.2 Traffic Control Methods

Nine conventional signal control methods and three adaptive control methods were implemented in the Lincoln Way network, as explained in Table 1. The conventional control methods span a variety of options emphasizing either system or local control at different priorities. At one end, CFL favors system control by favoring coordinated phases during actuation. At the other end, FA1 has no method to facilitate coordination and each movement is served using actuation rules that terminate green shortly after queues have cleared. Two methods (FA2 and CPT) are known to be suboptimal and are included to verify that such methods reside away from the Pareto front. Two adaptive control methods (one having two variants) are tested to determine whether they extend the Pareto front into the otherwise infeasible region.

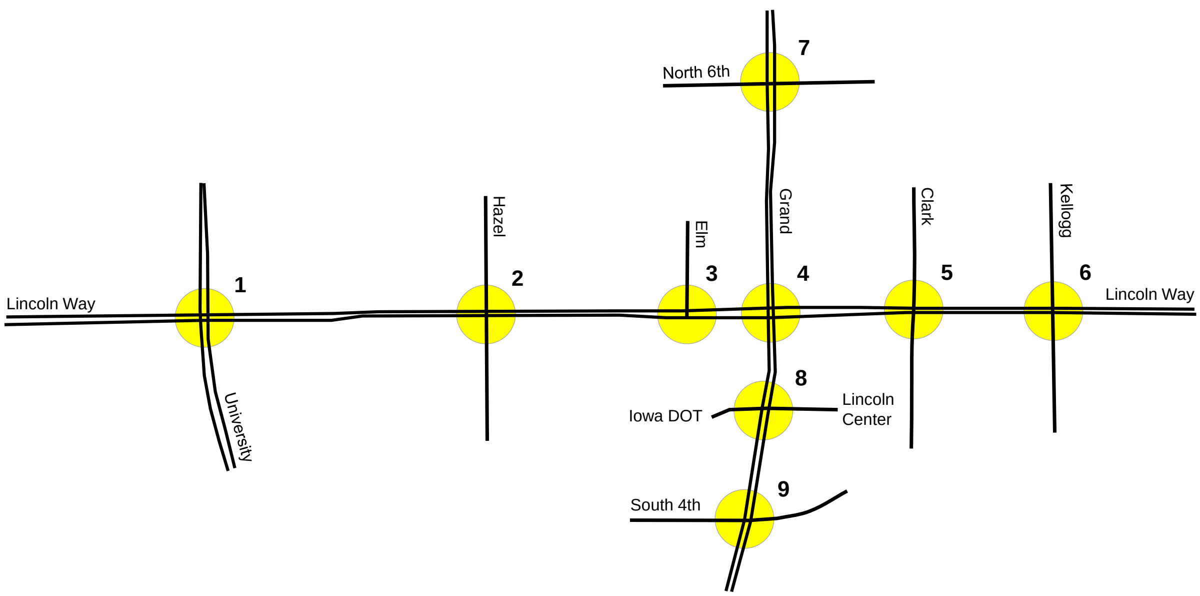

Figure 2. Location of the modelled signal network (Lincoln Way and Grand Ave., Ames, IA)

Table 1. Control methods examined in this study

Abbreviation	Method and Description
FA1	Fully-actuated control without coordination, with short extension times, lane-by-lane detection, and soft recall to the major through movements. Intended to represent locally-optimal fully-actuated control.
FA2	Fully-actuated control; identical to FA1 except that the major through movements are set on max recall and the maximum green times for the through movements are increased to 90 seconds. Intended to represent a poor control strategy that tries to coordinate by making the mainline greens as long as possible but without any real provision for coordination.
CPT	Coordinated pretimed control. All phases at all intersections operate with the same green time in every cycle, without use of any actuation.
CFL	Coordinated-actuated with floating force-off. All green time yielded by actuated phases is inherited by the coordinated phases.
CFX	Coordinated-actuated with fixed force-off. Green time yielded by actuated phases may be used by other actuated phases.

Table 1. Control methods examined in this study

Abbreviation	Method and Description
CY1	Coordinated-actuated with fixed force-off and early yield of 10% of cycle. Identical to CFX, but with a portion of the coordinated phases (equal to 10% of the cycle length) actuated. The coordinated phases may thus end when they have no remaining demand, and that time is accessible by other phases.
CY2	Coordinated-actuated with fixed force-off and early yield of 20% of cycle.
CY3	Coordinated-actuated with fixed force-off and early yield of 30% of cycle.
CY4	Coordinated-actuated with fixed force-off and early yield of 40% of cycle.
PAA	Phase Allocation Algorithm. A schedule-based real-time adaptive control method that uses a table of anticipated vehicle arrivals to determine the optimal phase sequence and duration within a planning horizon. The duration of the planning horizon is set equal to the cycle length used in coordinated methods. Vehicles are detected up to 1000 ft upstream of the intersection.
Self I	Self-Organizing Control, version 1. Identical to FA1, but with the inclusion of a “secondary extension” that will extend a currently green phase if there is a platoon of vehicles approaching it. In this version, secondary extension is available on major street through movements. Vehicles are detected up to 1000 ft of the intersection.
Self II	Self-Organizing Control, version 2. Identical to Self I, but with secondary extension additionally applied to side street through movements.

3. RESULTS

1.3 Character of the Control Methods

To illustrate each control method, Figure 3 presents a series of coordination diagrams [*7*]. These diagrams depict how well the vehicle arrivals (black dots) align with green intervals (shaded green region) on one signal approach. Clusters of dots represent platoons of vehicles. The diagrams show how consistent the patterns are from one cycle to the next and how well aligned arrivals are with green.

- CPT (Figure 3a) is the most rigid form of control, with each cycle having the same durations of red and green. CFL (Figure 3b) and CFX (Figure 3c) both introduce only minor variations in the start of green.
- PAA (Figure 3d) introduces adaptive adjustments of the starts and ends of green which leads to more variation. Interestingly, conventional methods CY1-CY4 (Figure 3e-h) appear to have a similar effect.
- The self-organizing methods (Figure 3i,j) have much more flexibility, which is not surprising as they are based on fully-actuated methods FA1 and FA2 (Figure 3k,l). Self-organizing control introduces some extensions to facilitate coordination in response to detected platoons, and there are more platoons coincident with green than the fully-actuated control methods that lack this mechanism.

Altogether, this collection of methods represents a spectrum of control policies that have different favor coordination or local control to various degrees.

1.4 Pareto Front

Figure 4 shows the performance of each control method using the total delay of the entire system. From this perspective, it is possible to observe that the fully-actuated and pretimed methods have higher delay (with FA2 performing very poorly), the actuated-coordinated methods have lower delay, while one of the adaptive methods (PAA) yields marginally lower delay than these whereas the other (Self I / II) seems to perform about the same as the actuated-coordinated methods. With PAA having 4.5% less total delay than CY4, there appears to be only a small difference between the actuated-coordinated and adaptive methods.

Figure 5 presents the same data, but with the delay broken out between the major movements and the minor movements. When arranged in this way, the position of the actuated-coordinated methods (CFL, CFX, and CY1-4) along with FA1 reveal the likely position of the Pareto front, assuming that their performance is close to optimal, for the given balance between objectives relevant to the control method. The upper end at FA1 represents methods that optimize local control, while at the other end, CFL emphasizes system control. Two methods (CPT and FA2) are contained inside of the feasible region, which shows that they are not optimal, as expected. The adaptive methods seem to be able to reach into the infeasible region. PAA seems very slightly below and to the left of the Pareto front, while the self-organizing methods seem to move to the right.

This arrangement of the data facilitates the inference of characteristics of the different control methods. The most common actuated-coordinated control methods CFL and CFX have similar performance, and strike a certain balance between local and system control. Use of early yield strikes a different balance, with less emphasis on system control (with an increase in major movement delay), balanced by better local control (with a decrease in minor movement delay). The larger the actuated portion of the coordinated phase (i.e., when moving from CY1 to CY4), the greater the effect, however, beyond CY2 there is virtually no additional reduction of minor movement delay, and only an increase in major movement delay. FA1 is positioned almost directly above CY2, CY3, and CY4. Meanwhile, the self-organizing methods have higher major movement delay compared to the conventional coordinated methods, but yield lower minor movement delay. Finally, PAA has similar performance to CY1, with marginally lower major and minor movement delays.

1.5 Applicability of the Method

These results demonstrate an application of the Pareto front concept in evaluating new traffic signal control policies when balancing multiple objectives. Often, new control policies or technologies such as adaptive control are compared against a single mode of operation that represents conventional control (or control that is likely to be quite far from optimal, such as fixed-time control). The results of such comparisons are likely to be misread if the objectives of the two alternatives are different. Rather than comparison against a single representative form of conventional control, using a few different options that bracket different balance points between competing objectives can offer a more comprehensive manner of comparison. This can help isolate the value added by the new method.

The main use case of this strategy would be simulation studies. It is impractical in most cases to operate a real-world traffic network under an array of alternative policies. However, most new methods are initially tested in simulation long before they see real-world use. In a simulation environment, it would be relatively easy to develop a series of perhaps 3-4 different scenarios to identify the range of possible performance with conventional controls. Results from this study show that fully-actuated control and actuated-coordinated control are likely to bracket the two ends of a spectrum of options that tradeoff between local and system control.

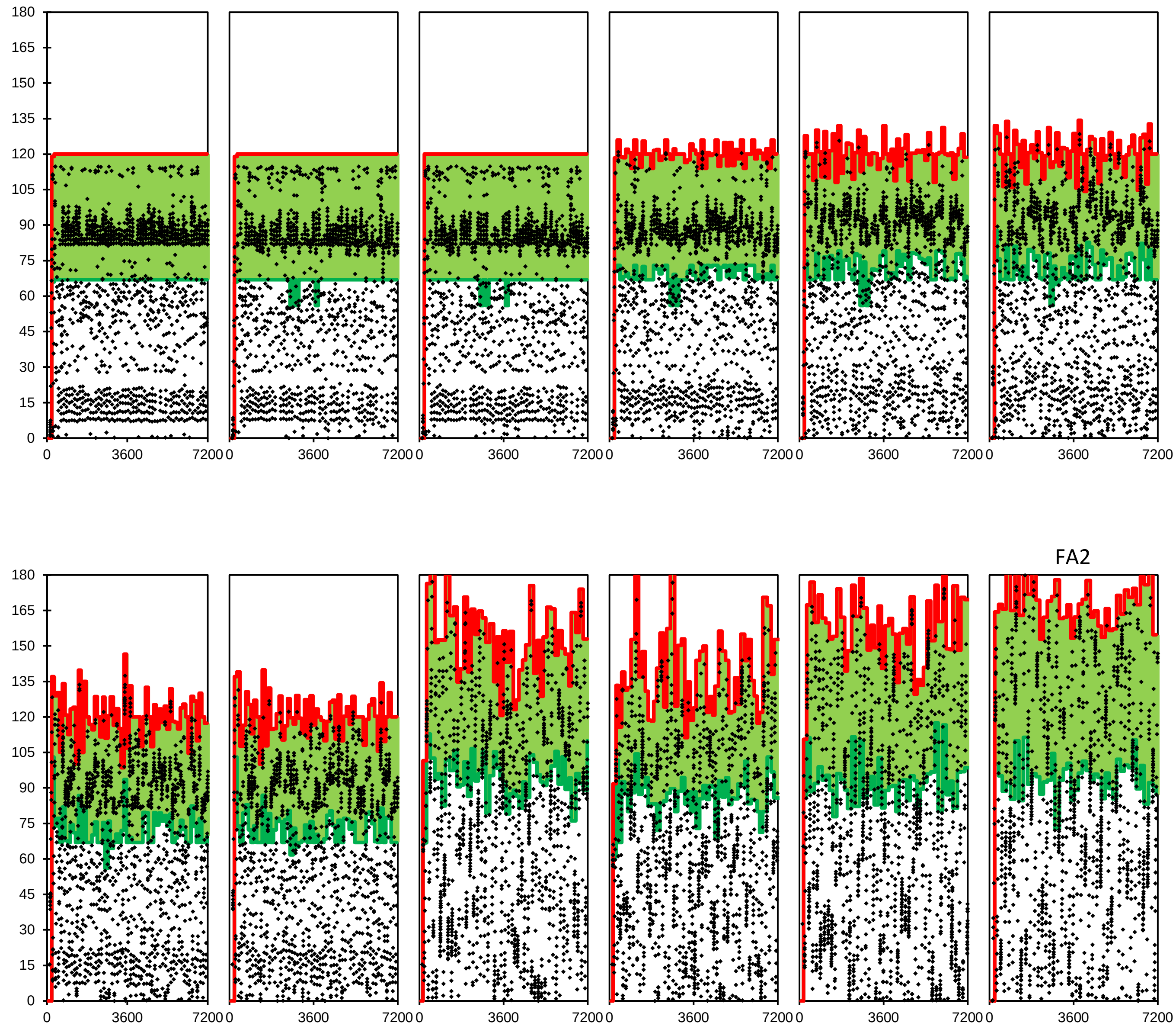

Figure 3. Example coordination diagrams (Westbound movement at Lincoln Way and Grand)

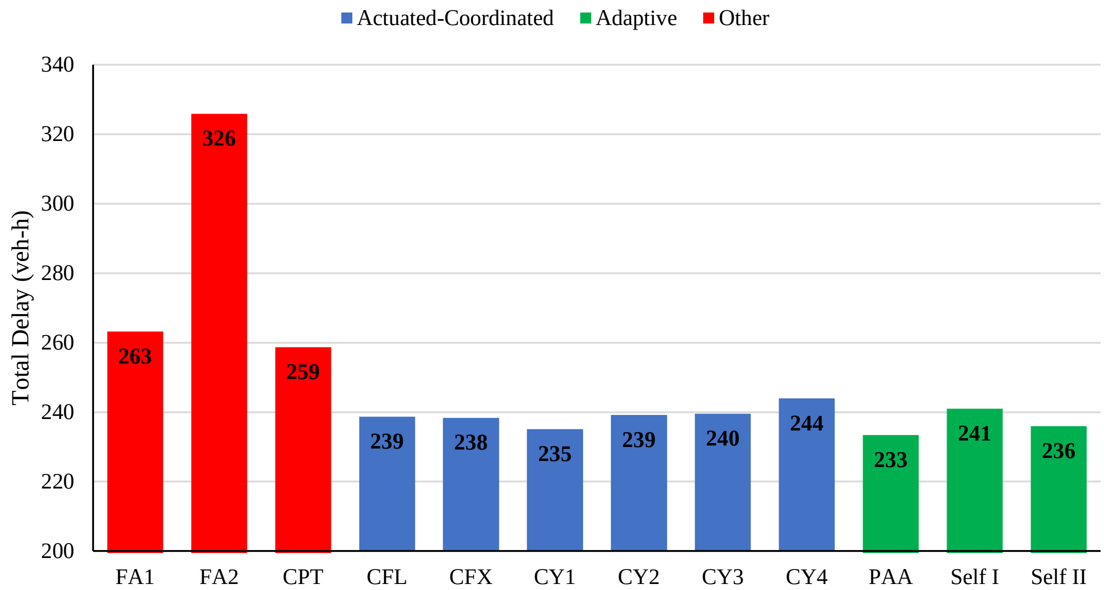

Figure 4. Total delay by control type

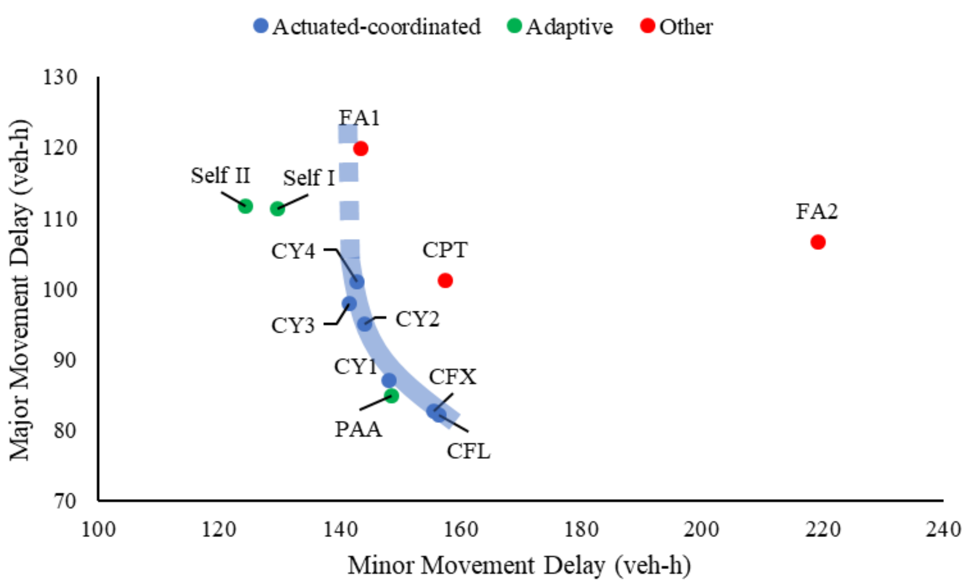

Figure 5. Pareto front found in a chart of major versus minor movement delay

4. CONCLUSION

This paper explored the application of the Pareto Front concept to traffic signal control, with an emphasis on the evaluation of adaptive control methods relative to conventional control methods. The concept was tested in a simulation of a signalized corridor with nine intersections and two crossing streets. An array of control methods was tested, including nine conventional and three adaptive control methods. Most of the conventional methods were selected to identify different potential locations on the Pareto front when considering objectives of minimizing delay for major or minor movements. Two methods were included to demonstrate that sub-optimal options reside within the feasible region. The adaptive control methods exhibited performance that was slightly more optimal than the methods residing on the Pareto front. The results demonstrate that a methodology for locating the Pareto front in a signal control system may provide a beneficial perspective for evaluating new control methods, especially in simulation studies where new methods are usually first tested. Future work would seek to improve this methodology by examining whether it works well for a variety of traffic scenarios and other sets of objectives.

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Journal Home: https://journals.gmu.edu/index.php/jmms
Mason Journals ● Mason Publishing Group
Journal of Modern Mobility Systems (JMMS), Vol. 02 (2021), 114-121
Document: https://doi.org/10.13021/jmms.2021.3174

Evaluating the Mobility Impacts of American Dream Complex Using Probe Vehicle Data

Parisa Hosseini[a], Mohammad Jalayer[a,*] Deep Patel[a], Thomas M. Brennan[b]

[a] *Rowan University, Department of Civil and Environmental Engineering, Glassboro, NJ 08028; *Corresponding Author*
[b] *The College of New Jersey, Armstrong Hall - RM 173, 2000 Pennington RD, Ewing Township, NJ 08628;*

Received: 29 Dec. 2021 ● **Revised 2**5 Jan. 2022 ● **Accepted**: 30 Jan. 2022 ● **Published**: 4 Feb 2022.

ABSTRACT

Traffic congestion and motor vehicle crashes are perceived as pivotal concerns that are particularly difficult to manage in high-density urban areas. Thus, mitigating traffic congestion and improving users' safety on roadways are top priorities of the United States Department of Transportation (USDOT). American Dream Complex, located outside New York City, is an entertainment and retail center that was officially opened in October 2019. The complex is expected to attract over 40 million annual visitors once fully operational, which may potentially result in substantial mobility and safety issues for road users in the area. The present research work evaluates the mobility concerns of the transportation network in the vicinity of the American Dream Complex due to its partial official opening. To achieve this goal, firstly, the performance of four surrounding corridors was explored by incorporating travel time inflation (TI) as a performance measure. In addition, to have a better visualization of the congestion, day-by-day heatmaps were developed. Based on the results obtained from the Corridor Increase in Mean Travel Time (CIMTT) heatmaps, it was shown that no considerable congestion was observed on the opening day of the American Dream Complex on surrounding corridors.

Keywords: American dream complex, mobility impact, travel time inflation, surrounding corridors

1. INTRODUCTION

Traffic congestion and motor vehicle crashes are major global challenges being faced every day. This is especially problematic in urban areas, where infill development will increase traffic volume in the region, thus impacting both congestion and crash frequency. Even as new developments are being constructed, reducing congestion and enhancing traffic safety on America's transportation roads remain top priorities of the United States Department of Transportation (USDOT). According to the American Transportation Research Institute (ATRI), New Jersey has the worst traffic bottleneck in the country [*1*]. Moreover, the state of New Jersey ranked second in the nation with respect to the ratio of pedestrian fatalities to the total number of motor vehicle deaths, necessitating further investigations. Therefore, it is especially important to understand on a quantitative level how a major commercial development will impact densely populated, highly congested region. The American Dream Complex, once complete, will be the second-largest retail and entertainment complex in the nation. The ongoing commercial development is located in East Rutherford, New Jersey, about 10 miles west of New York, NY. This complex officially opened at about 10% capacity to the public on October 25, 2019 [*2*]. Once fully open it is expected to attract over 40 million visitors annually. This will potentially result in substantial mobility and safety issues for pedestrians and motorists in the area.

In order to assess the mobility issues, probe vehicle data can be used to evaluate the congestion performance of roadways going to and coming from the American Dream Complex. This type of data is being used as a common data source for measuring the regional performance of roadway networks. By developing a performance evaluation method based on these data, the health of the roadway system can be monitored, and future improvement plans can be established. Probe data is a valuable source of speed information in terms of temporal and spatial coverage [*3*]. This type of data is increasingly incorporated in transportation analytics. Application of probe vehicle data in traffic congestion assessment, performance evaluation of highways and arterial roads, and travel time estimation has drawn considerable research interest over the last decades [*3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15, 16, 17*]. The main objective of this study is to visually quantify the baseline performance of arterials located around the American Dream Complex by determining Travel Time Inflation as a performance measure. Once established, a yearly evaluation of the regional congestion will be conducted to correspond to phased opening of the American Dream Complex. Future work will statistically compare specific time periods to determine changes in congestion patterns, but for this study only the baseline visualizations are discussed.

2. DATA

Probe vehicle data requires both a spatial component and temporal component. The spatial attributes are defined by Traffic

Message Channels (TMCs), which are pre-defined locations along roadways. (Table 1). As telematics device traverses a TMC the vehicle speed is captured along with a number of other attributes include TMC code, vehicle speeds, date-time stamp, c-value, and confidence score (Table 2). In this study, probe vehicle data for four major routes consisting of state routes, interstate highway/turnpike, and major arterials were obtained from the Regional Integrated Transportation Information System (RITIS) [*18*]. Figure 1 presents the selected TMCs along the four corridors. A total of 60 TMCs were selected surrounding the American Dream Complex covering RITIS data for 24-hours a day from September 1, 2019, to January 31, 2021. Based on previous studies [*11, 14*], only speed data with a confidence score value of 30 and a c-value of 100 were considered.

Table 1. Example of obtained TMCs attributes for Interstate 95

TMC Code	Road	Direction	State	Start Latitude	Start Longitude	End Latitude	End Longitude	Length (miles)
120+04603	I-95	NORTHBOUND	NJ	40.75777	-74.1166	40.79844	-74.0774	3.488163
120-04603	I-95	SOUTHBOUND	NJ	40.80966	-74.0634	40.802	-74.0733	0.741292
120-04604	I-95	SOUTHBOUND	NJ	40.81378	-74.056	40.81363	-74.0563	0.021945

Table 2. Example of TMCs recorded speed data for Interstate 95

TMC Code	Date Time Stamp	Speed	Average Speed	Confidence Score	C-Value
120+04603	9/1/2019 0:00	65.99	60	30	100
120-04603	9/1/2019 0:00	61.28	57	30	100
120-04604	9/1/2019 0:00	60.9	58	30	100

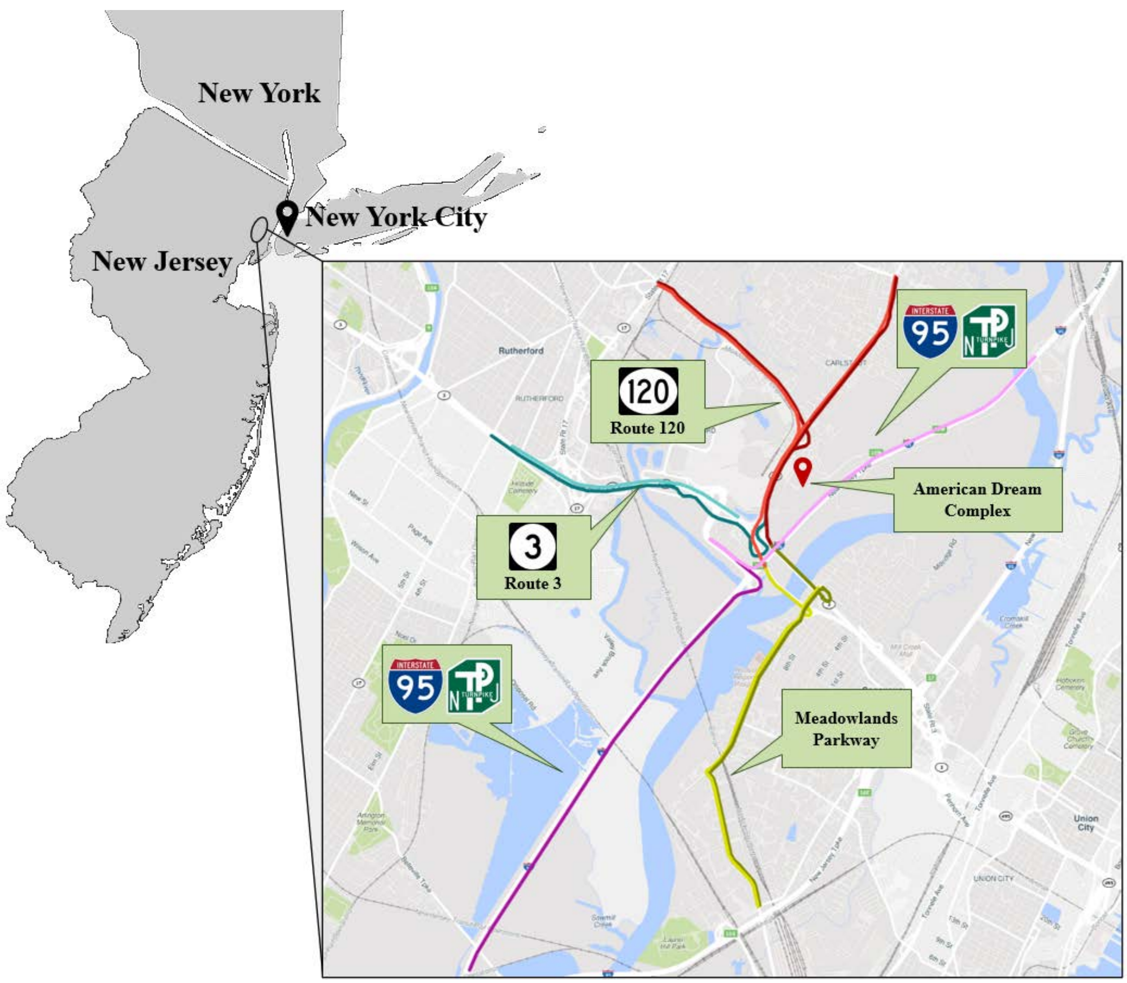

Figure 1. Study area around the American Dream Complex with 60 TMC segments

3. TRAFFIC PERFORMANCE MEASURE

Generally, congestion for a TMC can be defined as "70% of the average segment speed during periods where congestion is unlikely" [*11*]. In this study, a variable speed threshold is considered. This threshold can be calculated as 70% of the base free-flow speed (BFFS). BFFS can be determined using the following equation [*14*]:

$$v_{ia} = 0.7\frac{1}{n_j}\sum_{j\in F} v_{ij} \qquad (1)$$

v_{ia}: Variable speed threshold for TMC i
n_j: Total number of 15-intervals within free-flow time F
v_{ij}: Recorded speed for each TMC i

As part of this study, instead of using a benchmark base free-flow time, this research calculated a variable speed threshold for each corridor by considering the whole study period. A base travel time (BTT) was then calculated for each TMC. BTT can be calculated using the following equation [*14*]:

$$BTT_i = \frac{x_i}{v_{ia}} \qquad (2)$$

BTT_i: Base travel time for each TMC i (hours)
x_i: Length of each TMC i (miles)

Travel time for each TMC can be determined as follows [*14*]:

$$TT_{ij} = \begin{cases} \frac{x_i}{v_{ia}}, & v_{ij} < v_{ia} \\ 0, & v_{ij} \geq v_{ia} \end{cases} \qquad (3)$$

TT_{ij}: Travel time for each TMC i (hours) during the time period j

In this study, travel time inflation (TI) was selected as a performance measure. TI can be defined as the difference between the TT and the BTT. TI can be calculated as follows [*14*]:

$$TI_i = \sum_{j\in K}(TT_{ij} - BTT_i); \quad for\ TT_{ij} > 0 \qquad (4)$$

TI_i: The total travel time inflation for each TMC i (hours) for all the 15-min time period j during the analysis period K

In order to have a better view of daily congestion during the entire study period, a normalized form of the TI named the Corridor Increase in Mean Travel Time (CIMTT) is considered. To calculate CIMTT, the TI is divided by the travel time calculated for each TMC as reflected in the following equation [*14*]:

$$CIMTT_{ij} = \sum_{n}\frac{TI_i}{BTT_i} \qquad (6)$$

$CIMTT_{ij}$: The corridor increase in mean travel time for all TMCs (min)

4. DISCUSSION

The CIMTT for each study corridor is visualized in the heatmaps shown in Figures 2, 3, 4, and 5. In these heatmaps, y-axis represents the hour of the day (15-min bin), and x-axis represents the day of the week. Generally, it is expected that an increase in congestion will be observed due to the opening of any new development. Based on the ITE Trip Generation Manual, an equivalent land use (LU-820 'Shopping Center') would generate about 46.12 and 21.10 trips on Saturday and Sunday, respectively, for every 1,000 Square feet of retail space. For this case, the increase will be phased, which offers a unique perspective on gradual opening of a major development impacts the surrounding area.

As illustrated in Figure 2, for both northbound and southbound of Interstate 95, major congestions occurred during PM Peak hours, and no considerable congestion was observed during the AM Peak hours. Based on the graphs, the partial opening of the complex did not have an immediate impact on the congestion for this corridor since the congestion pattern on this day is almost visually the same as other days. Although this is not statistical proven, further research will document the statistical differences in the visualizations.

Based on Figure 3, there is not a considerable congestion pattern for the northbound of Meadowlands Pkwy during AM Peak hours; however, a steady pattern of congestion was observed for the PM Peak hours of the northbound direction. For the Southbound, interestingly, no considerable congestion was observed for both AM and PM Peak hours. The partial opening of the complex did not have a considerable effect on the congestion pattern for both AM and PM Peak hours in the Meadowlands Pkwy.

According to Figure 4, NJ Route 3, Eastbound, experienced only some minor congestions on some specific days. A steady pattern of very high congestion was recorded during the PM Peak hours for NJ Route 3, westbound. Similar to the other corridors, the partial opening did not affect the congestions pattern at NJ Route 3.

And finally, as shown in Figure 5, a steady pattern of congestion was only observed for PM Peak hours of NJ Route 120, northbound. For southbound of this route almost no congestions were observed. The same as the other corridors, the congestion on NJ Route 120 was not affected by the partial opening of the complex. Data loss from about 10 pm at night to 6 am in the morning for all corridors was another notable observation from these heatmaps. Also, some data loss during the entire day was observed for Meadowlands Pkwy specifically.

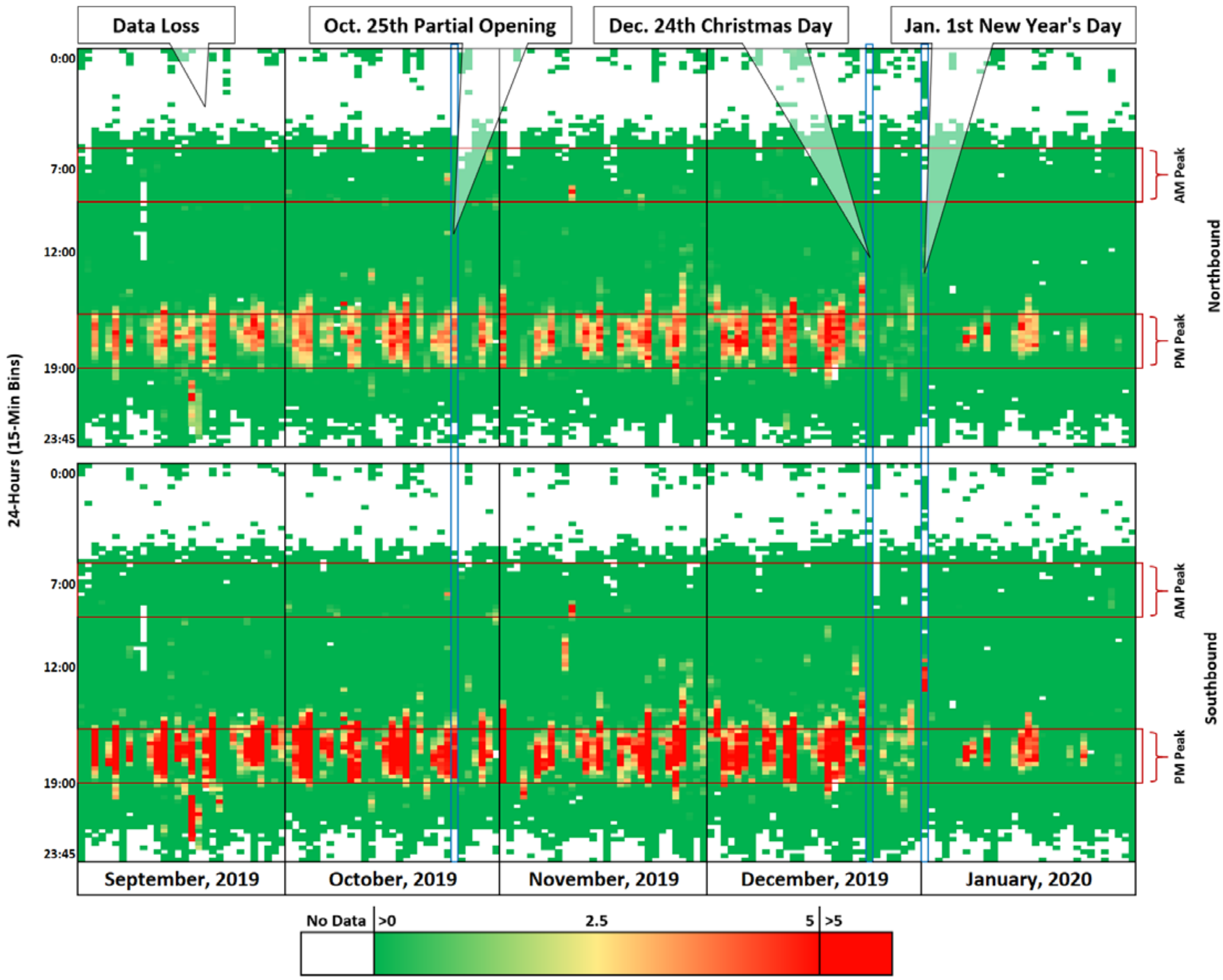

Figure 2 Daily CIMTT for Interstate 95 in 15-min bin

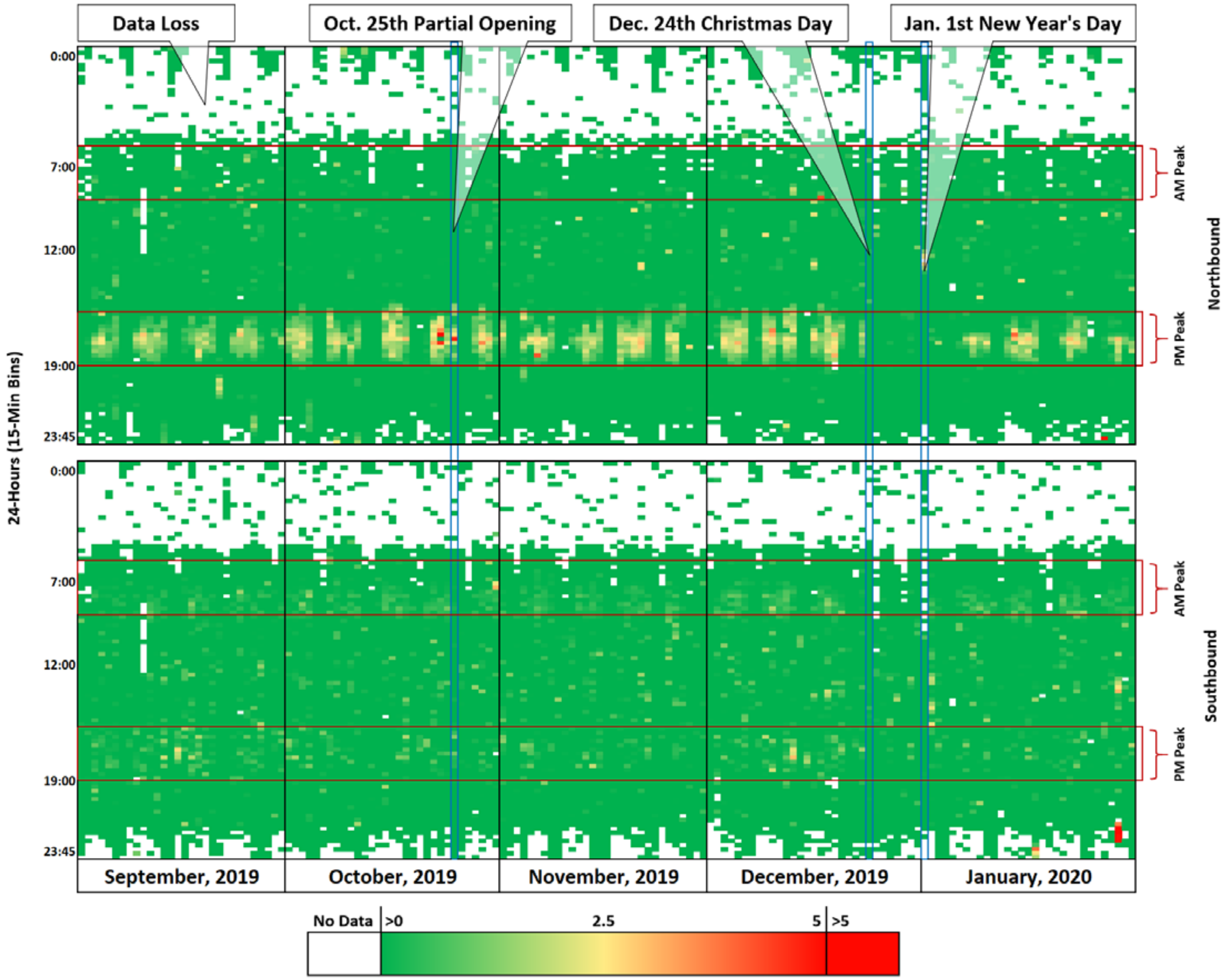

Figure 3. Daily CIMTT for Meadowlands Pkwy in 15-min bin

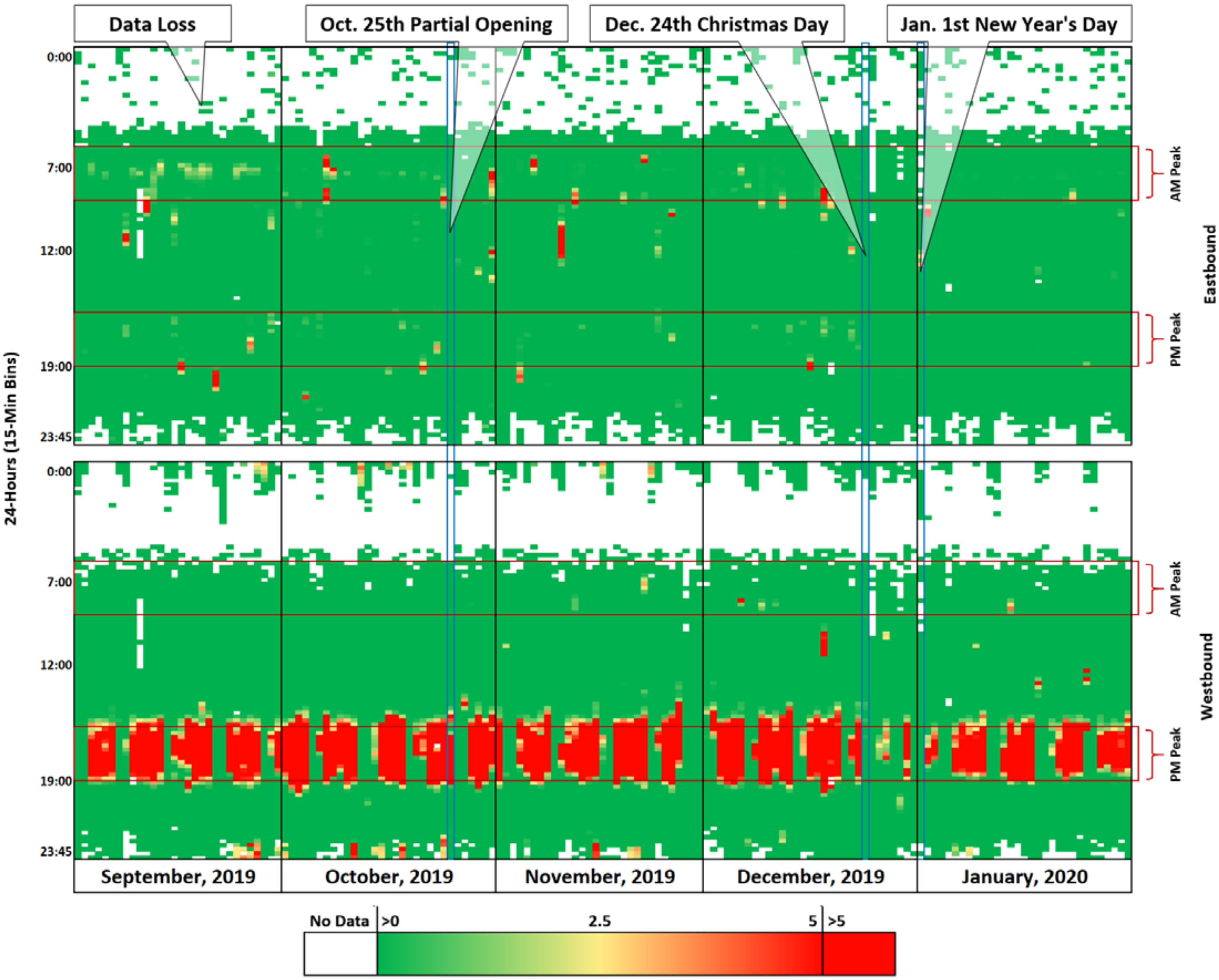

Figure 4. Daily CIMTT for NJ Route 3 in 15-min bin

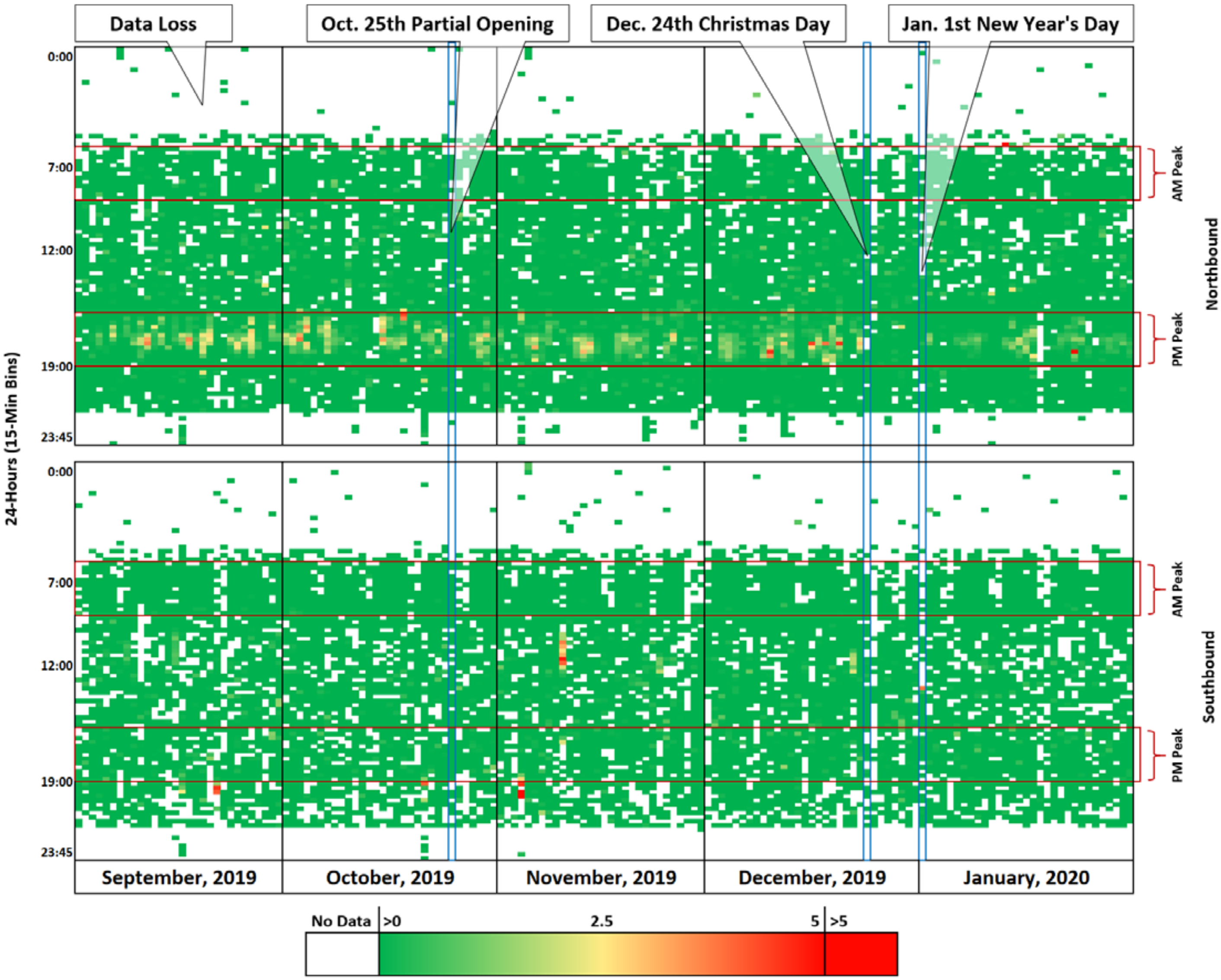

Figure 5. Daily CIMTT for NJ Route 120 in 15-min bin

5. CONCLUSIONS

The main objective of this research is to evaluate the mobility and safety concerns of the transportation network in the vicinity of this complex due to its partial official opening. For this goal, the performance of four surrounding corridors was explored by incorporating travel time inflation (TI) as a performance measure using probe vehicle data.

Results obtained from developed CIMTT heatmaps showed that the partial opening of the complex did not considerably affect the congestion of the surrounding corridors since no obvious decrease or increase in congestion was recorded following the opening of the complex. This result can be attributed to the fact that the complex was only partially opened and was not operated in full capacity. Also, there were many delays in the complex's opening schedule, and it could have been a reason why there were not any considerable changes in congestion in terms of visitors coming to the complex. It is noted that the complex was also shut down in March due to COVID 19 pandemic, and that during that time there was a dramatic decrease in congestion in the region [*19*].

6. ACKNOWLEDGMENTS

This publication was supported by a subaward from Rutgers University, Center for Advanced Infrastructure & Transportation, under Grant no. 69A3551847102 from the U.S. Department of Transportation, Office of the Assistant Secretary for Research and Technology (OST-R)." All materials, except scientific articles or papers published in scientific journals, must also contain the following disclaimer: "Any opinions, findings, and conclusions or recommendations expressed in this publication are those of the author(s) and do not necessarily reflect the views of Rutgers, the State University or those of the U.S. Department of Transportation, Office of the Assistant Secretary for Research and Technology (OST-R).

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