SCALABLE OPERATIONAL TRAFFIC SIGNAL PERFORMANCE MEASURES FROM VEHICLE TRAJECTORY DATA

by

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LIST OF ABBREVIATIONS

AADT	Annual Average Daily Traffic
AFP	Arrival Flow Profile
AM	AM Peak
AOG	Arrival on Green
ATSPM	Automated Traffic Signal Performance Measure
CV	Connected Vehicle
DOW	Day-of-week
EV	Evening
FFT	Free Flow Trajectory
HCM	Highway Capacity Manual
LOS	Level of Service
MD	Midday
NB	Northbound
PCD	Purdue Coordination Diagram
PM	PM Peak
PPD	Purdue Probe Diagram
SB	Southbound
TOD	Time-of-day
VPD	Vehicles-per-day

ABSTRACT

Operations-oriented traffic signal performance measures are important for identifying retiming needs to improve traffic signal operations. Enhancements on traffic signal timings can lead to a decrease on delays, fuel consumption, and air pollutants.

Currently, most traffic signal performance measures are obtained from high-resolution traffic signal controller event data, which provides information on an intersection-by-intersection basis and requires significant initial capital investment. Further, maintenance of the required sensing and communication equipment can represent a significant cost.

Over 400 billion vehicle trajectory points are generated each month in the United States. This high volume of data provides more than 95% of road network coverage. This thesis proposes using vehicle trajectory data to produce traffic signal performance measures such as: traditional Highway Capacity Manual (HCM) Level of Service (LOS), quality of progression, split failure, and downstream blockage.

Geo-fences are created at specific signalized intersections to filter vehicle's waypoints that lie within the generated boundaries. These waypoints are then converted into trajectories that are relative to the intersection. Subsequently, trajectory attributes, such as delay and location and number of stops, are analyzed to produce the mentioned performance measures.

A case study is presented to demonstrate the methodology, which summarizes the performance of an 8-intersection corridor with 4 different timing plans using over 117,000 trajectories and 1.5 million GPS samples collected during weekdays in July 2019. Graphics to analyze entire corridors and to effectuate temporal comparisons are proposed.

The thesis concludes by discussing the required effort and recommendations for scalability, cloud-based implementation opportunities and costs, reviewing current probe data penetrations rates, and indicating that these techniques can be applied to corridors with Annual Average Daily Traffic (AADT) of ~15,000 vehicles-per-day (VPD) for the mainline approaches.

1. INTRODUCTION

Traffic signal operations have a significant impact in road networks. Delays on major roadways due to traffic signals was estimated to be 295 million vehicle-hours in 2012 (1). According to the National Transportation Operations Coalition, a properly designed, and managed traffic signal can (1):

- reduce congestion,
- enhance mobility, and
- decrease delays and the number of vehicle stops, therefore reducing fuel consumption and air pollutants.

Of the 101 areas analyzed in the 2011 Urban Mobility Report, 61% implemented signal coordination projects, which resulted in a reduction in delay of 21.7 million person-hours (2).

Although it is possible to take actions that would improve network operations, if there is not an indication of which locations can (and need) to be improved, it is difficult to place limited agency resources. Hence, traffic signal performance need to be properly reported to operators (3).

1.1 Study Motivation

Traditionally, timing adjustments have been performed based on calls from motorists alerting about the poor performance of a particular traffic signal (4–6). Even though the existence of an issue may be real, the exact location and the cause of the problem has yet to be investigated by the responsible agency, making this method inefficient and time consuming.

In the last couple of years, agencies have started to rely on Automated Traffic Signal Performance Measures (ATSPMs) to manage the traffic signals in their systems (4). However, ATSPMs deployment requires significant investment in vehicle detection technology, communication devices, and data systems (3,7). Figure 1.1 shows common equipment needed for ATSPMs: callout i is a loop detector capable of sensing vehicles, and callout ii is the intersection's cabinet with the signal controller and communication devices. Additional to the capital investment, a shift in the business process of how to perform signal retiming is required (8). Thus, due to these challenges, many agencies will take several years before full-scale deployment is accomplished.

(a) Loop detectors and cabinet

(b) Cabinet with controller and communication devices

Figure 1.1 Common equipment required for ATSPMs

In contrast, high-fidelity vehicle trajectory data has been readily available from commercial sources and can provide a near-real-time, cost effective way to assess not only traditional travel time and delay characteristics on a corridor, but approach-level performance at the intersection (5,9,10). Recent advancements in connected vehicles (CVs) have increased the level of penetration and consistency of ping intervals of probes. In fact, over 400 billion vehicle position records are generated each month in the United States (11). This high amount of data makes it feasible to assess the operational performance of traffic signals at locations with enough traffic volume. For example, SR-37 and Southport Rd. (Figure 1.2), located south of Indianapolis, with an AADT over 42,000 VPD, is a good candidate for a trajectory-based analysis.

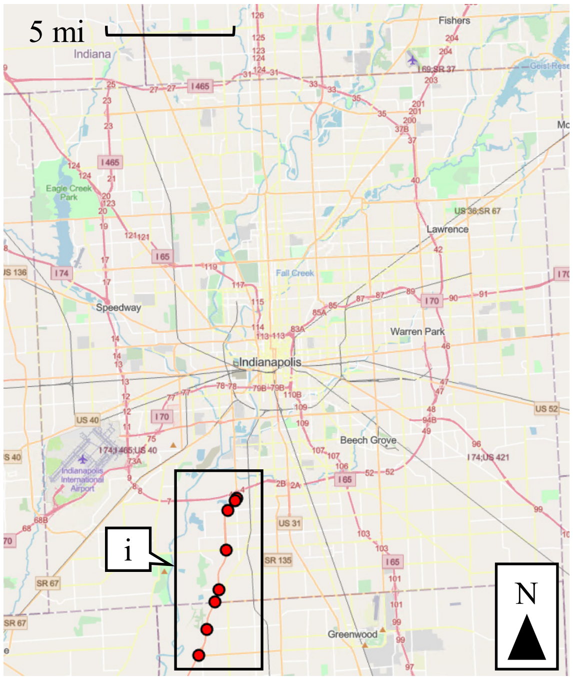
Figure 1.2 Traffic at SR-37 and Southport Rd.

The motivation of this thesis is to investigate opportunities to use this trajectory data to provide scalable operational traffic signal performance measures, without the barriers associated with deploying the infrastructure required for ATSPMs. These crowdsourced trajectory-based performance measures can then be used to prioritize retimings and further upgrades necessary to implement ATSPMs on critical corridors where more detailed monitoring is warranted.

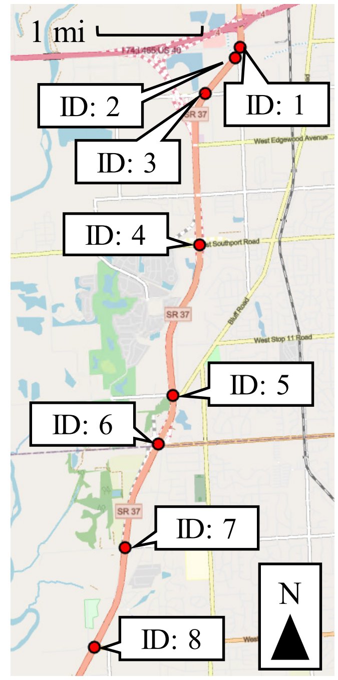
1.2 Study Corridor

In this study, crowdsourced performance measures are computed for a corridor located south of Indianapolis, IN (Figure 1.3a, callout i). The corridor is comprised of eight signalized intersections (Figure 1.3b). The first intersection when traveling southbound (SB) is Thompson Rd. (ID 1), followed by Harding St. (ID 2), Epler Ave. (ID 3), Southport Rd. (ID 4), Wicker Rd. (ID 5), County Line Rd. (ID 6), Fairview Rd. (ID 7) and Smith Valley Rd (ID 8). These intersections have four different time-of-day (TOD) timing plans:

- AM Peak (AM): 5:00 – 9:15
- Midday (MD): 9:15 – 14:30
- PM Peak (PM): 14:30 – 19:00
- Evening (EV): 19:00 – 22:00



(a) SR-37 located south of Indianapolis, IN (ESRI, license)



(b) SR-37 and intersections' IDs (ESRI, license)

Figure 1.3 Study corridor: SR-37

The corridor has a median AADT of 40,896 VPD, and the speed limit varies between 45 and 55 mph.

1.3 Study Period

The methodology to produce trajectory-based performance measures was demonstrated with third-party July 2019 data. In Section 7.1, a temporal comparison between July 2019 and July 2020 is presented. For consistency, only weekdays were analyzed, and special attention was given to the different TOD timing plans due to their characteristic traffic patterns.

1.4 Study Approach

This study proposes a methodology to reference vehicle trajectories to specific traffic signals. It then develops scalable trajectory analysis techniques to compute:

- movement level of service (LOS). This LOS thresholds are based upon the HCM control delay thresholds (12),
- proportion of vehicles arriving on green. We also call this arrival on green (AOG), and is calculated by dividing the number of vehicle trajectories proceeding through an intersection during the green interval, without stopping, divided by the total number of observed vehicles during the same interval (13),
- proportion of vehicles experiencing a split failure. A split failure is indicative of insufficient green to discharge a standing queue at a traffic signal (14), and
- frequency of downstream blockage. A downstream blockage typically occurs when an adjacent intersection queue grows long enough to impede the movement of traffic departing an upstream intersection.

Subsequently, a comparison between a traditional high-resolution Purdue Coordination Diagram (PCD) (3,15,16) and a crowdsourced performance measure is made. The thesis concludes with an explanation of corridor wide graphical summary techniques, that can quite efficiently be used to screen for performance problems across several hundred intersections.

2. LITERATURE REVIEW

This section provides an overview of traffic signal performance measures, different data sources, current implementation, and requirements. The objective of the literature review is to help understand current practices and new opportunities.

2.1 Automated Traffic Signal Performance Measures

ATSPMs are tools that automatically process data to provide an insightful assessment of a given traffic signal in the form of performance measures. ATSPMs rely on traffic signal controller high-resolution data, which consists of events (signal outputs and detector states) that are saved in logs with a resolution of a tenth of a second (3,4,8).

According to the HCM, the common methods to assess intersection performance is LOS, which is based on control delay (13). As more states have brought ATSPMS into their day-to-day workflows, operational performance metrics have been developed to help agencies make timing adjustments.

Tracking phase termination status by time-of-day (TOD) is essential for practitioners to determine whether specific movements at an intersection require more split time or if the intersection is at capacity (14,17,18). Freije, et al. proposed a method to estimate split failures using stop bar detection (14). Smaglik et al. used event data to quantify arrival type, which provides qualitative information on progression (3,19,20). Day et al. developed a graphic called Purdue Coordination Diagram, which provides insight on the level of progression, cycle length, and split times at an intersection by plotting vehicle arrivals and phase changes on a time in cycle vs. TOD graph (15,16). Wu, et al. used setback detector data to implement a shockwave-based queue estimation model to determine when an approach is at overcapacity (21). Emtenan and Day concluded that detectors with a fixed setback closer to the stop bar typically underestimate the number of stops due to queues. As the detector setback was increased, the accuracy of estimating the number of stops also increased (22).

In 2014, Day et al. published a report in which controller-based high-resolution data collection costs were presented. It was stated that a one-time cost of $3,120, plus an additional $420 per year for maintenance, were required for a single location. This represents a ten-year cost of $7,320 for an agency (3).

2.1.1 Current Implementation

ATSPMs have been institutionalized in only four states (IN, WI, UT, and GA) and are being assessed or demonstrated in 27 others, with additional deployments and pilots in at least 44 local jurisdictions around the country. To facilitate implementation, the Utah Department of Transportation has developed an open-source ATSPM software, which can be improved by the private sector or public agencies (4).

Key catalysts for adoption are having reliable communication links between the field cabinets and the traffic operations center, and having functional detection systems at the intersection (3). The quality of communication can be assessed based on ping frequency and the quantity of data retrieved over a period of time (23). Faulty detection equipment can be identified by reviewing the traffic signal controller's error reports (3), or by forcing phase terminations during low-volume periods (24).

2.2 Crowdsourced Data Performance Measures

Recently, performance measures developed from point-based probe GPS sources via smartphone applications, fleet telematics, and CVs have emerged. This type of probe or "trajectory" data offered by commercial providers typically contains latitude, longitude, timestamp, speed, heading, and a unique trip identifier. A major benefit of utilizing this data is that it leapfrogs the requirement to build and maintain communication and detection systems (8).

Studies have demonstrated that metrics such as travel time, delay, arrivals on green, and queue length can be produced using trajectories (9,25–30). Some of these studies are summarized in the subsequent sections.

2.2.1 Travel Time

Li et al. developed a methodology to calculate composite travel times on a corridor from trip trace data. Trajectories that travel different sections of the corridor are combined to increase the number of start-to-finish trip occurrences (25). Zhang et al. utilized vehicle trajectory data, and a Trip Information Maximizing Generative Adversarial Network, to calculate travel time distributions (26).

2.2.2 Delay

Waddell et al. proposed a method to calculate experienced delay at an intersection from vehicle trajectory data. First, the speed of the vehicle at the beginning of its approach is used to calculate the travel time through the intersection if the vehicle was undisturbed. Then, the difference between the real travel time and the undisturbed travel time is calculated to provide the value of the delay (9).

Huang et al. proposed an analytical formula to estimate delay at signalized intersections from vehicle trajectory data. However, factors in the formula need to be calibrated for each intersection; therefore, a specific-location pre-analysis needs to be performed before delay calculations can be carried out (27).

2.2.3 Arrivals on Green

Day et al. calculated vehicle arrivals at virtual detectors upstream of an intersection from CV data to obtain arrival profiles. The virtual arrivals were compared to physical measurements, resulting in a statically significant goodness-of-fit at a 90% confidence level. Then, green phase times were acquired from controller event logs to calculate the AOG. Finally, corridor offsets were optimized (28).

Waddell et al. utilized individual vehicle delays at an intersection to determine if the vehicle stopped on its approach to calculate AOG. A minimum 5-second delay threshold was utilized to filter vehicles that had a delay, but still arrived during the green phase of the cycle. Another methodology proposed by Waddell et al. to calculate AOG is based on the percentage of vehicles that stopped at an intersection, which inversely correlates to AOG. Stopped percentages were calculated by dividing the number of vehicles with speeds under 5 mph for 2 seconds or more over the total number of vehicles. These two methods produced AOG values 7.2 and 2.5 percent lower than ATSPM AOG, respectively (9).

2.2.4 Queue Length

Zhao et al. were able to estimate queue lengths from vehicle trajectory data. First, the penetration rate of the available data is calculated by analyzing the stopping distribution of the vehicles. Then, the number of vehicle trajectories are scaled based on the penetration rate to calculate the queue length (29). Cetin presented a methodology to estimate queue dynamics at signalized intersections based on shock wave theory and spatial-temporal information of when a vehicle joins the back of queue (30). The required levels of data penetration to produce reliable performance measures are discussed in the following section.

2.2.5 Required Levels of Data Penetration

Each performance measure requires some reasonable level of penetration for the data to accurately represent on-the-ground conditions. Currently, there are no data sources available in the United States with penetration levels high enough to obtain real-time performance measures. To acquire relevant traffic signal assessments, various studies have: estimated non-connected vehicle trajectories, aggregated trajectories for similar TOD and day-of-week (DOW) periods, and increased the sample period (31,32).

Day, et al. concluded that a penetration rate between 0.09 and 0.80 percent was sufficient to optimize offsets with similar performance to data collected by physical loop detectors by aggregating data over multiple days (28). Waddell et al. determined that even after extensive data cleaning, the remaining dataset with a penetration rate below 0.04 percent can still be used to identify offset adjustment opportunities (9). Zheng et al. were able to calculate traffic volumes from GPS trajectory data, with penetration rates between 3 and 12 percent, resulting in mean absolute errors of 9-12 percent (33). Zhao, et al. explored data with penetration rates as high as 15 percent to estimate queue lengths and volume (29), which approached the recommended rate proposed by Argote, et al. to estimate average delay in the oversaturated regime (34).

2.3 Problem Statement

Although there has been an increasing interest to develop new crowdsourced-based traffic signal performance measures, there are significant opportunity areas that are yet to be fulfilled.

Previous studies have developed a variety of graphics that provide operators with insight on the performance of a traffic signal; nevertheless, these graphics usually only provide information on one or two traffic signal metrics. This creates the need to analyze various graphics to obtain a holistic understanding of the traffic signal operation. A visualization that contains information on delay, progression, saturation, and adjacent influence is proposed in Section 4.3.1.

Additionally, most proposed performance measures focus on the events that occur upstream of the intersection. The causes of the calculated efficient or poor performance are then attributed to the traffic signal at the analyzed location. Nevertheless, some of the identified issues might be the result of queue spillbacks produced by a downstream intersection that operates at oversaturated conditions. For this reason, a methodology to identified downstream blockage is proposed in Section 4.3.3.

3. TRAJECTORY DATA DESCRIPTION

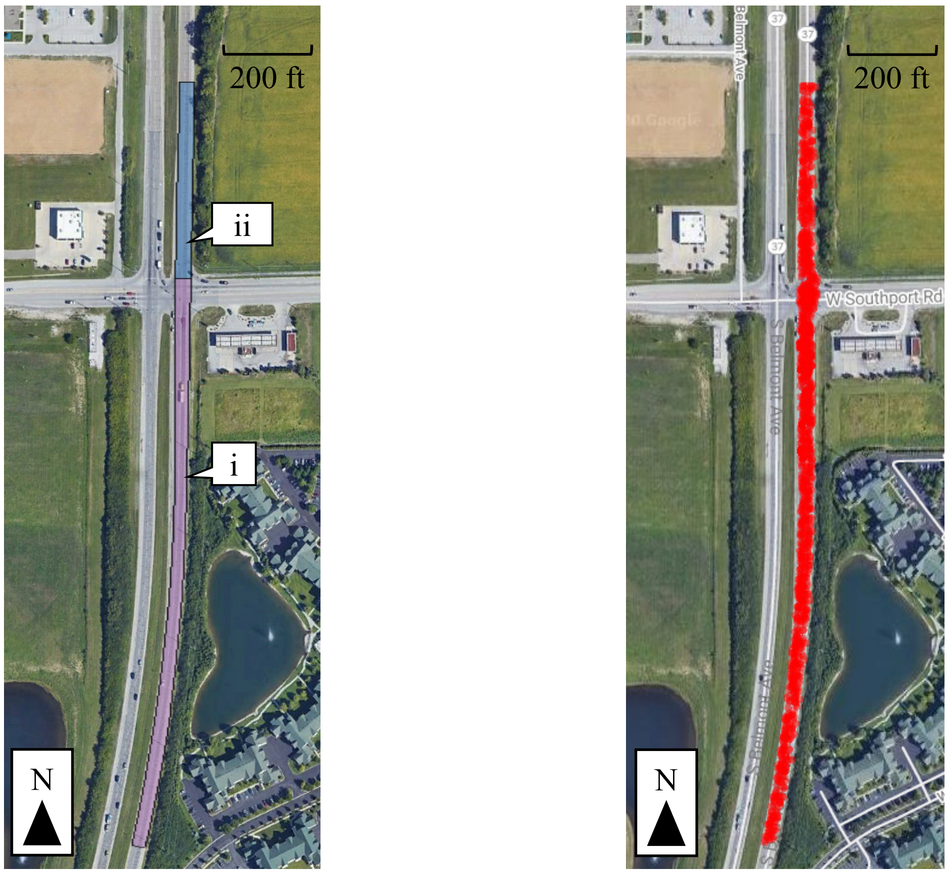
The third-party crowdsourced trajectory data used in this study is comprised of individual waypoints with a reporting interval of three seconds. Each waypoint has the following information: GPS location (1.5 m fidelity), speed, heading, timestamp, and an anonymous trajectory identification number. By linking individual waypoints by their trajectory identification number, a vehicle's trajectory can be obtained.

3.1 Trajectory Selection by Geo-fences

To reference trajectories to the study locations, geo-fences were created. By filtering trajectories that lie within the boundaries of the geo-fences, and by taking into consideration the position of the initial and final waypoints, trajectories that crossed a specific intersection with a particular movement can be obtained.

For a given through movement, two polygons are needed: one for the upstream segment of the movement (Figure 3.1a, callout i), and another for the downstream segment (Figure 3.1a, callout ii). More than one polygon per movement is required to allow for an efficient data filtering, since only trajectories that were in all the required polygons, with an appropriate heading, are analyzed. Figure 3.1b shows over 1,600 GPS points selected with Figure 3.1a polygons during the PM period on July 22nd, 2019.

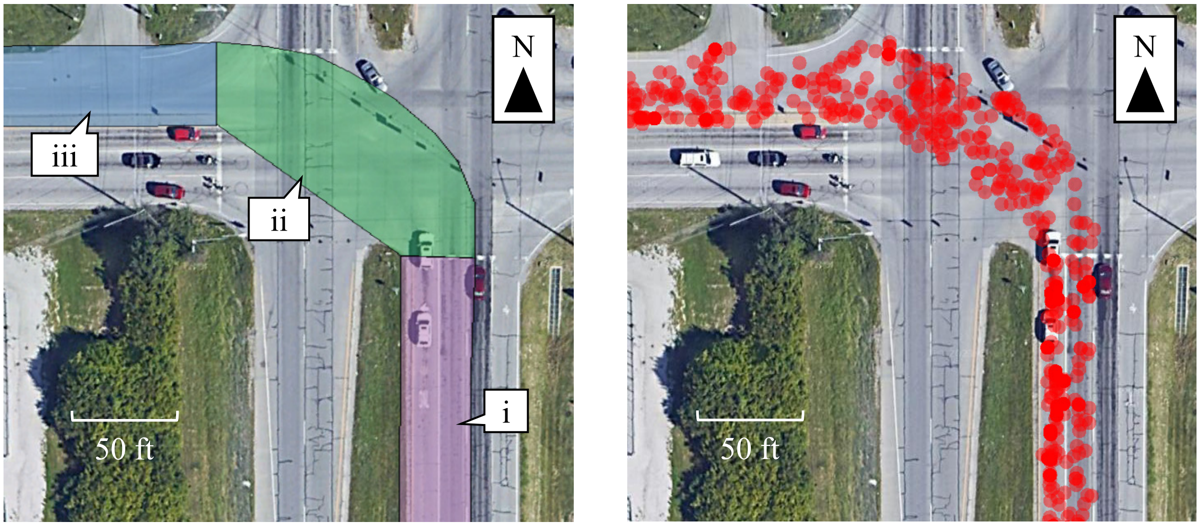
For a left movement, three polygons are needed: one for the upstream segment of the movement (Figure 3.2a, callout i), one for the crossing section of the movement (Figure 3.2a, callout ii), and another for the downstream segment (Figure 3.2a, callout iii). Similar to the through movements, these geofences are necessary to have an efficient data analysis. The additional polygon (Figure 3.2a, callout ii) adds versatility when analyzing different types of left turns. The lengths of the polygons can vary depending on the objective of the analysis. For this study, upstream geo-fences are ¼ mi long, and downstream polygons 500 ft. long, unless another intersection is closer. Figure 3.2b shows~1,500 of the over 2,800 GPS points selected with Figure 3.2a polygons during the PM period on July 22nd, 2019.



(a) Required polygons

(b) GPS points selected during the PM period on July 22nd, 2019

Figure 3.1 Waypoint selection at SR-37 and Southport Rd. for NB through movements (Map data: Google, IndianaMap Framework Data, Maxar Technologies, USDA Farm Service Agency)



(a) Required polygons

(b) GPS points selected during the PM period on July 22nd, 2019

Figure 3.2 Waypoint selection at SR-37 and Southport Rd. for NB left movements (Map data: Google, IndianaMap Framework Data, Maxar Technologies, USDA Farm Service Agency)

3.2 Data Penetration

During July 2019, over 4 billion data points were generated in the state of Indiana. Trip counts were calculated for each studied intersection to obtain the penetration level of the third-party crowdsourced data. Figure 3.3 shows a summary of the trip counts by TOD timing plans for July 2019 weekdays. The median penetration of the trajectory data in the corridor is 2% for weekdays in July 2019 during the different TOD timing plan periods.

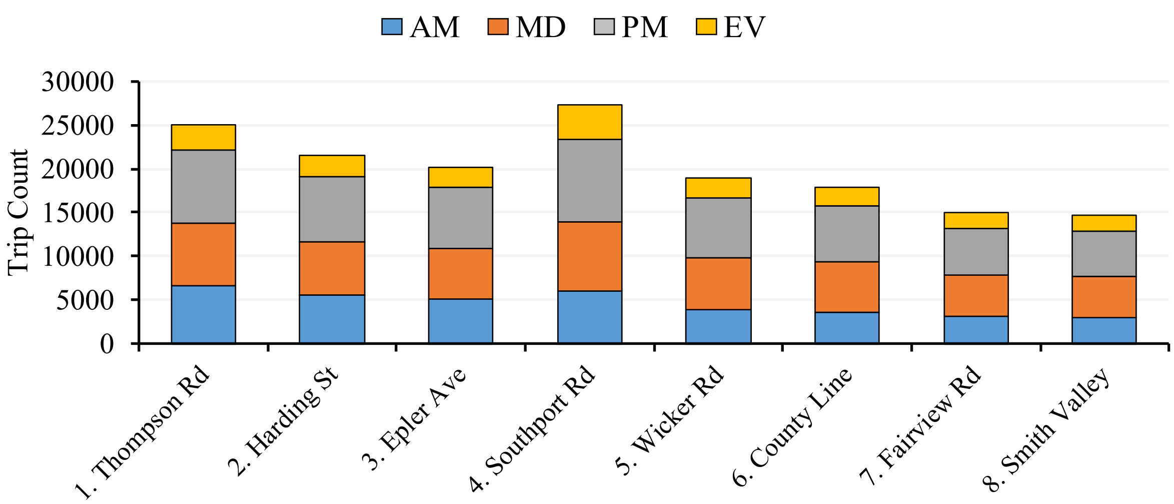


Figure 3.3 SR-37 trip counts, by intersection, in July 2019 weekdays for the different TOD timing plans

4. TRAJECTORY-BASED PERFORMANCE MEASURES

In this section, the methodology to calculate LOS, AOG, split failures, and downstream blockage from vehicle trajectory data is presented.

4.1 Delay-based Performance Measures Concepts

The two most popular delay definitions used to evaluate intersections are stopped delay and control delay (Figure 4.1) (3,35). Stopped delay is defined as the time that a vehicle has a speed of zero at an intersection, and it is obtained by calculating the difference between the time when a stopping vehicle starts accelerating (t_3) and the time when it came to a full stop (t_2). Control delay includes the delay due to deceleration, the stopped delay, and the delay due to acceleration. It is also important to define a free-flow trajectory (FFT), which is the trajectory of a vehicle traveling at the posted speed limit without stopping.

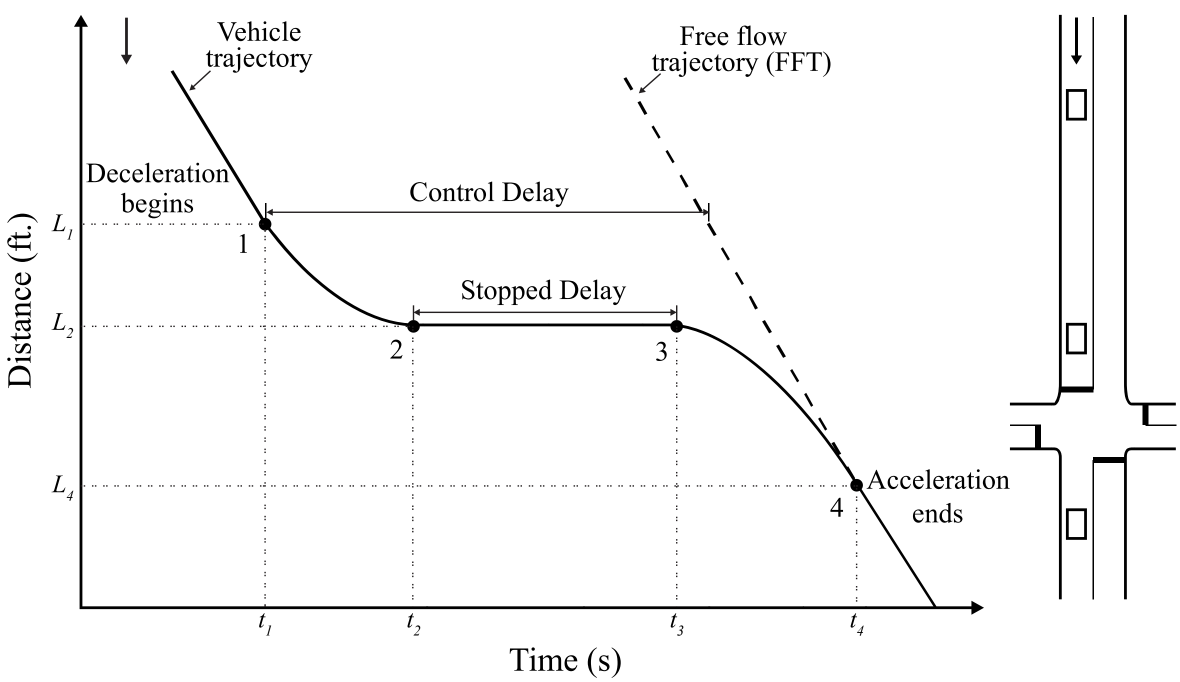


Figure 4.1 Delay definitions (35)

Thus, control delay can be calculated as follows:

$$Control\ Delay = t_4 - t_1 - Free\ Flow\ Trajectory\ Travel\ Time, \tag{1}$$

where

$$Free\ Flow\ Trajectory\ Travel\ Time = \frac{L_1 - L_4}{Speed\ Limit} \tag{2}$$

t_1 is the time when the vehicle started decelerating (s), t_4 is the time when the vehicle stopped accelerating (s), L_1 is the distance where deceleration started (ft.), L_4 is the distance where acceleration ended (ft.), and *Speed Limit* is the segment's posted speed limit (ft./s).

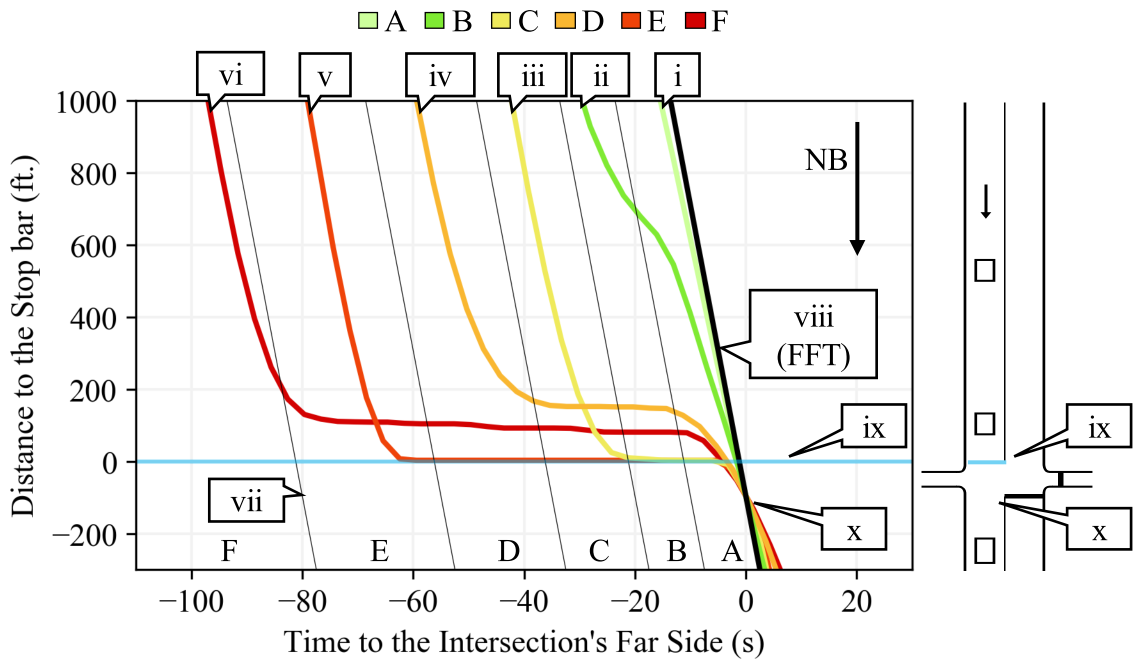
4.2 Control Delay Level of Service

Level of Service is a qualitative description of the operating conditions at an intersection. It is based on the control delay experienced by vehicles (12). Table 4.1 shows the different LOS ratings with qualitative descriptions and their respective range of control delay.

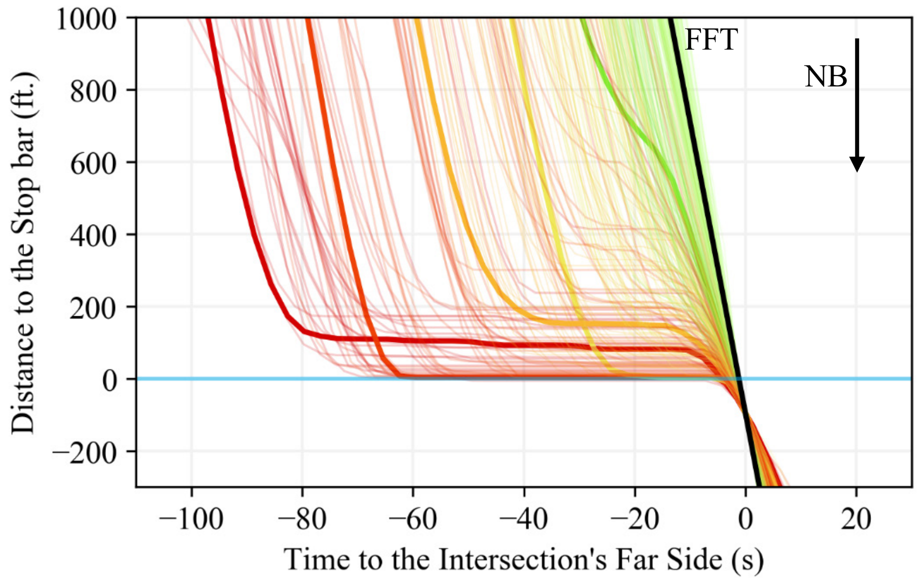
Table 4.1 HCM Level of Service Criteria for Signalized Intersection (12)

Level of Service	**Average Control Delay (s/veh)**	**Description**
A	≤10	Free Flow
B	>10-20	Stable Flow (slight delay)
C	>20-35	Stable Flow (acceptable delay)
D	>35-55	Approaching Unstable Flow (tolerable delay)
E	>55-80	Unstable Flow (intolerable delay)
F	>80	Forced Flow (congested and queues fail to clear)

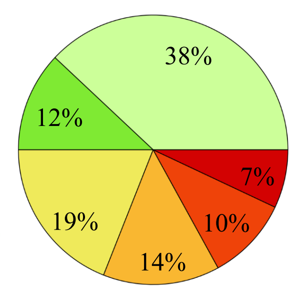
By utilizing Equation 1, Equation 2 and Table 4.1 criteria, individual trajectories can be assigned a LOS rating. Figure 4.2a depicts a time-space diagram where the vertical-axis is the distance in ft. to the intersection's stop bar (callout ix) and the horizontal-axis is the time in seconds relative to when the vehicle crosses the far side (callout x) of the intersection. Callout viii is a FFT. Callouts i-vi are a series of trajectories of vehicles traveling northbound (NB) through, at SR-37 and Southport Rd., color coded by their LOS rating, during the MD timing plan between July 22nd and July 26th, 2019. The farther away a trajectory approaches the stop bar from the FFT, the greater its delay will be.



(a) Six trajectories with the different LOS ratings



(b) All 452 trajectories available for the TOD and analysis period



(c) Percentage of trajectories by their LOS

Figure 4.2 Vehicle trajectories traveling NB through during the MD period at SR-37 and Southport Rd. from July 22nd to July 26th, 2019

Callout vii is a segregation line that helps to visually separate trajectories by their LOS; in this case, the boundary between LOS E and LOS F. It is important to note that the objective of the segregation lines is merely to help set visual boundaries, since they are only based on the deceleration and stopped delay components of control delay.

Figure 4.2a is a subset of Figure 4.2b, in which all the 452 trajectories of vehicles traveling NB through, during the MD TOD timing plan between July 22nd and July 26th 2019, are shown. Figure 4.2c is a pie chart of what percentage of the trajectories in Figure 4.2b were characterized with the different LOS ratings. In this case, 38% of the trajectories during the analysis period were classified as LOS A, but a considerable number of trajectories had a LOS E or LOS F (10% and 7% respectively).

4.2.1 Numerical Comparison on Estimated Control Delay and Stopped Delay

Table 4.2 shows the estimated control delay and stopped delay values for the trajectories presented in Figure 4.2a. The difference between these two delay definitions becomes clearer when we have trajectories that do not stop at the intersection, nonetheless they have to slow down or travel at slower speeds due to the intersection (callouts i and ii). The last column shows the corresponding LOS using the estimated control delay and the LOS thresholds shown in Table 4.1.

Table 4.2 Delays of trajectories in Figure 4.2a

Callout	Estimated Control Delay (s)	Estimated Stopped Delay (s)	LOS
i	3	0	A
ii	18	0	B
iii	34	12	C
iv	49	18	D
v	74	54	E
vi	113	60	F

4.3 Operational-based Performance Measures

Motorists general expectations of traffic signals are:

1. well synchronized signals so that they arrive during the green interval and do not have to stop upstream of the signal,
2. sufficient green time so they can proceed through in one cycle,
3. sufficient coordination with adjacent signal so they can proceed through an intersection unimpeded by downstream queues.

In the past, arrivals on green have been evaluated using the PCD (3,15,16) and diagnosis of sufficient green time has been made using the Purdue Split Failures (14,36). Downstream blockage has been quite difficult to differentiate from split failures using traditional high-resolution data.

Trajectory-based data provides an opportunity to holistically look these three operational performance measures from the individual vehicles' perspective. This section introduces a new visualization tool called the Purdue Probe Diagram (PPD).

4.3.1 Arrivals on Green: Purdue Probe Diagram

AOG is a performance measure that indicates the percentage of vehicles that arrive at a signalized intersection during the green phase of the cycle. This measurement provides an indication on the performance of coordinated intersections. Low AOG values indicate that vehicle platoons are not progressing through the corridor as intended.

Since crowdsourced trajectory data does not directly provide information on the state of signalized intersections, methods must be developed to infer the signal's condition at arrival. For this reason, a new trajectory-based performance measure graphic, capable of providing AOG, is proposed: Purdue Probe Diagram.

A PPD for the PM timing plan for vehicles traveling NB at SR-37 and Southport Rd. between July 22nd and July 26th 2019 is presented in Figure 4.3a. The graphic is similar to the one shown in Figure 4.2b, with the main difference being that trajectories in Figure 4.3a are color coded by the number of stops during the approach.

The first time a vehicle's speed goes to zero when approaching an intersection, the trajectory is attributed one stop. After this, every time a vehicle's speed goes from non-zero to zero, after traveling for at least 100 ft. following the previous stop, it is categorized with an additional stop. The 100 ft. filtering is done to avoid counting extra stops when vehicles are just inching forward when waiting for green in the queue. AOG is then calculated as the ratio between trajectories that had no stops during the approach and the total number of trajectories.

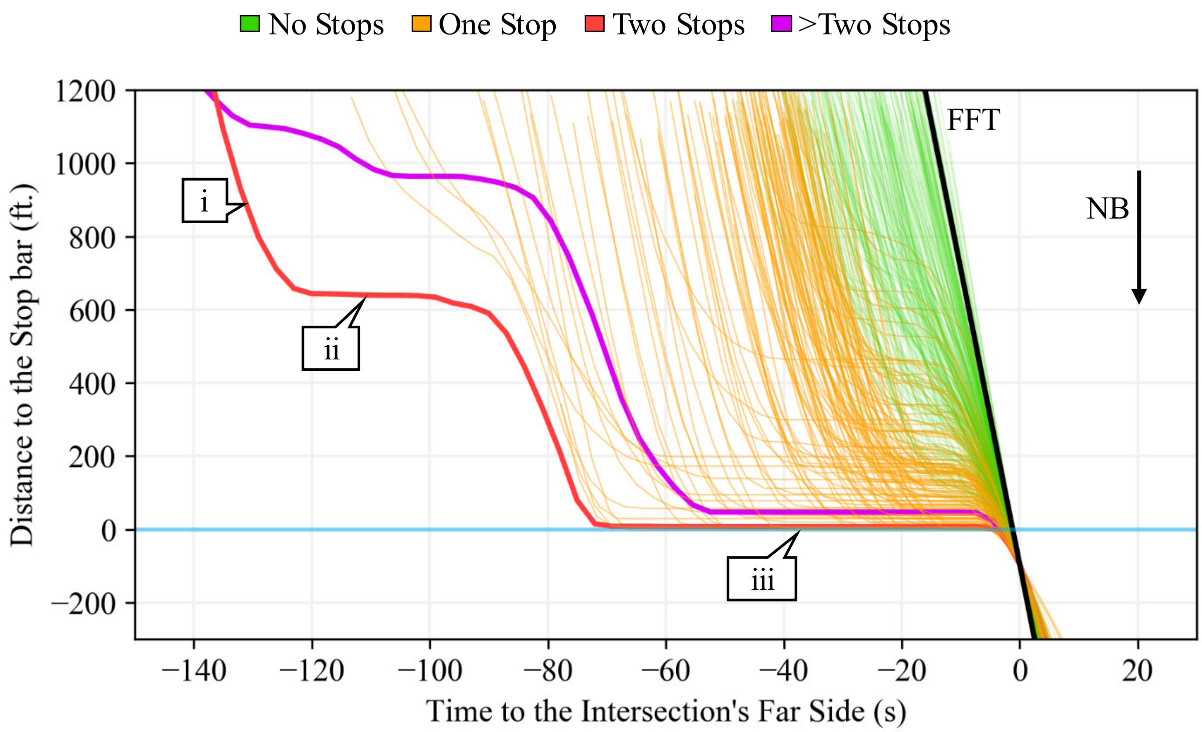
Figure 4.3a depicts trajectories that experienced none, one, two and more than two stops. Trajectories that did not stop during the approach (green) are closer to the FFT, and therefore have a smaller delay than trajectories with one or more stops. Additionally, some no-stop trajectories appear to the right of the FFT, which is an indication of vehicles traveling above the speed limit.

Figure 4.3b is a pie chart of what percentage of trajectories in Figure 4.3a were categorized with different number of stops. The percentage of vehicles that had no stops is the same as the AOG value. In this case, 65% of vehicles arrived at the intersection during green, 34% experienced one stop and only 0.4% had two stops or more.

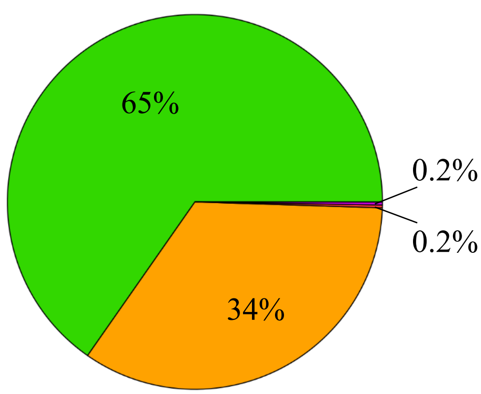
4.3.2 Split Failures

A split failure is when a traffic signal does not provide enough green time to allow vehicles in a particular movement to cross the intersection, thus making them wait for longer than one cycle length. Split failures occurring on an approach are an indicator of that approach operating at overcapacity. Being able to locate where and when there are split failures is important for agencies to identify opportunities to reallocate green time to improve system operation (14).

Using the PPD, a vehicle trajectory is categorized as having experienced a split failure when it stops for two times, or more, when approaching an intersection. In the PPD shown in Figure 4.3a, two vehicles experienced split failures. Focusing on the trajectory that stopped only twice (callout i), it can be observed how the vehicle stopped for the first time around 650 ft. away from the stop bar (callout ii) and a second time right before the stop bar (callout iii). Figure 4.3b shows that only 0.4% of vehicles experienced a split failure for the analyzed time period at the specified location.



(a) 415 trajectories with different number of stops



(b) Percentage of trajectories by their number of stops

Figure 4.3 Vehicle trajectories traveling NB through during the PM period at SR-37 and Southport Rd. from July 22nd to July 26th, 2019

4.3.3 Downstream Blockage

Downstream blockage is when there is a queue at the downstream intersection that obstructs the progression of vehicles. Identifying downstream blockage is important to pinpoint locations where an oversaturated intersection is impacting an adjacent location. In some cases, an adjustment of the downstream green may address the problem, in other cases an agency must make a policy decision on how to manage those oversaturated conditions and the impact on the overall network.

In this study, downstream blockage has been defined as any trajectory that after crossing the far side of the intersection has at least a 10 second delay compared to the FFT. A 10 second threshold is utilized since in the worst non-blocked scenario, a vehicle would take about 7 seconds to reach free-flow speed after crossing the far side at any of the studied intersections. The previous calculation is based on the geometry at County Line Rd. (narrowest intersection) and on a constant acceleration of 6.6 ft/s^2, as suggested by (37). Figure 4.4 shows a PPD with 735 trajectories traveling NB during the AM period from July 22nd to July 26th 2019 at SR-37 and Thompson Rd. All the trajectories that are located to the right of the line offset by 10 seconds from the FFT (callout i) were categorized as having experienced downstream blockage (callout ii). In this example, 22 of the trajectories, or 3%, were classified as experiencing downstream blockage.

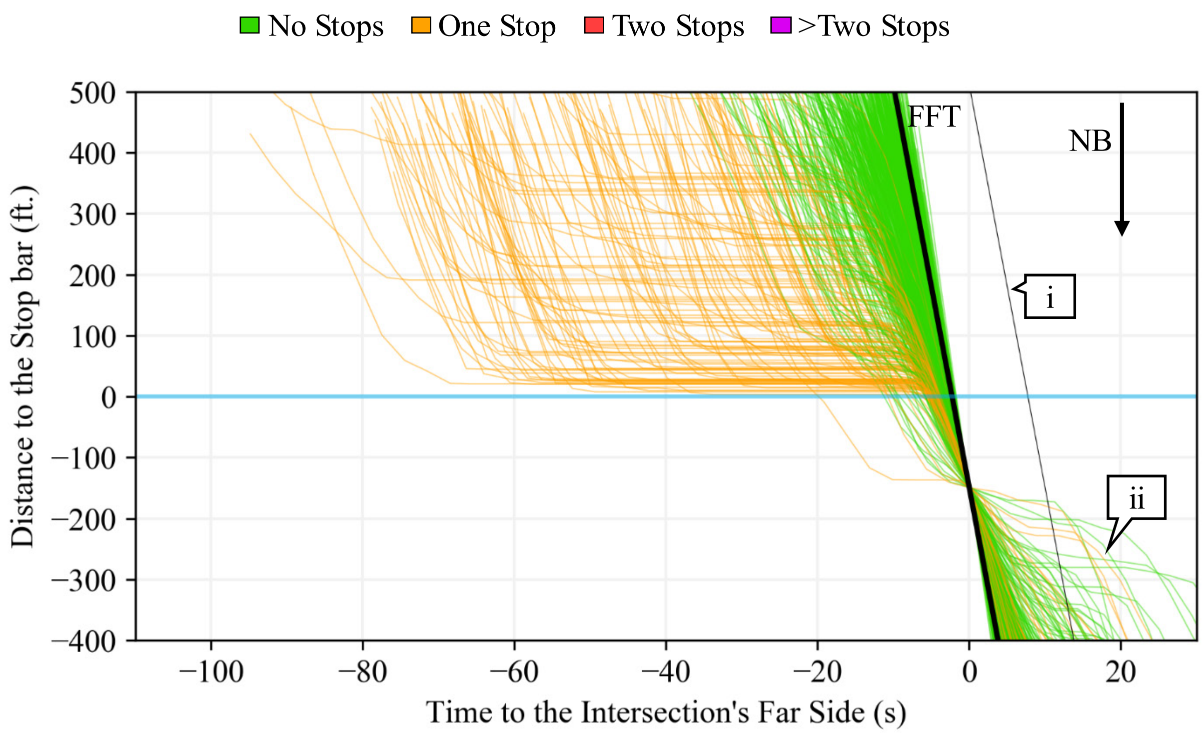


Figure 4.4 Vehicle trajectories with downstream blockage traveling NB through during the AM period at SR-37 and Thompson Rd. from July 22nd to July 26th, 2019

In the next chapter, a comparison between a traditional ATSPM and the proposed PPD is presented.

5. COMPARISON OF PCD AND PPD

The PCD has been the traditional graphic utilized to visualize the quality of progression. In a PCD, analysis pivots detector events on a cycle reference point. In a PPD, the analysis pivots the arrival trajectory-based upon the arrival time at the far side of an intersection.

A PCD for vehicles traveling SB at SR-37 and Southport Rd. on July 22^{nd} 2019 is shown in Figure 5.1. The vertical-axis is the time-in-cycle of the traffic signal and the horizontal-axis is the TOD. The traffic signal cycle is divided into two sections: effective red and effective green. The red line marks the beginning of effective red, and the green line marks the beginning of effective green. Thus, the time between the horizontal-axis and the green line is the time that the traffic signal displayed an effective red, and the time between the green line and the red line is the time that the traffic signal displayed an effective green. Vehicle arrivals at the advance detector are depicted by black dots (3). Therefore, black dots that lie within the horizontal-axis and the green line are vehicles that arrived to the intersection during the effective red; in contrast, black dots that lie between the green line and the red line are vehicles that arrived during the effective green. The PCD shown in Figure 5.1 also has vertical blue lines that separate the different TOD timing plans.

During the PM period in Figure 5.1, there are moments where there are no arrivals on green (callout i) while the time in cycle advances, but then arrivals suddenly appear. This is an indication that vehicles had to wait due to a long queue until they could cross over the advance detector. This suggests that the approach is operating at overcapacity and vehicles may have experienced split failures. However, with the traditional PCD graphic, it is impossible to be completely sure if vehicles are waiting for longer than one cycle length, since it is also possible that the queue is being completely discharged at every iteration.

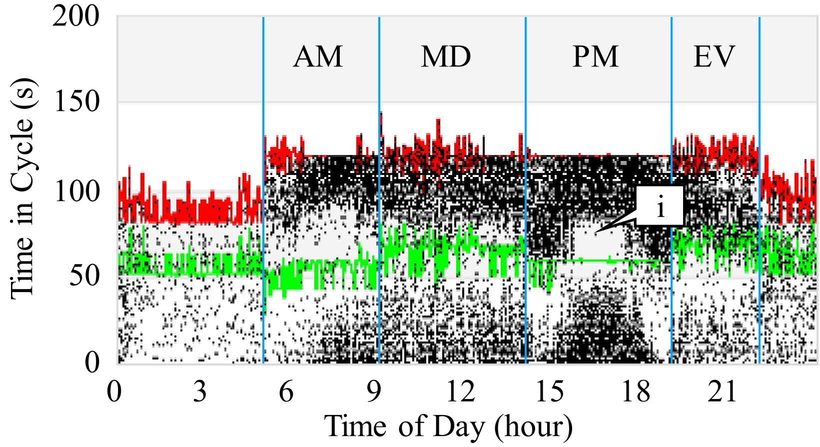


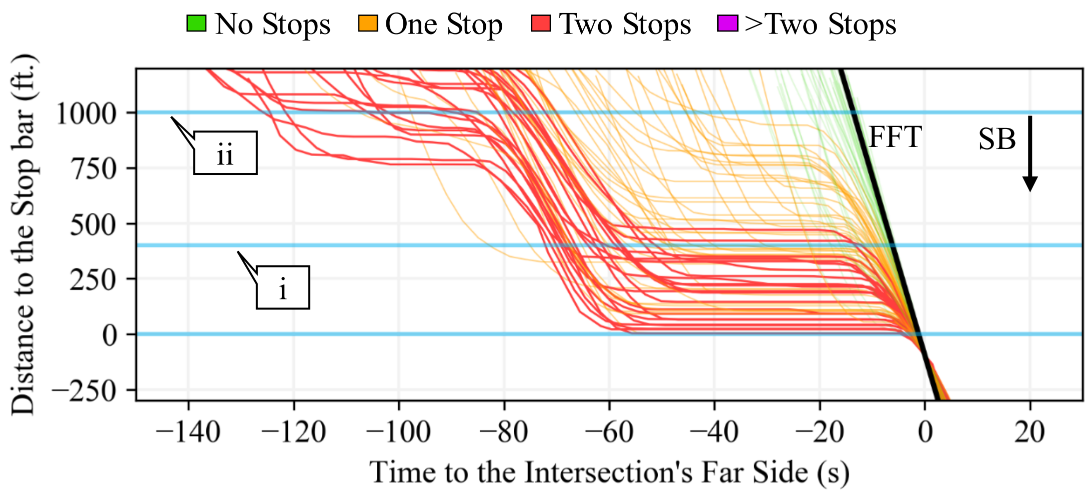
Figure 5.1 PCD for SB through at SR-37 and Southport Rd. on Monday July 22nd, 2019

Figure 5.2a shows a PPD for vehicle trajectories traveling SB at SR-37 and Southport Rd. on July 22nd 2019 during the PM timing plan. The PPD clearly shows trajectories that have experienced split failures (red), since they have stopped twice when approaching the intersection. The trajectory data verifies the assumptions made with the PCD regarding the approach operating at overcapacity, but this conclusion is not fully available using only traditional event-based traffic signal performance measures.

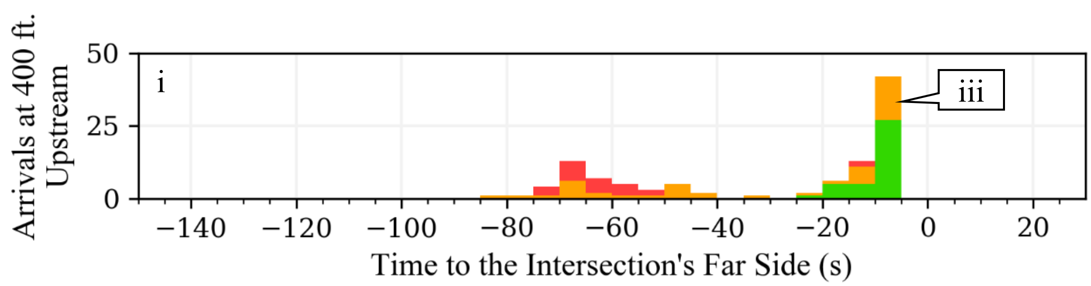
Another advantage of performance measures obtained from crowdsourced trajectories (like PPDs) rather than high-resolution controller data (like PCDs), is that the distance from the stop bar of virtual advance detectors can be modified. This allows for a more accurate representation of the state of the signal's operation (22).

Figure 5.2a, callout i, is the location where advance detectors are usually placed, 400 ft. upstream from the stop bar. Arrival Flow Profiles (AFPs) can be derived by counting when are vehicles crossing the advance detection line. AFPs are especially useful to visualize the number of vehicles that arrive at an intersection and the delay that was experienced (38).

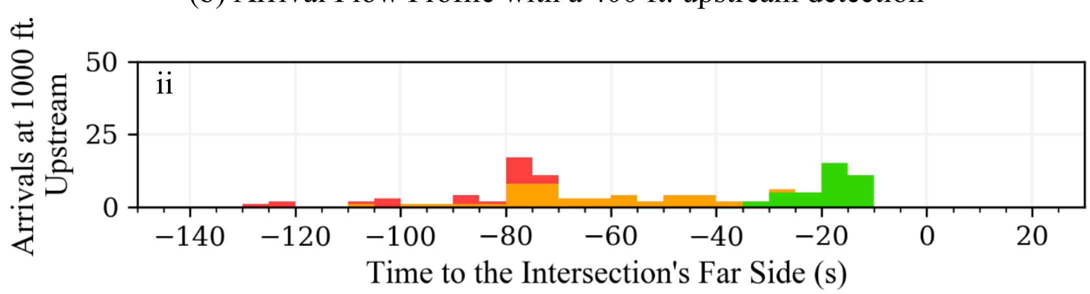
Two AFPs are created based on two different virtual advance detectors: one 400 ft. before the stop bar (callout i), and the other one 1000 ft. before the stop bar (callout ii). In the first case, with the 400 ft. virtual advance detector (Figure 5.2b), it would appear that there is a majority of vehicles, with diverse number of stops, arriving at the intersections without any significant delay (callout iii). This result is deceiving because, due to the proximity of the virtual advance detector to the stop bar, relevant information of the vehicle's trajectories from before crossing the detection line is lost. Conversely, an AFP based on the 1000 ft. virtual advance detector (Figure 5.2c) produces a more accurate characterization of when vehicles are arriving to the intersection (22).



(a) PPD



(b) Arrival Flow Profile with a 400 ft. upstream detection



(c) Arrival Flow Profile with a 1000 ft. upstream detection

Figure 5.2 PPD and AFP for vehicles traveling SB through during the PM period at SR-37 and Southport Rd. on Monday July 22nd, 2019

Additionally, from the PCD, an AOG of 66% is obtained for the PM timing plan; nevertheless, as mentioned before, this result might be deceiving due to the approach operating at overcapacity. On the other hand, from the PPD we can calculate a more accurate AOG of 36%.

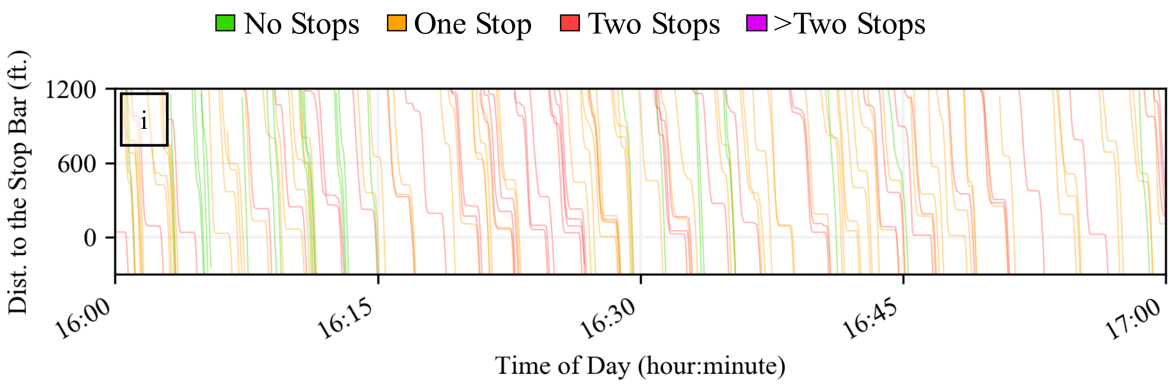
6. VISUALIZING COORDINATED MOVEMENTS BY TIME OF DAY

It is useful to visualize the color-coded trajectories of a PPD by the TOD in which they occurred. This provides a more detailed look of the time at which the different issues occur. Figure 6.1a shows a PPD by TOD between the 16:00 and 17:00 hrs of vehicle trajectories traveling SB through at SR-37 and Southport Rd. from July 22nd to July 26th, 2019. It is clear that various vehicles are experiencing split failures (red) and at what time these events are happening. If the TOD period increases (Figure 6.1b and Figure 6.1c), the variation on progression quality can be qualitatively viewed by looking for changes between green (good progression) and orange, red or purple (poor progression).

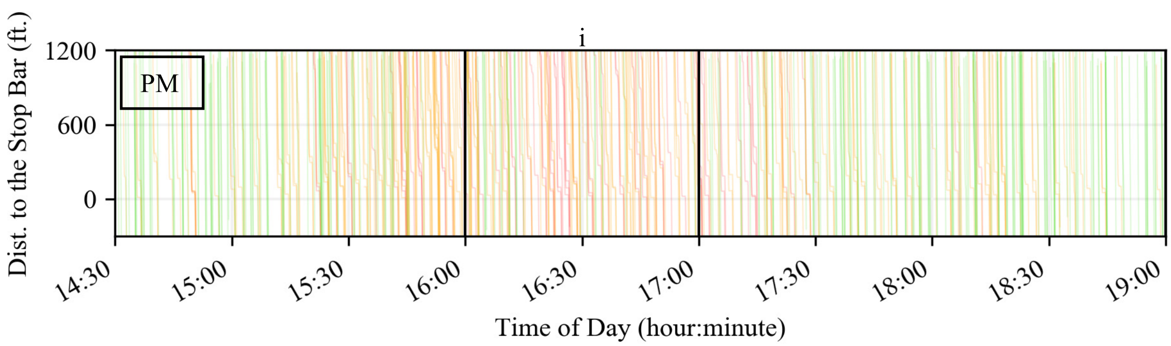
By displaying a standard PPD with its PPD by TOD, a more thorough analysis of an intersection can be made. Figure 6.2 and Figure 6.3 show PPDs of vehicle trajectories traveling SB and NB through, respectively, at SR-37 and Southport Rd. in July 2019 weekdays during all the TOD timing plans.

For this corridor, the peak flow are NB (Figure 6.3) in the morning and SB (Figure 6.2) late in the afternoon. Looking at the SB trajectories (Figure 6.2), the percent of vehicles arriving on green with no stops ranges from 49% to 79%. The southbound PM (Figure 6.2d) period has the highest proportion of split failures (12%) and the lowest proportion of vehicles arriving on green (49%).

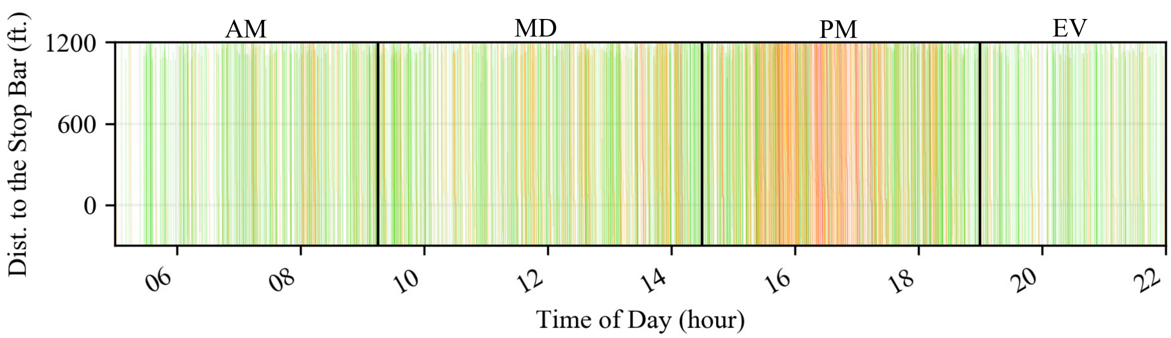
For the NB morning PPD (Figure 6.3b), there are 1358 trajectories depicted, 63% of the vehicles arrived on green with no stops. Throughout the day, the percentage of vehicles with no stops ranges between 57% and 73%. The number split failures (2 or more stops) is around 1% for the AM and PM periods.



(a) 16:00 to 17:00 hrs.

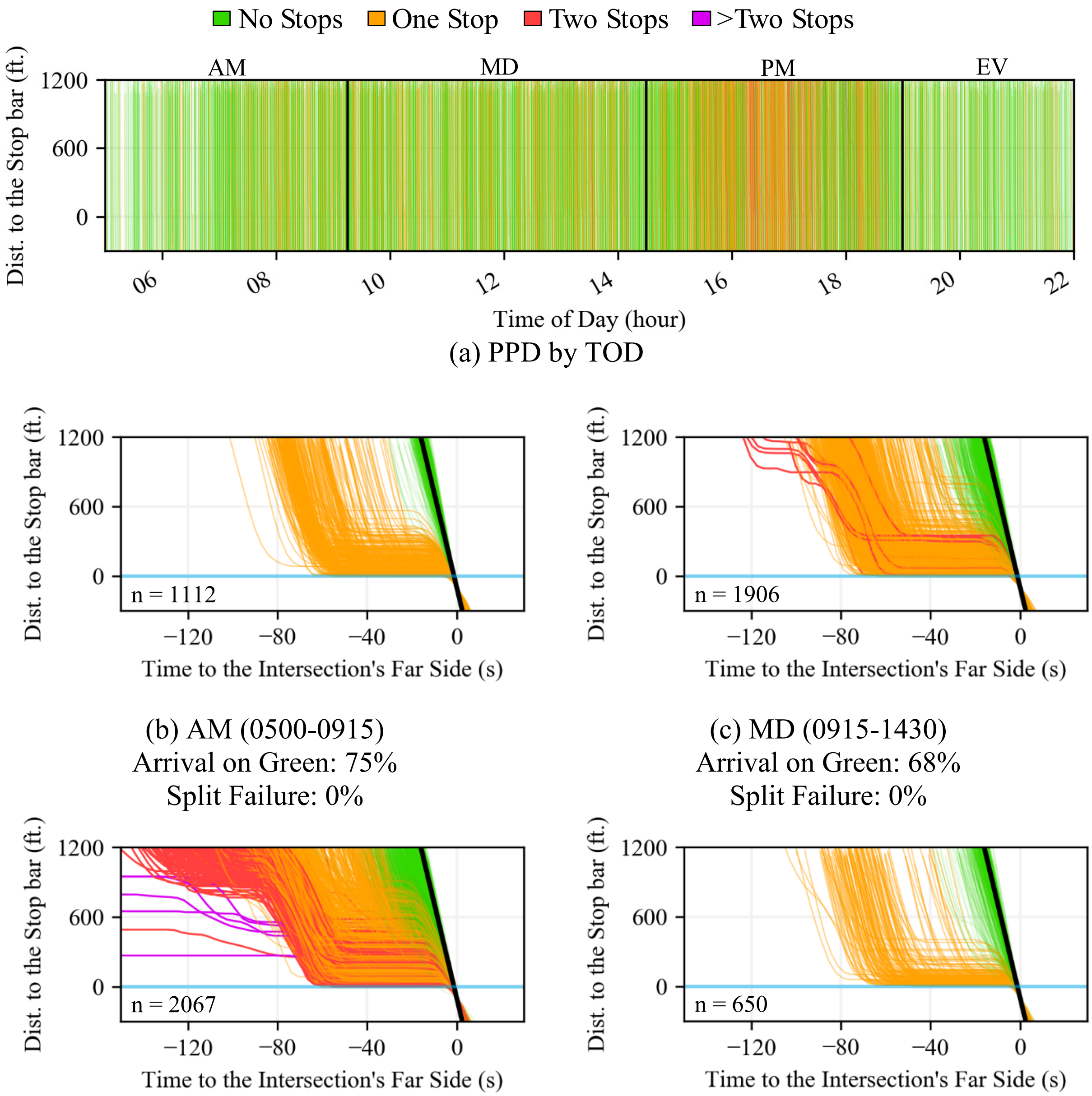


(b) PM period



(c) All TOD timing plans

Figure 6.1 PPD by TOD of vehicle trajectories traveling SB through at SR-37 and Southport Rd. from July 22nd to July 26th, 2019



(a) PPD by TOD

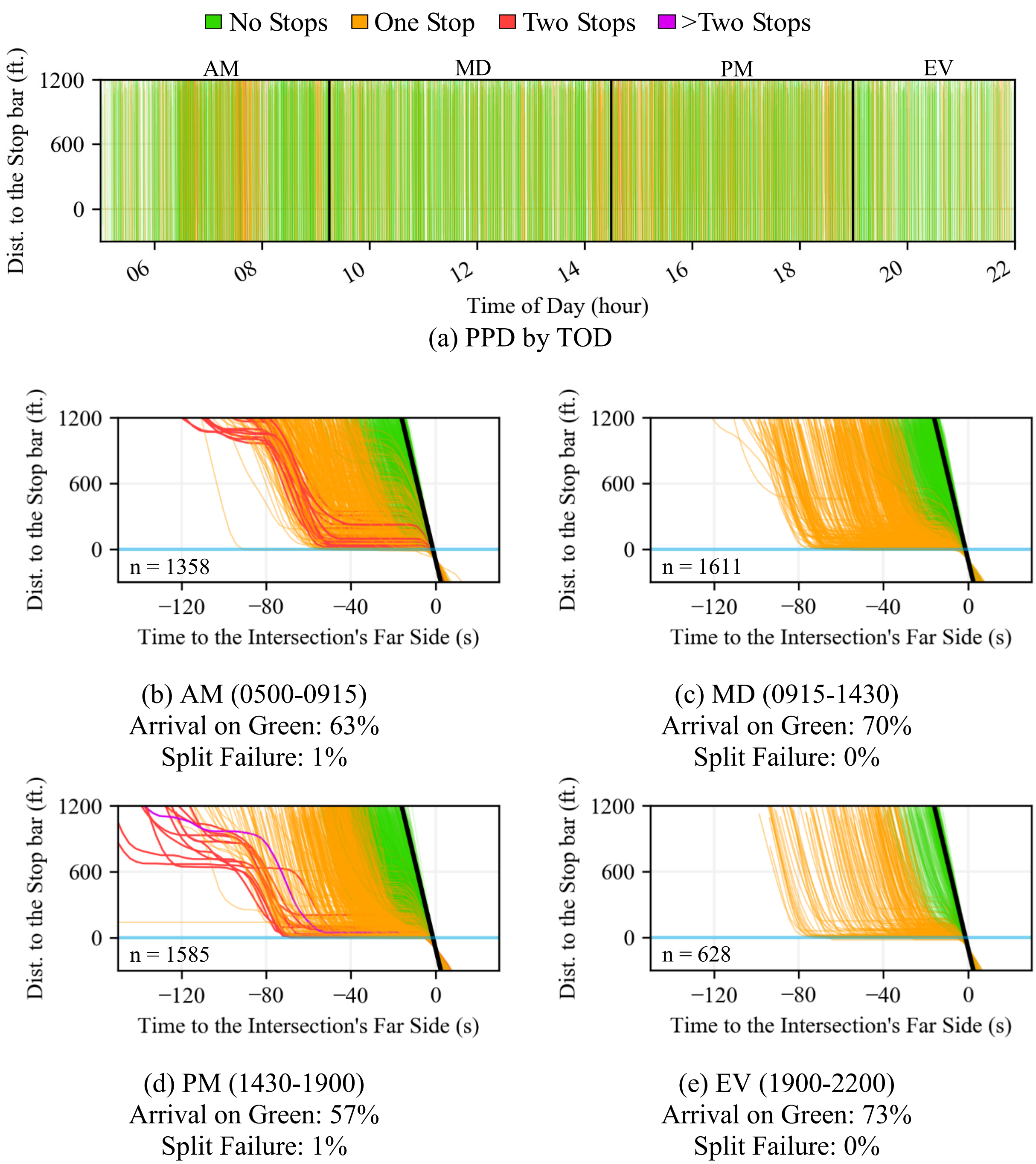
(b) AM (0500-0915)
Arrival on Green: 75%
Split Failure: 0%

(c) MD (0915-1430)
Arrival on Green: 68%
Split Failure: 0%

(d) PM (1430-1900)
Arrival on Green: 49%
Split Failure: 12%

(e) EV (1900-2200)
Arrival on Green: 79%
Split Failure: 0%

Figure 6.2 Vehicle trajectories traveling SB through at SR-37 and Southport Rd. during weekdays in July 2019 for the different TOD plans



(a) PPD by TOD

(b) AM (0500-0915)
Arrival on Green: 63%
Split Failure: 1%

(c) MD (0915-1430)
Arrival on Green: 70%
Split Failure: 0%

(d) PM (1430-1900)
Arrival on Green: 57%
Split Failure: 1%

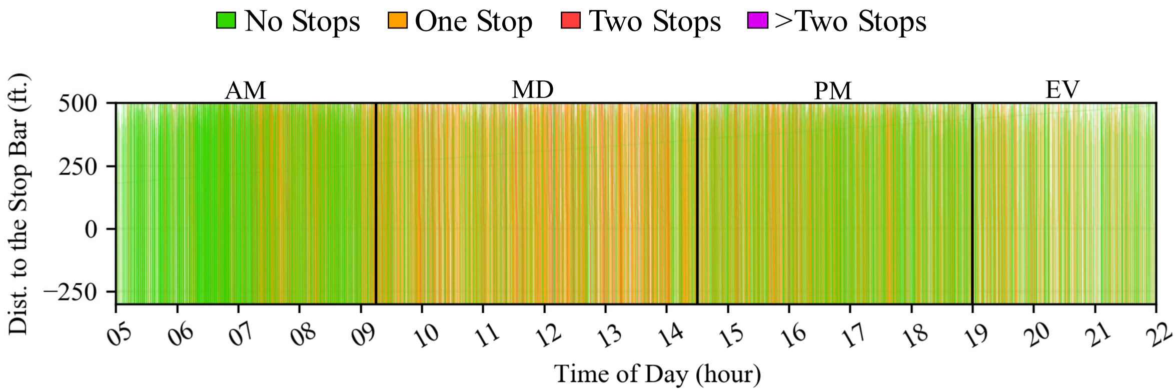
(e) EV (1900-2200)
Arrival on Green: 73%
Split Failure: 0%

Figure 6.3 Vehicle trajectories traveling NB through at SR-37 and Southport Rd. during weekdays in July 2019 for the different TOD plans

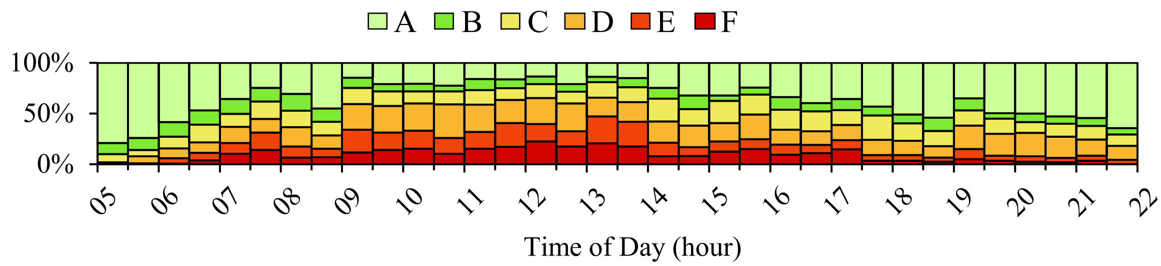
6.1 Performance Measures by Time-of-day

Similar to the visualization of color-coded trajectories by TOD (Figure 6.1), the calculated performance measures can also be presented with a temporal focus. This permits for an analysis that does not only provide information on the time that challenges occur, but also what specific problems are present.

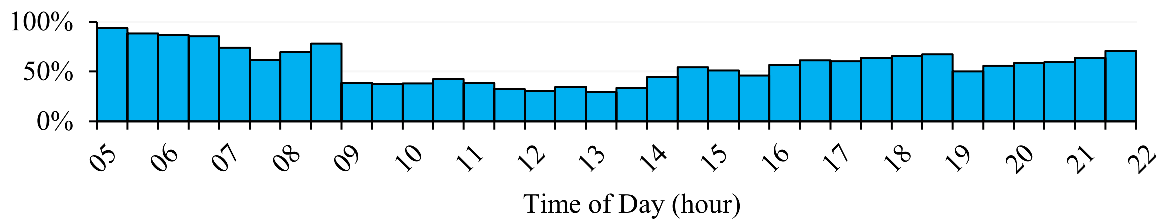
Figure 6.4 shows a PPD by TOD and the calculated performance measures for vehicle trajectories traveling NB through at SR-37 and Thompson Rd. in July 2019 weekdays. From Figure 6.4a and Figure 6.4d, it can be stated that vehicles are experiencing split failures during the MD period, suggesting oversaturated conditions. During the same period, Figure 6.4b and Figure 6.4c provide information on how this oversaturation increases delay and decreases the quality of progression. Finally, Figure 6.4e indicates that the downstream intersection affects the analyzed location during time periods where split failures are rare, which explains why delay and progression are a challenge even outside of the MD period.



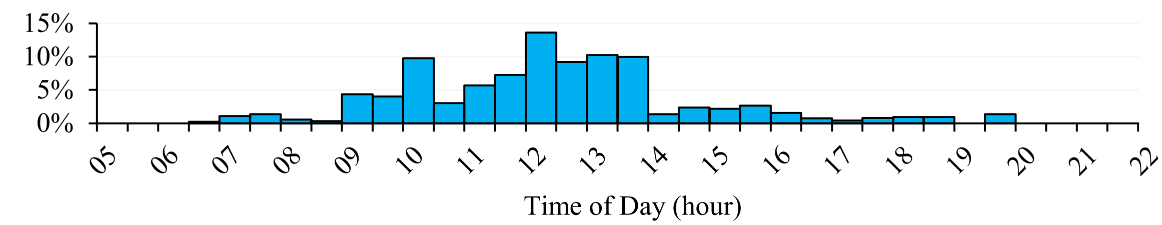
(a) PPD by TOD



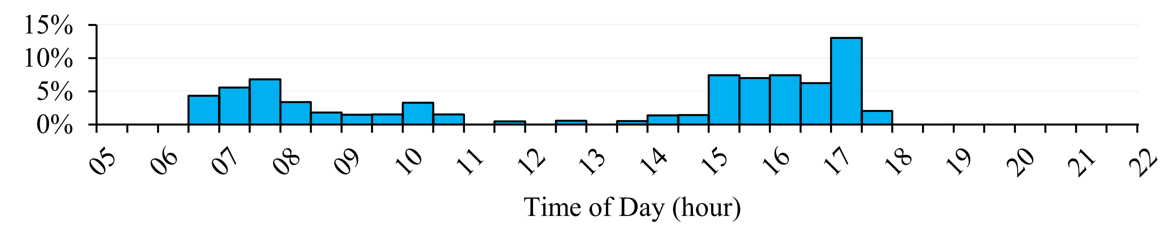
(b) Percentage of trajectories by LOS



(c) AOG



(d) Percentage of trajectories that experienced split failures



(e) Percentage of trajectories that experienced downstream blockage

Figure 6.4 PPD by TOD and performance measures results for vehicle trajectories traveling NB through at SR-37 and Thompson Rd. in July 2019 weekdays

7. CORRIDOR-WIDE SUMMARY GRAPHICS

Until now, only performance measures that describe the efficiency at the intersection level have been discussed. However, an agency needs corridor level reports and graphics for quickly assessing system level operation. To address this system overview need, different graphs are proposed to broaden the scope of the signalized intersection analysis. Figure 7.1 and Figure 7.2 characterize the SB through and protected left movements, respectively, by TOD timing plans for vehicle trajectories traveling in July 2019 weekdays. Additional details on how to interpret these graphics is provided below:

- Bar graphs indicating the number of unique trajectories that followed the analyzed movement by intersection and by TOD timing plan: Figure 7.1a and Figure 7.2a. These graphics provide practitioners with a sense of volume differences between intersections, which can facilitate comparisons.
- Stacked bar graphs portraying LOS by intersection and by TOD timing plan: Figure 7.1b and Figure 7.2b. Although this graphic is not particularly useful for operational decisions, agency planning departments use LOS quite frequently and this information can be easily included in the portfolio of summary graphics.
- Stacked bar graphs indicating number of stops by intersection and by TOD timing plan: Figure 7.1c and Figure 7.2c. These graphics are very useful for assessing quality of progression (smooth flow).
- Bar graphs portraying percentage of trajectories that experienced split failures by intersection and by TOD timing plan: Figure 7.1d and Figure 7.2d. These graphics are useful for identifying intersections where there may be opportunities to rebalance green times and what TOD plan to examine.
- Bar graphs portraying percentage of trajectories that experienced downstream blockage by intersection and by TOD timing plan: Figure 7.1e and Figure 7.2e. These graphics are useful for agencies to identify intersections impacted by adjacent intersections.

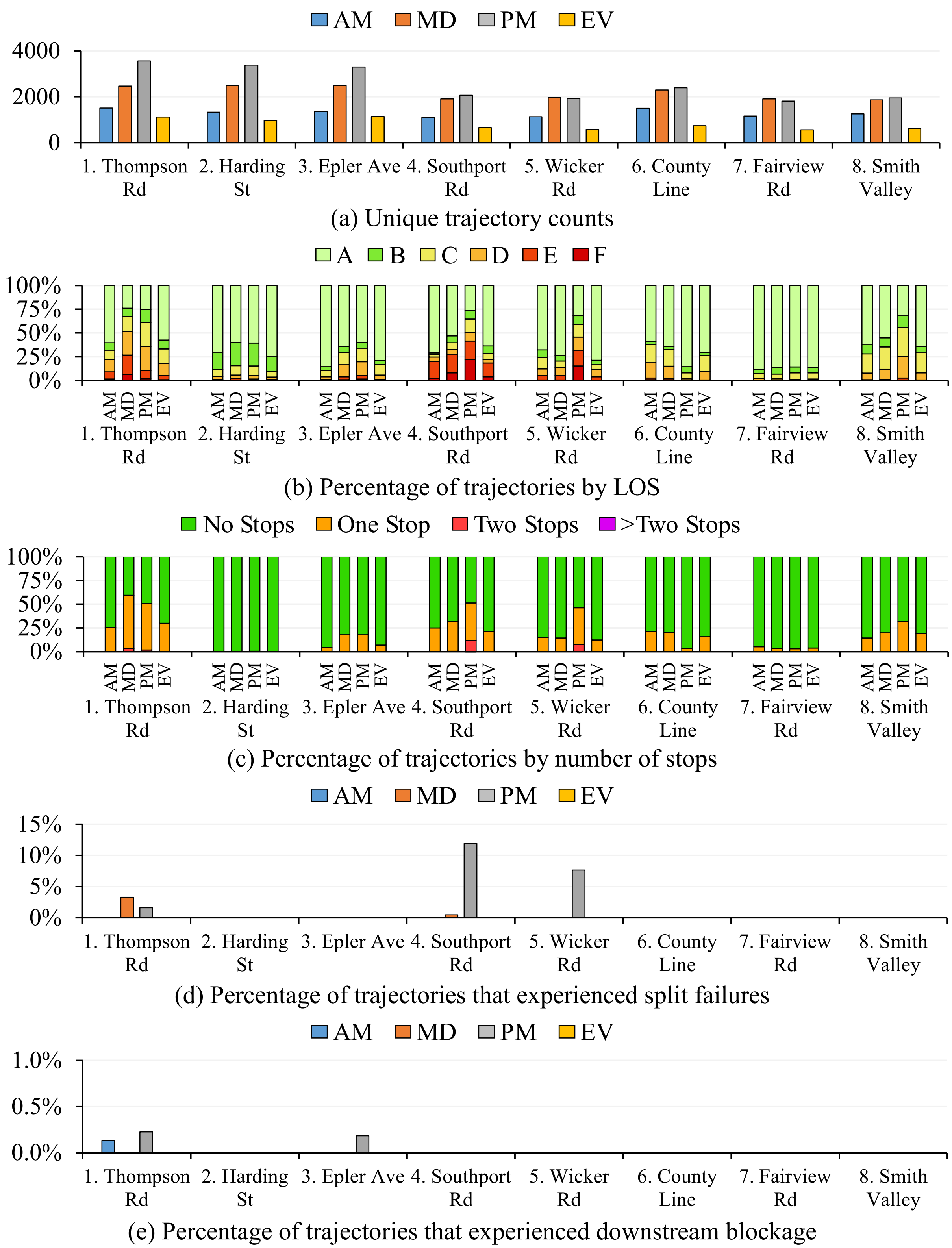


Figure 7.1 SR-37 results for vehicles traveling SB through during all the weekdays in July 2019 for the different TOD timing plans

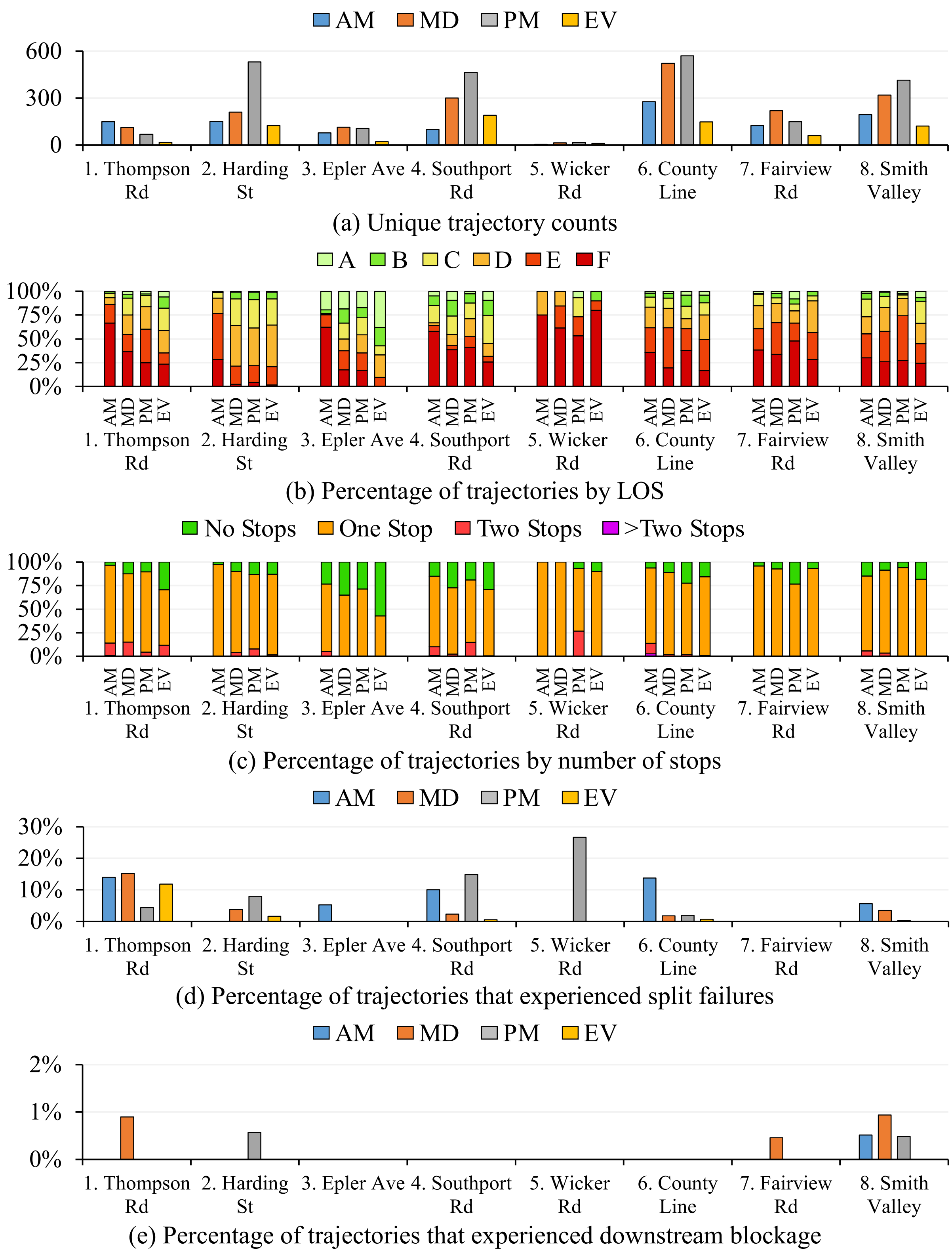


Figure 7.2 SR-37 results for vehicles traveling SB and turning left during all the weekdays in July 2019 for the different TOD timing plans

7.1 Temporal Comparisons

The Figures shown in this Section provide a comprehensive overview, in 15-minute periods, of calculated LOS, AOG, split failures, and downstream blockage at the study corridor. Results for mainline through and protected left movements in July 2019 and July 2020 weekdays are shown. These heat-maps provide a one-page graphic that broadly characterizes experienced delays, level of progression, green time allocation, and traffic signal influence at adjacent locations. They are particularly useful for sharing before/after studies. From these Figures, when comparing July 2019 and July 2020 results, it can be stated that:

- there was a notable decrease in delay for intersection ID 3 NB through, and intersections ID 4 and ID 5 SB through during the PM period (Figure 7.3 and Figure 7.4),
- the level of progression improved for the same locations as the previous point (Figure 7.5 and Figure 7.6), and
- there was a significant reduction on split failures for intersections ID 4 and ID 5 SB through during the PM period (Figure 7.7 and Figure 7.8).

As Connected Vehicles become more widely used, the available vehicle trajectory data increases significantly. Table 7.1 provides a summary of the available data for the study location during the weekdays in July 2019 and 2020. There was a 170% increase in the number of trajectories with through movements at the different intersection, and an 88% increase in trajectories with left turns. As the penetration increases, also does reliability.

Table 7.1 Available data at the study corridor for weekdays in July

Movement	Year	No. Trajectories	No. GPS Points
Through	2019	109,000	1,300,000
Through	2020	294,000	3,200,000
Left	2019	8,000	200,000
Left	2020	15,000	400,000

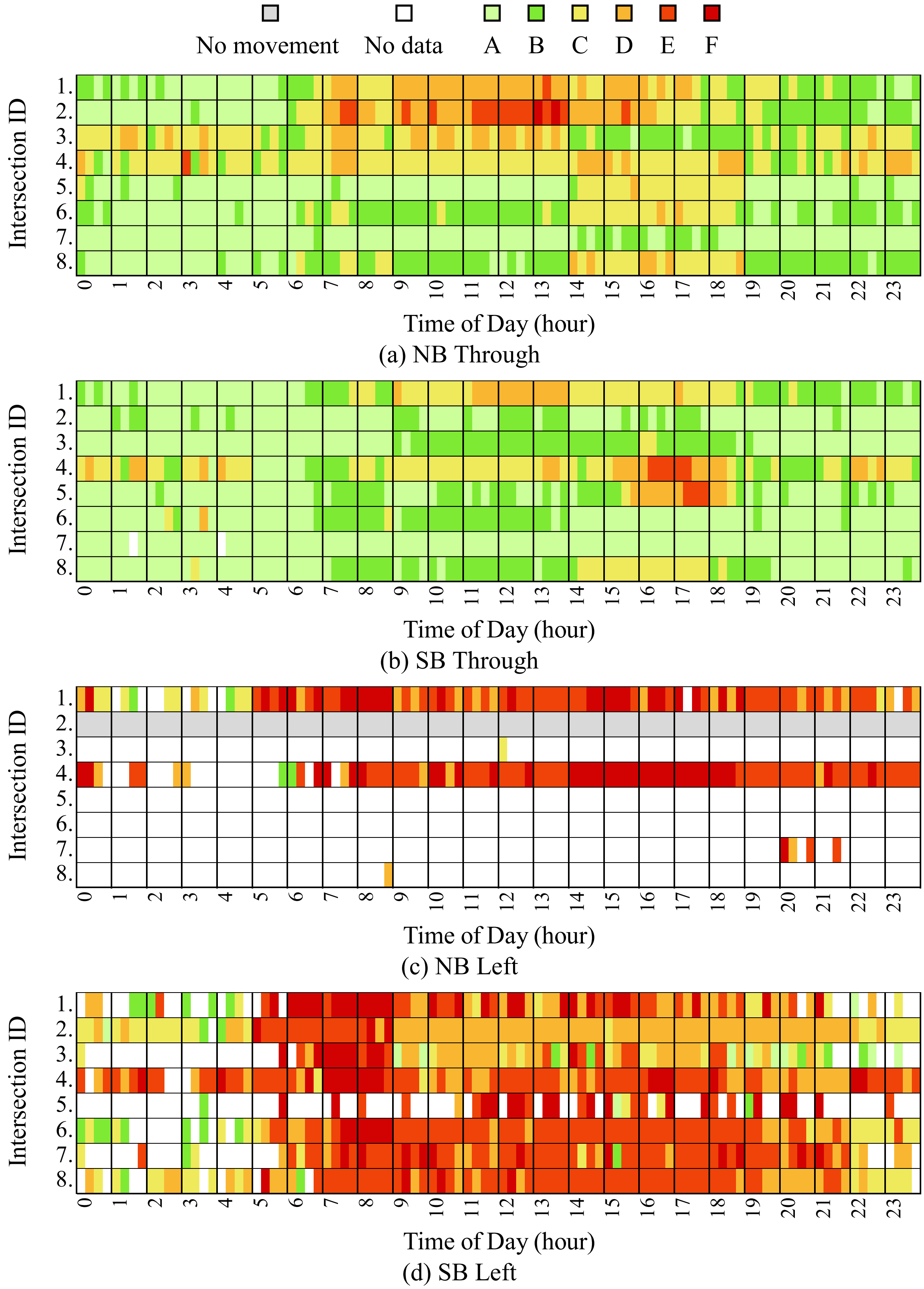


Figure 7.3 TOD LOS at SR-37 intersections in July 2019 weekdays

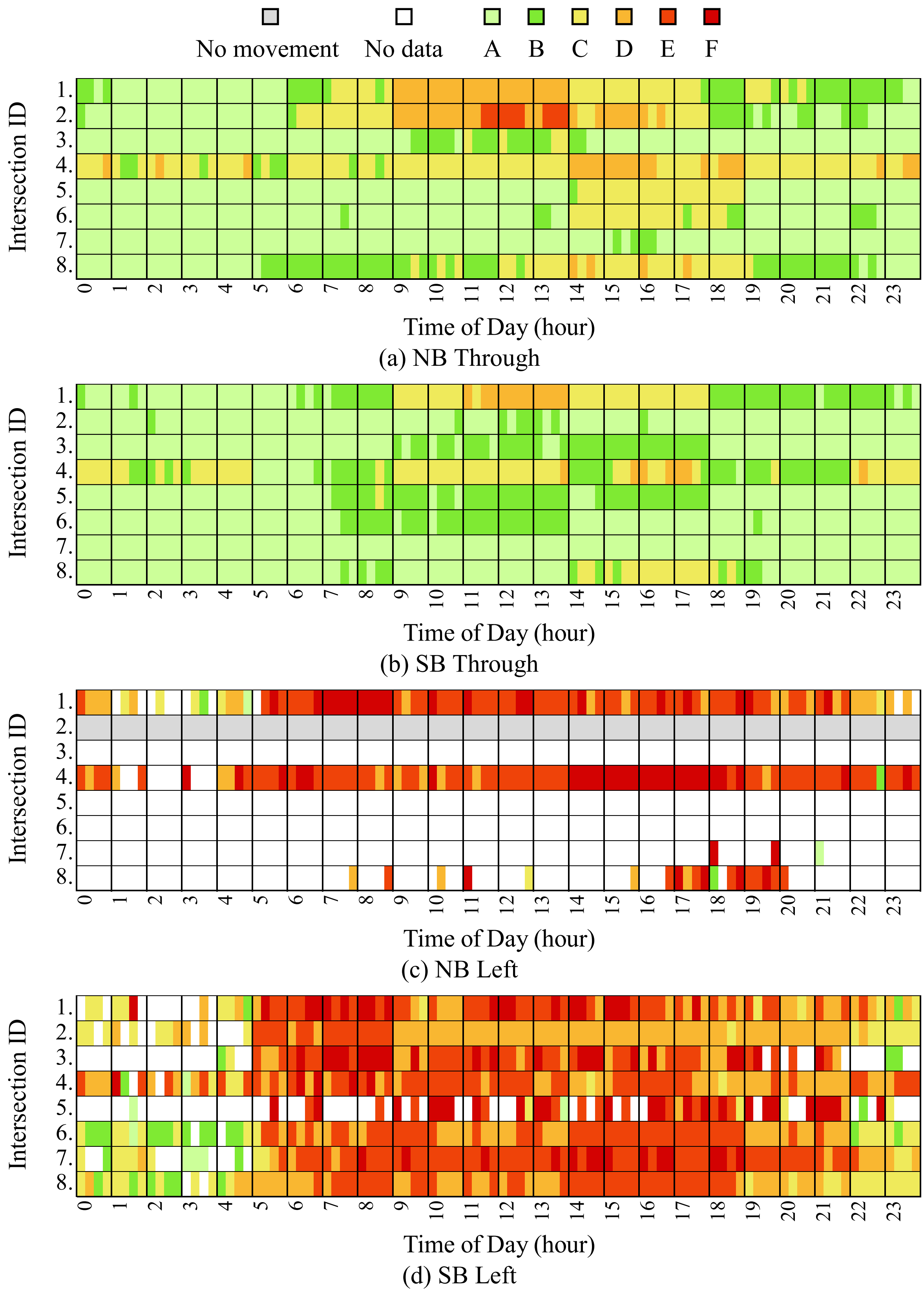


Figure 7.4 TOD LOS at SR-37 intersections in July 2020 weekdays

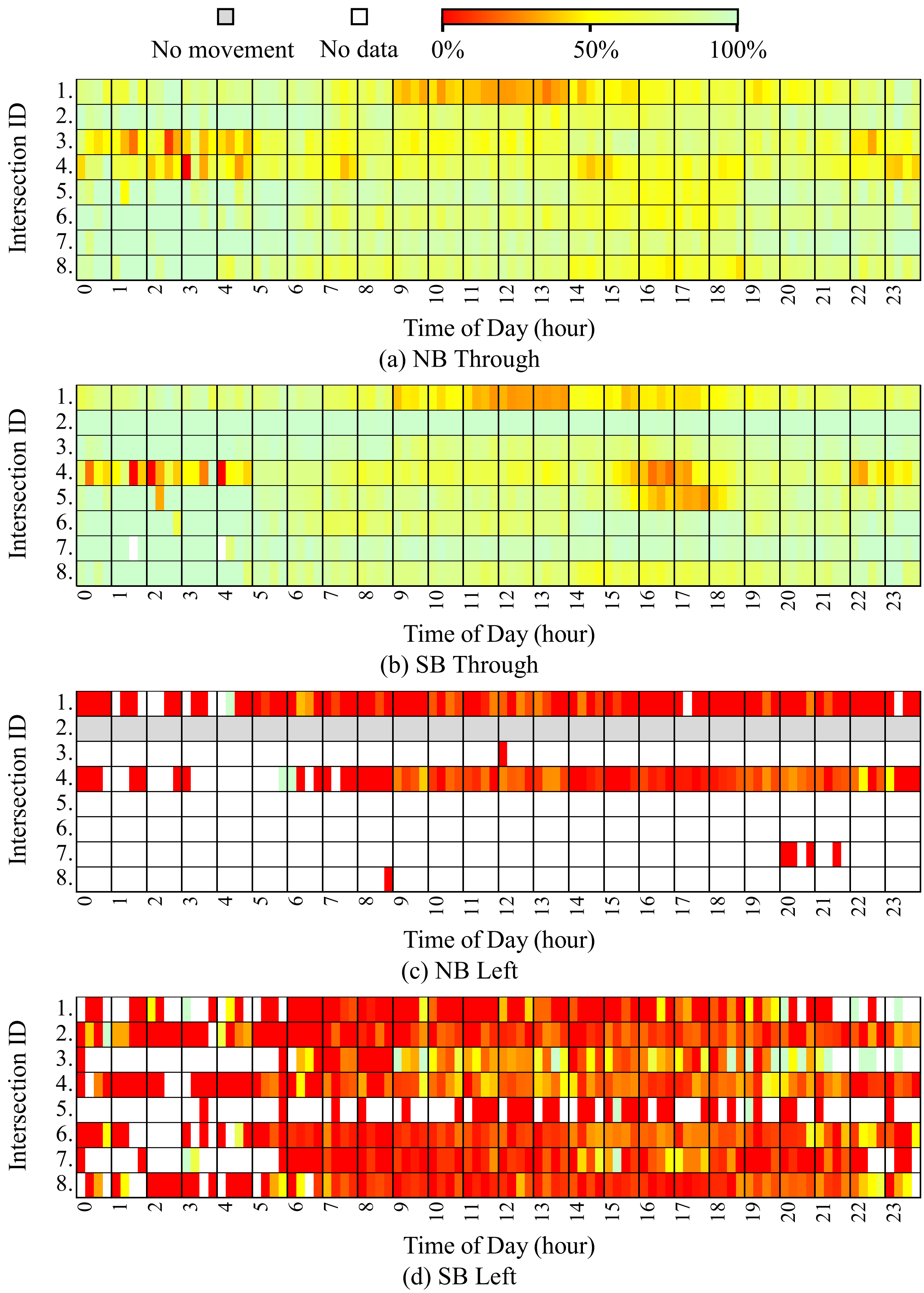
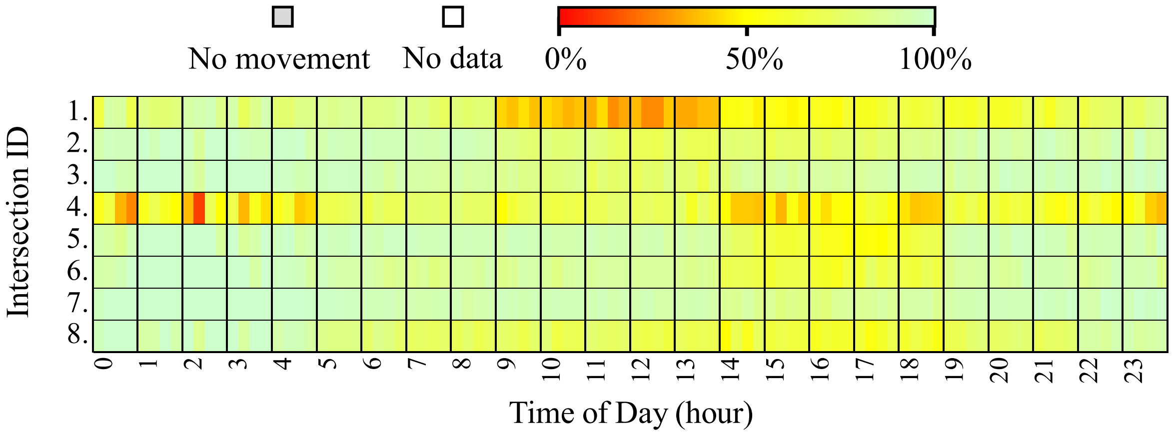
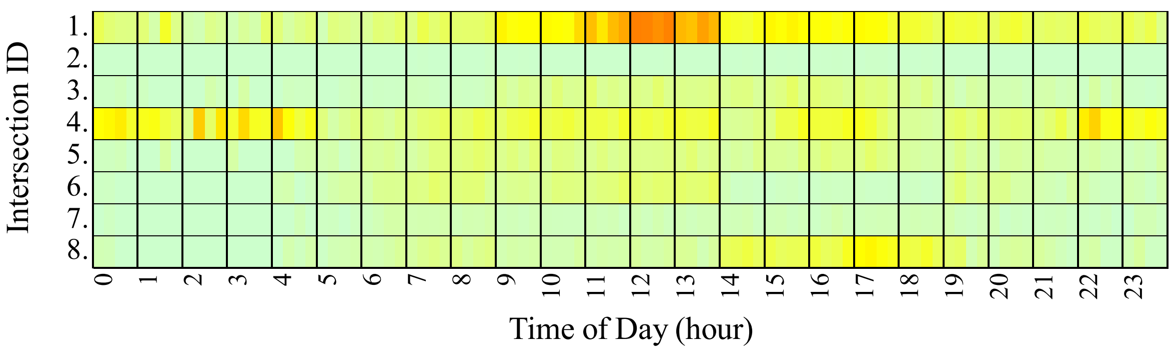


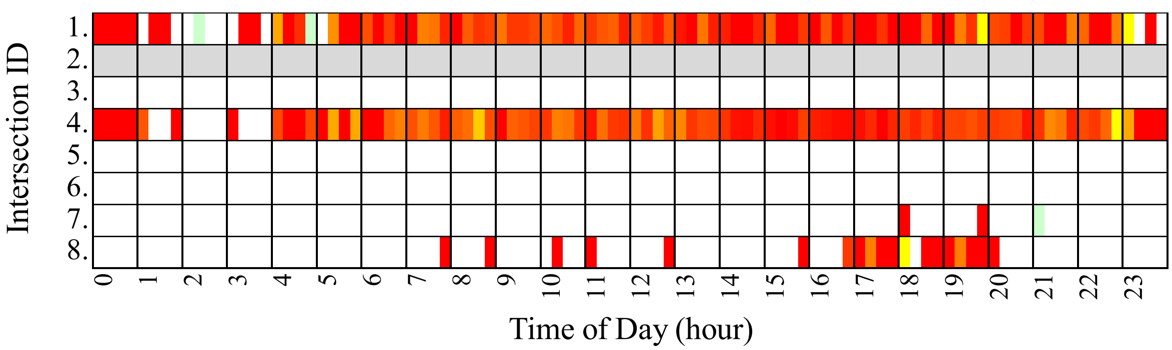
Figure 7.5 TOD AOG at SR-37 intersections in July 2019 weekdays



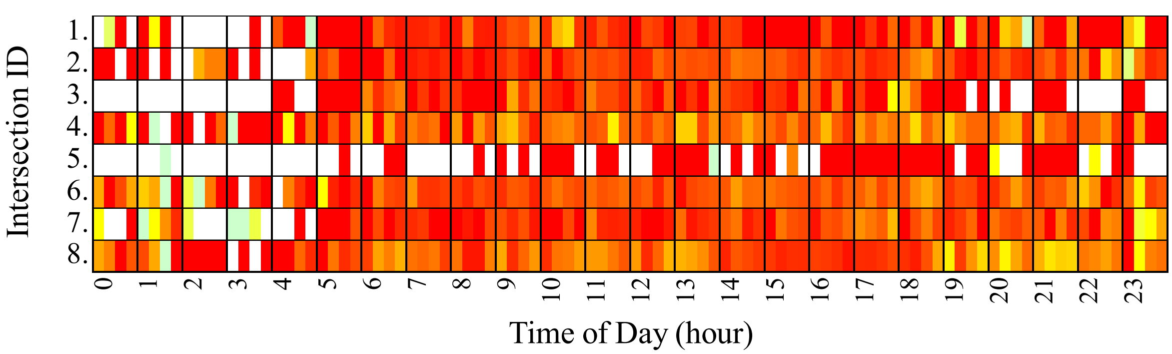
(a) NB Through



(b) SB Through



(c) NB Left



(d) SB Left

Figure 7.6 TOD AOG at SR-37 intersections in July 2020 weekdays

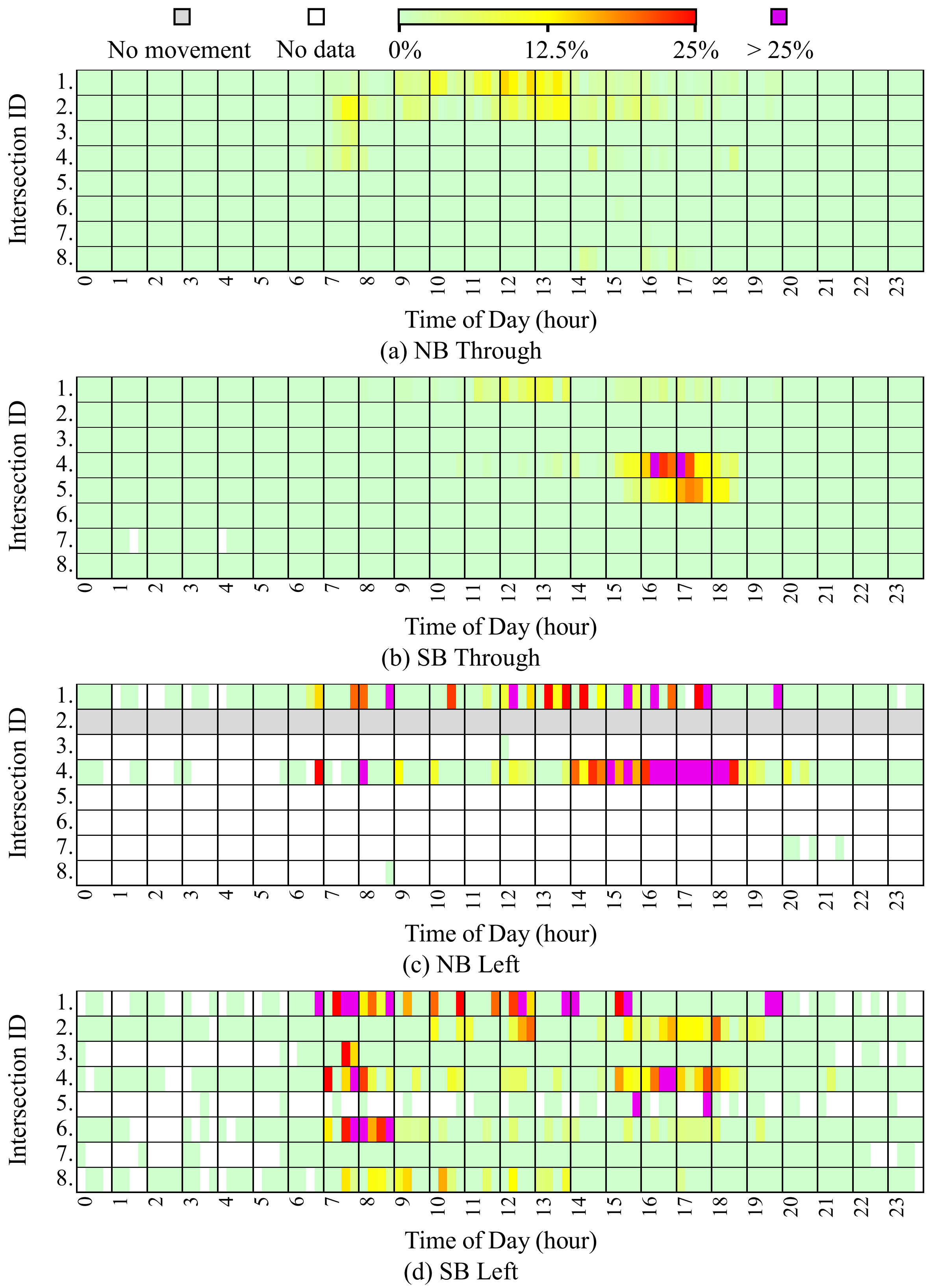


Figure 7.7 Percentage of vehicle trajectories experiencing split failures at SR-37 intersections during all weekdays in July 2019

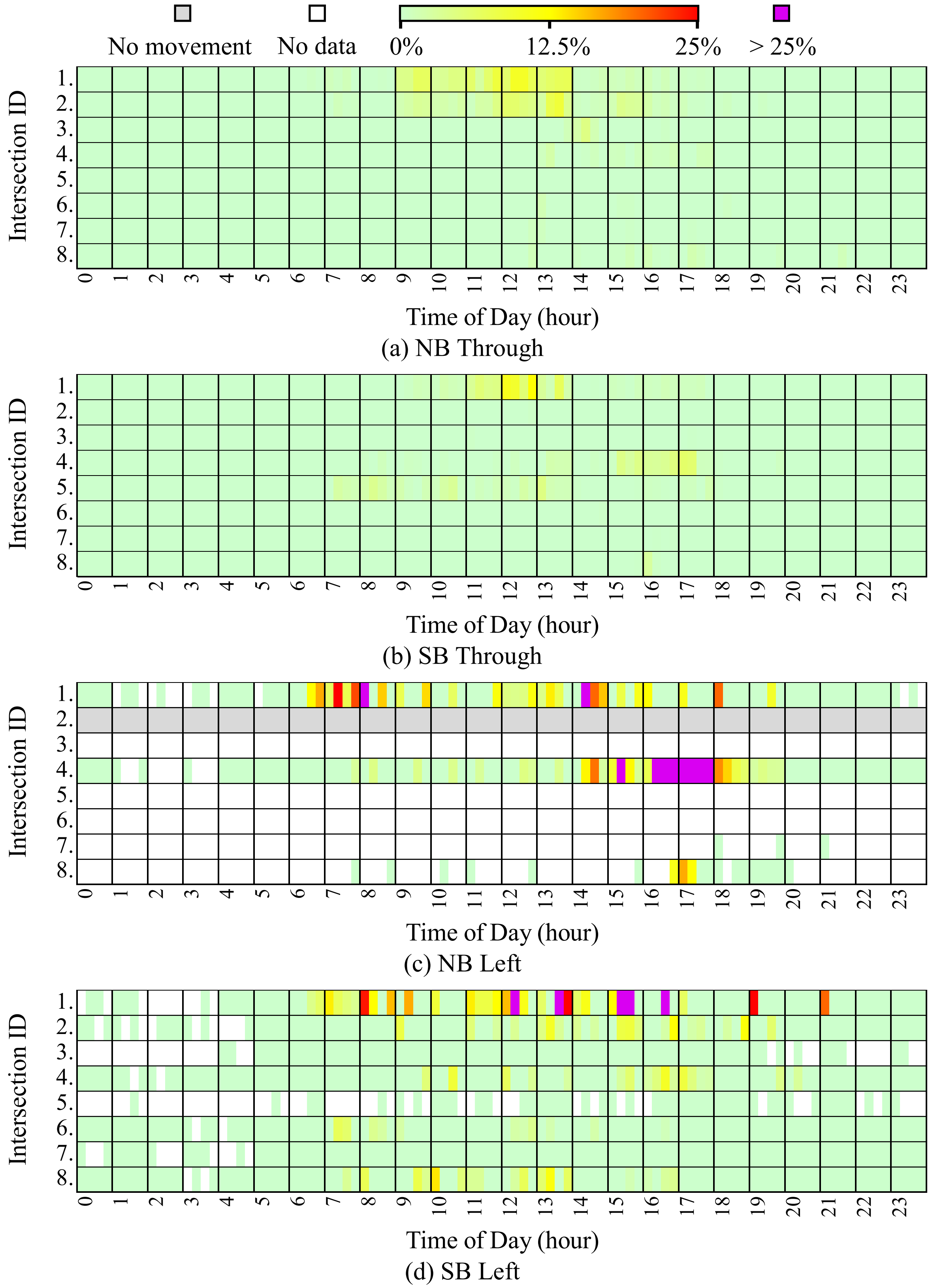
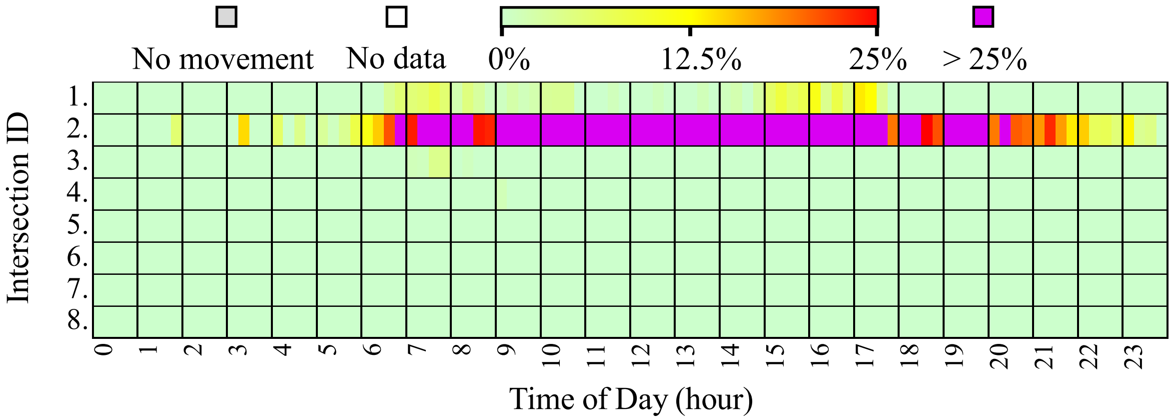
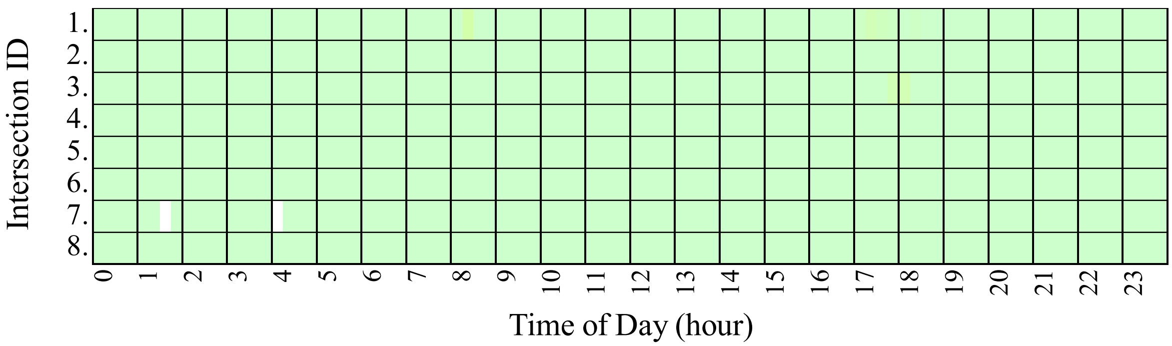


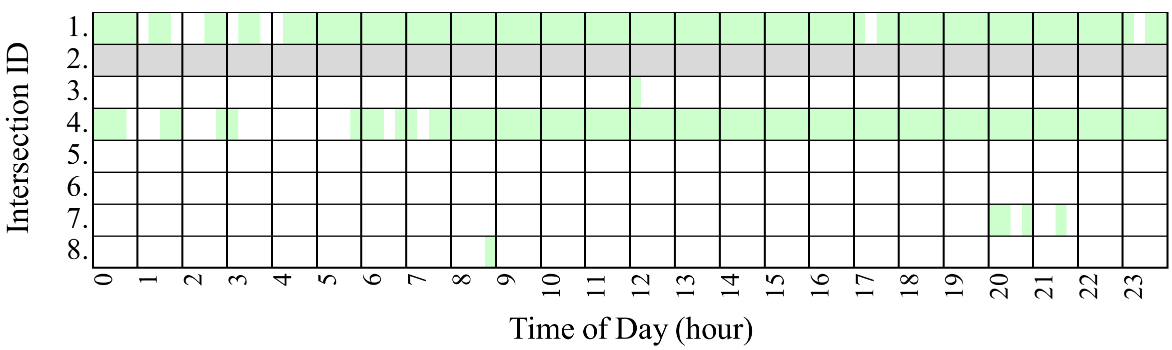
Figure 7.8 Percentage of vehicle trajectories experiencing split failures at SR-37 intersections during all weekdays in July 2020



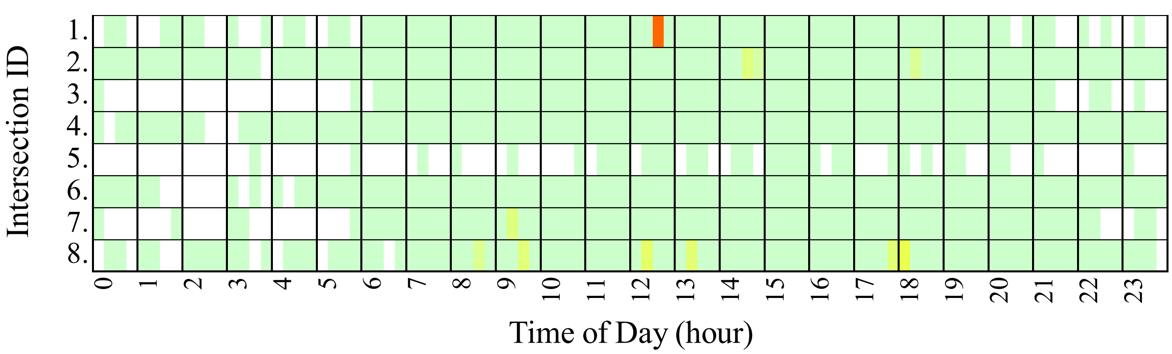
(a) NB Through



(b) SB Through



(c) NB Left



(d) SB Left

Figure 7.9 Percentage of vehicle trajectories experiencing downstream blockage at SR-37 intersections during all weekdays in July 2019

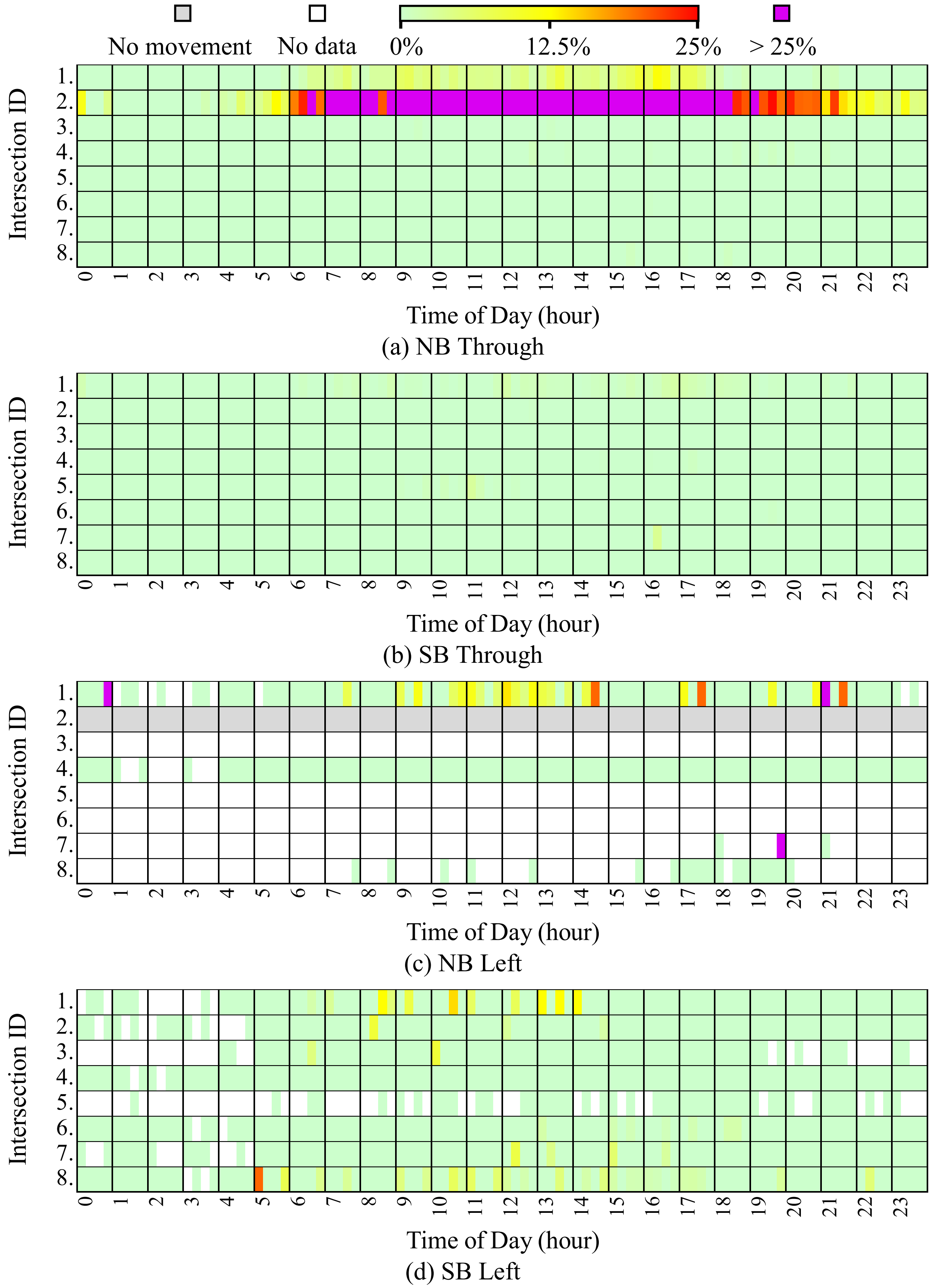


Figure 7.10 Percentage of vehicle trajectories experiencing downstream blockage at SR-37 intersections during all weekdays in July 2020

8. CONCLUSION

This thesis proposed a methodology for analyzing vehicle trajectories to derive operational performance measures for traffic signals. The methodology was demonstrated using an 8-intersection corridor in Indianapolis utilizing 1.5 million GPS points associated with 117,000 trips with a 3-second ping interval, during all the weekdays in July 2019.

A new visualization graphic, the Purdue Probe Diagram (PPD), was introduced that provides a holistic look of a vehicle experience on a corridor. The graphic provides a tool for quickly assessing the proportion of vehicles arriving on green (Figure 4.3b), locations with insufficient allocation of green time (Figure 6.2d), and impact of downstream intersection spillback (Figure 4.4). Intersection level summaries provide at-a-glance visualization (Figure 6.2 and Figure 6.3). The differences between this new PPD and the traditional PCD is illustrated in Figure 5.1 and Figure 5.2. Figures presented in Section 7 show how these graphics can be used to quickly assess the operation of a corridor.

8.1 Scalability

8.1.1 Required Effort

Table 8.1 shows a summary of 91 intersections in 6 states with 33 million GPS points associated with 2.1 million trajectories that were analyzed with the proposed methods to assess the amount of work required to scale. On average, only 21 hours are required to analyze any 10-intersection corridor in the United States, which represents only a fraction of time that would be spent with alternative methods.

Table 8.1 Effort required to scale

Corridor	State	No. Intersections	No. Trajectories (k)	No. GPS Points (M)	Effort (hours)
SR-37	IN	8	117	1.5	22
PA-611	PA	13	298	3.9	28
CA-74	CA	19	249	4.9	30
University	TX	9	193	3.5	28
Texas	TX	13	396	7.3	21
US-70	NC	8	185	2.8	24
US-27	OH	21	613	9.1	38
	Total	91	2,051	33.0	191

8.1.2 Implementation Recommendations

Data storage for generating the performance measures proposed in this thesis can be a challenge. With the emergence and increasing adoption of cloud storage and computing services, queries and processing of the data can reside in the cloud, as opposed to procuring and upgrading traditional on-premise systems to meet capacity requirements. For instance, using a popular cloud database platform for data queries and stores, automated dashboards can be developed to generate figures such as those shown in Figure 6.2, Figure 7.1, and Figure 7.3 in under 1 minute for computation costs of \$0.01, \$0.09, and \$0.38 respectively. Additionally, data ingestion and yearly storage for the state of Indiana July 2019 trajectory data can be acquired for a cost of \$2.11 and \$55.86 respectively.

Based upon the 2% penetration observed in this data set, it is believed that the methodologies presented in this thesis can be scaled to most urban areas without deploying any intersection-based hardware. For any agency wanting to prioritize infrastructure investments over 100 intersections, one could produce a report similar to those in Section 7 for less than \$5.00 in cloud computing costs without the need of any fixed-sensor or site visits. Additional costs for the data are needed and varies by state and locale. If the side streets were included, the cloud computation cost would be approximately \$10.00.

The analyzed signalized intersections count with AADTs of ~15,000 VPD for each mainline through movement. These volumes yielded accurate results. As penetration rates increase, the lower bound on the necessary AADT will decrease. Further, since the query cost represents a significant component of the total cost of producing reports and performance measures, creating subsets of state datasets with only records along the study corridor could reduce costs significantly.

APPENDIX A. CORRIDOR SUMMARY

To present a holistic view of a corridor's performance measures to stakeholders and operators, a poster displaying the most relevant information is proposed. SR-37 calculated performance measures from weekday July 2019 trajectories are presented in Figure A.1. For all the movements, 129,000 trajectories and 1,900,000 GPS points were analyzed to create the heat-maps. Table A.1 provides an explanation on how to read Figure A.1. A PDF version of Figure A.1 can be found here.

Table A.1 How to read Figure A.1

Callout	Meaning
i	Study location.
ii	Trajectory counts at the different analyzed intersections.
iii	Study period.
iv	Column with LOS results.
v	Column with AOG results.
vi	Column with split failure results.
vii	Column with downstream blockage results.
viii	Row with mainline through movements.
ix	Row with mainline left movements.
x	Row with side St. through movements.
xi	Row with side St. left movements.

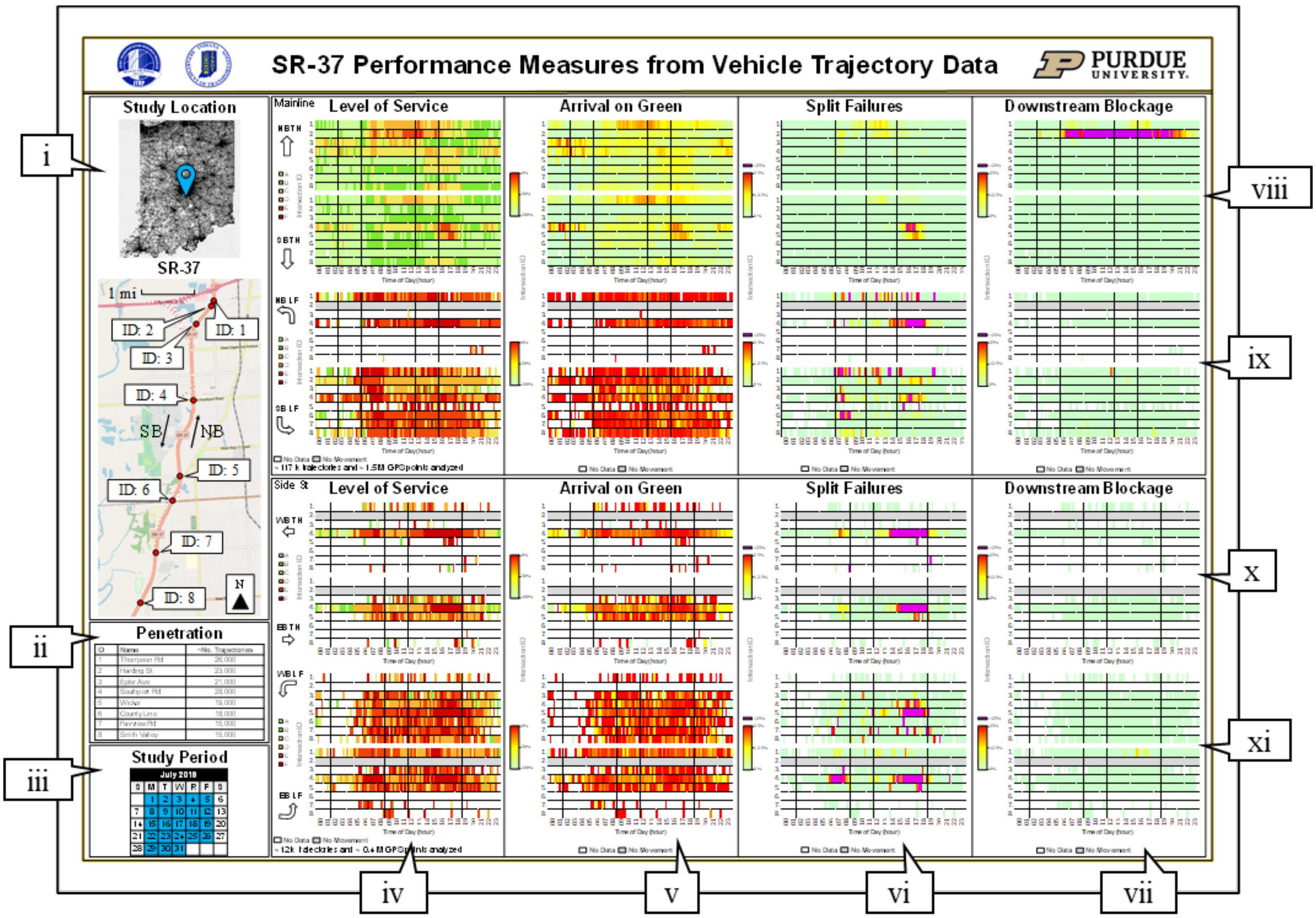
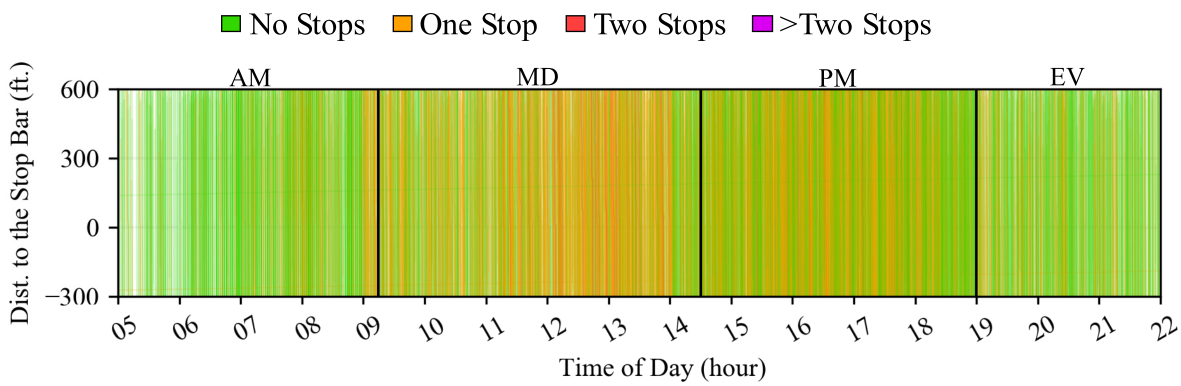


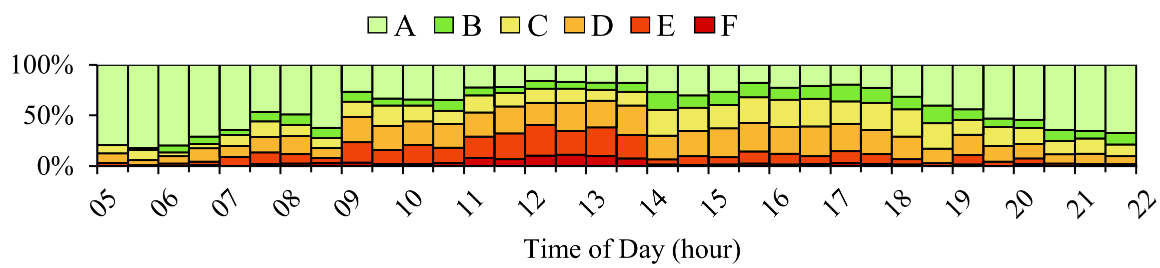
Figure A.1 SR-37 calculated performance measures from July 2019 weekdays trajectories

APPENDIX B. MAINLINE THROUGH PPD AND PERFORMANCE MEASURES BY TOD

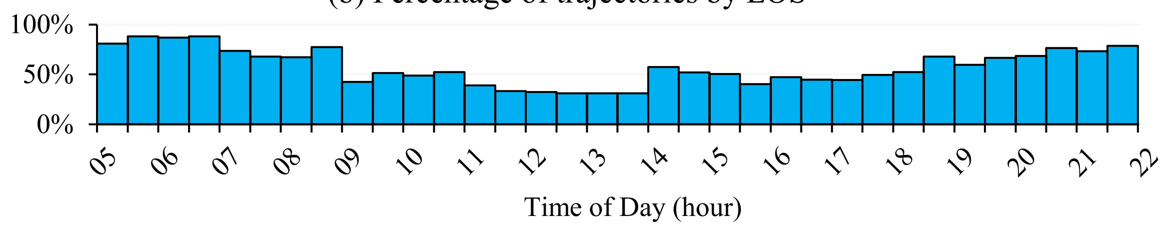
In this appendix, a detailed view of the performance measures of each intersection on the study corridor during July 2019 weekdays for the mainline through movements is presented.



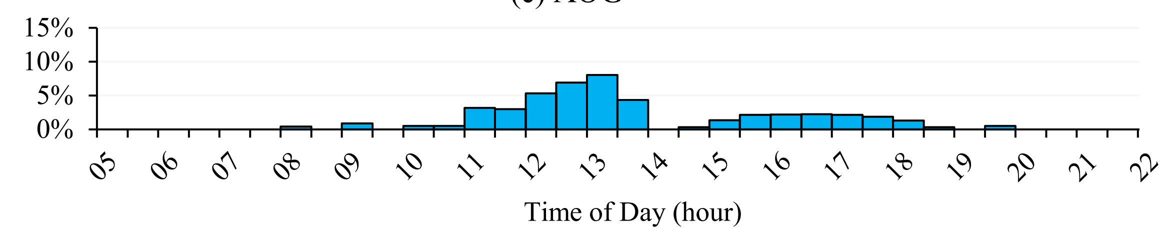
(a) PPD by TOD



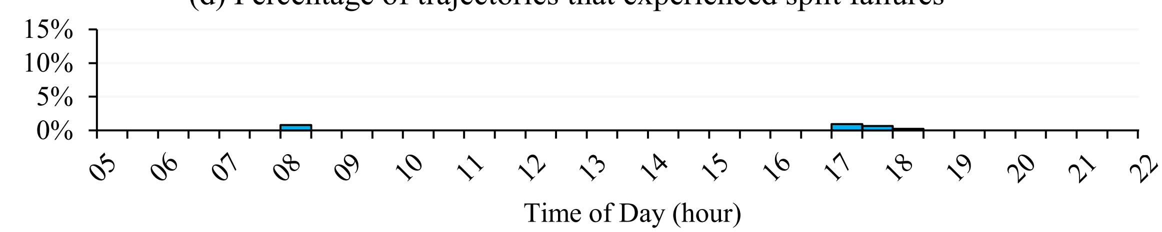
(b) Percentage of trajectories by LOS



(c) AOG

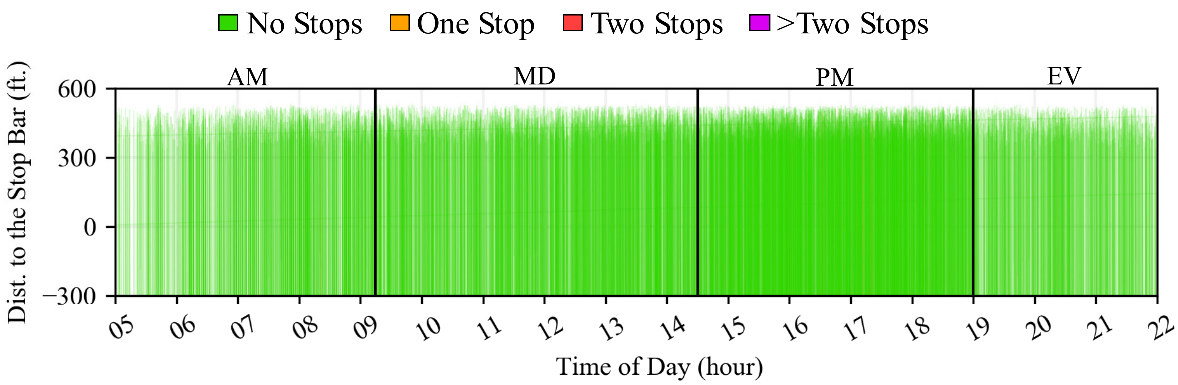


(d) Percentage of trajectories that experienced split failures

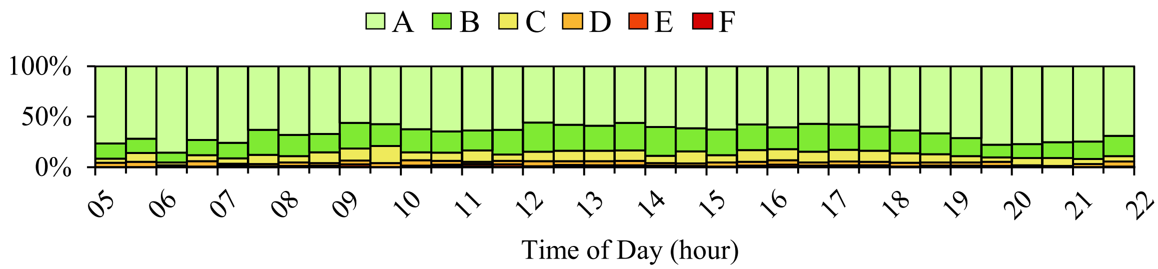


(e) Percentage of trajectories that experienced downstream blockage

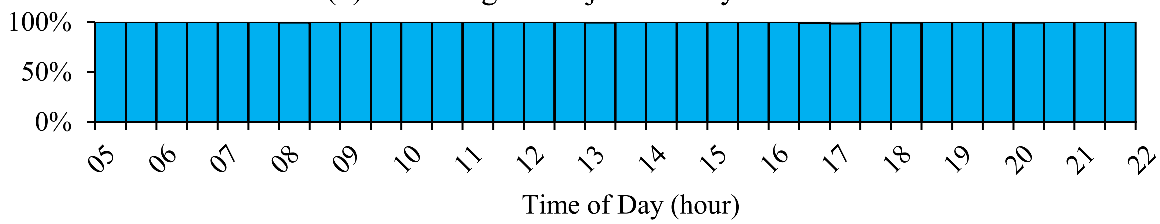
Figure B.1 PPD by TOD and performance measures results for vehicle trajectories traveling SB through at SR-37 and Thompson Rd. in July 2019 weekdays



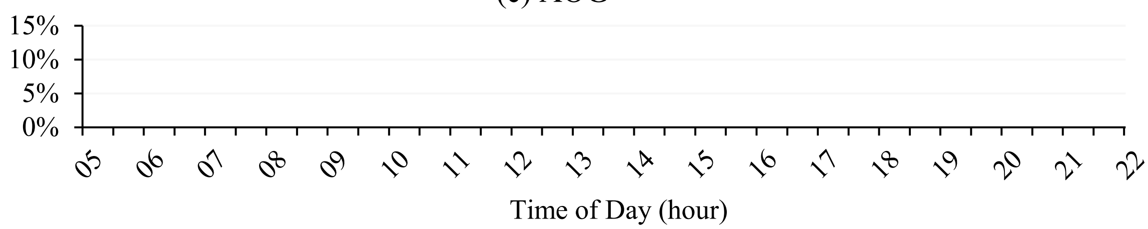
(a) PPD by TOD



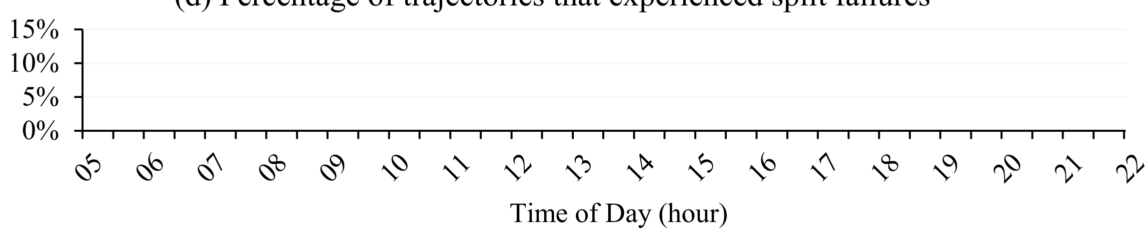
(b) Percentage of trajectories by LOS



(c) AOG

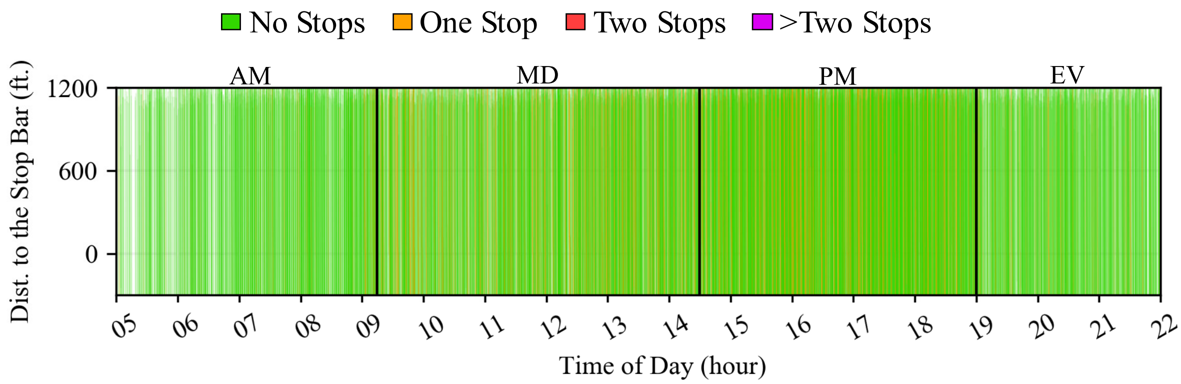


(d) Percentage of trajectories that experienced split failures

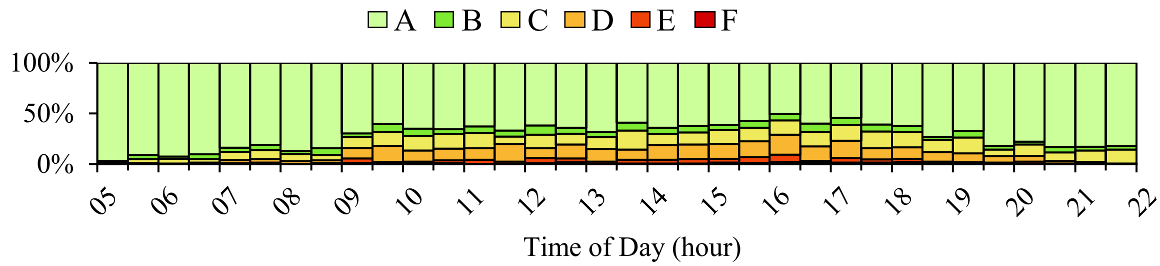


(e) Percentage of trajectories that experienced downstream blockage

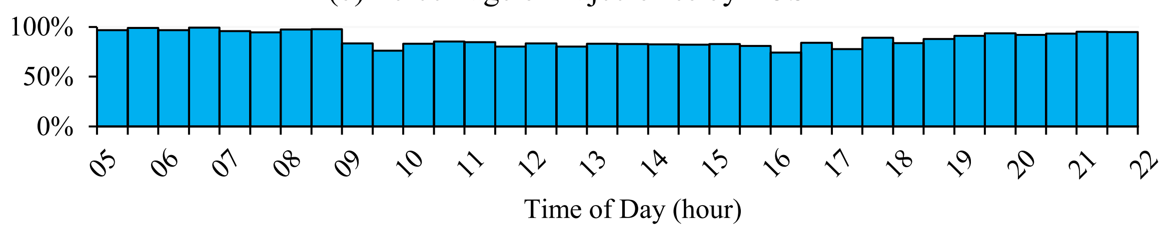
Figure B.2 PPD by TOD and performance measures results for vehicle trajectories traveling SB through at SR-37 and Harding St. in July 2019 weekdays



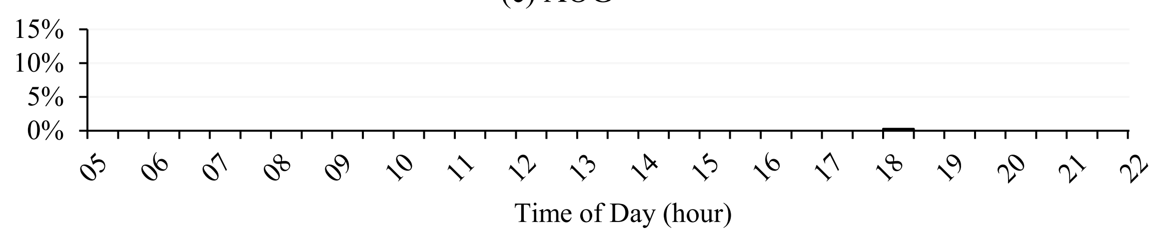
(a) PPD by TOD



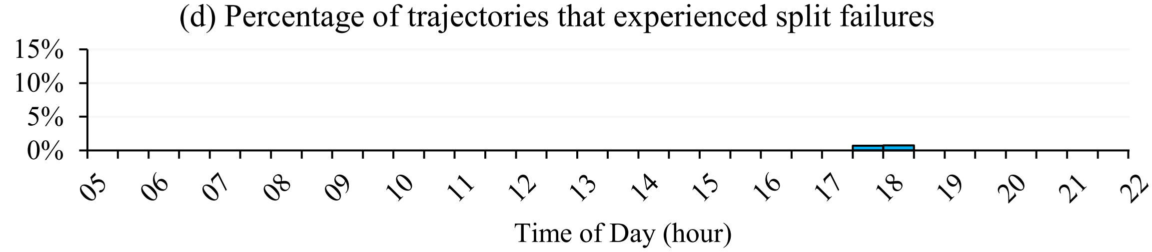
(b) Percentage of trajectories by LOS



(c) AOG

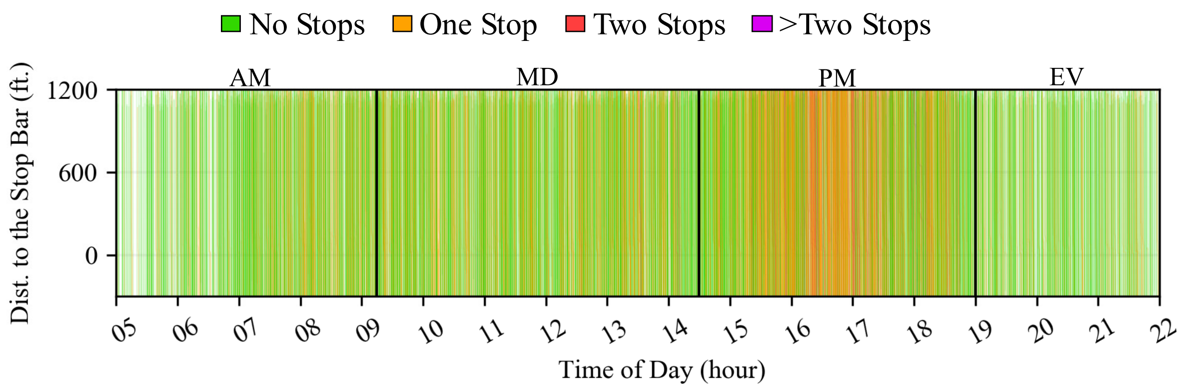


(d) Percentage of trajectories that experienced split failures

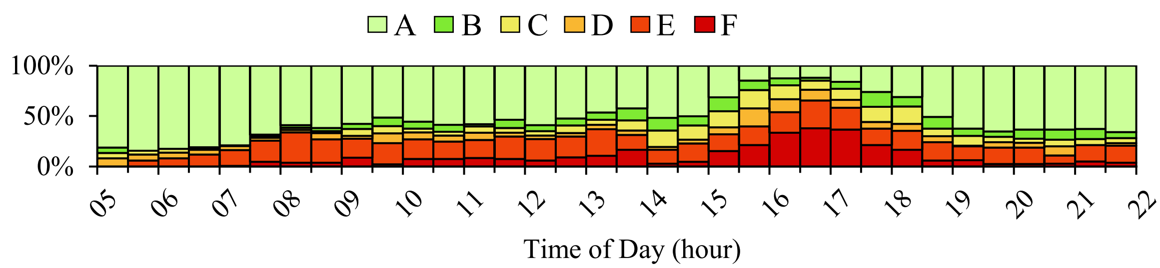


(e) Percentage of trajectories that experienced downstream blockage

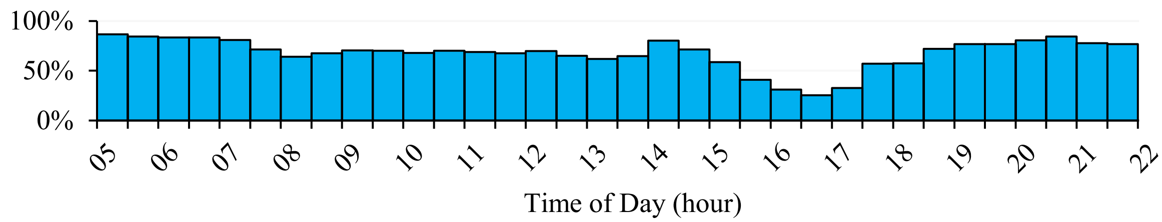
Figure B.3 PPD by TOD and performance measures results for vehicle trajectories traveling SB through at SR-37 and Epler Ave. in July 2019 weekdays



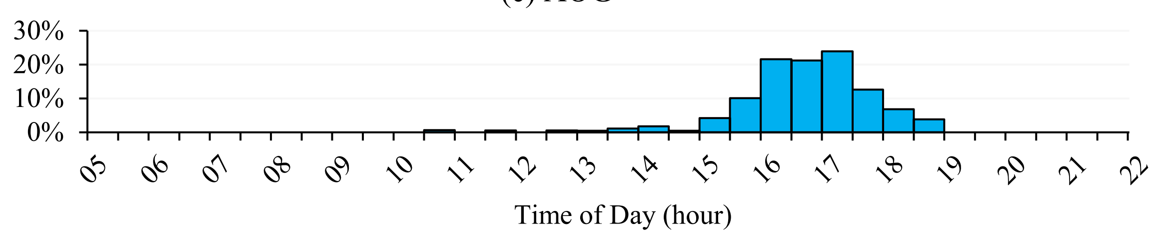
(a) PPD by TOD



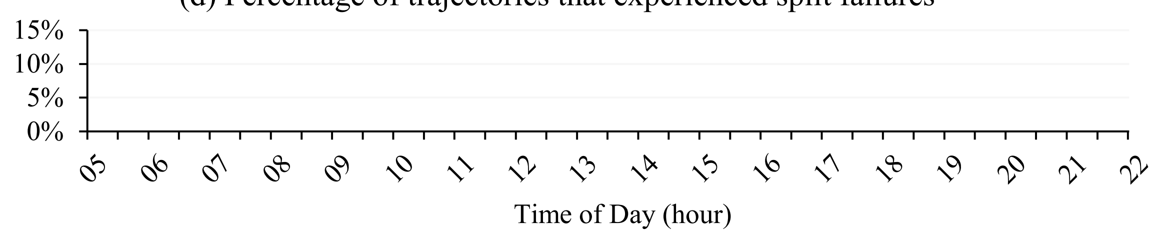
(b) Percentage of trajectories by LOS



(c) AOG

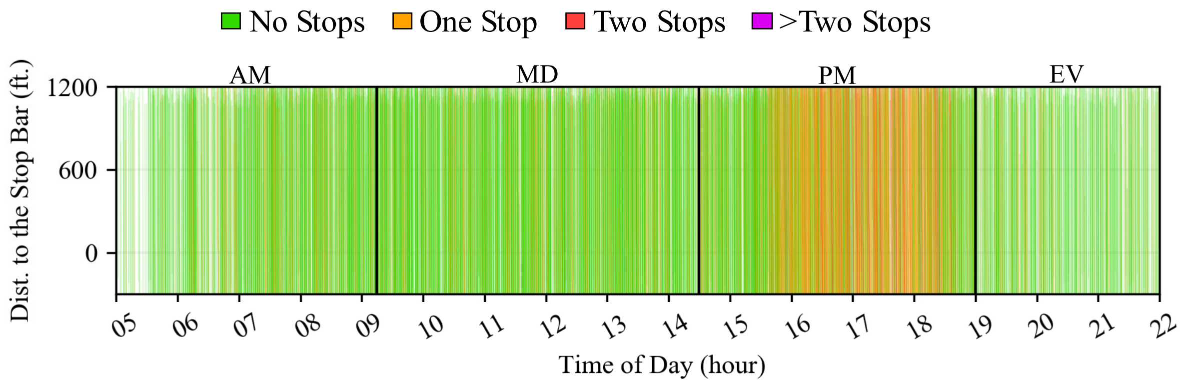


(d) Percentage of trajectories that experienced split failures

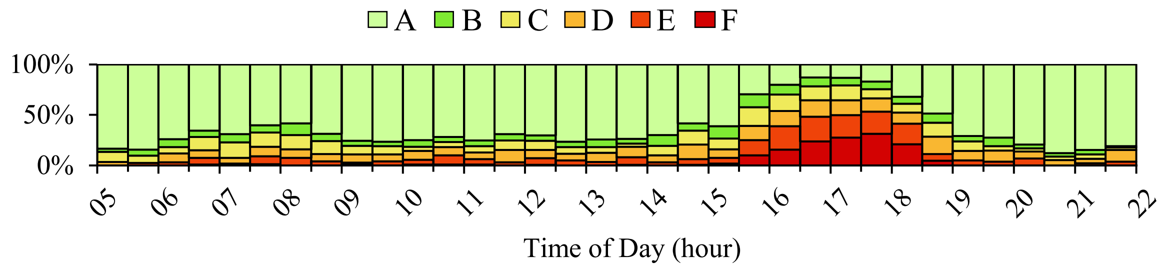


(e) Percentage of trajectories that experienced downstream blockage

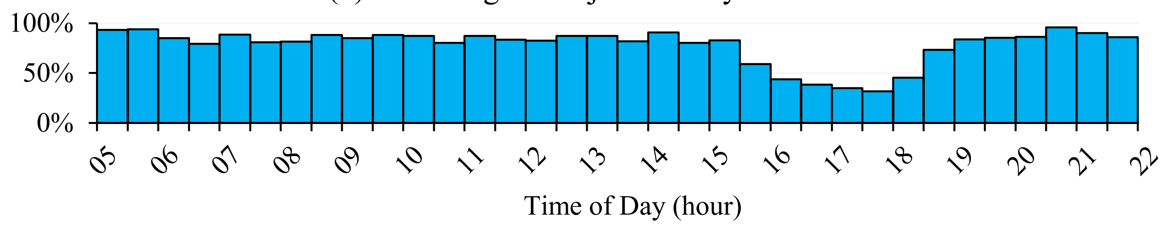
Figure B.4 PPD by TOD and performance measures results for vehicle trajectories traveling SB through at SR-37 and Southport Rd. in July 2019 weekdays



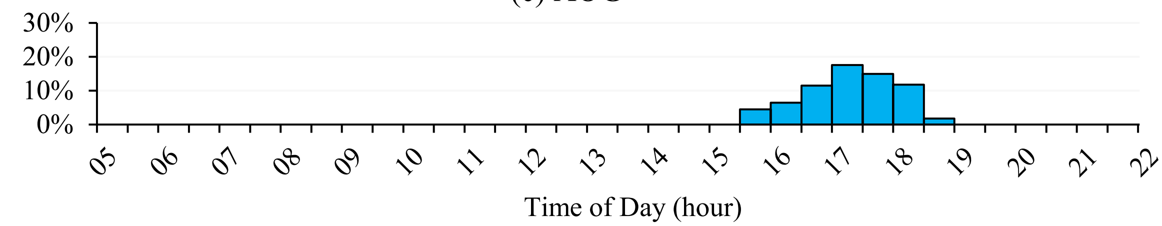
(a) PPD by TOD



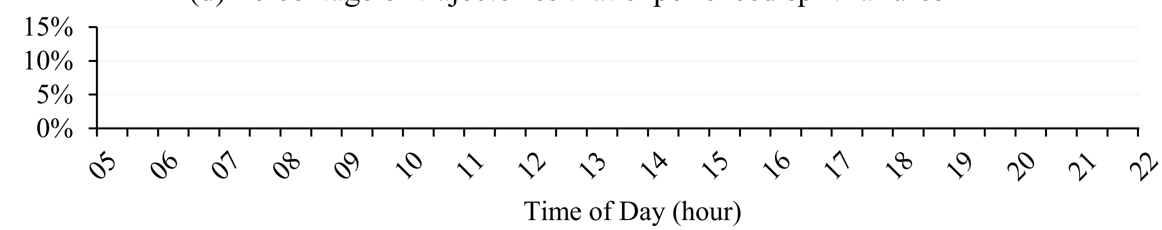
(b) Percentage of trajectories by LOS



(c) AOG

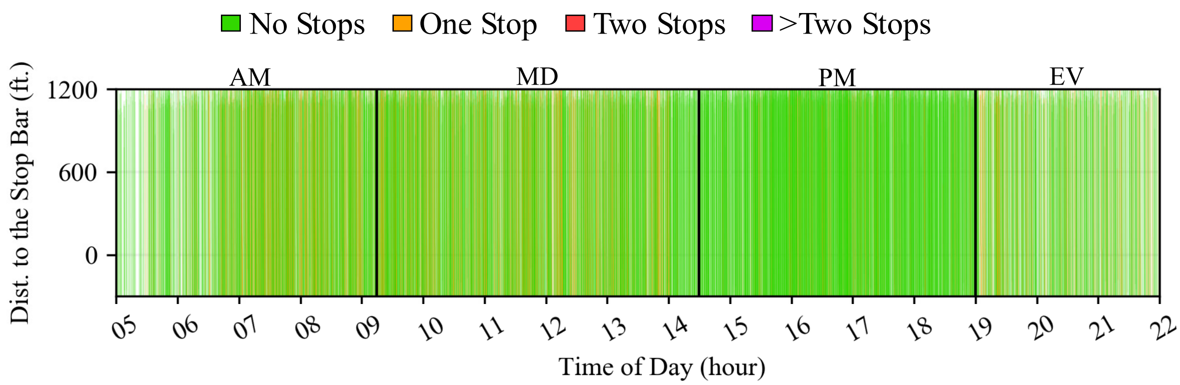


(d) Percentage of trajectories that experienced split failures

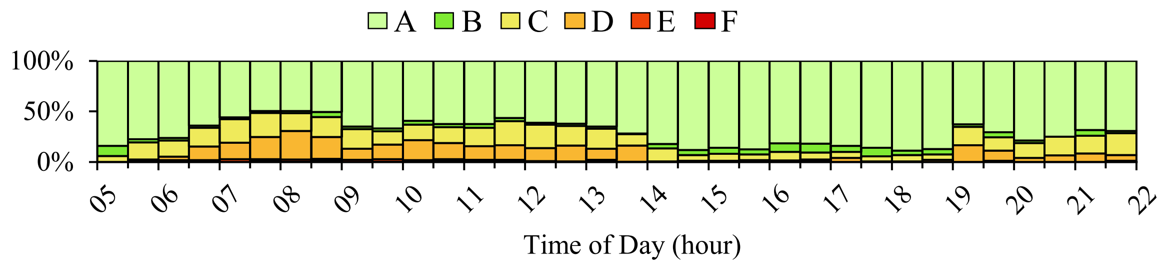


(e) Percentage of trajectories that experienced downstream blockage

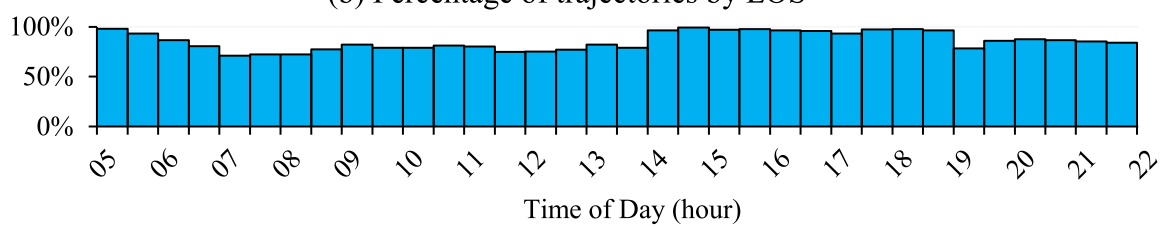
Figure B.5 PPD by TOD and performance measures results for vehicle trajectories traveling SB through at SR-37 and Wicker Rd. in July 2019 weekdays



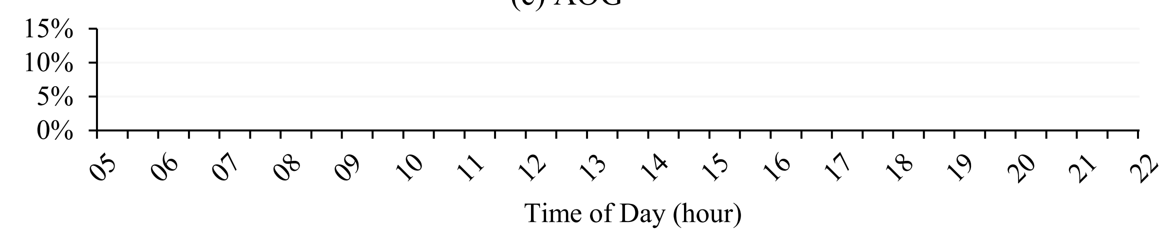
(a) PPD by TOD



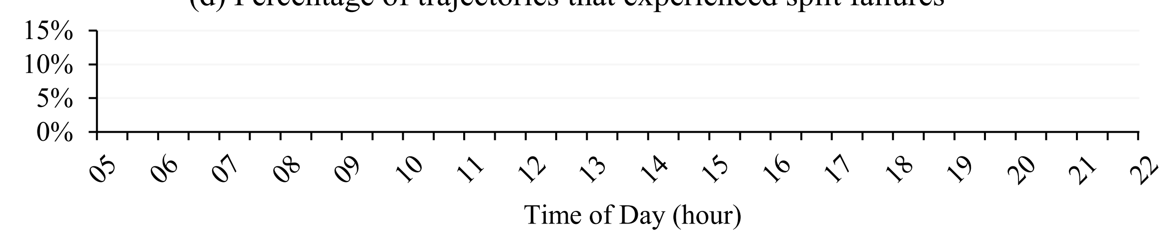
(b) Percentage of trajectories by LOS



(c) AOG

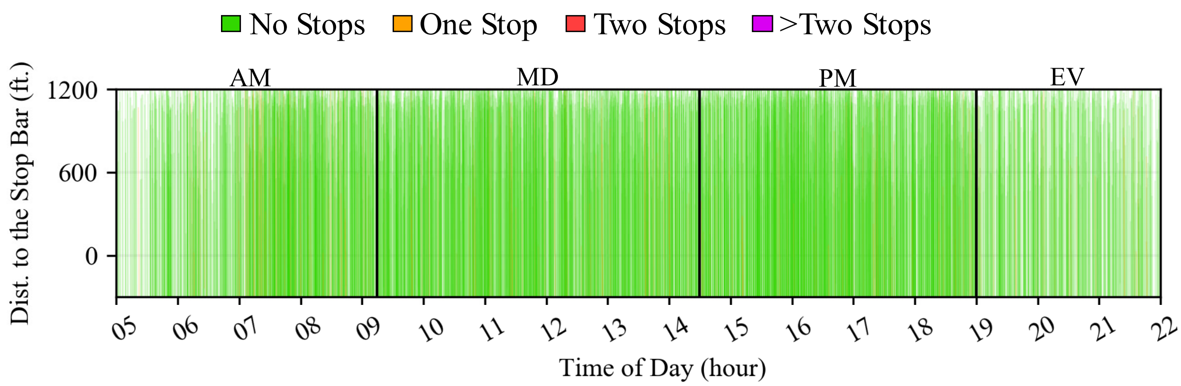


(d) Percentage of trajectories that experienced split failures

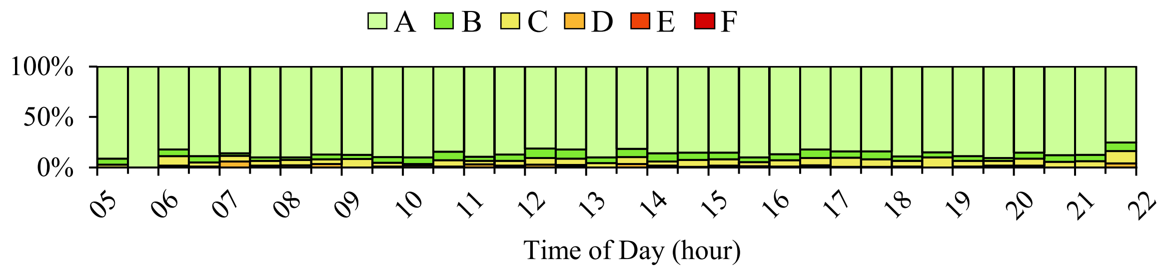


(e) Percentage of trajectories that experienced downstream blockage

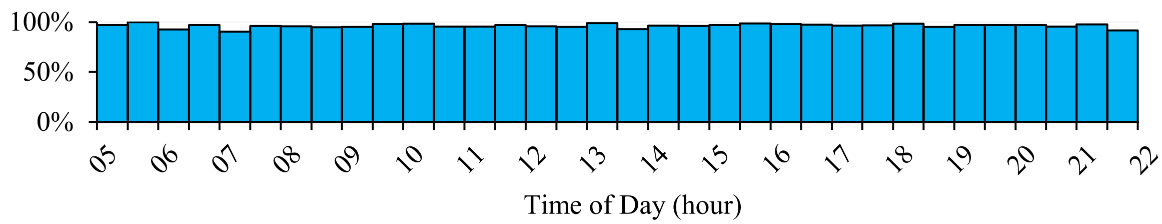
Figure B.6 PPD by TOD and performance measures results for vehicle trajectories traveling SB through at SR-37 and County Line Rd, in July 2019 weekdays



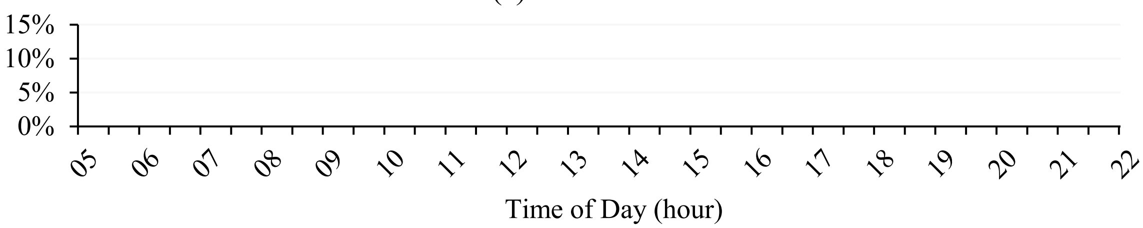
(a) PPD by TOD



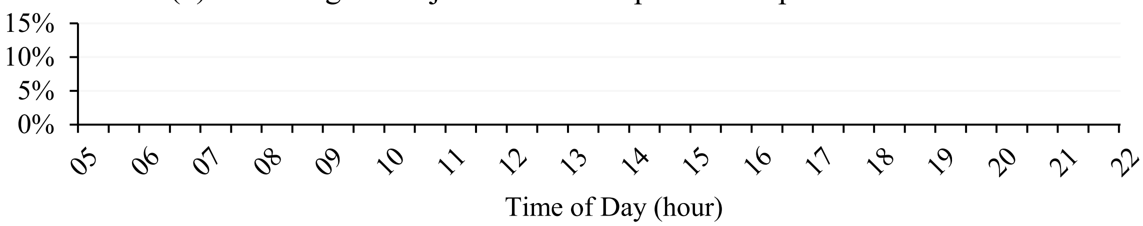
(b) Percentage of trajectories by LOS



(c) AOG

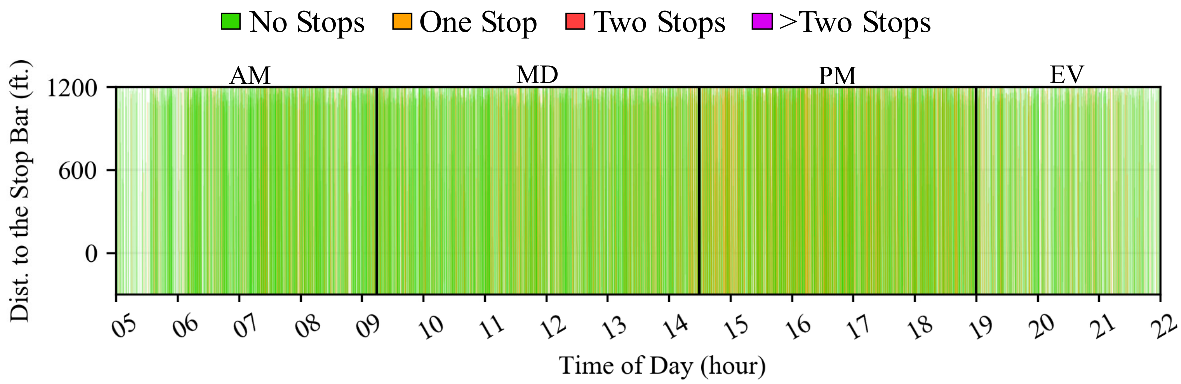


(d) Percentage of trajectories that experienced split failures

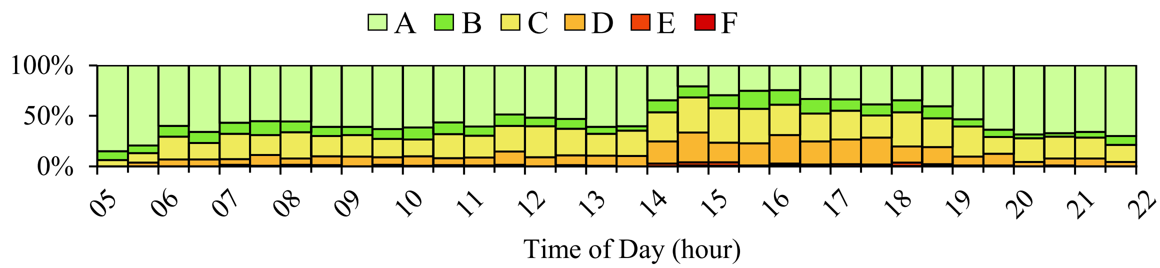


(e) Percentage of trajectories that experienced downstream blockage

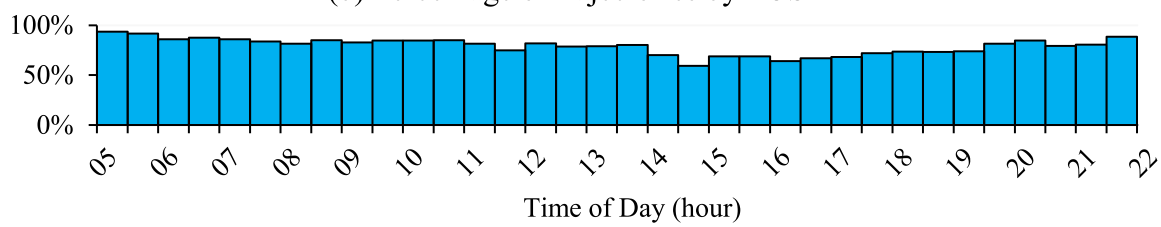
Figure B.7 PPD by TOD and performance measures results for vehicle trajectories traveling SB through at SR-37 and Fairview Rd. in July 2019 weekdays



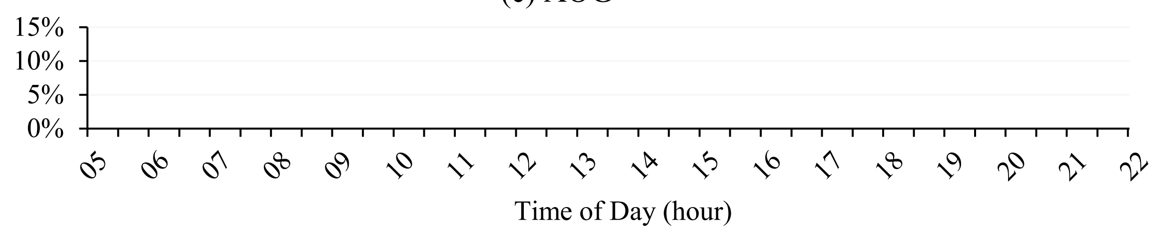
(a) PPD by TOD



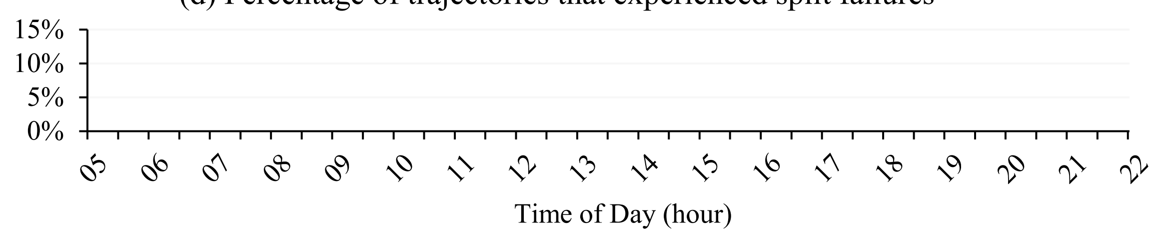
(b) Percentage of trajectories by LOS



(c) AOG

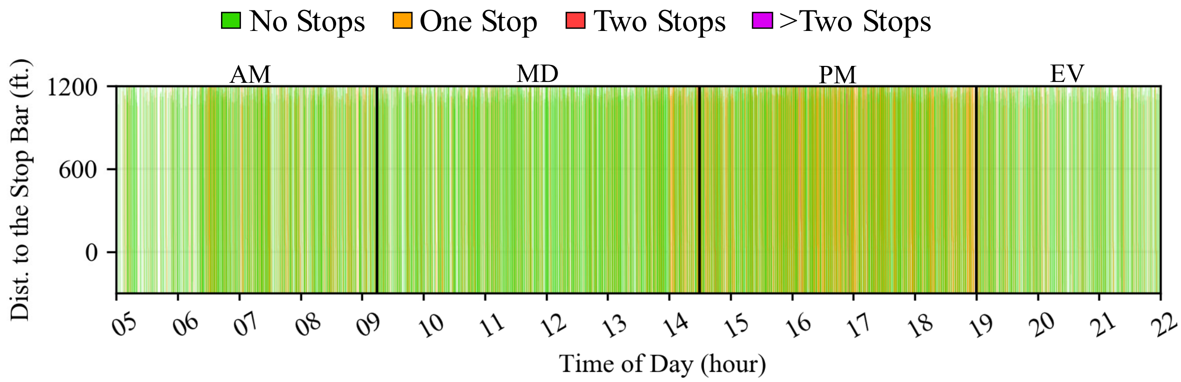


(d) Percentage of trajectories that experienced split failures

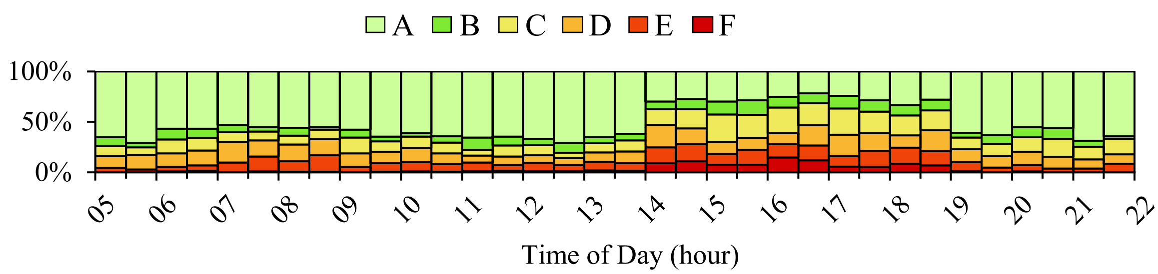


(e) Percentage of trajectories that experienced downstream blockage

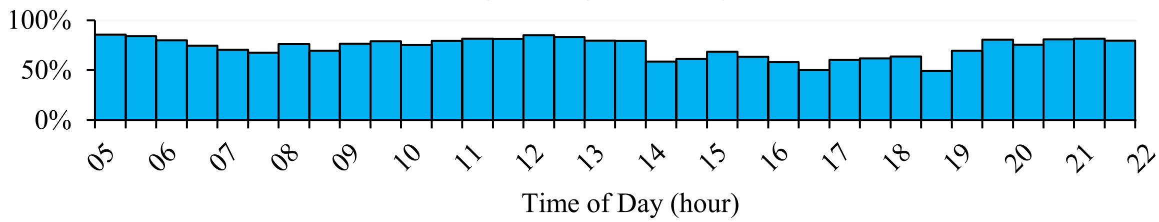
Figure B.8 PPD by TOD and performance measures results for vehicle trajectories traveling SB through at SR-37 and Smith Valley Rd. in July 2019 weekdays



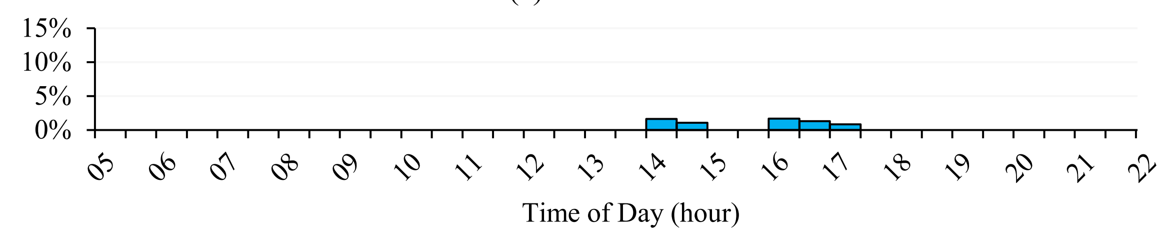
(a) PPD by TOD



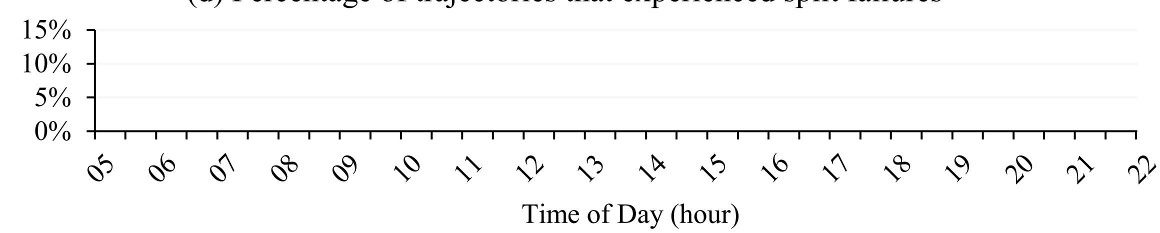
(b) Percentage of trajectories by LOS



(c) AOG

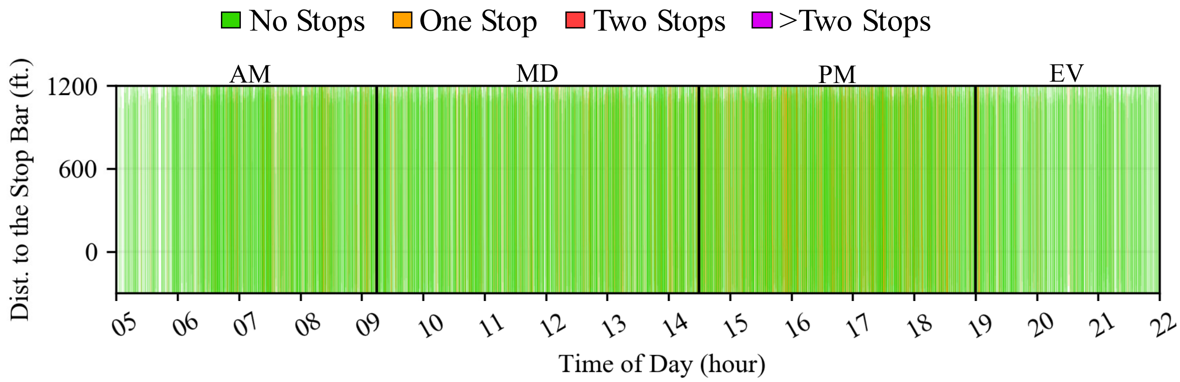


(d) Percentage of trajectories that experienced split failures

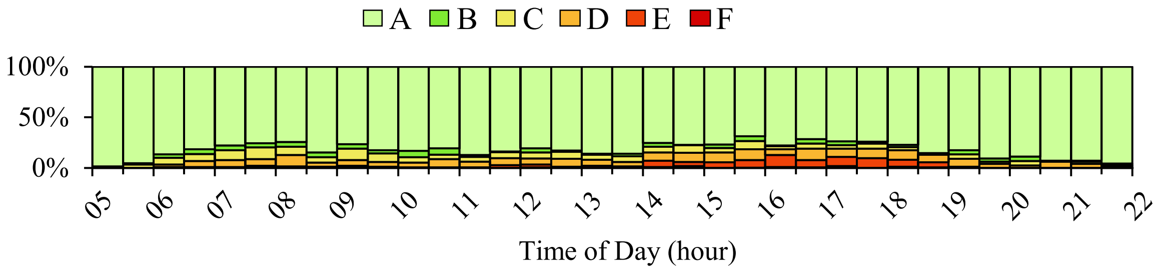


(e) Percentage of trajectories that experienced downstream blockage

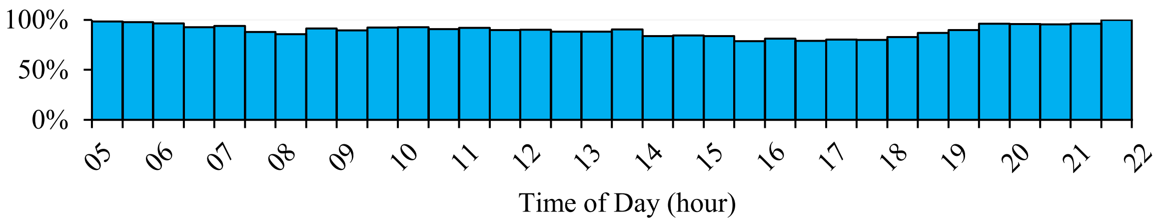
Figure B.9 PPD by TOD and performance measures results for vehicle trajectories traveling NB through at SR-37 and Smith Valley Rd. in July 2019 weekdays



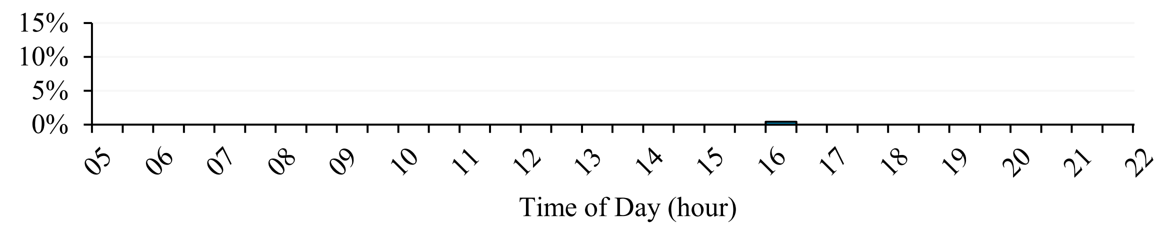
(a) PPD by TOD



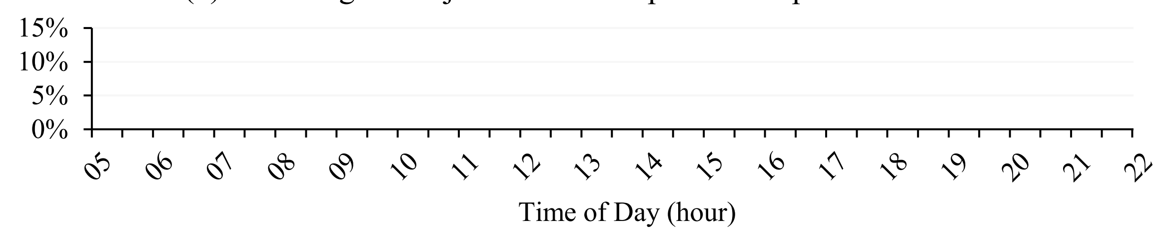
(b) Percentage of trajectories by LOS



(c) AOG

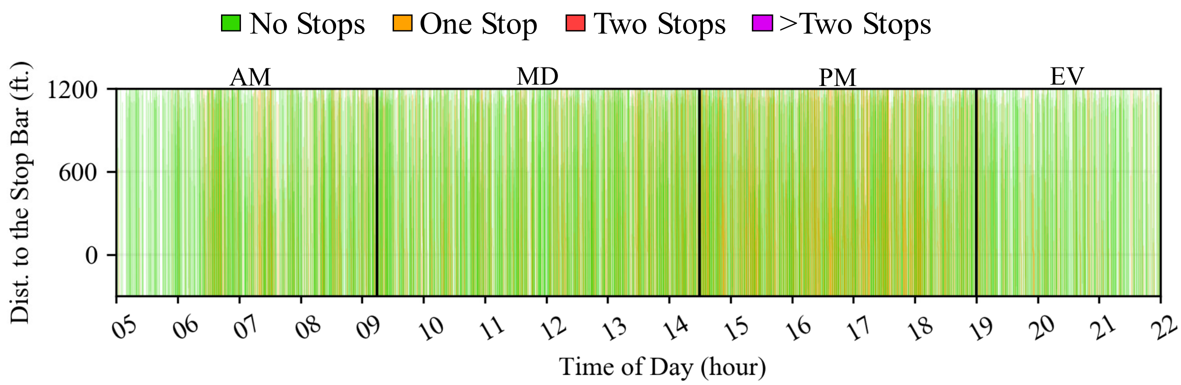


(d) Percentage of trajectories that experienced split failures

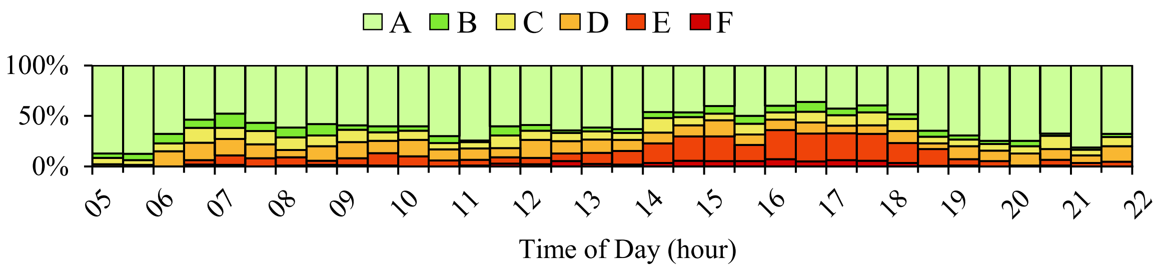


(e) Percentage of trajectories that experienced downstream blockage

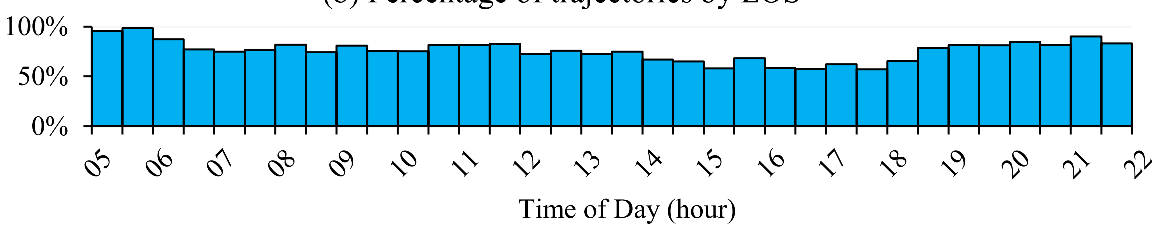
Figure B.10 PPD by TOD and performance measures results for vehicle trajectories traveling NB through at SR-37 and Fairview Rd. in July 2019 weekdays



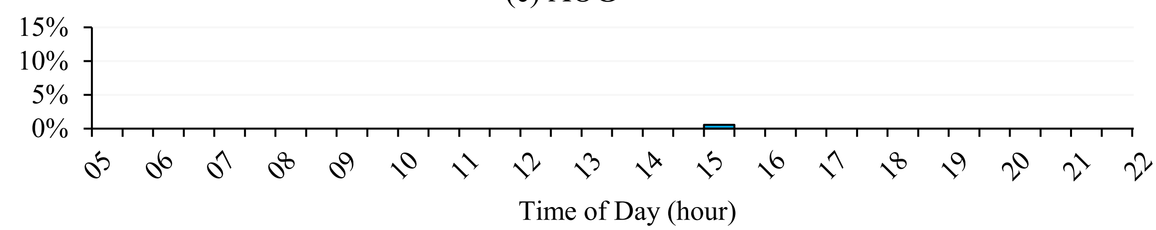
(a) PPD by TOD



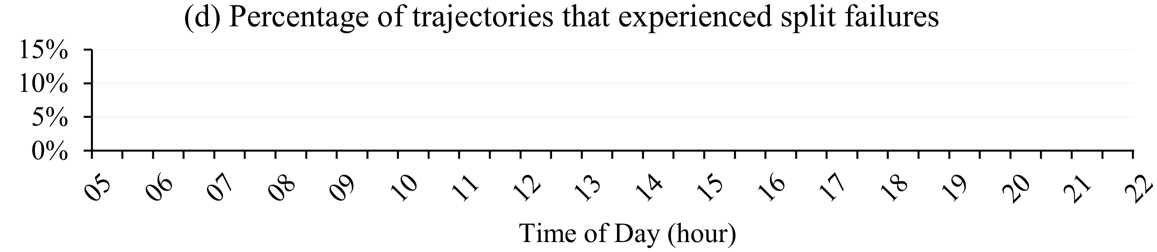
(b) Percentage of trajectories by LOS



(c) AOG

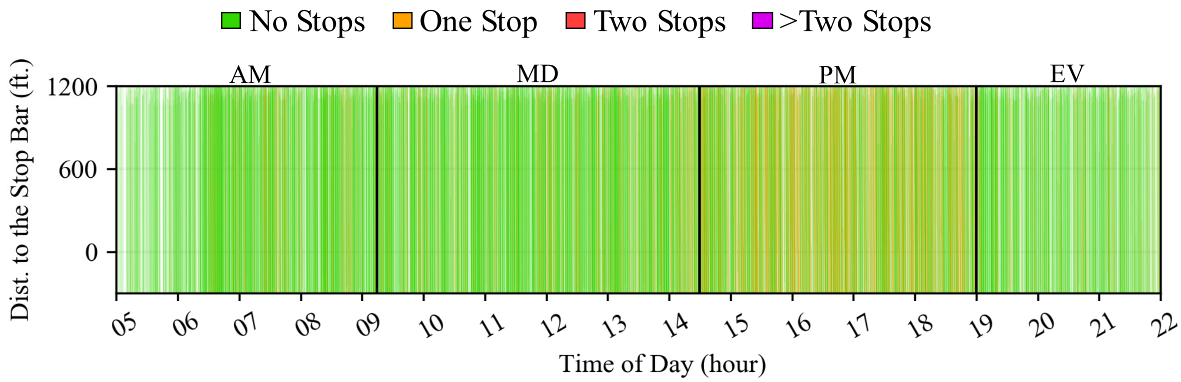


(d) Percentage of trajectories that experienced split failures

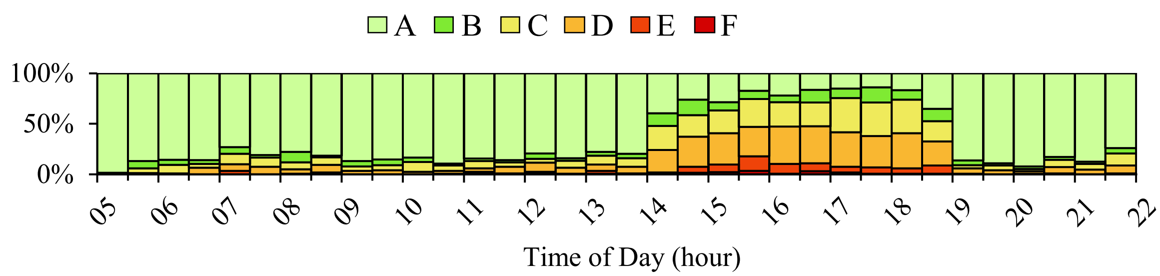


(e) Percentage of trajectories that experienced downstream blockage

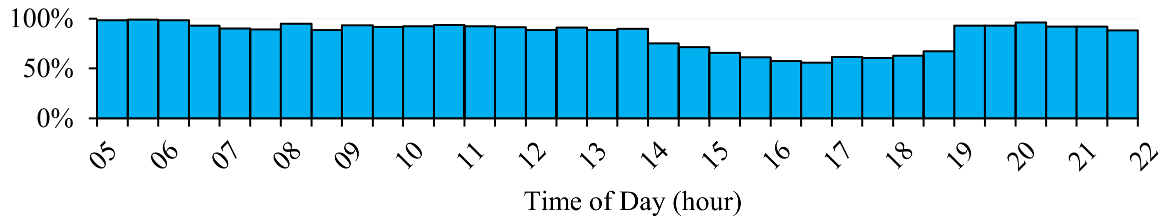
Figure B.11 PPD by TOD and performance measures results for vehicle trajectories traveling NB through at SR-37 and County Line Rd. in July 2019 weekdays



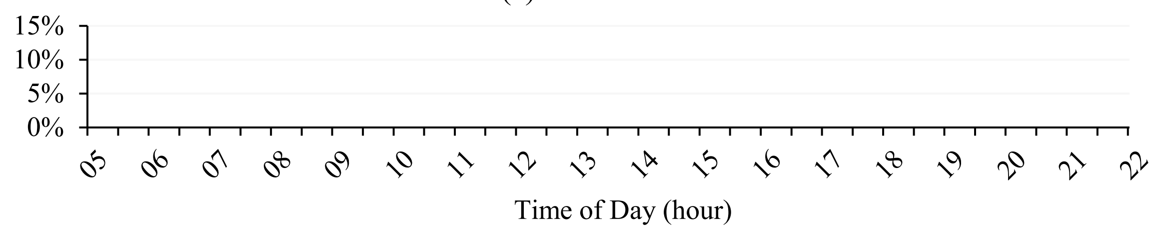
(a) PPD by TOD



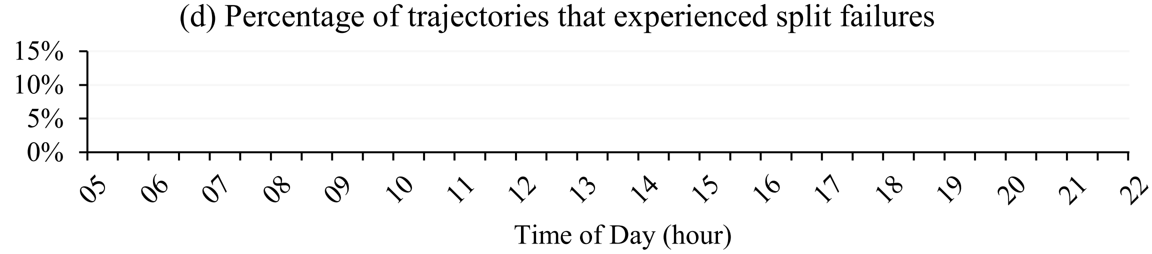
(b) Percentage of trajectories by LOS



(c) AOG

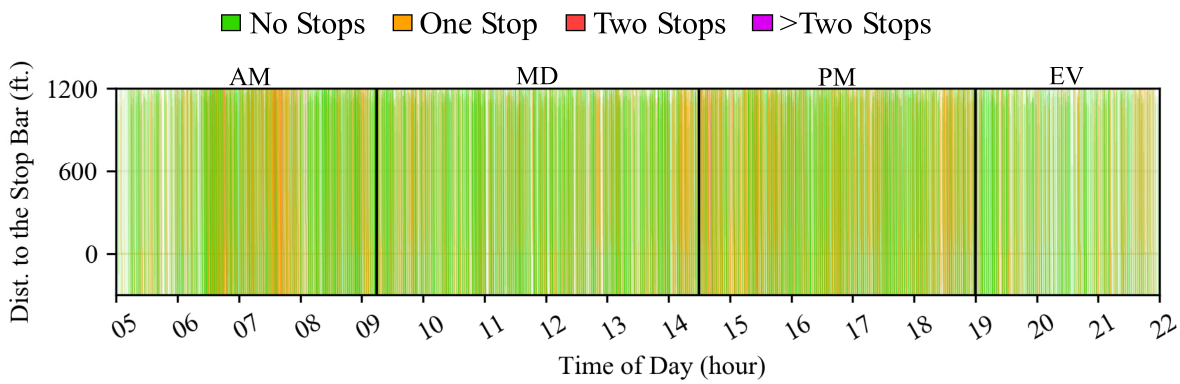


(d) Percentage of trajectories that experienced split failures

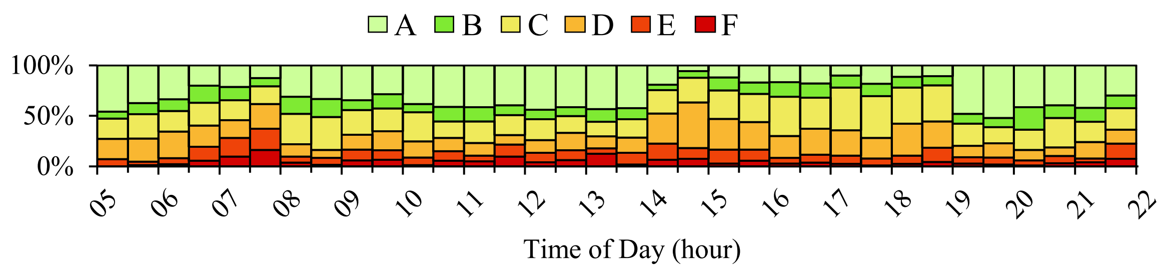


(e) Percentage of trajectories that experienced downstream blockage

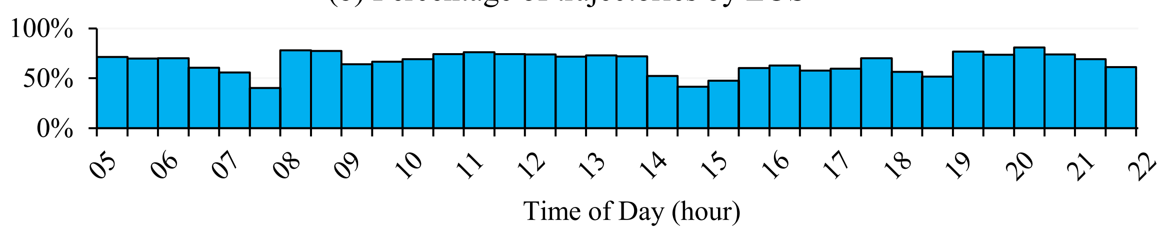
Figure B.12 PPD by TOD and performance measures results for vehicle trajectories traveling NB through at SR-37 and Wicker Rd. in July 2019 weekdays



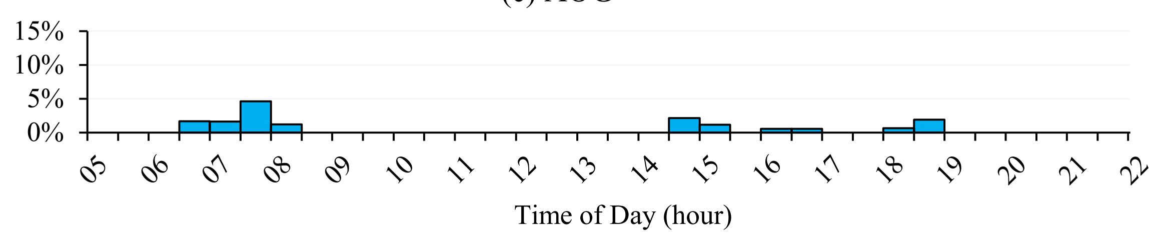
(a) PPD by TOD



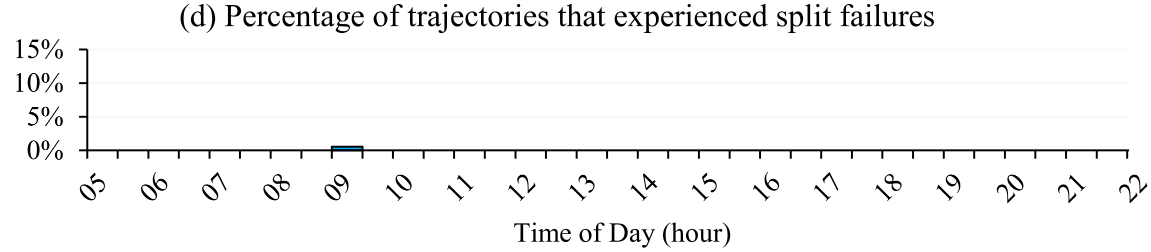
(b) Percentage of trajectories by LOS



(c) AOG

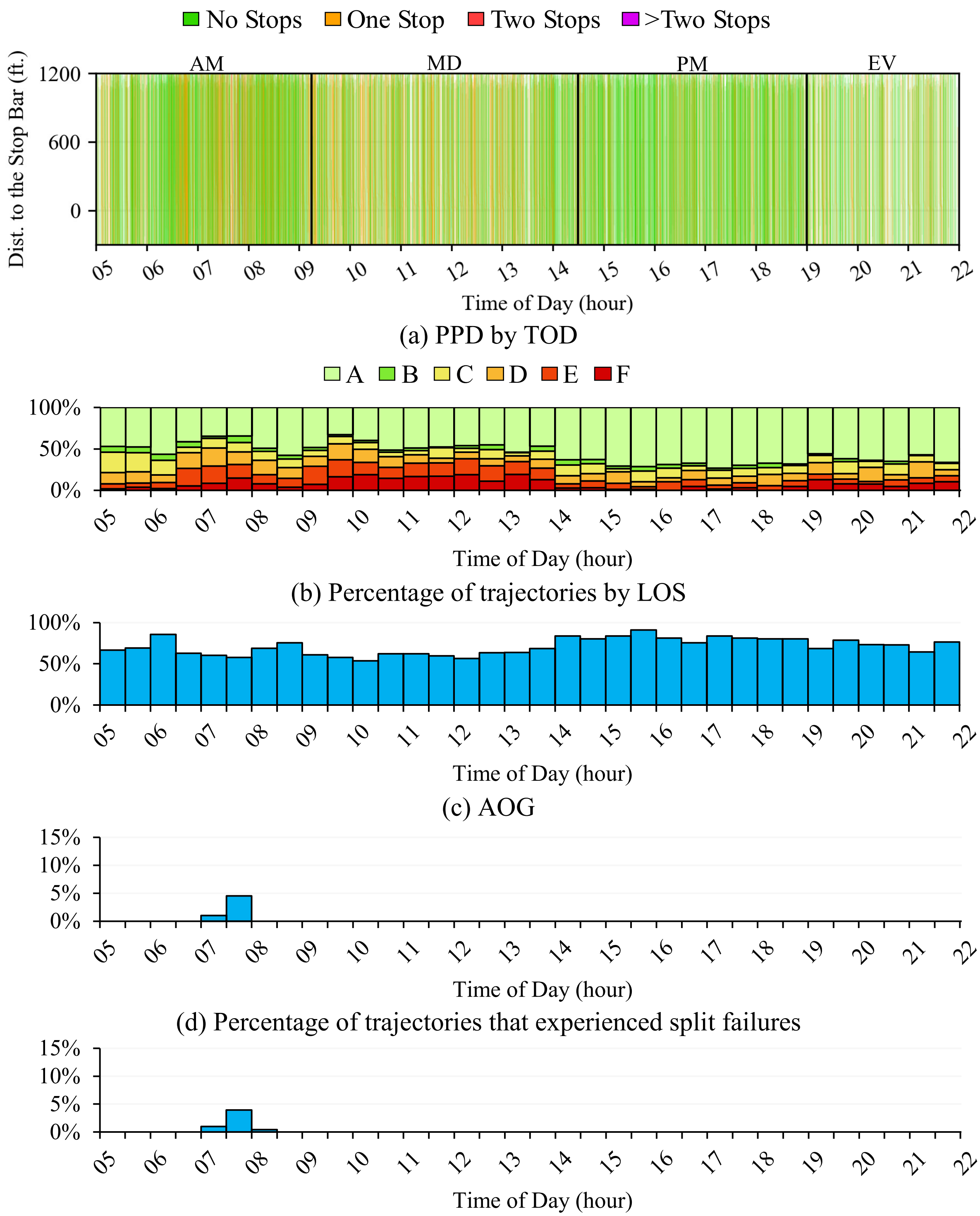


(d) Percentage of trajectories that experienced split failures



(e) Percentage of trajectories that experienced downstream blockage

Figure B.13 PPD by TOD and performance measures results for vehicle trajectories traveling NB through at SR-37 and Southport Rd. in July 2019 weekdays



(a) PPD by TOD

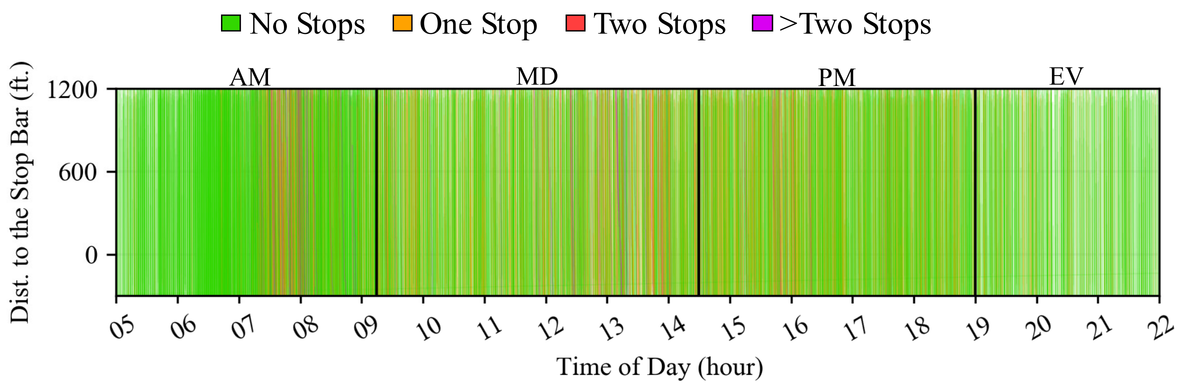
(b) Percentage of trajectories by LOS

(c) AOG

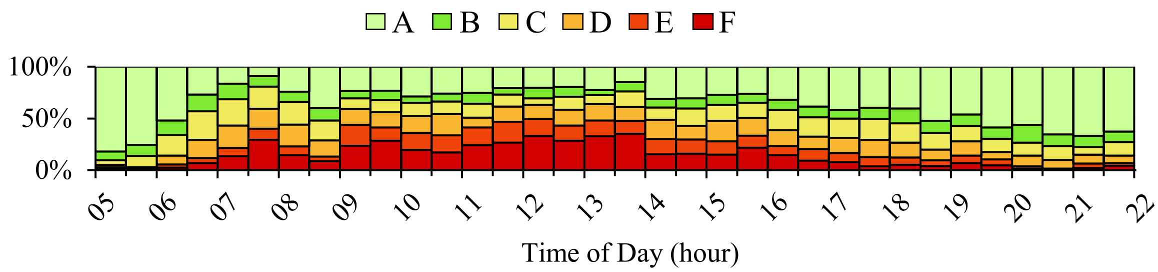
(d) Percentage of trajectories that experienced split failures

(e) Percentage of trajectories that experienced downstream blockage

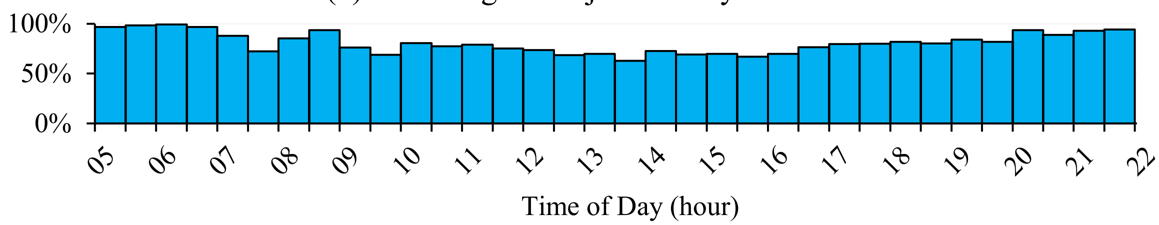
Figure B.14 PPD by TOD and performance measures results for vehicle trajectories traveling NB through at SR-37 and Epler Ave. in July 2019 weekdays



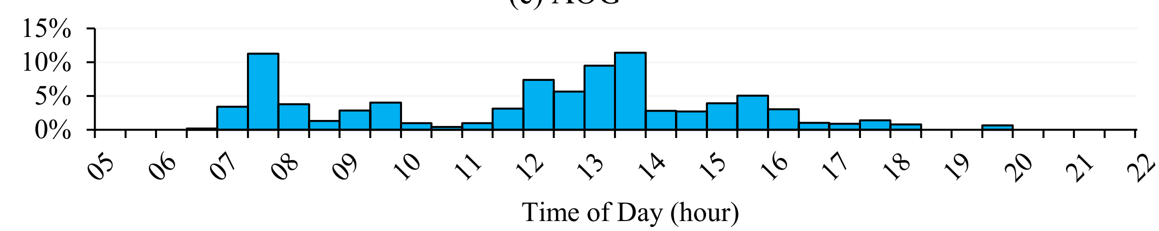
(a) PPD by TOD



(b) Percentage of trajectories by LOS



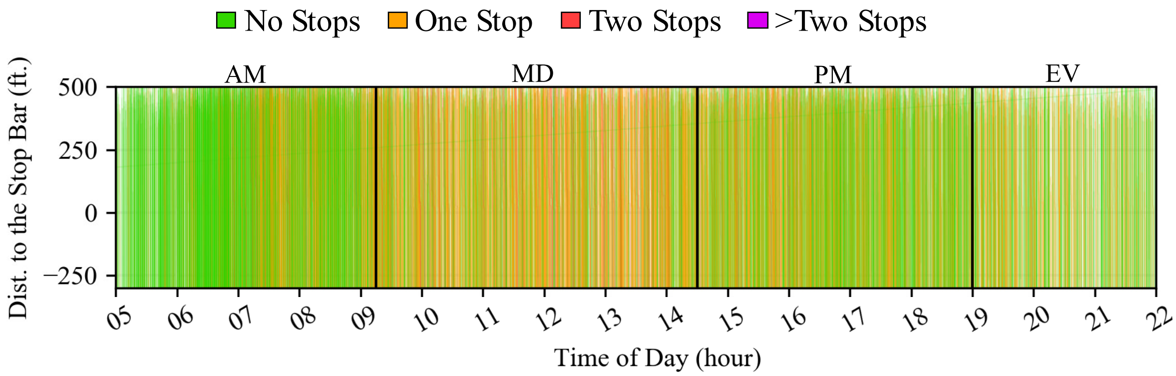
(c) AOG



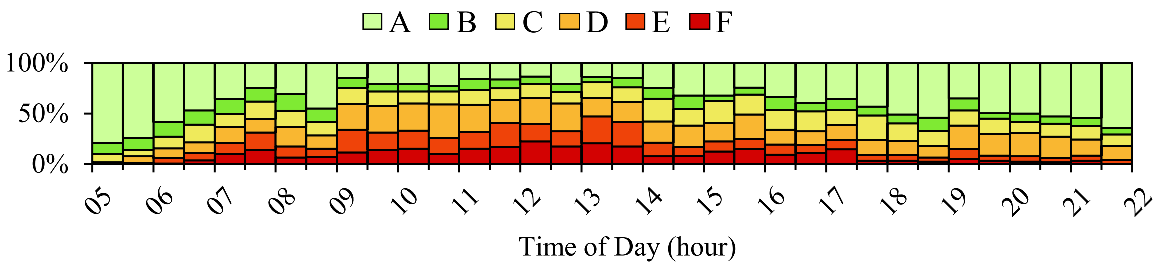
(d) Percentage of trajectories that experienced split failures

(e) Percentage of trajectories that experienced downstream blockage

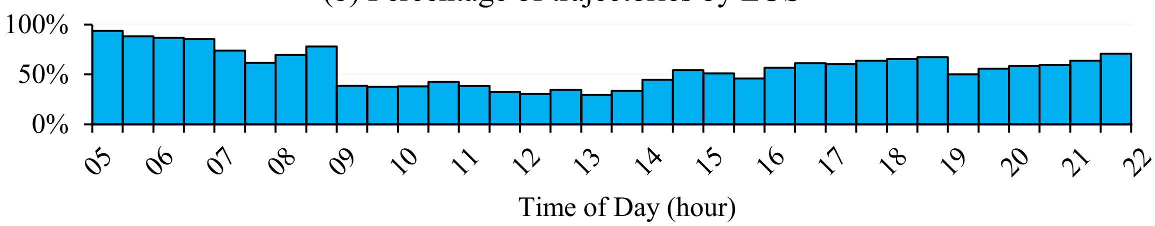
Figure B.15 PPD by TOD and performance measures results for vehicle trajectories traveling NB through at SR-37 and Harding St. in July 2019 weekdays



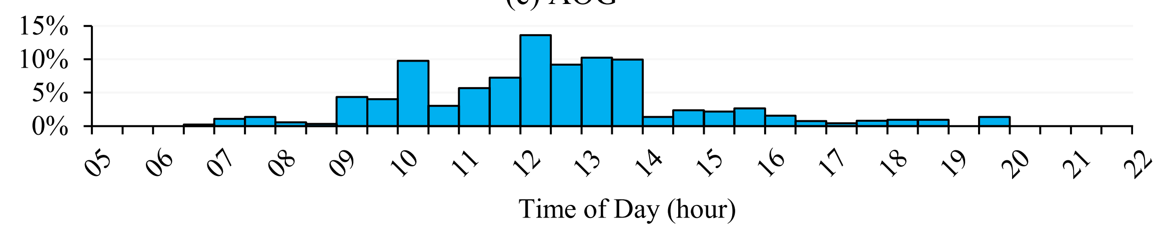
(a) PPD by



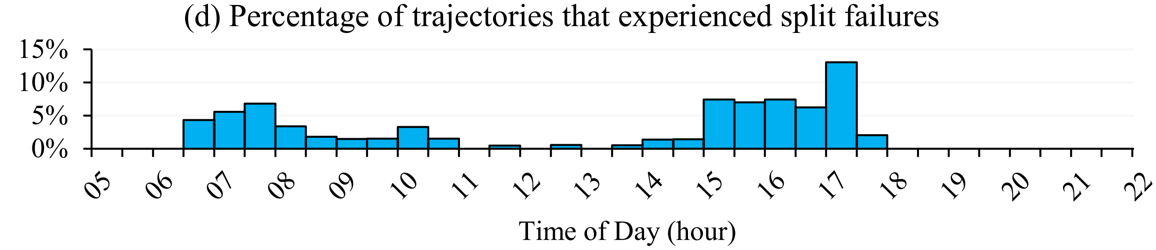
(b) Percentage of trajectories by LOS



(c) AOG



(d) Percentage of trajectories that experienced split failures



(e) Percentage of trajectories that experienced downstream blockage

Figure B.16 PPD by TOD and performance measures results for vehicle trajectories traveling NB through at SR-37 and Thompson Rd. in July 2019 weekdays

REFERENCES

1. National Transportation Operations Coalition. National Traffic Signal Report Card: Technical Report [Internet]. 2012. Washington DC. Available from: https://www.ite.org/pub/?id=e265477a-2354-d714-5147-870dfac0e294
2. Schrank D, Lomax T, Eisele B. 2011 Urban Mobility Report. 2011. College Station. Texas A&M Transportation Institute.
3. Day C, Bullock D, Li H, Remias S, Hainen A, Freije R, et al. Performance Measures for Traffic Signal Systems: An Outcome-Oriented Approach. 2014. Available from: https://docs.lib.purdue.edu/jtrpaffdocs/3/ DOI: 10.5703/1288284315333.
4. FHWA. Every Day Counts: An Innovation Partnership With States. 2019. 50 p. Report No.: FHWA-19-CAI-013.
5. Waddell JM, Remias SM, Kirsch JN, Young SE. Scalable and Actionable Performance Measures for Traffic Signal Systems using Probe Vehicle Trajectory Data. Transp Res Rec J Transp Res Board. 2020;2674(11):304–16. DOI: 10.1177/0361198120941847
6. Remias S, Waddell J, Klawon M, Yang K. MDOT Signal Performance Measures Pilot Implementation [Internet]. 2018. Report No. SPR-1681. Available from: https://www.michigan.gov/documents/mdot/MDOT-Signal-Performance-Measures-Pilot-Implementation_645942_7.pdf
7. Day C, Taylor M, Mackey J, Clayton R, Patel S, Xie G, et al. Implementation of Automated Traffic Signal Performance Measures. ITE Journal. 2016; 86(8):26–34. Available from: https://mydigitalpublication.com/publication/?m=19175&i=324591&view=articleBrowser&article_id=2544747&ver=html5
8. Day C, Bullock D, Li H, Lavrenz S, Smith WBB, Sturdevant J. Integrating Traffic Signal Performance Measures into Agency Business Processes. 2015. Available from: http://docs.lib.purdue.edu/jtrpaffdocs/24/ DOI: http://dx.doi.org/10.5703 /1288284316063
9. Waddell JM, Remias SM, Kirsch JN. Characterizing Traffic-Signal Performance and Corridor Reliability Using Crowd-Sourced Probe Vehicle Trajectories. J Transp Eng Part A Syst. 2020; 146(7). DOI: 10.1061/JTEPBS.0000378

10. Remias SM, Day CM, Waddel JM, Kirsch JN, Trepanier T. Evaluating the Performance of Coordinated Signal Timing: Comparison of Common Data Types with Automated Vehicle Location Data. Transp Res Rec J Transp Res Board. 2018;2672(18):128–42. DOI: 10.1177/0361198118794546
11. Downing R. 5 reasons why companies choose vehicle data over mobile data [Internet]. 2020 [cited 2021 Jan 7]. Available from: https://www.wejo.com/press/5-reasons-why-companies-choose-connected-car-data-over-mobile-data
12. Transportation Research Board (TRB). Highway Capacity Manual 2010. 5th ed. Washington DC: Transportation Research Board; 2010.
13. Transportation Research Board (TRB). Highway Capacity Manual, 6th Edition: A Guide for Multimodal Mobility Analysis. 6th ed. Washington, D.C.: Transportation Research Board; 2016.
14. Freije RS, Hainen AM, Stevens AL, Li H, Smith WB, Summers H, et al. Graphical Performance Measures for Practitioners to Triage Split Failure Trouble Calls. Transp Res Rec J Transp Res Board. 2014; 2439(1):27–40. DOI: 10.3141/2439-03
15. Day CM, Haseman R, Premachandra H, Brennan TM, Wasson JS, Sturdevant JR, et al. Evaluation of Arterial Signal Coordination: Methodologies for Visualizing High-Resolution Event Data and Measuring Travel Time. Transp Res Rec J Transp Res Board. 2010; (2192):37–49. DOI: 10.3141/2192-04
16. Brennan TM, Day CM, Sturdevant JR, Bullock DM. Visual Education Tools to Illustrate Coordinated System Operation. Transp Res Rec J Transp Res Board. 2011; (2259):59–72. DOI: 10.3141/2259-06
17. Day CM, Bullock DM, Sturdevant JR. Cycle-Length Performance Measures: Revisiting and Extending Fundamentals. Transp Res Rec J Transp Res Board. 2009 Jan; 2128(1):48– 57. DOI: 10.3141/2128-05
18. Li H, Richardson LM, Day CM, Howard J, Bullock DM. Scalable Dashboard for Identifying Split Failures and Heuristic for Reallocating Split Times. Transp Res Rec J Transp Res Board. 2017; 2620(1):83–95. DOI: 10.3141/2620-08
19. Smaglik EJ, Sharma A, Bullock DM, Sturdevant JR, Duncan G. Event-Based Data Collection for Generating Actuated Controller Performance Measures. Transp Res Rec J Transp Res Board. 2007;2035(1):97–106. DOI: 10.3141/2035-11

20. Smaglik EJ, Bullock DM, Sharma A. Pilot Study on Real-Time Calculation of Arrival Type for Assessment of Arterial Performance. J Transp Eng. 2007;133(7):415–22. DOI: 10.1061/(ASCE)0733-947X(2007)133:7(415)
21. Wu X, Liu HX, Gettman D. Identification of oversaturated intersections using high-resolution traffic signal data. Transp Res Part C Emerg Technol. 2010;18(4):626–38. DOI: 10.1016/j.trc.2010.01.003
22. Emtenan AMT, Day CM. Impact of Detector Configuration on Performance Measurement and Signal Operations. Transp Res Rec J Transp Res Board. 2020; 2674(4):300–13. DOI: 10.1177/0361198120912244
23. Li H, Hainen AM, Day CM, Grimmer G, Sturdevant JR, Bullock DM. Longitudinal Performance Measures for Assessing Agencywide Signal Management Objectives. Transp Res Rec J Transp Res Board. 2013 Jan; 2355(1):20–30. DOI: 10.3141/2355-03
24. Lavrenz S, Sturdevant J, Bullock D. Strategic Methods for Modernizing Traffic Signal Maintenance Management and Quantifying the Impact of Maintenance Activities. Journal of Infrastructure Sys. 2017; 23(4). DOI: 10.1061/(ASCE)IS.1943-555X.0000361
25. Li H, Mackey J, Luker M, Taylor M, Bullock DM. Application of High-Resolution Trip Trace Stitching to Evaluate Traffic Signal System Changes. Transp Res Rec J Transp Res Board. 2019; 2673(9):188–201. DOI: 10.1177/0361198119841043
26. Zhang K, Jia N, Zheng L, Liu Z. A novel generative adversarial network for estimation of trip travel time distribution with trajectory data. Transp Res Part C Emerg Technol. 2019;108:223–44. DOI: 10.1016/j.trc.2019.09.019
27. Huang J, Li G, Wang Q, Yu H. Real Time Delay Estimation for Signalized Intersection Using Transit Vehicle Positioning Data. 2013 13th International Conference on ITS Telecommunications. 2013. p. 216–21. DOI: 10.1109/ITST.2013.6685548
28. Day CM, Li H, Richardson LM, Howard J, Platte T, Sturdevant JR, et al. Detector-Free Optimization of Traffic Signal Offsets With Connected Vehicle Data. Transp Res Rec J Transp Res Board. 2017; 2620(1):54–68. DOI: 10.3141/2620-06
29. Zhao Y, Zheng J, Wong W, Wang X, Meng Y, Liu HX. Estimation of Queue Lengths, Probe Vehicle Penetration Rates, and Traffic Volumes at Signalized Intersections using Probe Vehicle Trajectories. Transp Res Rec J Transp Res Board. 2019; 2673(11):660– 670. DOI: 10.1177/0361198119856340

30. Cetin M. Estimating Queue Dynamics at Signalized Intersections from Probe Vehicle Data: Methodology Based on Kinematic Wave Model. Transp Res Rec J Transp Res Board. 2012;(2315):164–72. DOI: 10.3141/2315-17
31. Waddell JM, Remias SM, Kirsch JN, Kamyab M. Replicating Advanced Detection using Low Ping Frequency Probe Vehicle Trajectory Data to Optimize Signal Progression. Transp Res Rec. 2020;2674(7):528–39. DOI: 10.1177/0361198120923654
32. Feng Y, Head KL, Khoshmagham S, Zamanipour M. A real-time adaptive signal control in a connected vehicle environment. Transp Res Part C Emerg Technol. 2015;55:460–73. DOI: 10.1016/j.trc.2015.01.007
33. Zheng J, Liu HX. Estimating traffic volumes for signalized intersections using connected vehicle data. Transp Res Part C Emerg Technol. 2017;79:347–62. DOI: 10.1016/j.trc.2017.03.007
34. Argote-Cabañero J, Christofa E, Skabardonis A. Connected Vehicle Penetration Rate for Estimation of Arterial Measures of Effectiveness. Transp Res Part C: Emerging Tech. 2015 Nov; 60:298-312. DOI: 10.1016/j.trc.2015.08.013
35. Quiroga C, Bullock D. Measuring Control Delay at Signalized Intersections. J Transp Eng. 1999;125(4):271–80. DOI: https://doi.org/10.1061/(ASCE)0733- 947X(1999)125:4(271)
36. Richardson LM, Luker MD, Day CM, Taylor M, Bullock DM. Outcome Assessment of Peer-to-Peer Adaptive Control Adjacent to a National Park. Transp Res Rec J Transp Res Board. 2017;(2620):43–53. DOI: 10.3141/2620-05
37. Long G. Acceleration Characteristics of Starting Vehicles. Transp Res Rec J Transp Res Board. 2000;(1737):58–70. DOI: 10.3141/1737-08
38. Day CM, Brennan TM, Hainen AM, Remias SM, Premachandra H, Sturdevant JR, et al. Reliability, Flexibility, and Environmental Impact of Alternative Objective Functions for Arterial Offset Optimization. Transp Res Rec J Transp Res Board. 2011; (2259):8–22. DOI: 10.3141/2259-02

PUBLICATIONS

Saldivar-Carranza, E., Li, H., Mathew, J., Hunter, M., Sturdevant, J., Bullock, D. Deriving Operational Traffic Signal Performance Measures from Vehicle Trajectory Data. Transp Res Rec J Transp Res Board. 2021. DOI: 10.1177/03611981211006725.

Hunter, M., Saldivar-Carranza, E., Desai, J. et al. A Proactive Approach to Evaluating Intersection Safety Using Hard-Braking Data. J. Big Data Anal. Transp. (2021). https://doi.org/10.1007/s42421-021-00039-y.

Saldivar-Carranza, E., Li, H., Kim, W., Mathew, J., Bullock, D., Sturdevant, J. Effects of a Probability-Based Green Light Optimized Speed Advisory on Dilemma Zone Exposure. SAE Technical Paper 2020-01-0116. 2020. DOI: https://doi.org/10.4271/2020-01-0116.

Li, H., Saldivar-Carranza, E., Mathew, J. K., Kim, W., Desai, J., Wells, T., Bullock, D. M. (2020). Extraction of Vehicle CAN Bus Data for Roadway Condition Monitoring. Joint Transportation Research Program Publication No. FHWA/IN/JTRP-2020/20. 2020, West Lafayette, IN: Purdue University. https://doi.org/10.5703/1288284317212

Li, H., Platte, T., Mathew, J., Smith, B., Saldivar-Carranza, E., Bullock, D. Using Connected Vehicle Data to Reassess Dilemma Zone Performance of Heavy Vehicles. Transp Res Rec J Transp Res Board. 2020; 2674 (5):305–314. DOI: https://doi.org/10.1177/0361198120914606

Li, H., Mathew, J. K., Kim, W., Saldivar-Carranza, E. D., Sturdevant, J., Smith, W. B., Bullock, D. M. Connected Vehicle Corridor Deployment and Performance Measures for Assessment. Joint Transportation Research Program Publication No. FHWA/IN/JTRP-2019/28. 2019. DOI: https://doi.org/10.5703/1288284317108