

# Performance-Based Operations Assessment of Adaptive Control Implementation in Des Moines, Iowa

**Final Report  
August 2018**



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| <b>16. Abstract</b><br><p>Maintaining optimal mobility on high-volume arterial traffic corridors is important to transportation agencies and the public. Corridor performance often can be enhanced by updating traffic signal timing, but most agencies find it necessary to prioritize their retiming efforts based on resource constraints. To facilitate prioritization, a set of arterial corridor performance measures was developed using INRIX probe vehicle data. These commercially available data are derived from in-vehicle global positioning system (GPS) observations transmitted wirelessly, eliminating the need for supplemental traffic observation infrastructure to be installed in the field.</p> <p>The main objective of this study was to present a methodology to compare arterial corridors in terms of mobility-based performance measures. This process can help agencies select the corridors that are in need of signal retiming and can help identify corridors suited for adaptive signal control implementation. The two-step methodology began by identifying the number of days in a year with abnormal traffic patterns and comparing the volume-normalized performance of the remaining segments to identify corridors that are problematic on normal days.</p> <p>The proposed methodology was applied to 12 corridors in Des Moines, Iowa, and 1 in Omaha, Nebraska. Three corridors were found to have a high number of anomalous days. Among the remaining corridors, three were identified as under-performing on normal days. In addition, the impact of implementing an adaptive signal control system on one corridor (University Avenue) was evaluated, where small improvements in travel rate and daily variation were observed, but the overall variability increased.</p> |  |  |                        |
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# **PERFORMANCE-BASED OPERATIONS ASSESSMENT OF ADAPTIVE CONTROL IMPLEMENTATION IN DES MOINES, IOWA**

**Final Report  
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## EXECUTIVE SUMMARY

Nearly every urban area in the US has arterial corridors that include a series of closely-spaced intersections, and these roadways often handle high traffic volumes. Maintaining optimal mobility on such corridors is a matter of considerable importance to road users and transportation agencies. As time passes, traffic signal timing plans tend to become outdated due to changes in traffic volumes and land use, resulting in unnecessary traffic delays, increased fuel consumption, increased engine emissions, and (in some cases) adverse impacts on road safety. Arterial performance can often be enhanced by updating the signal timing or implementing an adaptive traffic signal control system, but most agencies face resource constraints that limit the number of retiming and adaptive control projects they can implement. As a result, agencies need an effective method for screening the performance of their arterial networks to set priorities for retiming and adaptive control efforts.

The present work develops a set of performance measures for arterial corridors using probe vehicle data provided by INRIX, a commercial traffic data vendor. The probe data are derived from in-vehicle global positioning system (GPS) devices that periodically transmit each participating vehicle's location to a central server using wireless communication networks. The vendor computes vehicle speeds by analyzing each vehicle's path over time. In some cases, probe data vendors also have access to speed information from vehicle engine control electronics.

The use of probe vehicle data as an arterial performance monitoring tool is advantageous because it eliminates the need for installing additional traffic detectors (and associated communications infrastructure) in the field. Many US agencies have already purchased probe data sets from INRIX or competing vendors or are able to obtain similar data from the Federal Highway Administration (FHWA) National Performance Monitoring Research Data Set (NPMRDS). Thus, in many cases, the use of probe-based arterial performance assessment is a relatively low-cost addition to existing traffic monitoring programs.

The main objective of this report was to present a methodology for comparing a set of arterial corridors in terms of mobility-based performance measures. This process can help transportation agencies select the corridors that are in need of traffic signal retiming and can also help identify corridors that might be suited to implementation of adaptive signal control.

The arterial mobility evaluation had two main steps:

1. Identify the number of "abnormal" traffic days in a year, which characterizes whether an adaptive system will be cost effective.
2. For "normal" days, compare the volume-normalized performance among the corridors to identify problematic segments.

The performance metrics used for comparative evaluation in this report included: median travel rate, within-day travel rate variability, and between-days travel rate variability.

The proposed methodology was used to evaluate a total of 13 arterial corridors: 12 in the Des Moines, Iowa, area and 1 in Omaha, Nebraska. Evaluation of the Des Moines corridors was carried out for the entire year of 2016, while the Omaha evaluation was based on data from June 2016 through November 2016. Some key findings were as follows:

- Anomalous days were evaluated for various segments. Three corridors (University Avenue, Hickman Road, and SE 14th Street) had the highest numbers of anomalous days. Thus, it can be said that these corridors are the ones handling the most dynamic travel patterns.
- For normal days, five performance metrics were defined: median travel rate (MTR), within day variability (WTV), minimum travel rate dispersion (MTD) and two overall travel rate variabilities (OTV\_POLY and OTV\_LINEAR). Based upon on these parameters, three areas (Jordan Creek Parkway and SE 14th Street in the Des Moines area and parts of Dodge Street in Omaha) were found to be the worst-performing segments.

In addition to the above comparison, a before/after analysis was conducted to evaluate the effect of implementing adaptive signal control on University Avenue in Des Moines. The analysis showed a small improvement in travel rate and daily variation, but the overall variability increased.

# CHAPTER 1. INTRODUCTION

## 1.1. Background

Transportation agencies install traffic signals to achieve three main objectives: optimize traffic flow, reduce crash frequency or crash severity, and give priority to a particular roadway user type or movement (Chandler et al. 2013). Traffic signals are intended to allow safe and efficient passage of road users in accordance with the spatial and temporal patterns of traffic demand at the site.

Modern traffic signals are computer-controlled, and the amount of time allocated to each traffic movement is typically programmed by the signal engineer based on the corresponding traffic volume, subject to constraints such as the minimum safe crossing time for pedestrians. As cities evolve, original signal timing plans become obsolete due to changes in traffic volume and land use. Some of these changes occur gradually, while others (such as the opening of a new bicycle trail or the relocation of a major business) can be quite abrupt.

According to the Federal Highway Administration (FHWA), issues related to the performance of most of the 300,000 traffic signals in the US are addressed predominantly on the basis of citizen complaints (Curtis and Denney 2017). Recognizing that a complaint-driven process is inefficient and prone to inequity, many transportation agencies have sought objective methods for identifying and prioritizing corridors that require signal retiming or the implementation of advanced signal control systems. This report explores one such method based on global positioning system (GPS)-derived traffic speed data from a commercial vendor.

Two-thirds of all miles driven each year are on roadways controlled by traffic signals, and poor traffic signal timing is a major cause of traffic congestion and delay (Wikibooks 2017). Traffic congestion is identified by the U.S. Department of Transportation (DOT) as “one of the three single largest threats” to the economic prosperity of the nation and poses a great challenge to transportation agencies as well as to the people using the roads (Owens et al. 2010).

From the public’s perspective, traffic congestion leads to unnecessary delays and associated frustrations. Some of the repercussions of congestion include late arrival at work or other events, lost business, disciplinary actions, and other personal losses. Poor signal timing can also result in emergency response delays, increased fuel consumption, increased vehicle emissions, and increased vehicle maintenance costs. According to one analysis, as of 2016, traffic jams cost the average American driver around \$1,200 per year for fuel and time (Cookson and Pishue 2017).

Another major effect of poor signal timing is traffic crashes and the resulting injuries and fatalities. Nationally, 40 percent of all crashes involve intersections, the second largest category of accidents (NHTSA 2009).

Most fatality crashes occur on arterial corridors. For example, a 2016 study by the Insurance Institute for Highway Safety (IIHS 2017) found that almost 67% of fatalities occur on arterial

corridors. A study in the Kansas City, Missouri, area reported that the crash rate at signalized intersections is much higher than the rate for intersections controlled by stop and yield signs (Abdel-Aty et al. 2005).

Another nationwide study found that as age increases, the rate of intersection crashes also increases: about a third of crashes occur at or near intersections for the youngest group (less than 20 years old), rising to about 54% for the oldest group (more than 65 years old) (Choi 2010).

Although signal retiming does not eliminate all intersection crashes, it can address certain types of crashes. For example, if progression along an arterial corridor is improved so that the number of times that vehicles must stop is decreased, the number of rear-end crashes can be expected to decrease (Antonucci et al. 2004).

A coalition of six national organizations has drawn attention to the problem of inadequate traffic signal performance through the National Traffic Signal Report Card (National Transportation Operations Coalition 2012). The report is based on transportation agency signal performance self-assessments covering six main areas: management, signal operations, signal timing practices, traffic monitoring and data collection, and maintenance. Although the overall score improved from a D- in 2005 to a D+ in 2012, many issues remain to be addressed.

Among the six criteria, traffic monitoring and data collection was rated F, indicating problems for signal systems and agencies of all sizes. As discussed in more detail in subsequent chapters of this report, the use of probe data can help address this important deficiency.

## 1.2. Type of Control

The three primary operational modes for traffic signals are pre-timed control, semi-actuated control, and fully actuated control (Koonce et al. 2010). Each of these modes is briefly described below.

- **Pre-timed** traffic control consists of a series of intervals that are fixed in their duration. Each signal cycles through a pre-defined set of green, yellow, and red intervals in a deterministic way. Pre-timed signals are usually applied to locations with high intersection density and predictable traffic patterns—sites where the timing plans do not need to be varied on a daily or weekly basis. The three main advantages are that pre-timed traffic control can be used to coordinate movements among adjacent pre-timed intersections, it does not require traffic detectors (so there is no risk of detector failure), and it is relatively simple and inexpensive to maintain.

Pre-timed signals are popular in grid networks, where an agency wants to coordinate traffic flow in multiple directions (for example, simultaneously achieving acceptable progression on both east-west and north-south streets in a business district). Pre-timed signals cannot adjust for traffic-flow fluctuations.



- **Semi-actuated** traffic signal control typically involves the use of traffic detection for minor movements. In this design, the signal controller is configured to favor major (high-volume) movement, which is allowed to proceed with relatively little interruption unless vehicles are detected on a cross street. Thus, the signal timing will vary depending on the amount of cross-street traffic.

Typically, the result is less delay to the major street compared to the pre-timed system, while avoiding the need to install traffic detectors for the major traffic movements. Nevertheless, semi-actuated signal control can cause excessive delay to the major movement if minor movements tend to have frequent calls, especially if the maximum green and the extension timer are not set appropriately.

- **Fully actuated** signals have detectors for all movements. This design is ideal for isolated intersections where the traffic varies widely throughout the day and for locations where traffic surges occur at difficult-to-predict times (for example, traffic leaving a stadium at the end of a game).

A major advantage of fully actuated control is the delay reduction that can be accomplished by skipping unneeded phases or ending a phase early when traffic is light. This advantage comes at the cost of greater complexity, including additional equipment to install and maintain.

During peak hours (when there is heavy demand for all movements), the actual operation is likely to be similar to pre-timed operation; the delay savings occur mainly during off-peak hours when phases associated with minor movements can be skipped or terminated early.

### 1.3. Signal Retiming

Regardless of the type of signal control that is used (pre-timed, semi-actuated, or fully actuated), nearly all locations eventually require some kind of improvement that requires re-evaluation of the timing plan by an engineer or technician (Curtis 2017, Tarnoff and Ordonez 2004).

Typically, the need for signal retiming is invoked in response to one of the following situations:

- Major changes in the land-use pattern
- Public requests
- Traffic conditions such as oversaturation or queue spillback
- Detector or traffic camera video that suggests changes in volume and congestion (Gordon 2010)

The retiming process is typically accomplished by gathering field data such as turning movement and pedestrian traffic volumes, followed by detailed analysis using specialized software packages such as SIDRA and Synchro software. From a mathematical perspective, the retiming process is mainly solved by minimizing a delay-based objective function or maximizing progression on an arterial's through movement (Gordon 2010).

Signal retiming is seen to have several advantages (Sunkari 2004): reduction in delay (13–37%), fewer red light stops (10–49%), increase of fuel efficiency (2–9%), reduction in accidents (31%), and lower travel time (8–25%)

#### **1.4. Adaptive Signal Control**

Adaptive signal control technology (ASCT) was developed to improve signal performance in locations with highly variable traffic demand (Curtis 2017). Based on the output from permanent traffic detectors, some types of ASCT continuously update the signal timings, while others work to select the best available signal timing plan from a very large library of pre-defined scenarios. In either case, the use of ASCT is intended to maximize the capacity of the existing system, which reduces the cost to both system users and signal operating agencies.

Compared to actuated signal control, ACST allows many more adjustments to the timing plan. For example, actuated signals are often configured to terminate a phase early if a detector indicates that all vehicles making that movement have been served. ACST goes well beyond this, with the possibility to implement an entirely different timing strategy in response to an unusual traffic pattern, such as a freeway incident that unexpectedly increases the volume on a nearby arterial.

The use of adaptive signal control strategies began in the 1970s with the development of the Sydney Coordinated Adaptive Traffic System (SCATS) in Australia and Split Cycle Offset Optimization Technique (SCOOT) in the United Kingdom. Among adaptive control strategies designed specifically for North America, Optimization Policies for Adaptive Control (OPAC) (Gartner et al. 2001) and the Real-Time Hierarchical Optimized Distributed and Effective System (RHODES) (Mirchandani and Head 2001) were among the first to be developed. Other examples include Adaptive Control Software Lite (ACS-Lite) and InSync. These systems use detector data as an input, analyze the traffic flow, and allocate green time for each phase.

The benefits of ACST are site-specific: sites with considerable minute-to-minute traffic volume fluctuations will typically show more benefit than those with relatively uniform demand. One study showed that the use of adaptive systems can reduce stops by 28–41% (Hicks and Carter, 1997). The systems help distribute green time equitably for all traffic movements (Curtis 2017). In some cases, this can reduce the travel time by as much as 35–39% (Sims and Dobinson 1980). Adaptive control has also been shown to reduce fuel consumption and vehicle emissions, resulting in improved air quality.

One of the main drawbacks of adaptive control is the high initial cost for installation of field equipment and the traffic management software. The systems need to be tuned and set up initially, which is also labor-intensive. Agencies often choose to limit the extent to which the systems can automatically adjust the timing plan (for example, by disallowing cycle lengths greater than a preset threshold and ongoing performance monitoring is required to assure that these threshold values remain valid). The field components also tend to have a higher maintenance cost.

The typical cost of implementing adaptive control appears to range from \$6,000 to \$65,000 per intersection. Thus, agencies need to consider the performance of the existing signal system carefully before deciding whether to implement an adaptive signal system (Sunkari 2004, Sprague 2012, Zhao and Tian 2012, Stevanovic 2010).

### **1.5. Performance Measures**

Performance measures based on traffic monitoring can assist transportation agencies in setting priorities for retiming or implementing adaptive signal control systems. They also provide a basis for evaluating the traffic network periodically, to see whether performance is improving or degrading. However, without data-driven performance evaluations to serve as a screening and prioritization tool, some corridors that need retiming could be overlooked, while others with less need for updates might incur considerable expense for signal retiming and the associated manual data collection and traffic analysis (Curtis and Denney 2017). The evaluation process requires a strong set of performance data.

Automated traffic signal performance measures (ATSPMs) are an increasingly popular method for obtaining information about the performance of a traffic signal system. These measures are obtained by analyzing high-resolution data logs generated by certain models of advanced signal controllers. Although ATSPMs were developed for corridors with modern traffic signal control equipment, the research conducted for this project adapted several ATSPM concepts to obtain performance measures using probe data—a process that is feasible even for corridors with “vintage” electromechanical controllers. Thus, it is useful to review some recent research to understand how agencies are applying ATSPM data to corridor-level performance evaluation. Some examples include the following:

- An adaptive real-time offset transitioning algorithm has been used to enhance the performance of arterial corridors (Abbas et al. 2001).
- Several studies have found that estimation of performance measures is the most suitable when it is based upon cycle-by-cycle analysis (Abbas et al. 2001, Luyanda et al. 2003, Smaglik et al. 2005).
- Maximum queue length has proved to be an important performance measure to determine the performance of arterial corridors. This includes the use of a queue polygon method to determine delay and queue length (Sharma and Bullock 2008, Sharma et al. 2007).
- Queue length, turning movement proportion, and arterial travel time have been used to compare performance for signalized intersections, as well as the whole corridor (Liu et al. 2008).
- Analysis has been conducted to determine intersection performance based on the level of progression and delay (Smaglik et al. 2007a).

- Volume-to-capacity ratio and arrival type have been used to address the performance of signalized intersections for arterial corridors (Day et al. 2008).
- Research has identified the use of arrival type (AT) as a means to describe the quality of progression from one signalized intersection to the next along a coordinated corridor (Smaglik et al. 2007b). The arrival time metric uses the percentage of vehicles arriving on green and the density of the arriving platoon.
- Another performance measure that has been used is the green-occupancy-ratio (Smaglik et al. 2011).
- Network-level analysis has been conducted to determine the specific phases that are problematic for an intersection (Day et al. 2010).
- Measures like delay, number of stops, and arrival rate on green have been used to evaluate the performance of intersections on arterial corridors (Day et al. 2012).
- High resolution signal event data have been used to identify opportunities for improving signal timing parameters and improving signal operations (Day et al. 2014).
- In a very recent study that is closely related to this research, probe data were used to evaluate the normalized travel time for comparison of different arterial networks using the average and the standard deviation of these values (Day et al. 2015).
- Another study developed ATSPM improvements called intelligent traffic signal performance measurements (ITSPMs) (Huang et al. 2018). The ITSPMs presented graphical tools to identify erroneous logs and data from bad sensors. The authors also determined the travel demand, which is required to determine the need for coordination at an intersection. They also came up with stream analytics measures to quickly identify anomalous behavior at intersections, batch analytics to provide trends that can serve as a backbone for determining anomalies, and also a spatial resolution study that can be either at phase or approach level for a given intersection or at a network level, depending on the desired objective.

Table 1 summarizes several methods used for calculating the intersection performance.

**Table 1. Automated methods to measure performance measures of arterial corridors and intersections**

| <b>Performance measure</b>   | <b>Methods to measure</b>   |
|--|---|
| Delay  | Stop bar and advanced detectors (Sharma and Bullock 2008, Sharma et al. 2007)<br>Video recording (Sharma and Bullock 2008)<br>High-resolution event data (Day and Bullock 2010)   |
| Number of stops  | Connected Vehicle (Argote-Cabañero et al. 2015)<br>Video recording (Fernandes et al. 2015)  |
| (Maximum) queue length   | Stop bar and advanced detectors (Sharma and Bullock 2008, Sharma et al. 2007)<br>Video recording (Sharma and Bullock 2008)<br>Stop bar and advanced detectors (Sharma and Bullock 2008)<br>Probe data (Comert and Cetin 2009)<br>Stop bar and probe data combined (Comert 2013) |
| Arrival type, Arrival rate on green, Degree of intersection saturation, Volume/capacity ratio, Level of progression, Split failure | Stop bar and setback detectors (Smaglik et al. 2007a, Smaglik et al. 2007b)<br>High-resolution event data (Day and Bullock 2010, Day et al. 2010, Day et al. 2014)  |
| Purdue Coordination Diagram  | High resolution event data (Day et al. 2014)  |

Several of these measures rely on sensing/detection methods that are not entirely error-free. For example, methods that utilize vehicle presence data from in-pavement detector loops can underestimate the traffic volume if the queue extends too far beyond the farthest-upstream loop (Smaglik et al. 2007a, Li et al. 2014).

Travel time has been shown to be a consistent measure of corridor performance (Li et al. 2014). Several automated travel time determination methods have been developed, including anonymous wireless address matching (by detecting signals from in-vehicle Bluetooth or Wi-Fi devices), electronic toll tag matching, cellular phone subscriber identity matching, automatic license plate number matching, and probe data from GPS-equipped vehicles or connected vehicles (Turner and Qu 2013, Singer et al. 2013, Venkatanarayana 2017, Quayle et al. 2010, Day et al. 2012).

Many of these methods are based on vehicle re-identification using paired sensors: the upstream sensor observes an in-vehicle device such as a Bluetooth headset, the downstream sensor identifies the same device at a later time, and the sensor-to-sensor distance and time offset are used to compute the vehicle's speed. While several re-identification methods have proven reliable in daily service, they require installation and maintenance of roadside sensors and do not necessarily represent an unbiased sample of vehicles in the traffic stream (Chitturi et al. 2014, Shaw and Noyce 2014). Additionally, some methods have practical limitations. For example, cell phone subscriber identity matching is problematic in the US due to privacy concerns, and toll tag

readers are impractical in Iowa since the state has no tollway system. The use of GPS-based probe data overcomes some of these limitations, since acquiring the data requires no roadside infrastructure, and the process of joining the pool of probe vehicles typically occurs with the consent of the GPS device owner.

An important stream of research has investigated relationships between travel time and travel time reliability for arterials (Remias et al. 2013, Haghani et al. 2010, Hu et al. 2015). In general, these studies define delay as the difference between the actual travel time and the ideal travel time (at free-flow speed) along a corridor. A comparison of the delay values over an extended period of time can be used to compute the travel time reliability of an arterial. Typically, travel times are classified as “reliable” if similar delays are frequent along a corridor, and “unreliable” if the delay fluctuates widely (List et al 2014).

While travel time provides an excellent proxy of traffic conditions within one segment, the measurement has inherent aggregate-level comparison problems (Day et al. 2014). Because different corridors often have varying lengths and individual ideal speed characteristics, travel times must be normalized before an accurate comparison is feasible; therefore, travel time is not optimal for a multi-segment (or corridor-level) analysis. To circumvent this situation, travel rate, or slowness, can be utilized as a performance measure for arterial corridors. The travel rate can be defined as the time needed to traverse one unit of distance along an arterial (for example, minutes per mile). Mathematically, travel rate is simply the inverse of speed.

The use of travel rate as a performance measure provides unique benefits over other methods. In addition to the additive nature of this metric, travel rate can be converted into user delay, which is often the basis for economic analyses of corridors. Travel rate is also easily displayed using a cumulative distribution function (CDF) (Day et al. 2010, Mathew et al. 2017). In one of the closely related studies, the performance of the arterial corridors was ranked based upon a normalized travel rate (Day et al. 2015). The work used the normalized travel rate to determine a composite score based upon the time of day and ranked the different arterial corridors in Indiana. The present study involves the use of such empirical CDF plots of travel rate (travel time per mile) to evaluate the performance of arterial corridor segments.

## **1.6. Conclusion**

Transportation agencies and the public face many challenges related to the operational performance of high-volume arterial corridors. For example, the National Traffic Signal Report Card found unacceptable performance in many signalized corridors, mainly due to underinvestment in updated traffic signal timing (National Transportation Operations Coalition 2012). Resource constraints limit the number and scope of retiming and other interventions by transportation agencies, and it can be difficult to achieve consensus about priorities when arterial corridors cross or straddle jurisdictional boundaries. Consequently, there is a large and growing need for objective performance metrics that agencies can use to prioritize their signal investments.

Arterial performance measurement is a valuable technique for prioritizing signal retiming and other operational improvements on arterial corridors. Many agencies already have access to probe vehicle data suitable for this type of analysis. In Iowa, probe vehicle data suitable for computing arterial performance measures are already being procured from a commercial vendor, compiled in real time, and archived in a database.

Building on the research described in the previous section, CDF plots of the travel rate can be developed to make use of the probe vehicle data. As described in more detail in Chapter 3, this process allows useful arterial performance measures to be derived using the following approach:

- Anomalous days for different segments of the road can be identified. This ensures that all atypical days are removed from the data set so that they do not skew the general performance analysis (Day et al. 2015). Where appropriate, anomalous days can be evaluated separately to identify the extent of the anomalies and potential interventions relevant to unusual situations, such as special events, severe traffic incidents, extreme weather, and construction.
- Performance metrics can be developed using travel time data to identify well-performing and underperforming roadway segments. Relevant performance metrics include the median travel rate (MTR), within-day variability (WDV) of travel rate, and the between-days variability of travel rate (minimum travel rate dispersion [MTD] and two overall travel rate variabilities [OTV\_POLY and OTV\_LINEAR]). If desired, the analysis can be stratified based on the roadway's geometric characteristics, annual average daily traffic (AADT) per lane, intersection density, or similar criteria.

Using the methods defined in this study, agencies could more frequently monitor corridor performance, more easily identify problematic segments, and more quickly identify system management solutions. To support this process, the remainder of this report is organized as follows:

- Chapter 2 reviews the characteristics of the INRIX probe data and discusses some associated performance measures.
- Chapter 3 presents the computational logic of the proposed arterial performance monitoring methodology.
- Chapter 4 presents a case study that was performed by applying the methodology to several arterial corridors in the Des Moines, Iowa and Omaha, Nebraska areas and discusses a separate analysis of the impact of implementing adaptive signal control on an arterial corridor in Des Moines.
- Chapter 5 reviews the results of the analytical process and presents some recommendations for future work.

- The appendices present additional details of the methodology's mathematics, along with detailed performance metric scores for each of the corridors used in the case study.



## **CHAPTER 2. PERFORMANCE MEASURE USING VEHICLE PROBE DATA**

This chapter provides a detailed description of the INRIX probe data purchased by the Iowa DOT, followed by a literature review covering probe data accuracy and probe data applications.

### **2.1. INRIX Data**

This study used the real-time traffic data provided by INRIX and purchased by the Iowa DOT. INRIX data represent a fusion of real-time and historical traffic speed data. The historical data are used to predict the speed and travel time when the real-time data are not available. The product merges data from several sources, most notably real-time GPS probe data from approximately 650,000 commercial vehicles operating in the US. Real-time information from participating vehicles that are traveling on a specific road segment during a particular time window is combined with other real-time data available to the company, such as roadside speed sensor data gleaned from data feeds provided by transportation agencies.

Since there are hundreds of thousands of roadway segments in each state, not every segment will have a participating probe vehicle operating on it at all times. When real-time data are unavailable, the product estimates the traffic speeds based on historical data from similar days and times, adjusted for any travel conditions known to the vendor, such as construction, road closures, traffic incidents, sporting and entertainment events, weather forecasts, and school schedules.

A proprietary data fusion algorithm gathers all input points, weights them based on input quality and latency, and calculates (or estimates) the speed occurring on each road segment in the network. The vendor also provides an index intended to indicate the accuracy of each segment-level speed estimate. For example, a speed based on real-time data from several participating vehicles will receive a better confidence score than one based purely on historical data. Consequently, speeds at peak hours on high-volume corridors tend to receive better confidence scores than those for off-peak periods on low-volume roads.

#### *2.1.1. INRIX Data Format*

The INRIX data utilized for this project was provided to the research team in a comma separated value (.csv) format. The available data fields are shown in Table 2.

**Table 2. Examples of INRIX data**

| <b>XD segment</b> | <b>Speed</b> | <b>Date-time</b>    | <b>Confidence</b> | <b>C-value</b> | <b>Average speed</b> | <b>Reference speed</b> | <b>Travel time</b> |
|-------------------|--------------|---------------------|-------------------|----------------|----------------------|------------------------|--------------------|
| 63366025          | 60           | 2016-01-30T09:10:00 | 30                | 100            | 58                   | 60                     | 0.7                |
| 63366025          | 61           | 2016-01-30T09:10:00 | 20                |                | 57                   | 60                     | 0.6885             |
| 63366025          | 62           | 2016-01-30T09:10:00 | 10                |                | 58                   | 60                     | 0.6774             |
| 63366025          | 65           | 2016-01-30T09:10:00 | 20                |                | 55                   | 60                     | 0.6461             |
| 63366025          | 63           | 2016-01-30T09:10:00 | 20                |                | 59                   | 60                     | 0.6666             |
| 63366025          | 36           | 2016-01-30T09:15:00 | 30                | 80             | 56                   | 60                     | 1.1667             |
| 63366025          | 66           | 2016-01-30T09:10:00 | 20                |                | 54                   | 60                     | 0.6364             |

The data set was quite large. For example, for the entire year of 2016, the average monthly size of 27,000 segments spread across Iowa has a size of around 120 gigabytes (GB). The fields are as follows:

- **XD segment.** In the late 1980s and early 1990s, a roadway segmentation system called Traffic Message Channels (TMCs) was developed to support radio traffic alerts. The system subsequently became an international standard (ISO 14819-3). It assigns 16 bits for TMC segment codes, allowing a maximum of 65,535 segments per state (ISO 2013). As a result, TMCs represent long roadway segments (typically from interchange to interchange on freeways, or from one major intersection to the next on arterials). To provide more granular information, INRIX has divided each TMC into shorter segments called XDs. The XD segments used in this analysis are generally 0.2 to 1.2 miles long and tend to cover 0 to 7 intersections along an arterial corridor.
- **Speed.** This represents the speed for the segment in a certain time interval. For example, in Table 2, the speed for segment #63366025 at 09:10 a.m. on 01/30/2016 was 60 mph.
- **Date-time.** This represents the date and the time at which the speed is recorded for that segment. For example, the second to last line of Table 2 represents a speed of 36 mph on segment 63366025 on 01/30/2016 at 09:15 a.m.

- **Confidence.** This attribute is an indicator of the vendor’s confidence in the accuracy of the reported speed. It is provided by INRIX using three levels: 10, 20, and 30. A confidence value of level 30 indicates that enough base data were available to estimate the traffic conditions in real time, rather than using either historical speed based on time-of-day and day-of-week (level 20 data) or free-flow speed for the road segment (level 10 data).
- **C-value.** This is a confidence value (0–100) designed to help agencies determine whether the INRIX value meets their criteria for real-time data. A confidence level of 30 will generally have a C-value score associated with it.
- **Average speed.** This is the historical average mean speed for the reporting segment for that time of day and day of the week in miles per hour.
- **Reference speed.** This represents the segment’s speed under uncongested or “free-flow” conditions. It is determined for each TMC segment using the INRIX traffic archive.
- **Travel time.** This is calculated in the same manner as the speed. The unit here is in minutes.

## 2.2. Probe Data Accuracy Studies

Several studies have evaluated the accuracy of vendor-supplied probe data and their associated performance measures. Typically, the studies compare archived data from the vendor’s probe data feed with ground truth data from specially instrumented vehicles or roadside speed sensors. In general, the studies seem to suggest gradual, long-term improvement in probe data accuracy, which is consistent with increasing numbers of in-vehicle, GPS-enabled devices to serve as raw data sources. Some examples of these studies are listed below in chronological order:

- The concept of using probe data to evaluate freeway performance emerged in the mid-1990s, but very little probe data were actually available for research at that time. For example, a 2003 study used simulated probe data to establish traffic volume, space mean speed, and density measures for a 3.5 mile freeway segment near Tokyo, Japan (Nanthawichit et al. 2003). Fixed-detector data were combined with the simulated probe-vehicle data to determine whether robust travel time metrics could be computed by combining both of them. The authors concluded that this would result in a mean absolute relative error (MARE) of about 0.04. The results were only validated using a single freeway section, and potential sources of bias in the probe data were neglected.
- One of the largest early applications the probe based data in the United States was the I-95 Corridor Coalition’s Vehicle Probe Project. Currently, the probe data is used by 19 different agencies. They also provide travel times for dynamic message signs in states of Maryland, North Carolina, and South Carolina. A study of the I-95 coalition’s project showed that there was improvement in the accuracy of the commercial probe data as compared to the Bluetooth

reference data. The improvement of the data was shown by accuracy in capturing vehicle slowdowns (Sharifi et al. 2016).

- When probe data became commercially available, transportation agencies were very interested in benchmarking their accuracy. Variable levels of amplitude bias between probe data and benchmarked data were found. Although the speeds from probe data were generally reliable, speeds on segments less than one mile long were not reliable on freeways (Haghani et al. 2010, Haghani et al. 2009). The probe data set tended to overestimate speed when the actual speed was below 45 mph and underestimate it when the actual speed was above 60 mph. (During this era, INRIX relied heavily on raw data from trucking fleets, which were mainly vehicles equipped with speed governors set at about 68 mph.)
- In recent years, another study has computed absolute average speed error, average speed bias, absolute average travel time error, and travel time bias measures to show that probe data sets from Navteq, TrafficCast, and INRIX were all generally consistent with the ground truth data (Florida DOT 2012, Lattimer and Glotzbach 2012). The roadways consisted of freeways, state highways, and arterials in the Tallahassee, Florida region. INRIX data on one of the interstate routes were more accurate than the other probe data sets.
- Nevertheless, INRIX TMC segments located in urban areas had a larger variation of the performance metrics.
- A study that compared speeds from probe data and Bluetooth sensors showed that probe data were consistent with ground truth (obtained from video), with the variation within 6%. The probe data were slightly more accurate than the Bluetooth sensors. (Li 2013).
- Although probe data sets are often marketed as “real-time” data, there is inherently some latency (time lag) between the collection of GPS coordinates by in-vehicle sensors and transmission and processing of these coordinates by the data vendor’s servers. A study of this latency on 14 miles of urban interstate freeway determined that speeds from the probe data tend to lag loop detector speed by 6 minutes (Kim and Coifman 2014). Although INRIX reported speed every minute, very often the reported speed was identical to the previous sample, suggesting that the company was calculating speeds over a longer time period than it used to report the speeds. The confidence measures reported by INRIX did not seem to reflect the latency or the occurrence of repetition of speeds.
- A three-way comparison of travel times for a 4.2 mile suburban corridor in Oregon showed speed deviations that varied by time of day. At mid-day the INRIX estimates were either within 0.36 minutes or 22% of the ground-truth probe runs, while the Bluetooth estimates during the p.m. peak were either within 1 minute or 24% of the ground-truth probe runs (Alhajri 2014). Both data sources were deemed accurate enough to be used for analysis. The study also found that probe data tends to have a steady latency.

- Recent studies using INRIX data to derive speed bias, latency, and a similarity index found that the data was reliable for monitoring the performance of transportation infrastructure over time (Adu-Gyamfi et al. 2017, Adu-Gyamfi et al. 2015). Latency measurements on freeways and non-freeways were identified to be 12 and 8 minutes, respectively. Short-term events (duration less than 30 minutes) were detected at an accuracy of 74% and 63%, while long-term events (duration 1 to 3 hours) were detected at an accuracy of 95% and 68% on freeways and non-freeways, respectively.

### **2.3. Probe Data Applications and Associated Performance Measures**

Numerous studies have reported applications of probe data for performance assessment. Although some of these studies address arterial corridors, most focus on freeway performance. Some examples are summarized below:

- An early study developed several metrics for freeway speed performance reporting (Lomax et al. 2003). These included the travel time window, percent variation, variability index, displaying variation, buffer time, buffer time index, planning time index, travel rate envelope, on-time arrival, and misery index, each of which was assigned specific mathematical definitions. The study described travel time reliability as a measure of the amount of congestion that transportation system users experience at a given time. An important limitation of this early demonstration was the small number of probe vehicles, which resulted in data quality issues.
- Short-term travel time predictions have also been found to be useful (Fabritiis et al. 2008). The authors used the live travel time obtained from the probe-based floating car data and showed that the 15-minute speed prediction can be made with a mean absolute percentage error (MAPE) of 2% to 8% on the Rome, Italy ring road.
- Travel time reliabilities and level of service are some of the other measures derived from the bus-based probe data obtained from the Ministry of Land, Infrastructure, Transport and Tourism operating over arterials and other motorway (Uno et al. 2009).
- By the early 2010s, probe-based travel time monitoring for freeways was becoming fairly routine. Performance metrics such as the 95th percentile travel time, standard deviation, coefficient of variation, percent variation, skew statistic, buffer index, planning time index, frequency of congestion, failure rate, and travel time index were used (Pu 2011). Some of these metrics were more salient than others. For example, the coefficient of variation was found to be a good alternative to other reliability measures (such as the planning time index, median-based buffer index, and skew statistic). Computational refinements were suggested, such as computing the buffer index and failure rate with respect to the median (instead of the mean) to prevent abnormal data points from unduly affecting the metrics.
- Several studies have described the use of probe data to evaluate freeway work zone performance. For example, a 2012 study computed the 95th percentile travel time, buffer

time index, and planning time index. It concluded that the probe data provided enough information to show that certain interventions increased travel time reliability in the studied work zones (Edwards and Fontaine 2012). The study drew attention to the importance of segmentation, as its accuracy was hampered by the fact that the TMC segments did not perfectly match the start and end of the work zones.

- Travel speed, travel delay, annual person delay, annual delay per auto commuter, total peak period travel time, travel time index, planning time index, commuter stress index, roadway congestion index, number of rush hours, and percent of daily and peak travel in congested conditions were used as performance measures to detect congestion during the midday, night, and weekend time periods over the entire state of Texas (Schrack et al. 2015, Schrack et al. 2011).
- Congestion hours, congestion index, location ranking, and user delay costs have been used to compare highway corridors at a regional or statewide scale (Brennan et al. 2013). This work provided elaborate route assessments to identify the location of operational problems and the impacts of congestion improvement measures, with proposed methodologies that can be used at a state agency level. The methodology assumed that if the segment speed dropped to zero during a 15-minute analysis period, then the volume was very low and the traffic speed was equal to the speed limit. Another limitation of the methodology was that congestion was calculated using a fixed threshold of 45 mph. A Florida study used probe data to calculate highway travel time reliability, vehicle hours of delay, and percent of miles severely congested (Florida 2013). Mobility performance measures were grouped into quantity, quality, accessibility, and utilization. As with the Brennan study, a major limitation was that the travel rate reliability on freeways was defined using a fixed threshold of 45 mph.
- Speed information from probe data was used in combination with data clustering and genetic programming to develop a dynamic travel time prediction model for a freeway. (Elhenawy et al. 2014).
- A freeway patrol service model was developed to manage incidents, help disabled vehicles along congested freeway segments, and reduce nonrecurring congestion through fast response to crashes using vehicle miles traveled, vehicle hours traveled, and traffic delays derived from probe data and a portable emissions measurement system (PEMs) (Mauch et al. 2014).
- Analysis of probe data found that traffic jams on highways were better identified than those on other streets (Belzowski and Ekstrom 2014). The study also found that jams of longer duration had more probability of being accurately identified by probe data. Operational delays in the study area might have caused some biases in the results.
- A study in Washington reported congested lane-miles, cost of delay, and the travel time index to flag areas with congestion and delays (WSDOT 2014). Congestion was assumed to occur when the speed fell below 70% of the posted speed limit. Delays were defined on the

basis of maximum throughput speeds (85% of posted speed limit). Travel time index was calculated using reference speed rather than free-flow speed.

- Probe data has been used to estimate level-of-service for intersections, arterial segments, and freeways (Mahapatra et al. 2015).
- Several new performance metrics have been suggested in recent years, including congestion hours, distance-weighted congestion hours, congestion index, speed profile, speed deficit, travel time deficit, and congestion cost (Remias et al. 2013, Mekker et al. 2016). For freeways, it was asserted that the addition of crowd-sourced data (from consumer GPS devices) resulted in improved INRIX data granularity and accuracy.
- Probe data were used to compute the percentage of on-time arrival for freeways and arterials (Venkatanarayana 2017). This was calculated as the proportion of days when peak period travel time was less than 1.1 times the mean peak period travel time. More traditional measures such as delay per vehicle, total delay, travel time index, buffer index, planning time index, misery index, and congested travel were also derived in the study. Vehicle costs, delay, and work zone queue length were used to calculate and visualize speed and delay associated with work zones both spatially as well as temporarily (Chien et al. 2017). The tool named Work Zone Interactive Management Application-Planning (WIMAP-P) was developed to examine the impacts of construction staging by location, time of day (peak versus off-peak), and season (summer versus winter). The authors (Chien et al. 2017) concluded that the methodology could be refined by replacing the TMC segments with shorter XD segments.
- Travel time reliability, planning time index, and frequency of congestion have been used to identify and rank recurrent freeway bottlenecks (Gong and Fan 2017). Challenges remain in identifying the degree of congestion or the intensity of bottlenecks.
- Recent work has explored the use of speeds from probe data as a surrogate for estimating the hourly traffic volume (Sekuła et al. 2017). This study proposed that by using probe data, the traffic volume prediction can be improved by 26% as compared to the present estimates by volume profiles.
- Traffic data vendors have published a number of national-level analyses aimed at demonstrating applications of their data to potential customers. For example, INRIX used the annual hours of delay per mile, hours of target delay per mile, travel time index, and planning time index to identify cities and corridors with severe congestion (INRIX 2017). Performance measures for arterial roads compare the peak-traffic to light-traffic conditions, based on the assumption that the “normal” performance of an arterial is under light traffic conditions. The resulting lists of “most congested cities” and “worst traffic hotspots” were deemed newsworthy by several media outlets.

- The Second Strategic Highway Research Program (SHRP2) also uses the probe based data to calculate the travel time reliability (Sadabadi et al. 2015). The program's research tried to add a value to the travel time reliability study conducted in Maryland using a cost-benefit analysis. In another study by a SHRP2 project in Portland, the estimation and use of travel time reliability was analyzed for multi-modal corridor analysis (University of Arizona 2015). They also tried to find a value to travel time variability and tried to spread its importance to similar policy groups.
- Probe-based study is being intensively carried out for Iowa (REACTOR 2018). The Realtime Analytics of Transportation Data (REACTOR) Laboratory has developed tools such as an analysis of mobility performance over the past six years, interstate and metro congestion comparisons, and speed profiles on interstates throughout Iowa. Data quality checks are also being performed on the probe-based INRIX data.

Taken together, these studies indicate that in spite of its technical limitations, probe data from commercial vendors is a practical source of data for a wide range of traffic performance and congestion analyses. To date, the majority of probe data applications have been oriented toward freeway corridors, with arterial performance monitoring emerging as an important new category of applications.



### CHAPTER 3. METHODOLOGY

This chapter describes the proposed methodology for developing arterial performance measures based on probe data (see Figure 1). The details of each step are covered in the sections that follow.

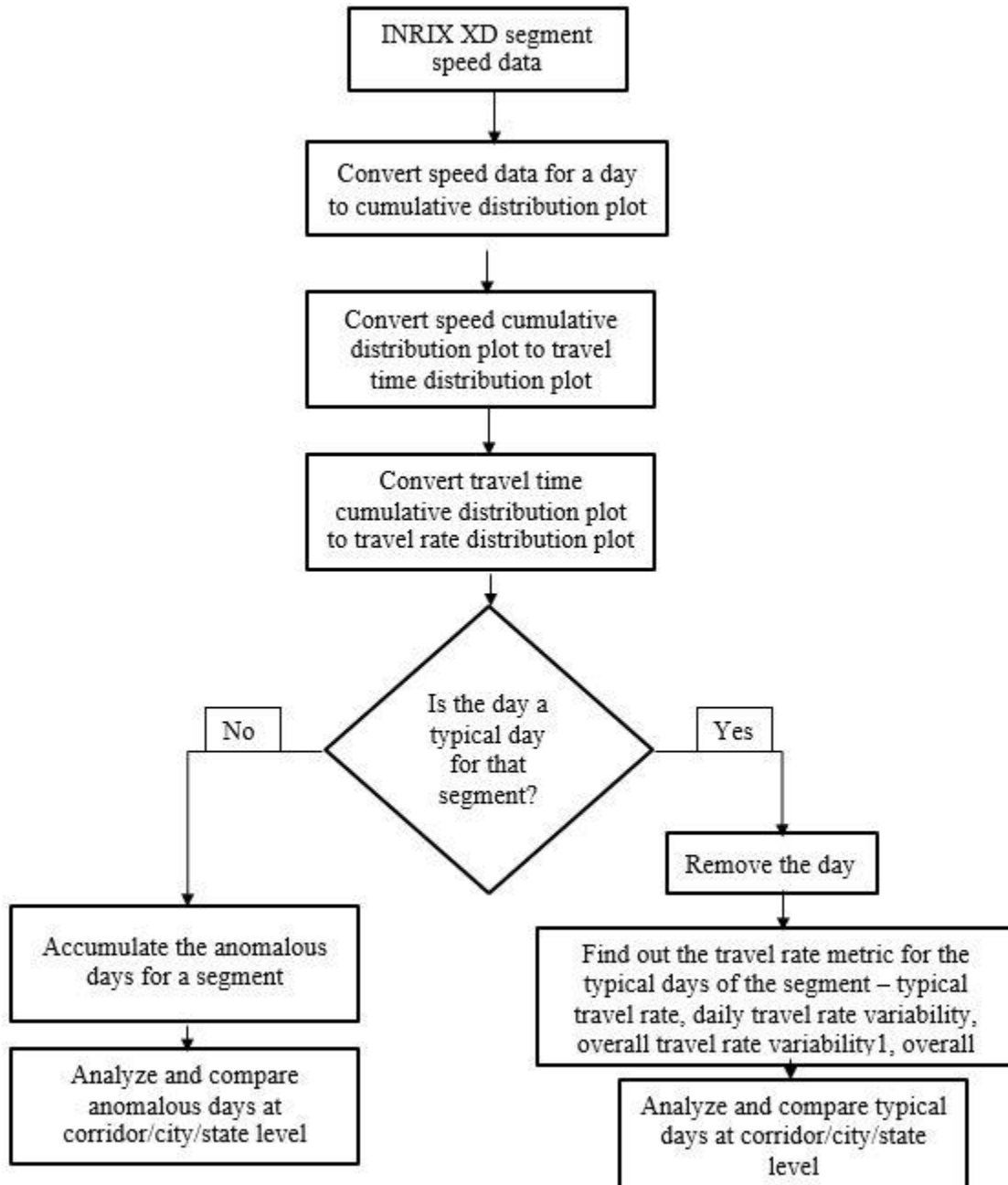


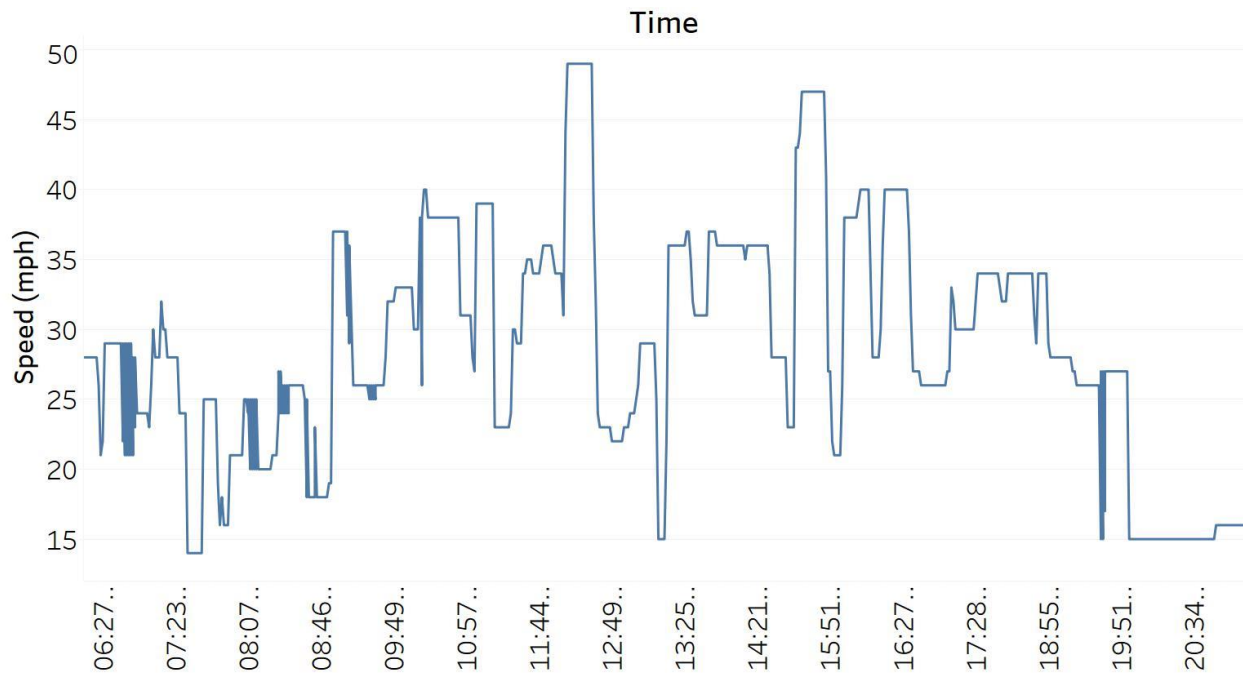
Figure 1. Flowchart of the methodology

### 3.1. INRIX XD Segment Speed Data

INRIX XD probe data were used as the basis for the arterial performance comparison. The data set was purchased by the Iowa DOT and shared with the research team, where it resides in the high-performance computing (HPC) cluster at the Institute for Transportation’s REACTOR Laboratory in Ames, Iowa. Days with more than 100 speed counts were taken into the analysis to ensure that each percentile of speed is composed of separate values.

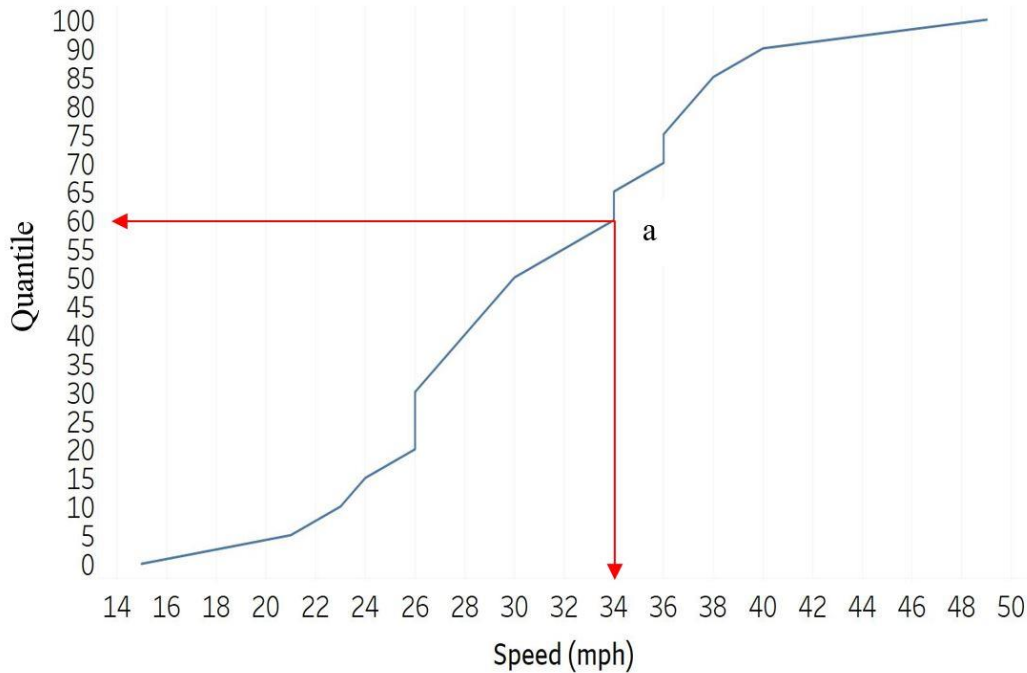
### 3.2. Convert Speed Data for a Day to Cumulative Distribution Plot

Traditionally, the hour-by-hour or minute-by-minute speed profile for a specific location in the traffic network has been represented in the format shown in Figure 2, with speed plotted on the vertical axis and time-of-day on the horizontal axis.



**Figure 2. Distribution of speed for a certain day**

This information was converted to a cumulative distribution plot (CDF) as shown in Figure 3.



**Figure 3. Cumulative distribution function plot for speed**

The CDF plot indicates the probability that the speed falls below a certain value. For example, if the 60th percentile is 34 mph (Point “a” in Figure 3), it means that the probability of vehicles traveling at a speed below 34 mph is 0.6 (the speed was less than 34 mph 60% of the time).

The shape of the CDF plot provides a quick indication of a roadway segment’s reliability during the analysis period. The flatter the curve, the less reliable the speed is for that segment. CDFs have an important drawback: the temporal speed variation pattern is lost in the conversion process. Nevertheless, since the main purpose of this study was to evaluate the overall performance of each segment, the CDF plot was quite useful.

### 3.3. Convert Speed Cumulative Distribution Plot to Travel Time Distribution Plot

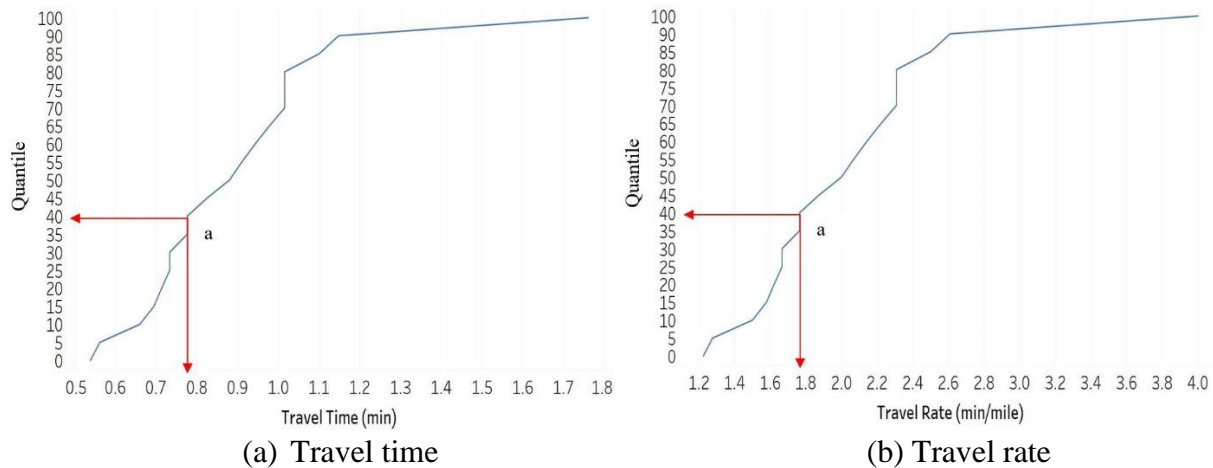
The disadvantage of speed CDF plots is that they represent the speed performance for individual roadway segments—not for a corridor as a whole. For instance, if an arterial corridor is made up of four segments, the speed CDF for an individual segment might be better or worse than the performance of the entire corridor. For this reason, *speed* CDFs were converted to *travel time* CDFs. Travel time CDFs are simpler to use, and their additive nature allowed computation of corridor-level performance measures.

A travel time CDF was obtained by simply dividing the length of the segment by the speed. Figure 4(a) represents the CDF plot for travel time using the speed CDF obtained in Figure 3. Thus, what was previously point “a” in Figure 3 becomes point “a” in Figure 4(a). Travel time

CDFs can be used directly to compute performance metrics such as the buffer time index and planning time index.

### 3.4. Convert Travel Time Cumulative Distribution Plot to Travel Rate Distribution Plot

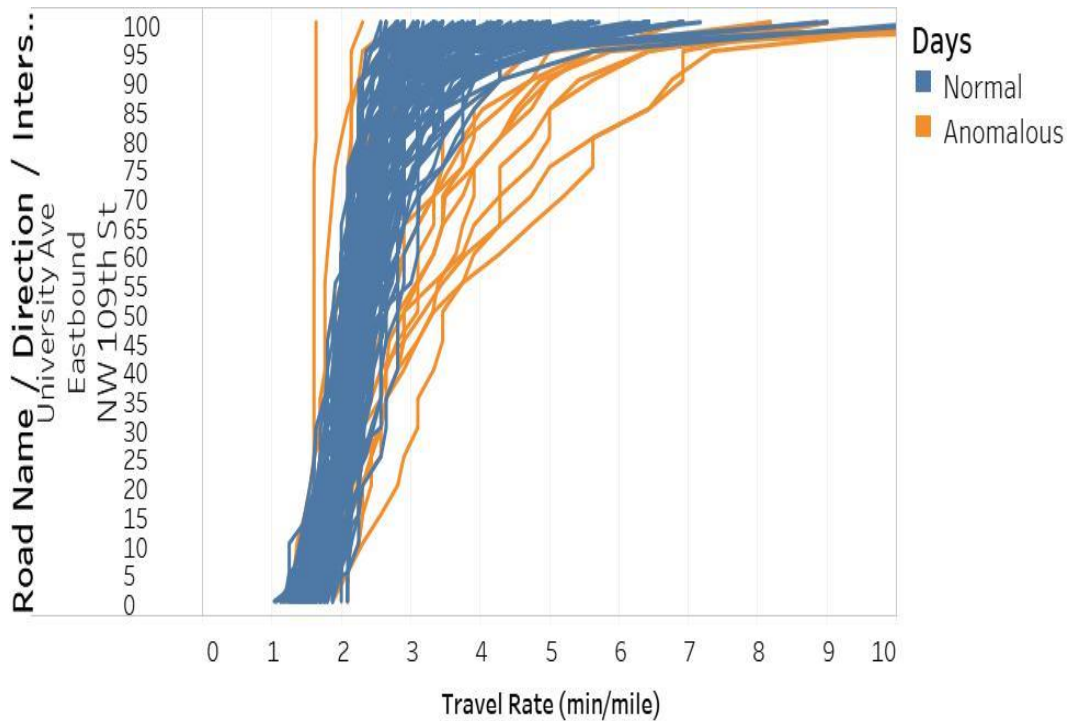
The travel time CDF is a very useful plot with a small drawback: it cannot compare segments of unequal length. As indicated in Chapter 2, the length of INRIX XD segments ranges from 0.2 to 1.2 miles, so there was a need to normalize the travel time CDF. This was done by converting travel time to travel rate (travel time per mile). For instance, a travel rate of 1.2 mile/minute means that 1.2 miles on that segment can be covered in 1 minute. (Mathematically, travel rate is the reciprocal of speed; thus, a travel rate of 1.2 miles per minute is equivalent to an average speed of 72 mph). Travel rate is a very powerful metric as it allows comparison of all segments, irrespective of their length. Figure 4(b) represents the travel rate CDF for the travel time CDF plotted on Figure 4(a). The shape of the curve is identical to the travel time CDF, except for scale on the horizontal axis. Point “a” on Figure 4(a) gets transferred to an identical point in Figure 4(b).



**Figure 4. Cumulative distribution plots related to travel**

### 3.5. Is the Day a Typical Day for that Segment?

Having obtained the travel rate CDF, the next step was to find out whether the day was an anomalous day for that segment. For this reason, the daily CDF plots of travel rate were accumulated for the entire segment and an anomalous detection algorithm was run on them. The details of the algorithm can be found in Appendix A. Figure 5 represents the comparison of the anomalous or atypical days from the normal or the typical days.



**Figure 5. Anomalous and normal days for segment near NW 109th Street, eastbound on University Avenue**

Anomalous days can be defined as those days where the performance is far from the normal behavior of the segment. Such days should be removed before further analysis to avoid skewing the results of the rest of the analytical process.

### 3.6. Accumulate the Anomalous Days for a Segment

This step was rather straightforward: simply accumulate the anomalous days obtained in the previous step.

### 3.7. Analyze and Compare Anomalous Days at Corridor/City/State Level

Anomalous roadway performance usually has an underlying cause, such as a traffic incident, road construction project, special event, or holiday. To explore the causes of anomalies, it was necessary to accumulate them across a corridor level. The analysis of anomalies (and similarities) can be carried out at various levels of aggregation: corridor level, regional level, state level, or even national level.

Analysis of the prevalence of anomalous performance can help agencies determine whether interventions aimed at improving traffic flow have been effective. For example, in Iowa, heavy traffic tends to occur near suburban shopping centers in the days before Christmas. These conditions could be used to help assess the performance of an intervention such as an adaptive signal control system. If the proportion of anomalous segments in adaptive corridors is less than

the proportion in corridors with non-adaptive control, then it is possible to conclude that the adaptive control system helped improve traffic flow during the holiday period.

The extent of anomalous performance is also a measure of the dynamic nature of an individual segment. If a segment has many anomalous days, then it can be said that its traffic patterns are more dynamic than other segments in the study area.

### **3.8. Remove the Day**

This was also a simple step: remove the anomalous or atypical day for the remaining analysis.

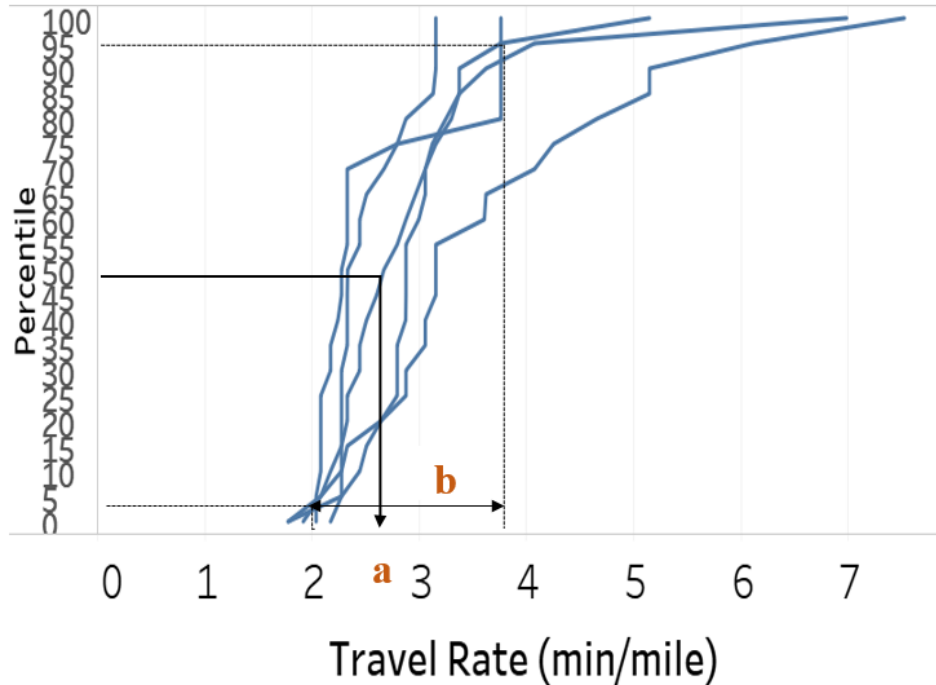
### **3.9. Compute Travel Rate Performance Metrics for Typical Days for the Segment**

The performance metrics analysis were computed for those locations that had more than 100 typical days. This was to ensure that the observations were independent of one another. These were the five parameters:

- Median travel rate (MTR)
- Within-day variability (WDV)
- Minimum travel rate dispersion (MTD)
- Overall travel rate variability polynomial (OTV\_POLY)
- Overall travel rate variability linear (OTV\_LINEAR)

The metrics were defined as follows:

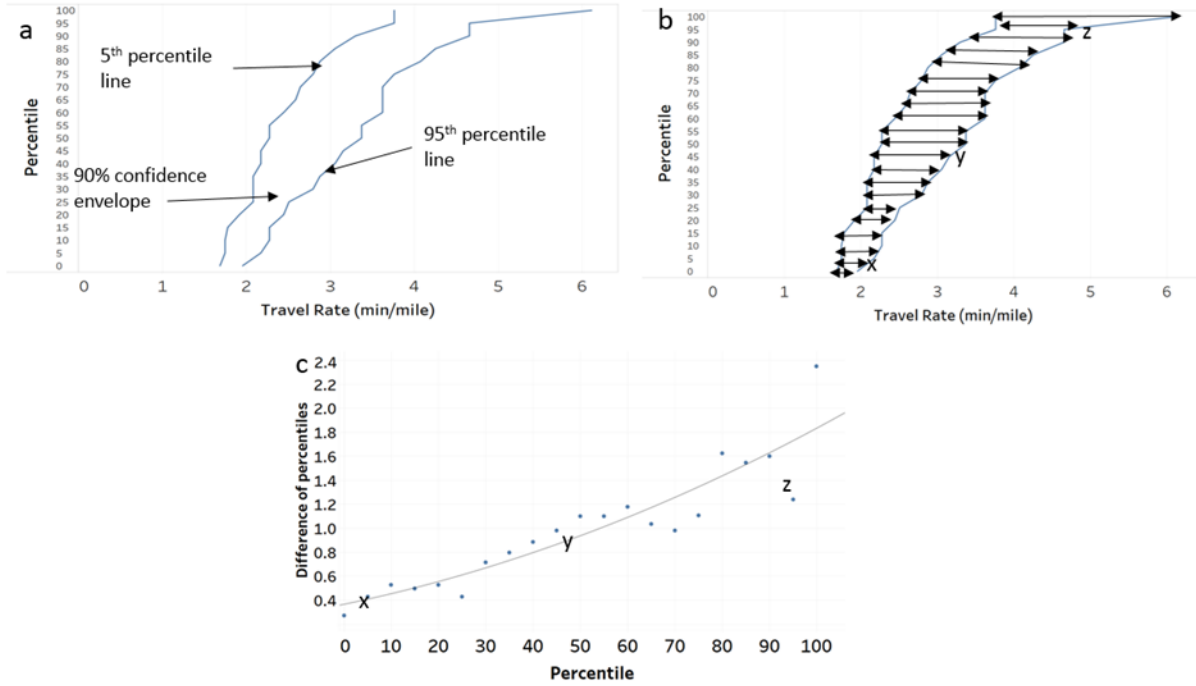
- **Median travel rate.** The MTR, as the name suggests was the median time required to cross one mile of the segment. It was obtained as the 50th percentile of the median of each day's travel rate. The median travel rate is shown as point "a" in Figure 6 below.
- **Within-day variability.** The WDV was the difference between the median of the 95th percentile and the 5th percentile of a segment. It was a measure of the daily variability expected on a segment. This metric tried to capture the variation within a day. High WDV values meant that there was a lot of fluctuation in travel rate for that segment. The WDV for a segment is shown as point "b" in Figure 6.



**Figure 6. Plot showing the MTR as point “a” and WDV as point “b”**

- Minimum travel rate dispersion and overall travel rate variabilities.** The zeroth percentile on the travel rate CDF curve represented the minimum travel rate possible for the segment. Thus, it was a representation of the free flow speed of the segment. The hundredth percentile corresponded to the maximum travel rate possible; that is, the condition corresponding to the heaviest traffic condition in a day. Generally, the travel rate for a segment, over different days, was expected to have similar minimum travel rate at free flow speed while the maximum travel rate was expected to be influenced by the traffic on the segment. To capture these, the overall travel rate was used with three parameter coefficients, which were determined through statistical interpolation (curve fitting) based on the daily travel rate data for each segment.

First, the statistical 90% confidence envelope was obtained. This was done by plotting the 5th and 95th percentiles of the travel rate CDF data. Observations falling between the 95th and 5th percentile bound lines were retained to establish the 90% confidence interval as shown in Figure 7.



**Figure 7. Figures showing (a) the 95% and 5% confidence lines and the 90% envelope, (b) the difference between the 95th percentile and the 5th percentile lines, and (c) the quadratic plot using the difference of the 95th and 5th percentile lines**

Next, intermediate quantiles differences were calculated at each 5% interval for 21 percentiles (0, 5, 10, and so on), and a second degree polynomial equation (quadratic) was fitted to the resulting data points as shown in Figure 7. Thus, the points x, y, and z change accordingly from Figure 7(b) to Figure 7(c). The equation is as follows:

$$Y = Ax^2 + Bx + C \tag{1}$$

The resulting coefficients A, B, and C are the OTV\_POLY, OTV\_LINEAR, and MTD values, respectively.

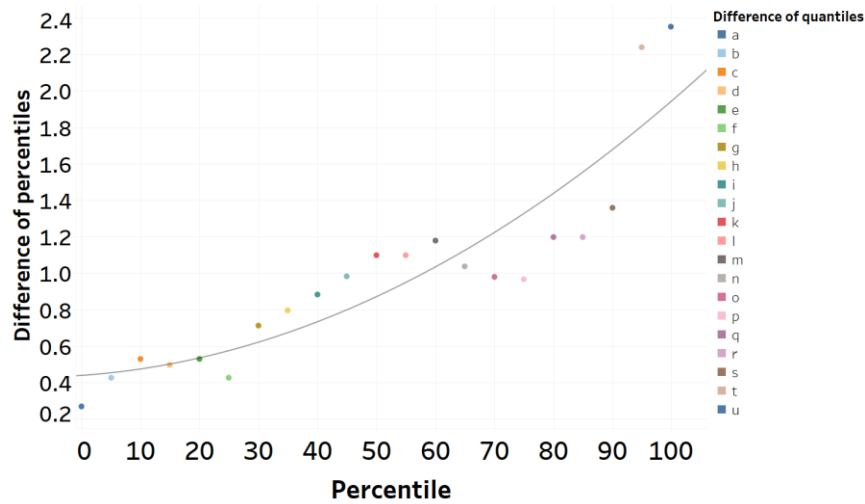
Coefficient C explained the difference between the two lines at the 0th percentile and was referred to as the minimum travel rate dispersion (MTD). The MTD can be thought as a measure defining the range of minimum possible travel rates (maximum possible speed) with which a vehicle could move on that segment on different days. Coefficients “A” and “B” represented how the 90% envelope was changing linearly and quadratically, respectively. They were referred to as the overall travel rate variability polynomial (OTV\_POLY) and overall travel rate variability linear (OTV\_LINEAR), respectively.

The coefficient A represented the quadratic nature of the change of quantiles while the coefficient B represented the linear change of quantiles. The OTV\_POLY showed the change of the difference while the OTV\_LINEAR showed the rate of change of difference of travel



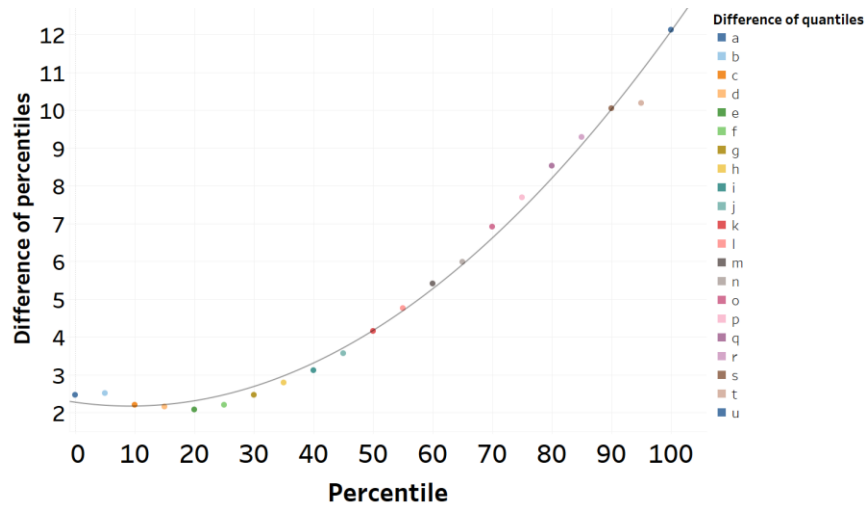
rate at different quantiles. Since one expects the maximum travel rate to vary widely as compared to the minimum travel rate, the following cases are possible for these parameters:

- Both OTV\_POLY and OTV\_LINEAR are positive. This meant that the difference of travel rate was very high at the lower travel rate (higher speed) and very low at the higher travel rate (lower speed). The rate of the difference of travel rate kept on increasing. An example is shown in Figure 8.



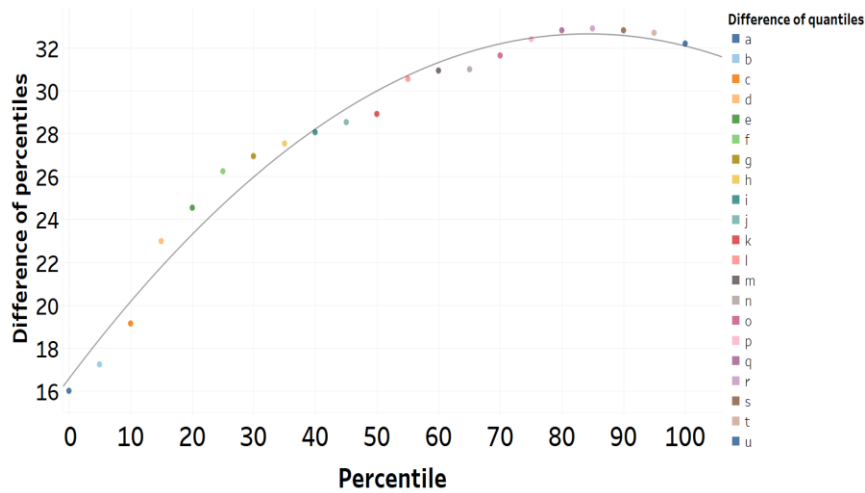
**Figure 8. Difference of percentiles versus percentile when OTV\_POLY and OTV\_LINEAR are positive**

- OTV\_POLY is positive and OTV\_LINEAR is negative. The detail of such a case depends upon the focus of the parabola. The following subcase can occur:
  - Focus is between 0 and 100. The difference of percentile first decreases until the focus and then increases as shown in Figure 9.



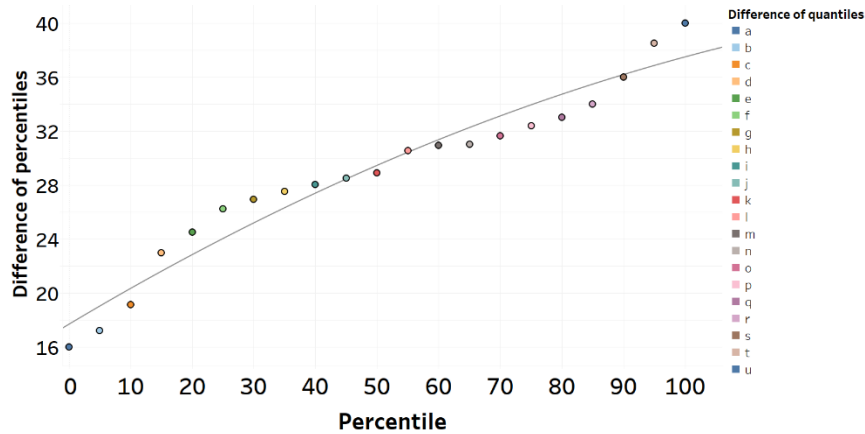
**Figure 9. Difference of percentiles versus percentile when OTV\_POLY is positive, OTV\_LINEAR is negative, and focus is between 0 and 100**

- OTV\_POLY is negative and OTV\_LINEAR is positive. The detail of such a case depends upon the focus of the parabola. The following subcases can occur:
  - Focus is between 0 and 100. The difference of percentile first increase until the focus and then decreases as depicted in Figure 10.



**Figure 10. Difference of percentiles versus percentile when OTV\_POLY is negative, OTV\_LINEAR is positive, and focus is between 0 and 100**

- Focus is beyond 100. The difference of travel rate keeps on increasing. However, the rate of increasing decreases. Such a plot is shown in Figure 11.



**Figure 11. Difference of percentiles versus percentile when OTV\_POLY is negative, OTV\_LINEAR is positive, and focus is more than 100**

### 3.10. Analyze Days at Corridor/City/State Level

Having obtained the five parameters for each segment, the next task was to analyze them at a broader level. Since each segment had different traffic flows and different numbers of intersections, they needed to divide based upon the following geometric parameters: AADT per lane and number of intersections per segment. To divide them into a similar geometric performance, a mean-shift clustering algorithm was used. Based upon this, each cluster was analyzed separately and the low, normal, high, and anomalous segments were identified among each of them. Another mean-shift was run to determine the performance of the segments in that geometric cluster.

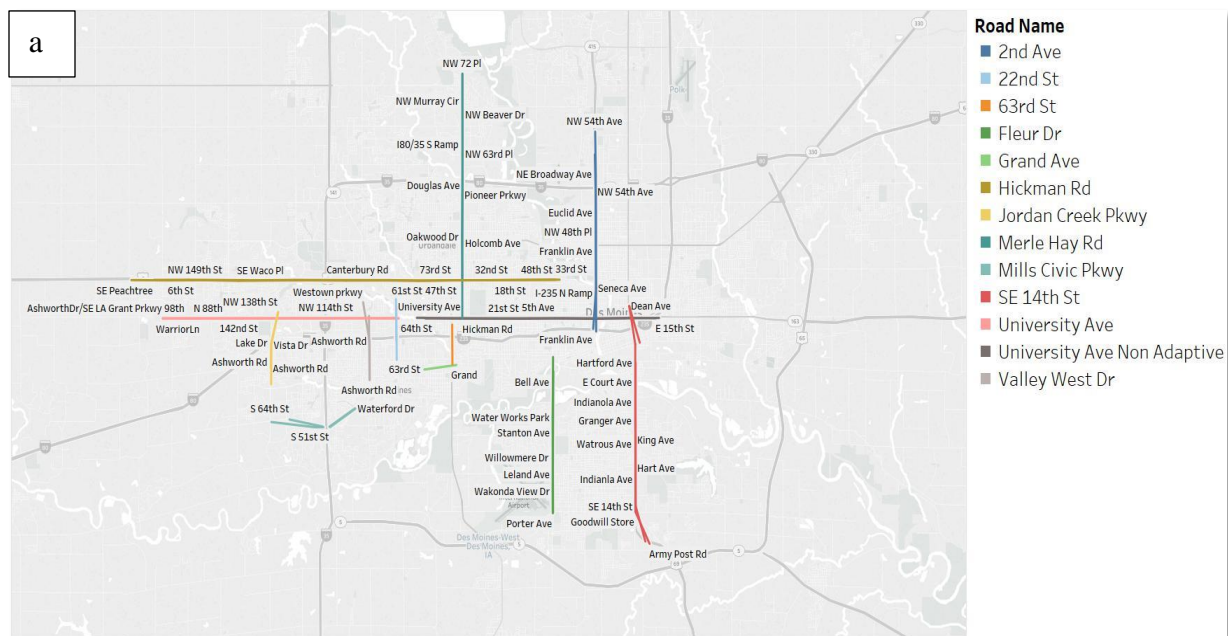
## CHAPTER 4. CASE STUDY: DES MOINES, IOWA AND OMAHA, NEBRASKA

A case study is presented in this Chapter to illustrate the use of the data sources and analytical methodology described in the previous chapters of this report.

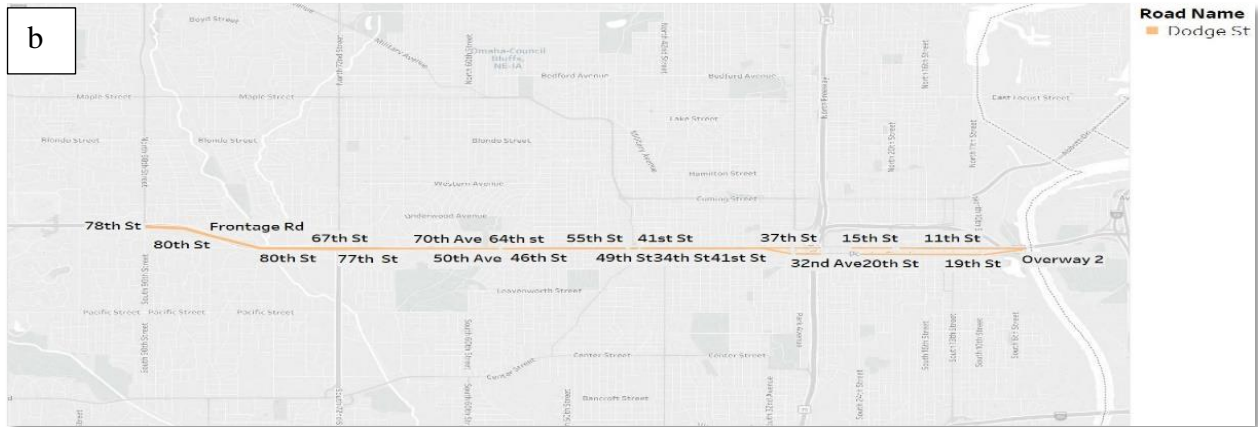
### 4.1. Corridor Locations

The Iowa DOT and Nebraska DOT procured the INRIX XD data sets described in Chapter 2. A case study was conducted to demonstrate the use of these data for arterial performance evaluation. Twelve major arterial corridors in the greater Des Moines area were considered: 2nd Avenue, 22nd Street, 63rd Street, Fleur Drive, Grand Avenue, Hickman Road, Jordan Creek Parkway, Merle Hay Road, Mills Civic Parkway, Southeast 14th Street, University Avenue, and Valley West Drive. In addition, the Dodge Street corridor in Omaha was analyzed using six months of data to compare the performance of the Des Moines corridors with a busy street in another Midwestern city.

Figure 12(a) illustrates the Des Moines corridors and their color codes. Figure 12(b) shows the Dodge Street corridor in Omaha.



(a) Des Moines, Iowa



(b) Dodge Street corridor in Omaha, Nebraska

**Figure 12. Locations included as part of the case study**

A total of 147 roadway segments were analyzed, spread over the 13 corridors. This included 29 segments on the 5 corridors equipped with adaptive signal control. The analysis was conducted using only days that had real-time data observations (INRIX confidence level 30) for at least 100 counts for each day. Performance was evaluated only for the 6:00 a.m. to 9:00 p.m. time periods. This limitation was necessary because the INRIX night time data were few, and the adaptive signals are generally not implementing special timing plans during low-volume night time hours.

Based upon the methodology described in Chapter 3 the analyses described below were completed.

## 4.2. Anomaly Detection

The count of anomalous days is an indicator of the dynamic nature of a roadway segment. If a segment has many anomalous days, it means the travel rate varies widely over the course of the year. Figure 13 shows the “top 15” segments, i.e., those with the most anomalous days, and Table 3 lists them in rank order.

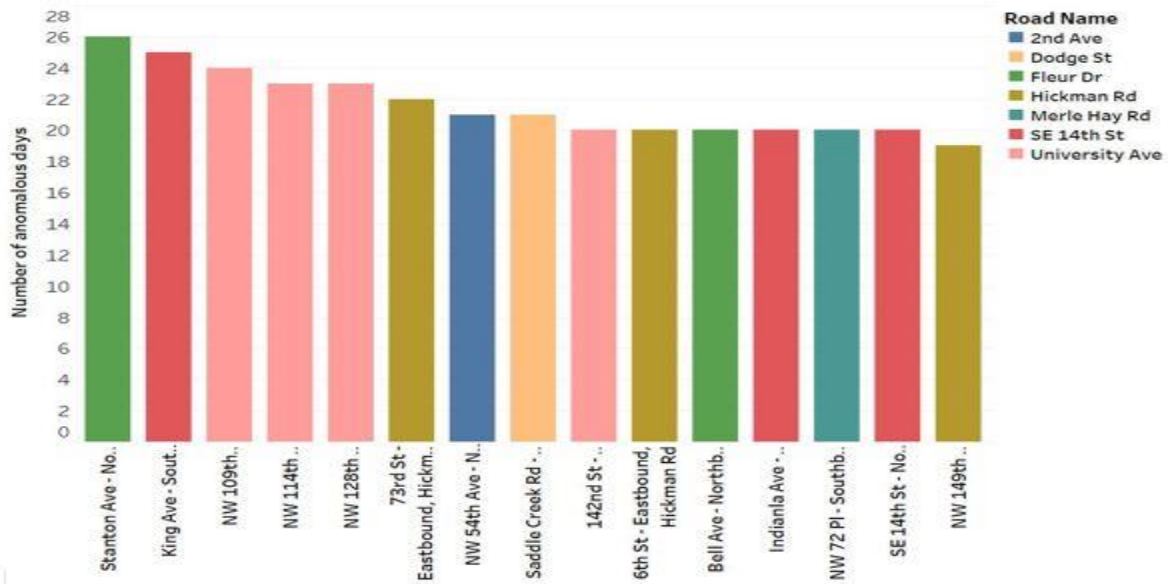


Figure 13. 15 segments with the highest number of anomalous days

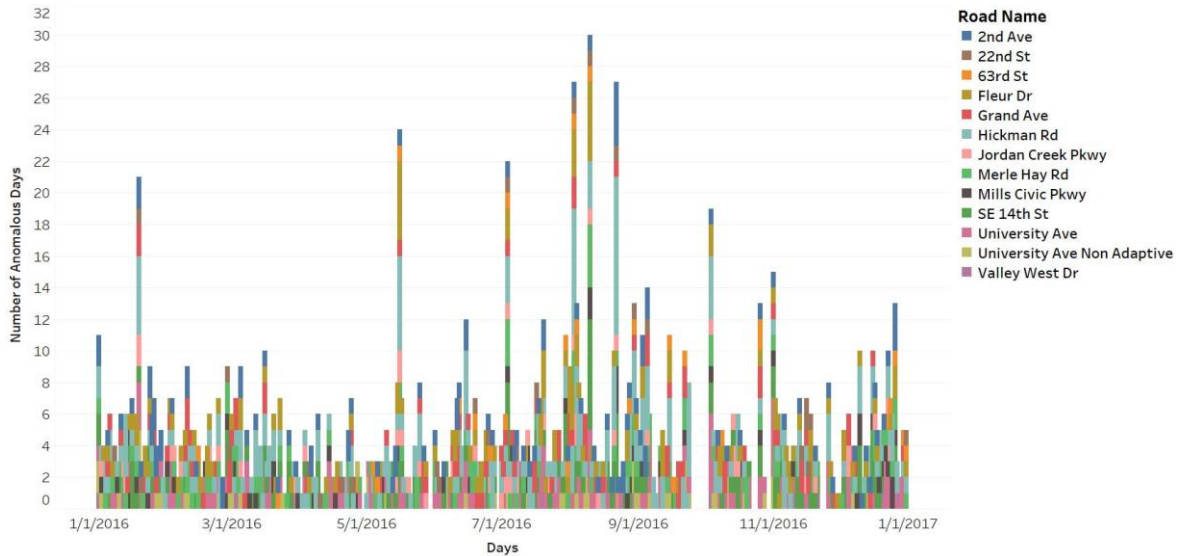
Table 3. 15 segments with the highest number of anomalous days

| Rank | Road name         | Location and direction        | Number of anomalous days |
|------|-------------------|-------------------------------|--------------------------|
| 1    | Fleur Drive       | Stanton Avenue - Northbound   | 26                       |
| 2    | SE 14th Street    | King Avenue - Southbound      | 25                       |
| 3    | University Avenue | NW 109th Street - Eastbound   | 24                       |
| 5    | University Avenue | NW 128th Street - Westbound   | 23                       |
| 5    | University Avenue | NW 114th Street - Westbound   | 23                       |
| 6    | Hickman Road      | 73rd Street - Eastbound       | 22                       |
| 8    | Dodge Street      | Saddle Creek Road - Westbound | 21                       |
| 8    | 2nd Avenue        | NW 54th Avenue - Northbound   | 21                       |
| 14   | University Avenue | 142nd Street - Westbound      | 20                       |
| 14   | Fleur Drive       | Indianola Avenue - Southbound | 20                       |
| 14   | SE 14th Street    | NW 72nd Place - Southbound    | 20                       |
| 14   | University Avenue | 6th Street - Eastbound        | 20                       |
| 14   | University Avenue | Bell Avenue - Northbound      | 20                       |
| 15   | University Avenue | NW 149th Street - Westbound   | 19                       |

From the figure and table, it is certain that the University Avenue (adaptive corridor) followed by Hickman Road and SE 14th Street are the corridors that have the highest number of segments with anomalous days. Among individual segments, the one with the most anomalous days is northbound Fleur Drive at Stanton Avenue (26 anomalous days), followed by southbound SE 14th Street at King Avenue. In addition, 10 of the top 15 are non-adaptive segments, which suggests that the variation of travel rate is reduced somewhat when adaptive control is in use. As

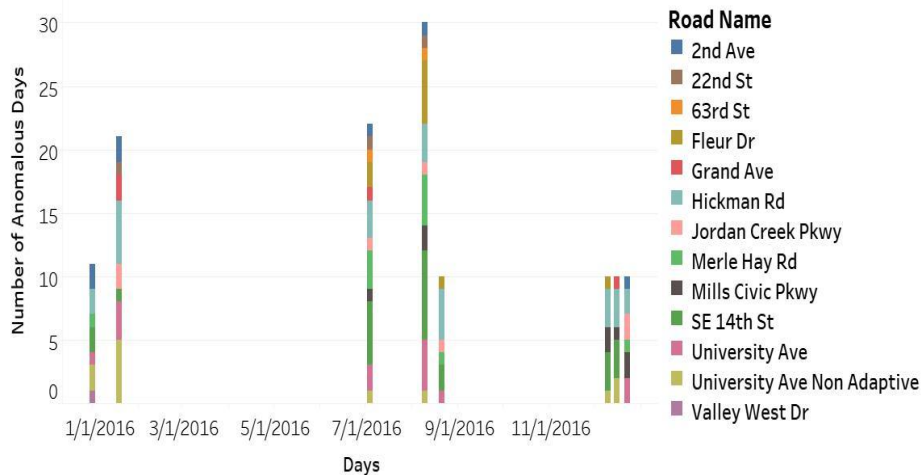
for University Avenue, in fall 2016, there was construction from Northwest 104th Street to the I-35/80 interchange, which might have contributed to the high number of anomalous days. The entire anomalous day analysis is presented in Appendix B.

The next step was to identify the pattern of anomalous days for the entire analysis period. Figure 14 presents the segment anomaly counts for each day in 2016 for the Des Moines segments.



**Figure 14. Distribution of anomalous days of the segments of Des Moines for 2016**

Based on this information, the top anomalous days are highlighted in Figure 15, and the reasons for these anomalies are listed in Table 4.



**Figure 15. Some of the top anomalous days of Des Moines**

**Table 4. Reasons for some of the top anomalous days**

| <b>Date</b> | <b>Reason</b>          | <b>Number of anomalous segments</b> |
|-------------|------------------------|-------------------------------------|
| 8/10/2016   | Iowa State Fair parade | 30                                  |
| 7/4/2016    | Long weekend day       | 22                                  |
| 1/19/2016   | Snow                   | 21                                  |
| 1/1/2016    | Holiday                | 11                                  |
| 8/21/2016   | Iowa State Fair        | 10                                  |
| 12/10/2016  | Snow and rain          | 10                                  |
| 12/16/2016  | Snow                   | 10                                  |
| 12/23/2016  | Snow                   | 10                                  |

The Omaha (Dodge Street) site was excluded from this analysis, since only six months of data were available to the research team.

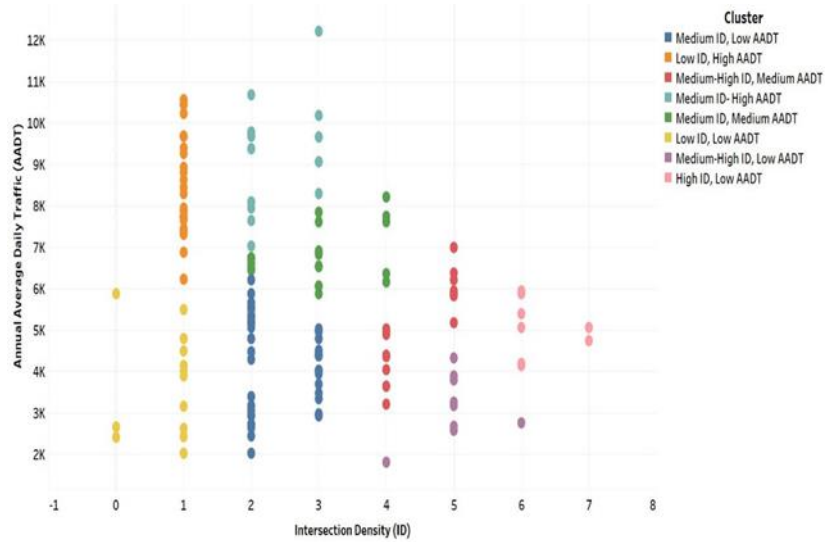
### **4.3. Travel Rate and Travel Rate Reliability**

Based on the AADT per lane and the number of intersections per segment, a mean-shift clustering algorithm was applied to the data set. This process divided the segments into eight categories:

- medium intersection density (ID), low AADT
- low ID, high AADT
- medium-high ID, medium AADT
- medium ID, high AADT
- medium ID, medium AADT
- low ID, low AADT
- medium-high ID, low AADT
- and high ID, low AADT

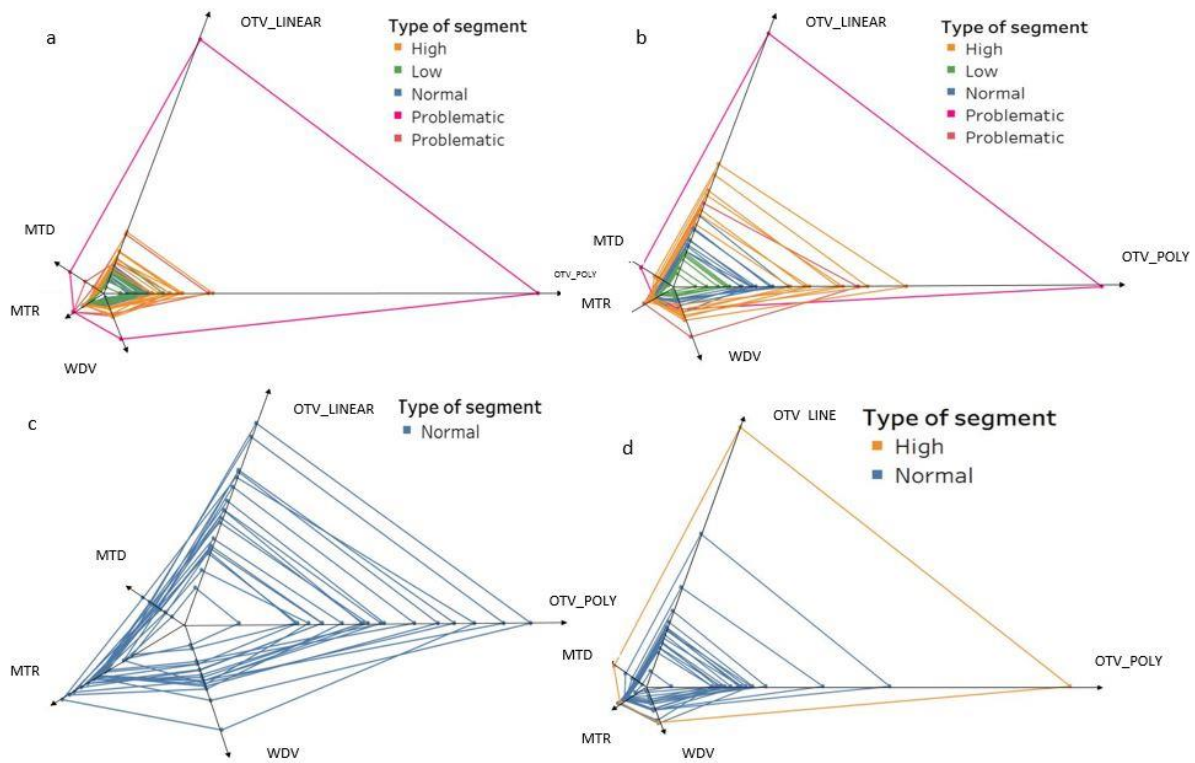
The representation of the different groups is shown in Figure 16.



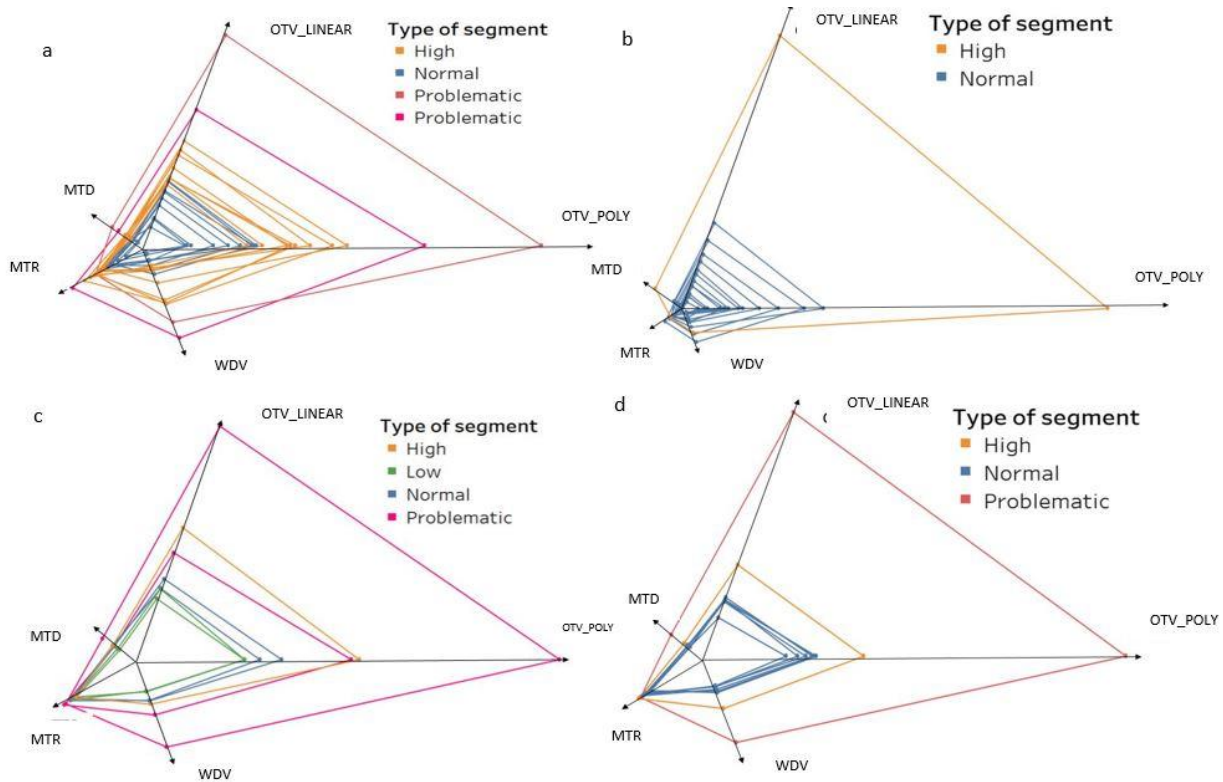


**Figure 16. Different types of segments based on ID and AADT per lane**

The next step was to identify the problematic segments. For this process, each of these groups of segments were clustered to identify the problematic and high-metric segments, if any. Figure 17 and Figure 18 show spider plots of the five parameters (OTV\_POLY, OTV\_LINEAR, MTD, MTR, and WDV) for the eight condition categories.



**Figure 17. Spider plots showing the variation for the five parameters for a) medium ID, low AADT; b) low ID, high AADT; c) medium-high ID, medium AADT; and d) medium ID, high AADT**



**Figure 18. Spider plots showing the variation for the five parameters for a) medium ID, medium AADT; b) low ID, low AADT; c) medium-high ID, low AADT; and d) high ID, low AADT**

Each of the five performance measures (OTV\_POLY, OTV\_LINEAR, MTD, MTR, and WDV) is represented along each axis of the spider plot. Each segment is plotted with its corresponding performance values (magnitude) for each parameter. The segments are color-coded based on the type of performance (low, normal, high, or problematic).

The plots can be used for comparison of the different parameters for the different type of segments. For example, Figure 17(a) shows that there are two types of problematic segments: one due to the very poor performance values of all measures (pink line) and one due to very high MTD and MTR (red line). Also, for Figure 17(c), it can be noted that none of the segments are distinctly different from one another, which makes all of the segments as normal.

The variation of each of the parameters and other distributions are shown in Figure 19 through Figure 26. Table 5 lists the segments that have high or problematic behavior.

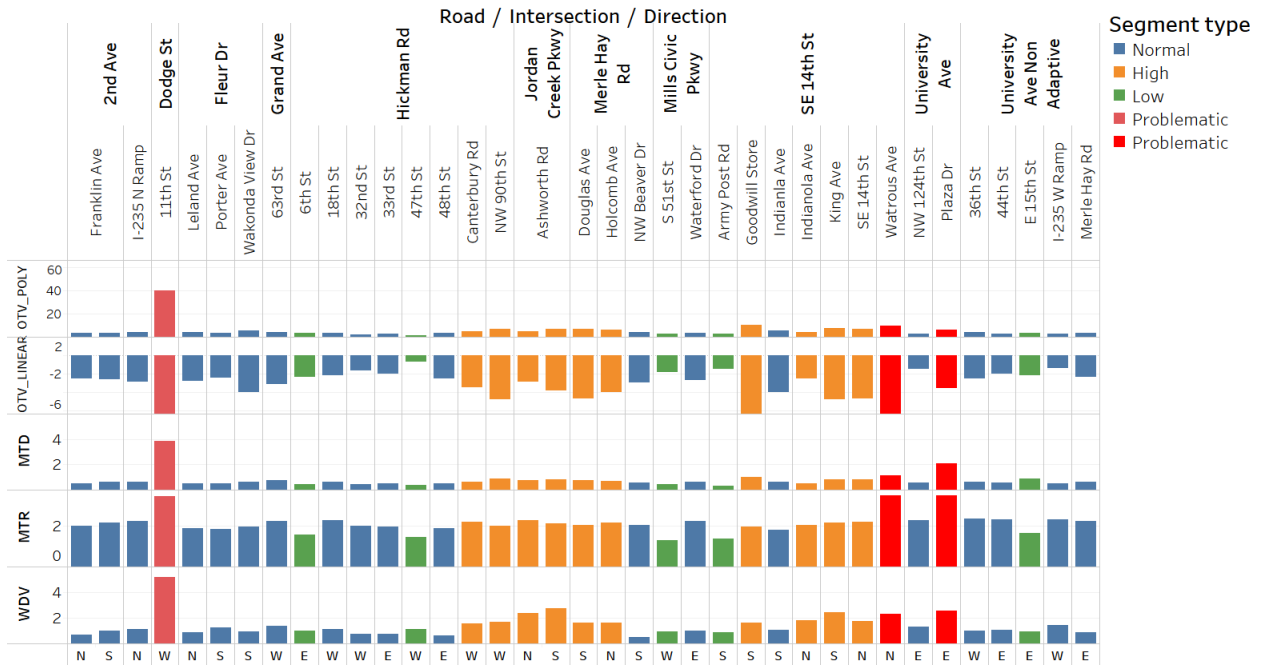


Figure 19. Bar plots for the five parameters of OTV\_POLY, OTV\_LINEAR, MTD, MTR, and WDV for medium ID, low AADT

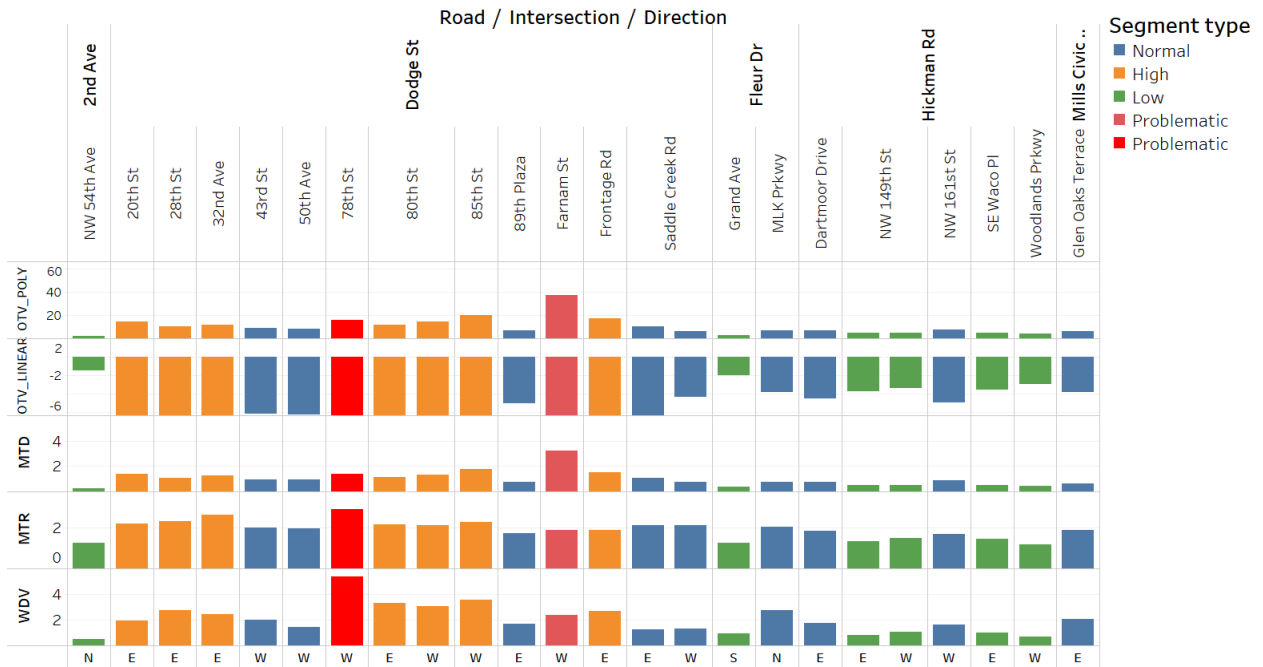


Figure 20. Bar plots for the five parameters of OTV\_POLY, OTV\_LINEAR, MTD, MTR, and WDV for low ID, high AADT

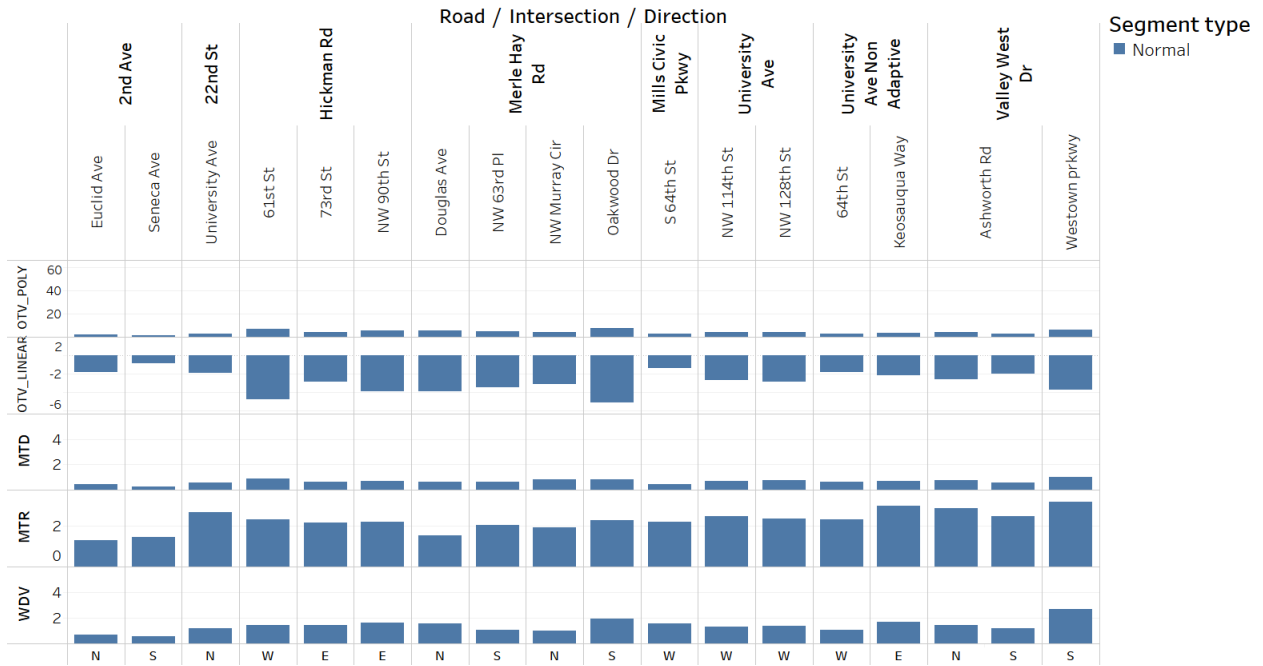


Figure 21. Bar plots for the five parameters of OTV\_POLY, OTV\_LINEAR, MTD, MTR, and WDV for medium-high ID, medium AADT

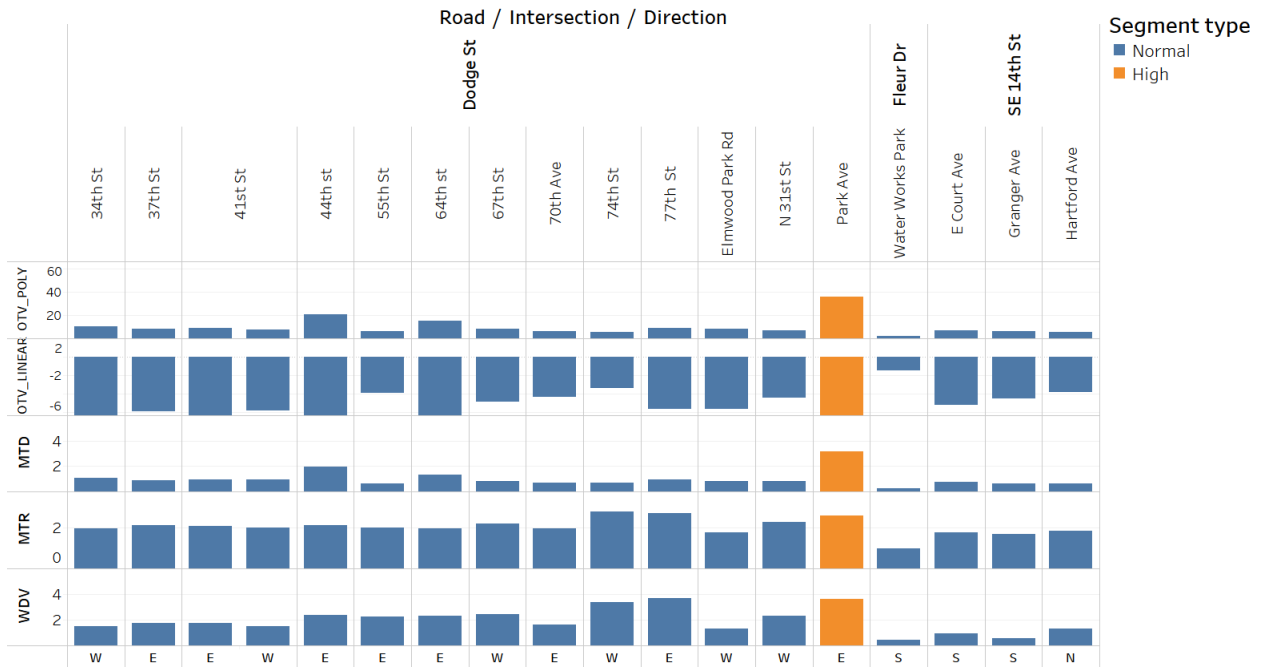


Figure 22. Bar plots for the five parameters of OTV\_POLY, OTV\_LINEAR, MTD, MTR, and WDV for medium ID, high AADT

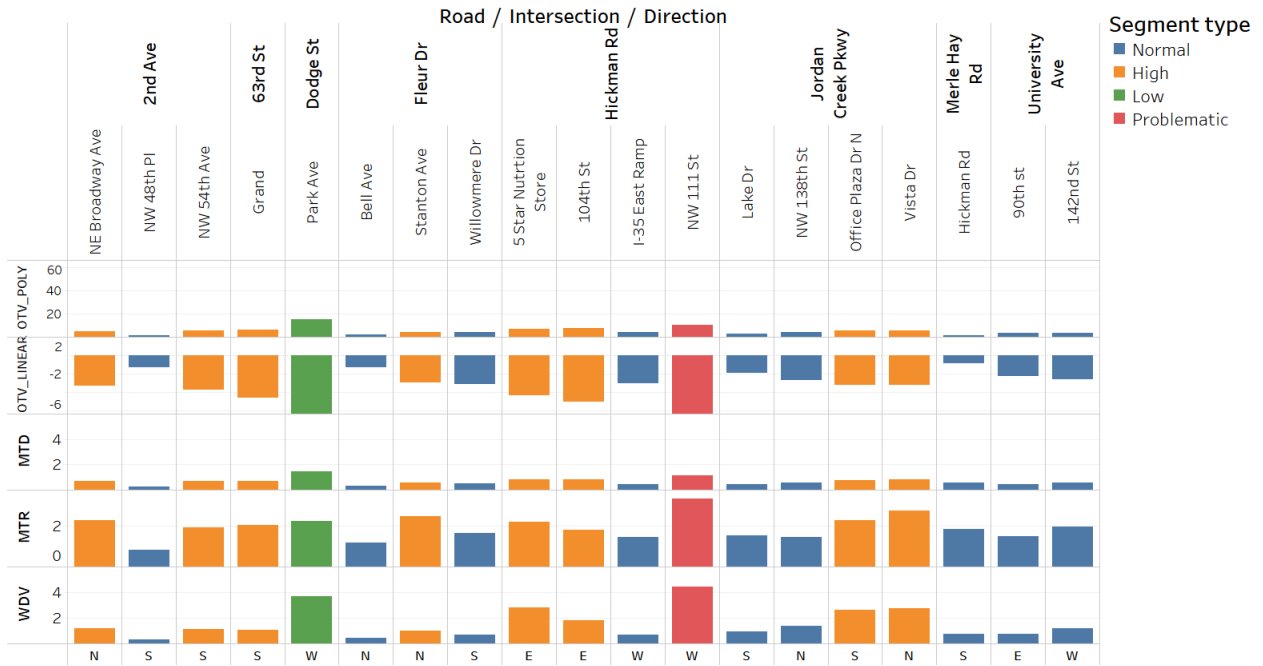


Figure 23. Bar plots for the five parameters of OTV\_POLY, OTV\_LINEAR, MTD, MTR, and WDV for medium ID, medium AADT

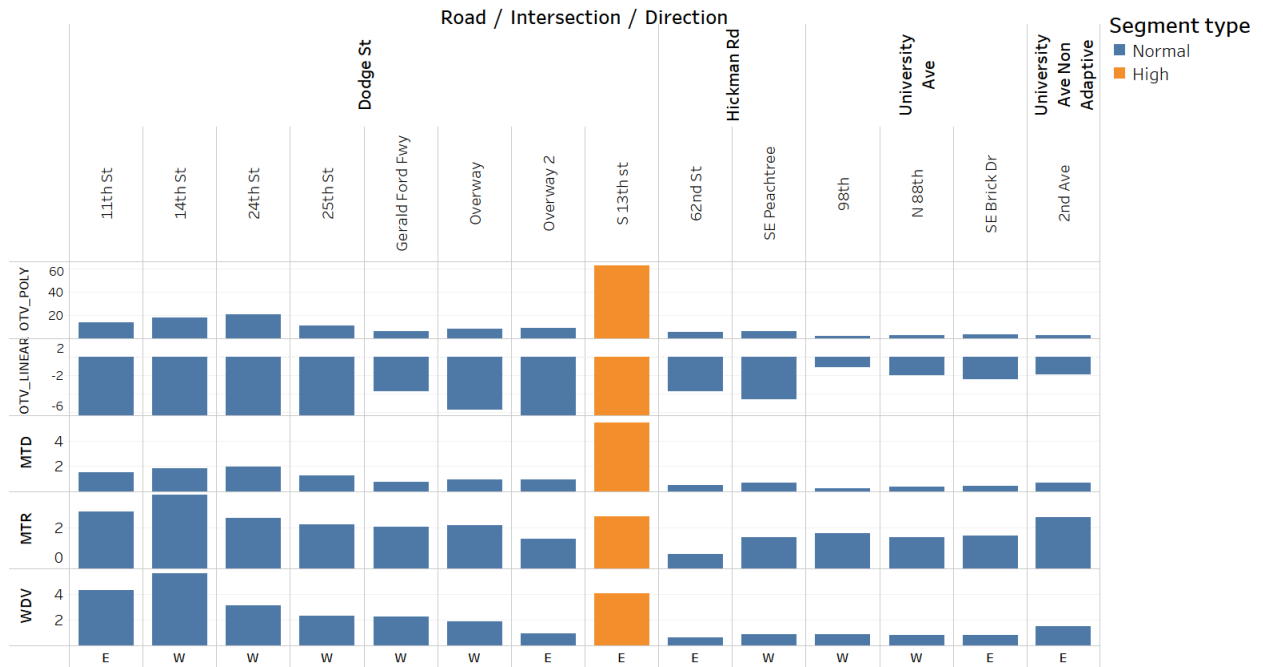


Figure 24. Bar plots for the five parameters of OTV\_POLY, OTV\_LINEAR, MTD, MTR, and WDV for low ID, low AADT

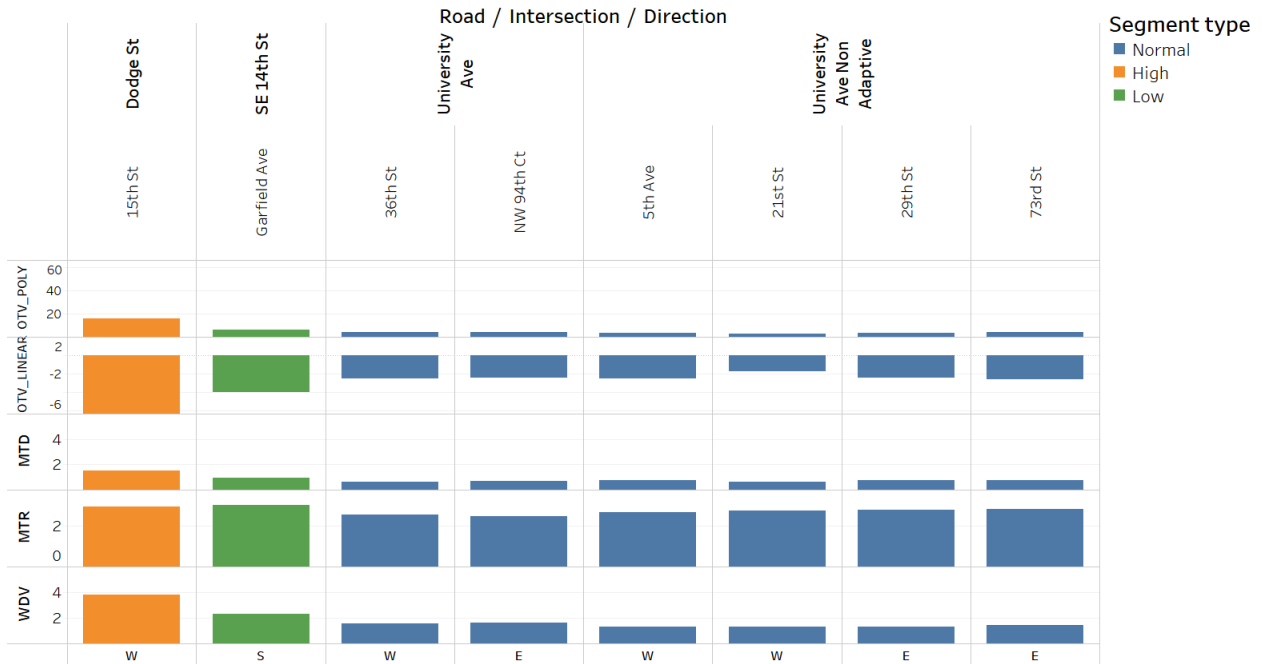


Figure 25. Bar plots for the five parameters of OTV\_POLY, OTV\_LINEAR, MTD, MTR, and WDV for medium-high ID, low AADT



Figure 26. Bar plots for the five parameters of OTV\_POLY, OTV\_LINEAR, MTD, MTR, and WDV for high ID, low AADT

**Table 5. Segment on adaptive corridors with high or problematic performance metrics**

| <b>Road</b>          | <b>Intersection</b>    | <b>Direction</b> |
|----------------------|------------------------|------------------|
| 2nd Avenue           | NW 54th Avenue         | Southbound       |
| 2nd Avenue           | NE Broadway Avenue     | Northbound       |
| 63rd Street          | Grand Avenue           | Southbound       |
| Dodge Street         | S 13th Street          | Eastbound        |
| Dodge Street         | Park Avenue            | Westbound        |
| Dodge Street         | Park Avenue            | Eastbound        |
| Dodge Street         | Frontage Road          | Eastbound        |
| Dodge Street         | Farnam Street          | Westbound        |
| Dodge Street         | 85th Street            | Westbound        |
| Dodge Street         | 80th Street            | Westbound        |
| Dodge Street         | 80th Street            | Eastbound        |
| Dodge Street         | 78th Street            | Westbound        |
| Dodge Street         | 32nd Avenue            | Eastbound        |
| Dodge Street         | 28th Street            | Eastbound        |
| Dodge Street         | 20th Street            | Eastbound        |
| Dodge Street         | 19th Street            | Eastbound        |
| Dodge Street         | 15th Street            | Westbound        |
| Dodge Street         | 11th Street            | Westbound        |
| Fleur Drive          | Stanton Avenue         | Northbound       |
| Hickman Road         | NW 111th Street        | Westbound        |
| Hickman Road         | NW 90th Street         | Westbound        |
| Hickman Road         | Canterbury Road        | Westbound        |
| Hickman Road         | 104th Street           | Eastbound        |
| Hickman Road         | 5 Star Nutrition Store | Eastbound        |
| Jordan Creek Parkway | Vista Drive            | Northbound       |
| Jordan Creek Parkway | Office Plaza Drive N   | Southbound       |
| Jordan Creek Parkway | Ashworth Road          | Southbound       |
| Jordan Creek Parkway | Ashworth Road          | Northbound       |
| Merle Hay Road       | Pioneer Parkway        | Southbound       |
| Merle Hay Road       | Holcomb Avenue         | Northbound       |
| Merle Hay Road       | Douglas Avenue         | Southbound       |
| SE 14th Street       | Watrous Avenue         | Northbound       |
| SE 14th Street       | SE 14th Street         | Northbound       |
| SE 14th Street       | King Avenue            | Southbound       |
| SE 14th Street       | Indianola Avenue       | Northbound       |
| SE 14th Street       | Goodwill Store         | Southbound       |
| SE 14th Street       | Garfield Avenue        | Southbound       |
| SE 14th Street       | Dean Avenue            | Northbound       |
| University Avenue    | Plaza Drive            | Eastbound        |

The greatest variations were seen on parts of SE 14th Street, Jordan Creek Parkway, and Dodge Street. The reason maybe that for Jordan Creek Parkway and Dodge Street, both corridors have



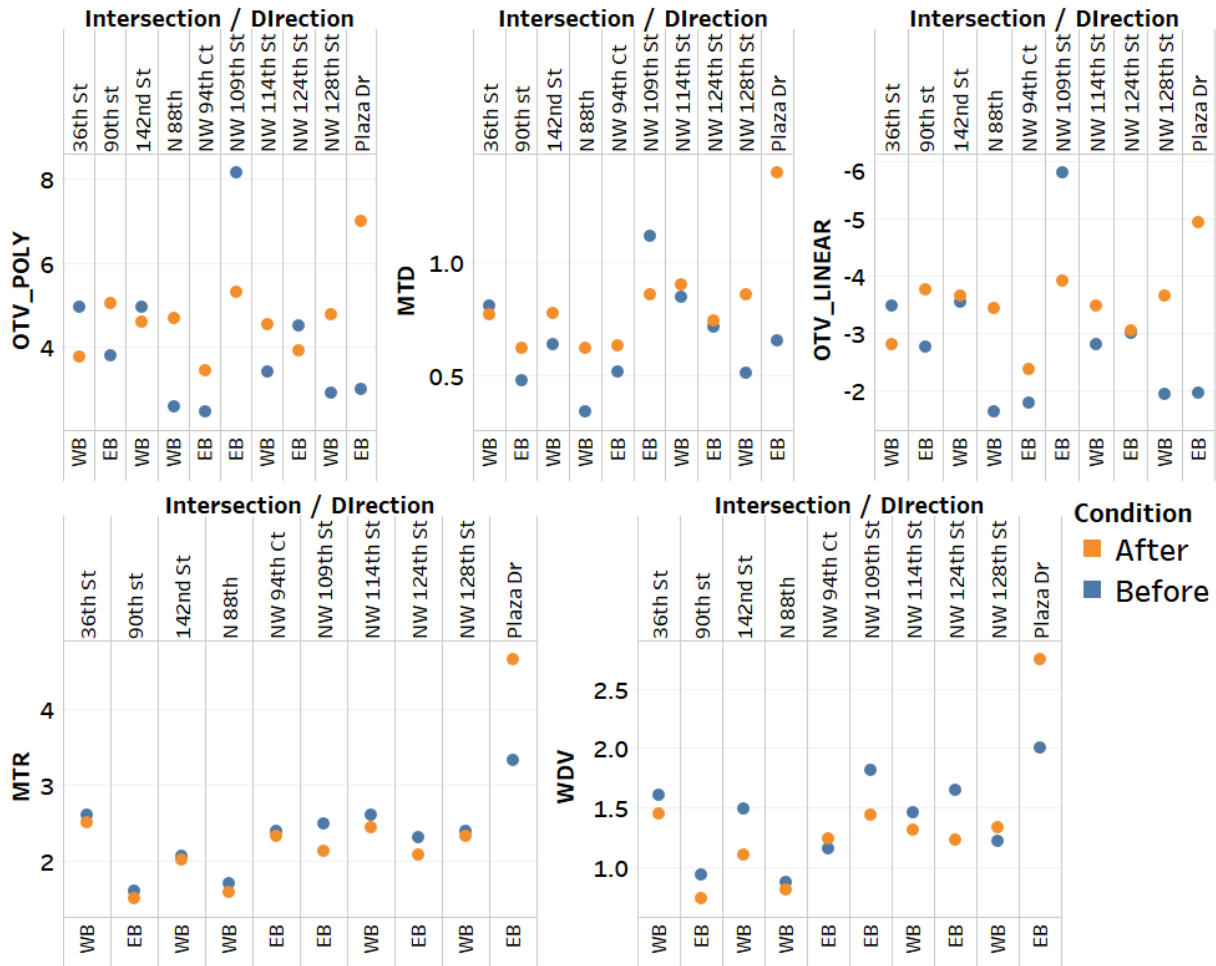
complex temporal traffic patterns related to intensive suburban office and retail development. Additional details of the parameters are shown in the Appendix C.

#### **4.4. Impact of Adaptive System on Des Moines**

The University Avenue corridor is located mainly along the boundary between two Des Moines suburbs, the cities of Clive and West Des Moines. The corridor is intensively developed with office, retail, and residential land uses. An adaptive signal control system became operational between 25th Street and 92nd Street on October 27, 2015. To understand its effect, a before-after study was conducted by comparing the July–October time periods in 2015 and 2016.

As noted earlier in this report, in fall 2016, there was construction on University Avenue from NW 104th Street to the I-35/80 interchange (about a mile west of the adaptive control area). Both construction and non-construction dates were included in the 2016 data set.

The same five performance measures used in the arterial performance evaluation were applied to these segments. None of the individual segments showed any drastic improvements after implementation of the adaptive signals. A comparison of the parameters is presented in Figure 27.



**Figure 27. Comparison of OTV\_POLY, OTV\_LINEAR, MTD, MTR, and WDV for the University Avenue corridor before and after converting to adaptive signalized intersections**

As the figure indicates, following the implementation of adaptive control the typical travel time improved for 90% of the segments and the within day variability improved for 70% of the segments. Year-on-year, the overall variability worsened for more than 60% of the segments. These mixed findings suggest that while the adaptive control system did not result in dramatic traffic flow improvements, it was generally beneficial and probably helped offset some of the effects of the nearby road construction in fall 2016.

## CHAPTER 5. CONCLUSION

In recent years, vendors such as HERE Technologies (formerly Nokia/Navteq), INRIX, TomTom NV, and TrafficCast International Inc. have actively marketed GPS-based arterial and freeway travel time data to public agencies. The Iowa DOT is one of several agencies that have purchased near-real-time data feeds from INRIX. This project demonstrated the use of archived INRIX data to establish performance measures for identifying problematic segments on arterial corridors. The method proved straightforward to implement and successfully flagged problematic areas. The analysis outputs can be used to prioritize agency actions such as corridor-level signal retiming or the installation of advanced traffic signal systems.

To test the computation and reasonableness of the probe-based arterial performance measures, the methodology was demonstrated on 12 arterial corridors in the Des Moines, Iowa area and 1 corridor in Omaha, Nebraska. The two-step methodology included determining the number of anomalous days for each segment and the travel rate (travel time per mile) for each segment. The analysis of anomalous days found that University Avenue, Hickman Road, and SE 14th Street had the most segments with high numbers of anomalous days. After removing these anomalous days from the data set, the remaining days were used to evaluate all segments based upon five parameters: median travel rate (MTR), within day variability (WDV), minimum travel rate dispersion (MTD) and two overall travel rate variability coefficients (OTV\_POLY and OTV\_LINEAR). Based upon on these parameters, major problematic segments were identified on Jordan Creek Parkway and SE 14th Street in the Des Moines, Iowa, area, and the Dodge Street corridor in Omaha, Nebraska.

The same five metrics were applied to evaluate the impact of implementing an adaptive signal control system, which was put into service on approximately 0.3 miles of University Avenue in fall 2015. Year-on-year data was used to compare the performance for the July–October periods in 2015 and 2016. The analysis showed small improvements in travel rate and within-day variation, but overall variation increased. Thus, it appears that implementation of the adaptive system was moderately beneficial overall, and may have helped mitigate some of the effects of a fall 2016 construction project on University Avenue about one mile west of the adaptive segment.

This study revealed that the performance metrics were quite flexible and robust, and were able to identify the problematic segments in each corridor with reasonable accuracy. The analysis conducted is extensible and can be used to identify the high or problematic segments and for classifying any new segment in the future. The tool can assist in identifying locations where delay is high, day-to-day traffic patterns are dynamic, or the minute-to-minute demand at signalized intersections is highly variable. Through the measures defined in this work, transportation agencies can more easily automate the process of monitoring the arterial network to identify, screen, and prioritize locations that require signal retiming or other traffic control upgrades.

A limitation of this study was that only the main-roadway through movements were analyzed on each corridor. Thus, as currently constructed, the methodology is not sensitive to delays for

turning movements or side-street movements. These limitations could be partially addressed by adding additional segments to the analysis, such as the through movements on streets that cross the major arterial corridors. Since the quality of the INRIX data is dependent on the number of probe vehicles present on each segment, a data quality evaluation for segments immediately adjacent to intersections would likely be the first step toward such an expansion of the methodology.

This work provides a basis for several possible future studies. For example, this work could serve as the basis for a future cost-benefit analysis for adaptive signal control systems in the Des Moines, Iowa, area or elsewhere. The methodology could also provide insights about relationships between operational and safety performance, by spatially comparing arterial corridor crash hotspots with the traffic flow performance metrics for example. Additionally, composite metrics based on the methodology could be developed and applied on a regional or statewide scale to provide objective operational performance scores and help build consensus about priorities for urban arterial improvements.

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## APPENDIX A. LITERATURE REVIEW

### Anomaly Detection

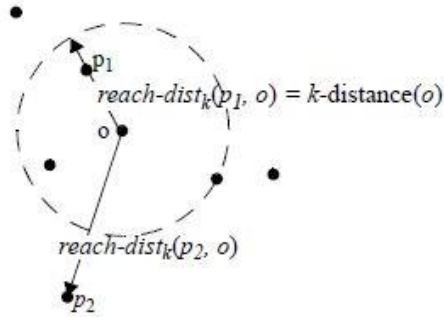
Data cleansing is necessary to remove anomalous information that will impact the resultant analysis. An elaborate comparative study discussed the following data cleansing methodologies (Chandola et al. 2007).

- Classification– These methods are of a supervised nature, where a point is identified as an anomaly because it is distinct from the other points in a feature space. The main disadvantage of this method is that it cannot assign an anomaly score to any points within the space.
- Statistical - These methods of outlier analysis identify a point as an outlier based upon a generated distribution. These methodologies assume that the sample is drawn from some underlying distribution (Gaussian, Poisson, etc.) and that data points outside of the base distribution are anomalous in nature.
- Clustering – These methods are unsupervised in nature, but lack the proper resources to detect an anomaly. A data point in the cluster must be either an outlier or a non-outlier within the data set. Further anomalies are identified as byproducts of the original clustering analysis.
- Nearest Neighbor– These methods are an unsupervised form of modeling that considers the concentration and distance of a group of points around a single point. This method is the most suitable for transportation data analysis. It has been used widely for flow prediction and travel time prediction alike (Münz et al. 2007, Chen et al. 2010, Myung et al. 2011, ul Islam Bajwa et al. 2005). The method used in this analysis is generated from the density-based local outlier factor (LOF).

#### *Local Outlier Factor*

Density-based algorithms can detect the volume of points surrounding a specific point in the domain space. As determined by Breunig et al. (2000), algorithms such as density-based spatial clustering of applications with noise (DBSCAN), Clustering in QUEst (CLIQUE), or WaveCluster can conduct clustering, but they are not robust enough in terms of outlier detection. Additionally, research by Chandola et al. (2007) has demonstrated that the k-nearest neighbor method has the power to identify clusters as well, but it is incapable of detecting outliers when the clusters are of variable density. Because of this, there is a need to identify points based on their location relative to their nearest neighboring point. The method that quantifies the points in this manner is known as the LOF.

The LOF method identifies a group of k-objects, known as the minimum points, near each point of interest and denotes it as k-distance from that object. For instance, in Figure A.1, the k is assumed to be 4 and k-distance of the object is shown.

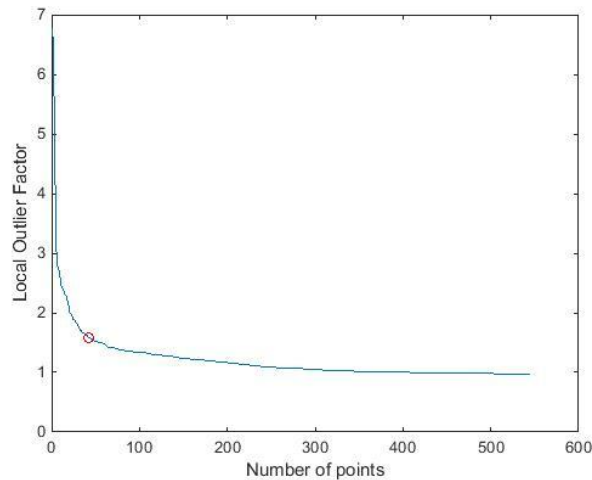


**Figure A.1. Reachability distance and k-distance with  $k = 4$**

The reachability distance of an object “o” with respect to another object “p2” is measured as the maximum of the distance of o from p2 and o’s k-distance. After this, the local reachability density of o is determined as the inverse of the reachability distance of object o with respect to its minimum nearest neighboring points. Finally, the LOF is defined as the sum of the ratio of the object o with respect to its neighboring data points.

### *Elbow Method*

The main challenge of an unsupervised learning method is how to establish a cutoff between normal and anomalous data. Research has been conducted on a multitude of methods, including K-means clustering by Thorndike (1953). Despite this, the elbow method is one of the most popular methods utilized to date to establish a cutoff threshold. The elbow method cutoff sorts the parameter that is to be cut off and then joins the consecutive points. An imaginary line is then drawn joining the start and the end points within the domain space. The cutoff point is proposed as that point that has the maximum perpendicular distance from this imaginary line. Figure A.2 displays a visualization of the elbow method. The purpose of locating the cutoff point is to determine the point where the LOF values become more or less close to one another.

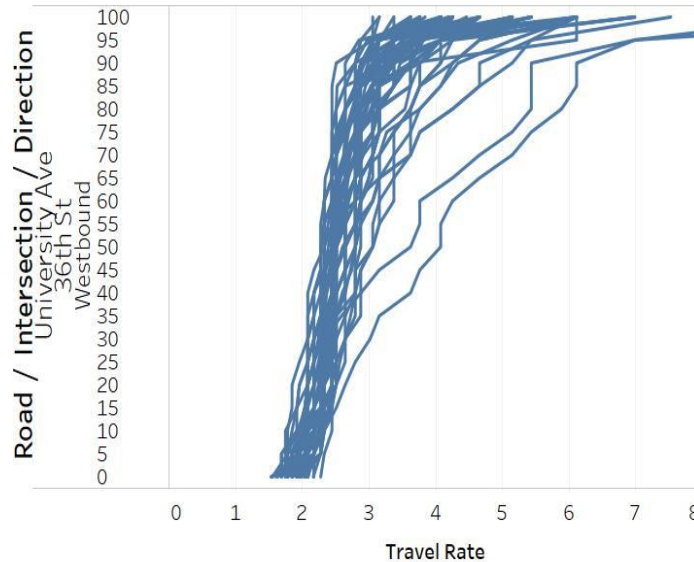


**Figure A.2. Explanation of the elbow cutoff point**

## APPENDIX B. DATA DESCRIPTION

### Anomaly Detection

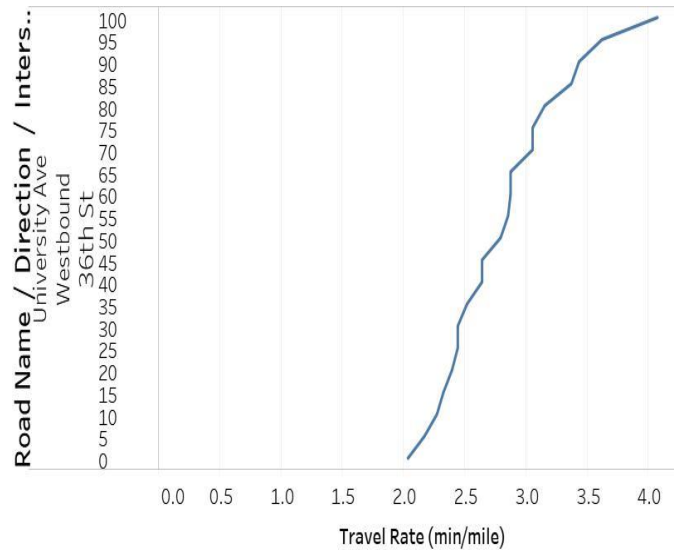
After data retrieval, travel rate reliability plots were estimated. The travel rate reliability plots display the corridor travel rate (or travel time per unit mile of the segment) for each day of each year in 5-percentile increments. Figure B.1 displays an example plot of the resultant reliability for the westbound direction of 36th Street on the University Avenue corridor.



**Figure B.1. Example of CDF plots of 36th Street, westbound, University Avenue**

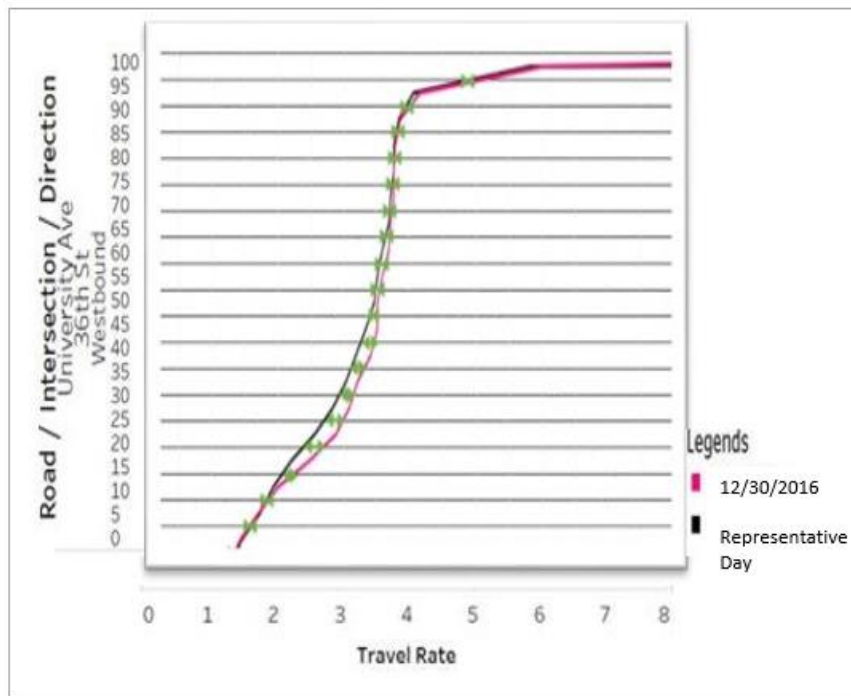
Based on the previous figure, some of the travel rate calculations derived from the INRIX probe estimates are inaccurate and classified as outliers. The reason for conducting anomaly detection and classifying estimates as outliers is to remove inaccurate or median travel rates (MTR) from the analysis. Outliers are abnormal days when the travel rate is different than normal due to some event, such as construction, work zones, or adverse weather. To conduct the necessary anomaly detection, the following process is applied:

**Step 1:** The travel rate CDF plots of the various segments are merged together to create a travel rate plot representative of the entire corridor for a day. The principle of comonotonicity is applied to achieve the resultant plot. Isukapati et al. (2013) has previously applied this methodology and demonstrated a maximum error of 6%. The principle states that for two monotonically increasing functions, the  $n$ th quantile can be added together to obtain the resultant CDF's  $n$ th quantile. After applying the independent and identical plot for the different days for a direction of the corridor, the representative plot of the entire corridor is obtained. Figure B.2 shows the representative plot for the westbound direction of University Avenue.



**Figure B.2. Daily CDF plot for a segment on University Avenue**

**Step 2:** The next step is to compare the daily CDF plots to the base day for each corridor and measure the resultant dispersion. The mean and standard deviation of these differences are utilized for this analysis. Figure B.3 shows the differences between the quantile values for the base day with an example day.



**Figure B.3. Example showing the differences between the different quantiles of representative plot and daily plot**



**Step 3:** Based upon the computed mean and standard deviation, the LOF score is calculated for each segment individually. The LOF is estimated by considering the minimum points from 10 to 20 (in intervals of 1). The average LOF is computed for each point.

**Step 4:** All of the LOF values from the previous step for each segment are assembled in a decreasing fashion, and a line is drawn to connect them. Next, an elbow method cutoff is proposed to locate the “higher than average” LOF values. Note that the red circular mark in the Figure A.2 denotes the elbow cutoff point. As used in Chen et al. (2010), the days with a positive mean, a LOF value greater than 1.5, and those beyond the cutoff point were determined to be anomalies and removed from the data set to ensure that typical behavior is considered for the remaining analysis.

**Step 5:** Using the five parameters, the next step is to identify the segments that are experiencing high variability and travel time on them. On these five parameters, the following algorithm is run to determine the high and the low performance metrics segments.

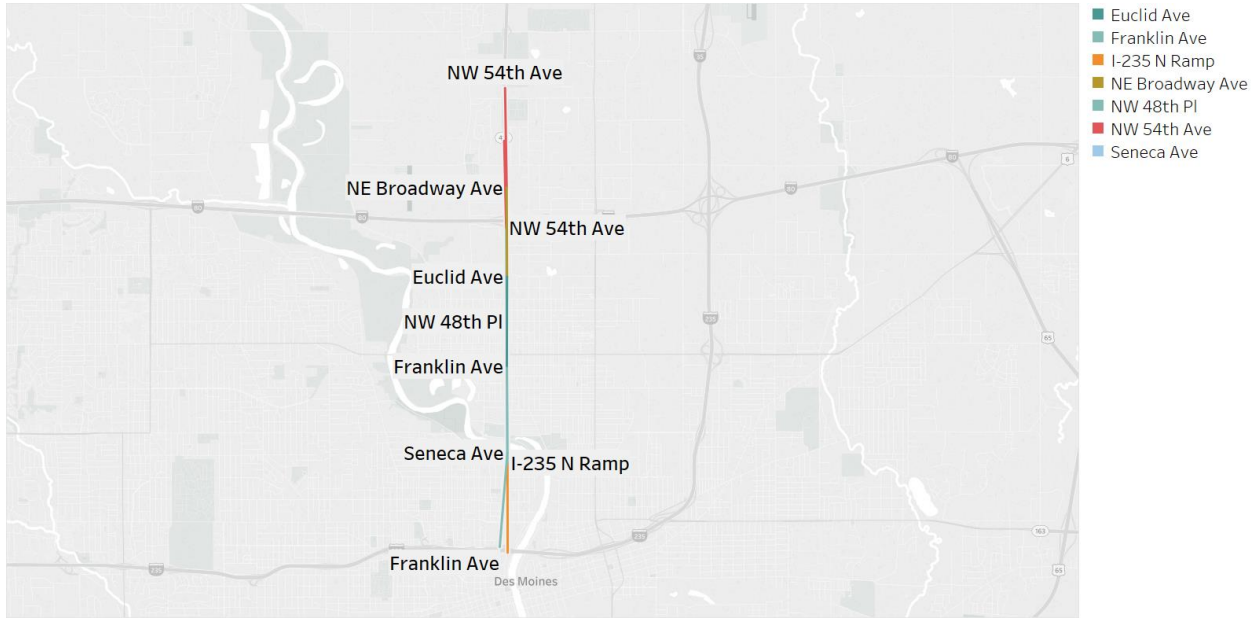
- First, a mean-shift clustering algorithm is used to determine the number of clusters using these five parameters. The mean-shift algorithm is a mode-seeking algorithm and has been used in transportation and other fields. The working principle is as follows.
  - First, it assumes each feature point as a cluster center.
  - Take all the points within the bandwidth or radius of a feature center, and recalculate the mean of these feature points as the new center.
  - Repeat this for all the points until convergence is achieved; that is, the center points remain unchanged. Further, the details of the algorithm can be found in Huang et al. (2018), Cheng (1995), Fukunaga and Hostetler (1975), and Golubev et al. (2015).
- After this, the remaining corridors are predicted using the parameters obtained in the step before.



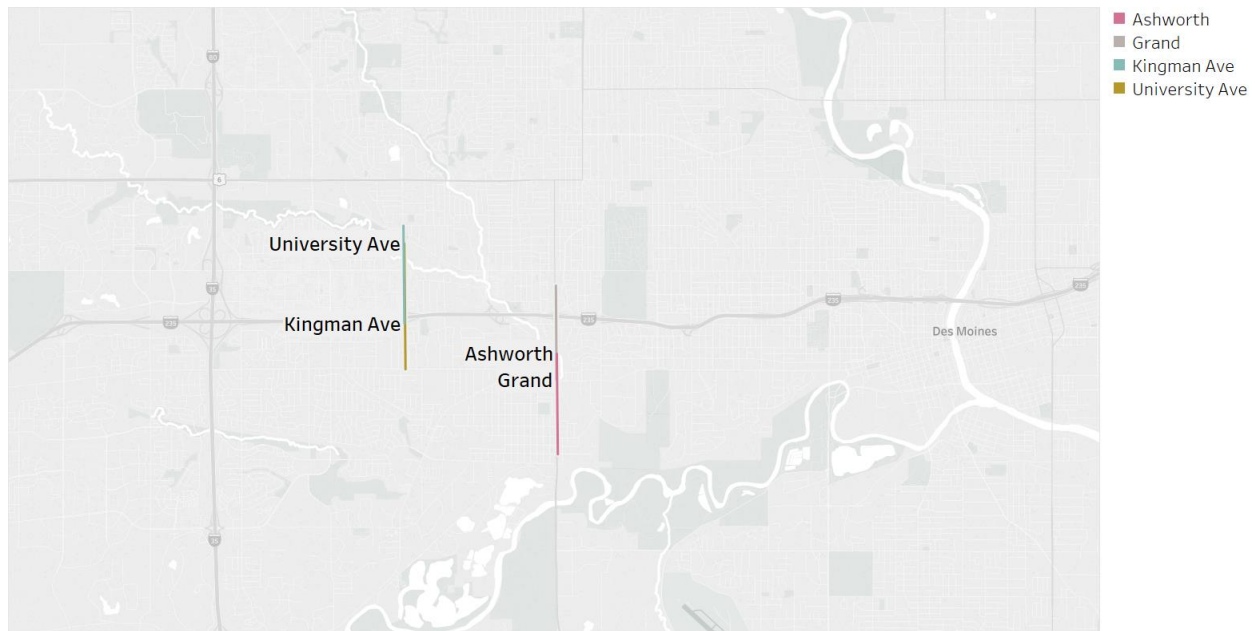
## APPENDIX C. LOCATIONS AND RESULTS

### Locations

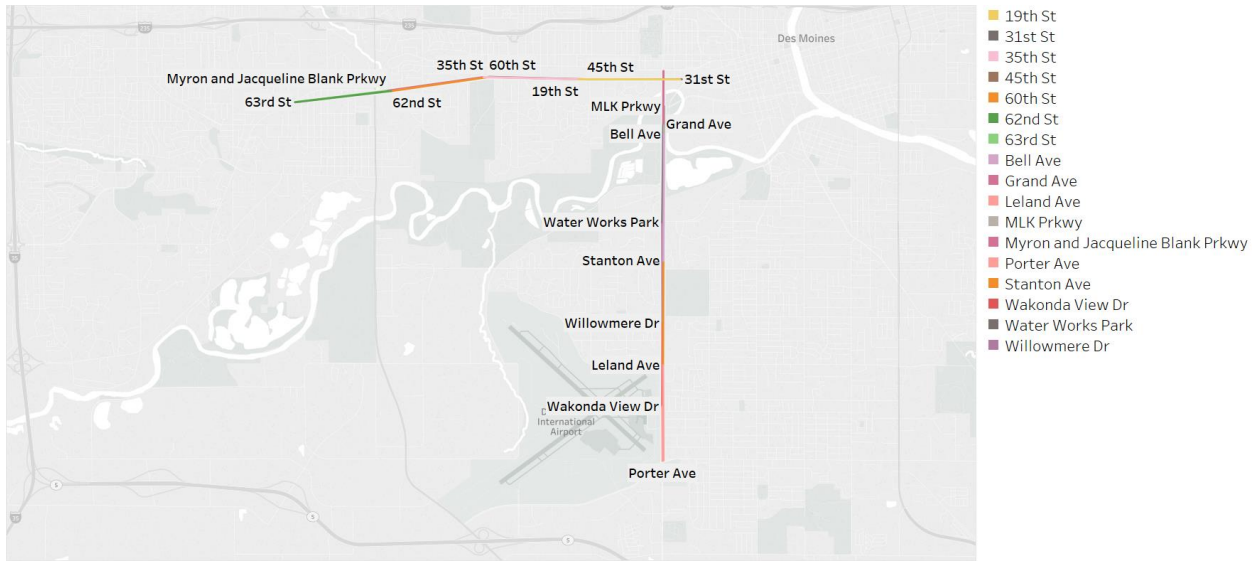
Figure C.1 through Figure C. 8 show the extent of each segment in Des Moines.



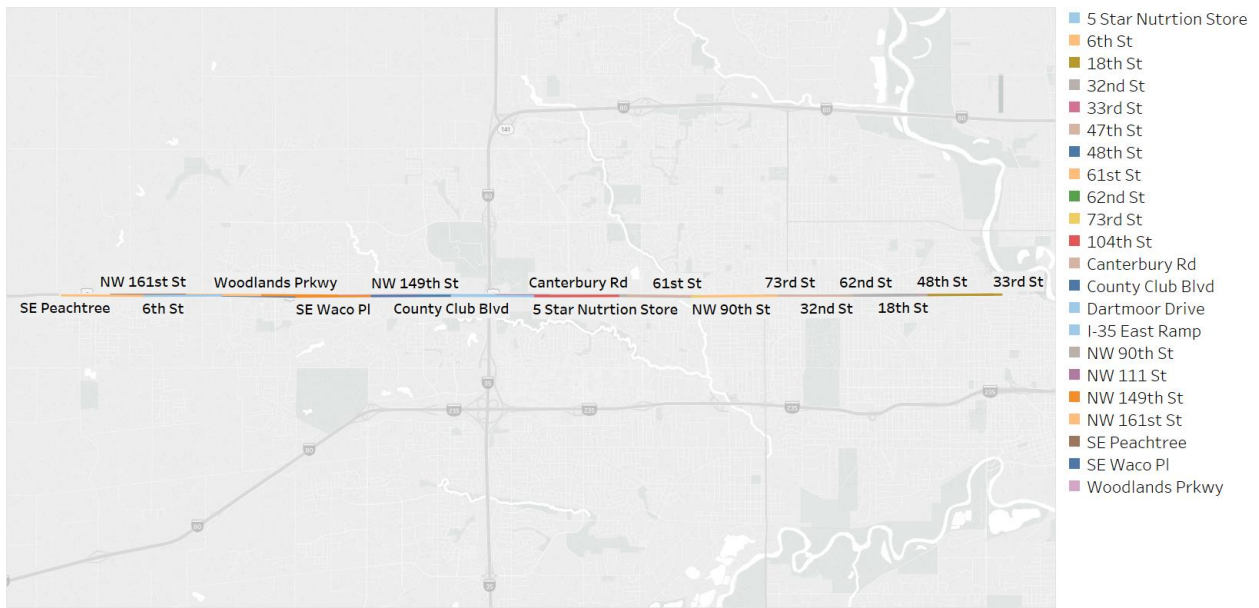
**Figure C.1. Location of 2nd Avenue, Des Moines**



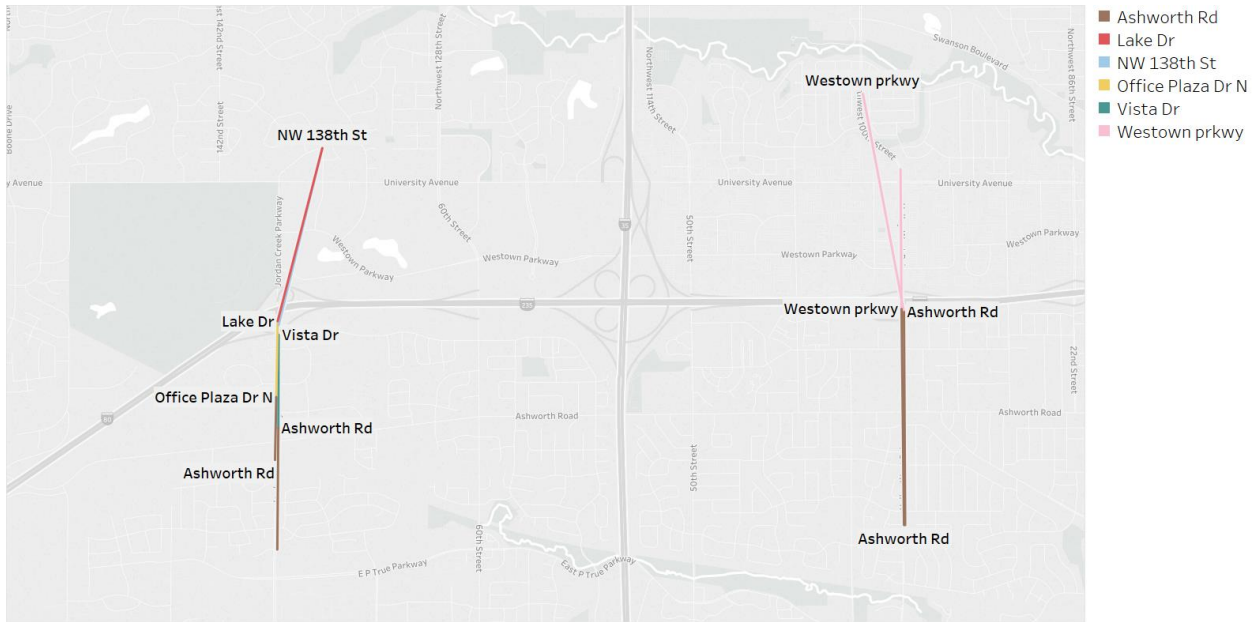
**Figure C.2. Location of 22nd Street and 63rd Street, Des Moines**



**Figure C.3. Locations of Fleur Drive and Grand Avenue, Des Moines**



**Figure C.4. Location of Hickman Road, Des Moines**



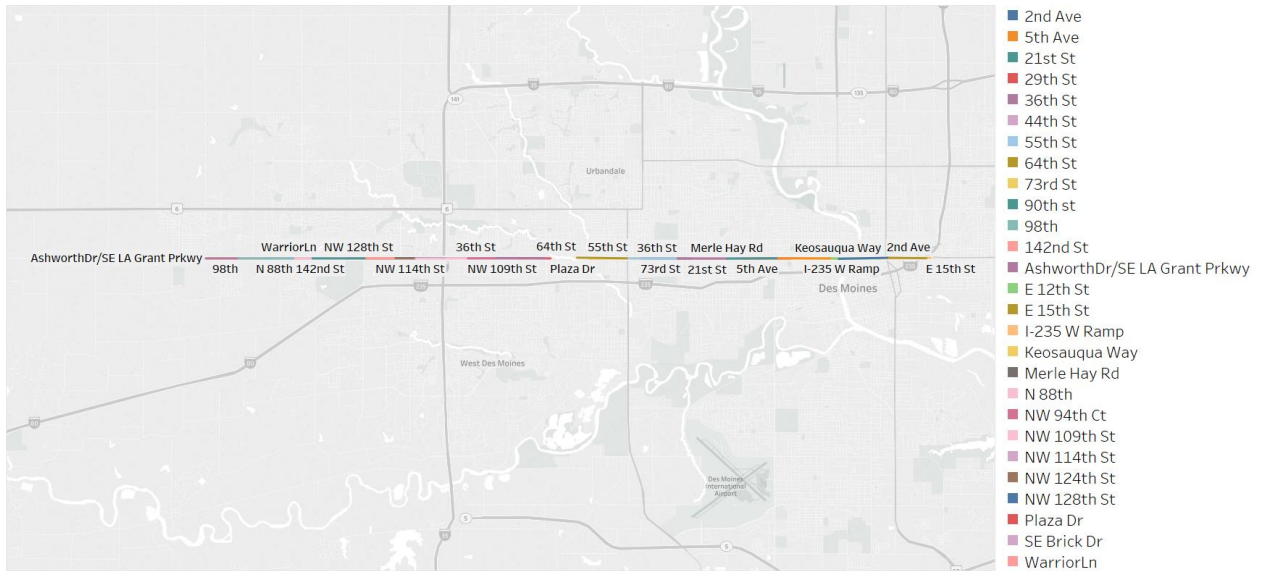
**Figure C.5. Locations of Jordan Creek Parkway and Valley West Drive, Des Moines**



**Figure C.6. Location of Merle Hay Road, Des Moines**



**Figure C.7. Location of SE 14th Street, Des Moines**

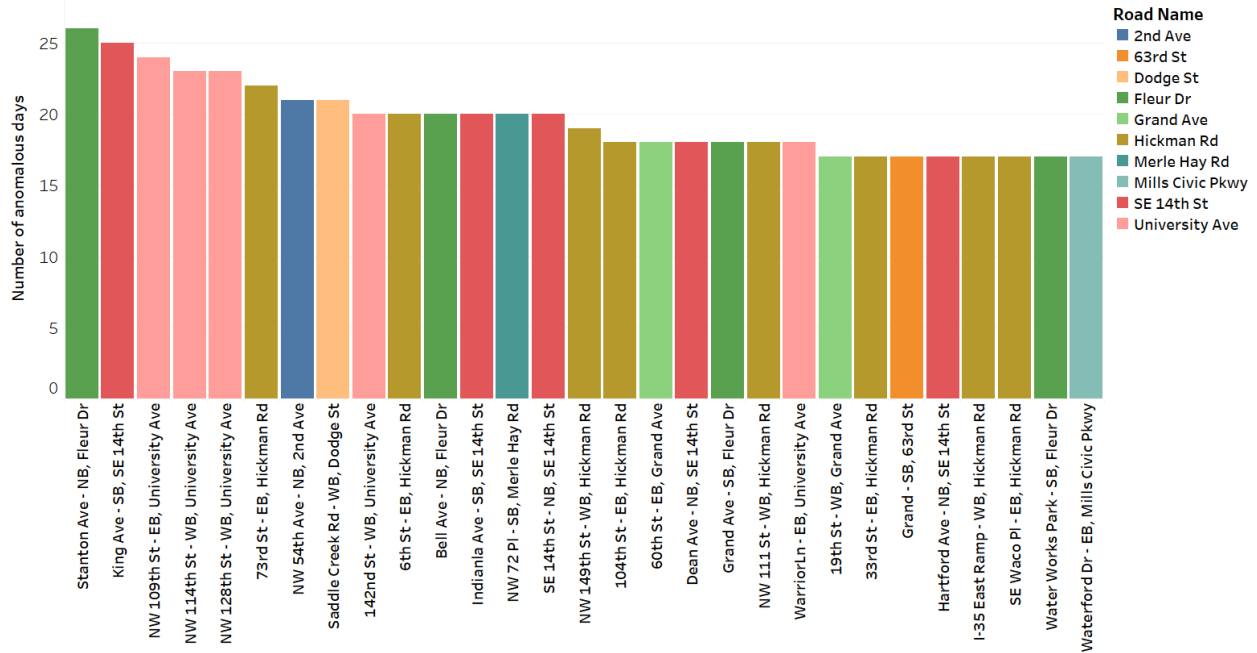


**Figure C.8. Location of University Avenue (adaptive and non-adaptive), Des Moines**

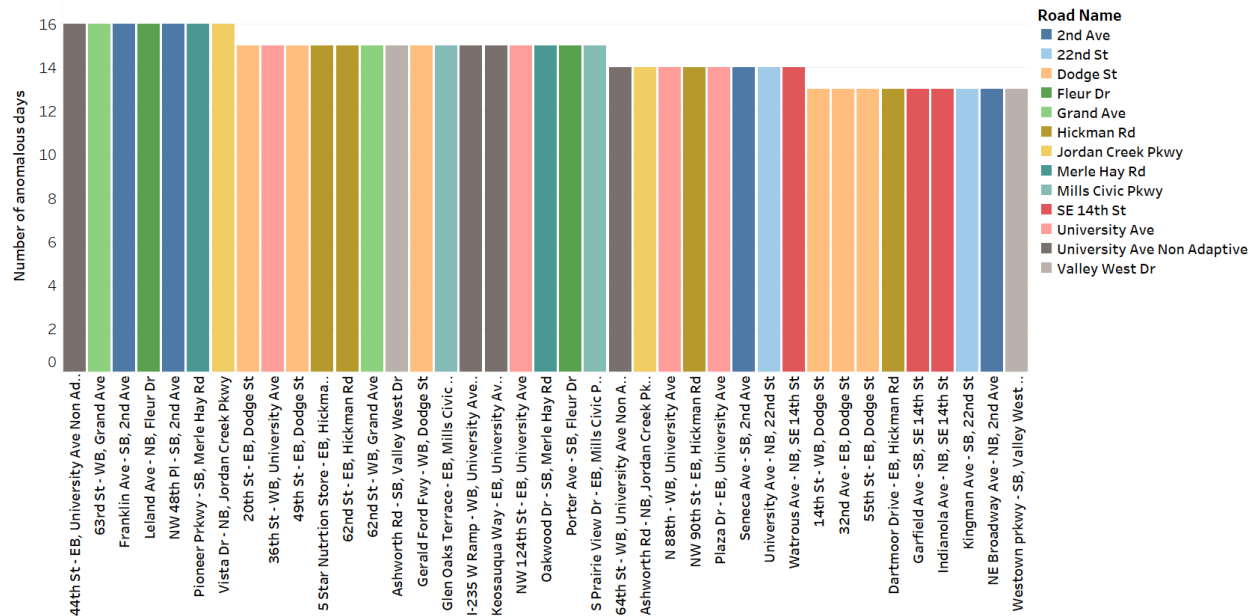


# Anomaly Detection

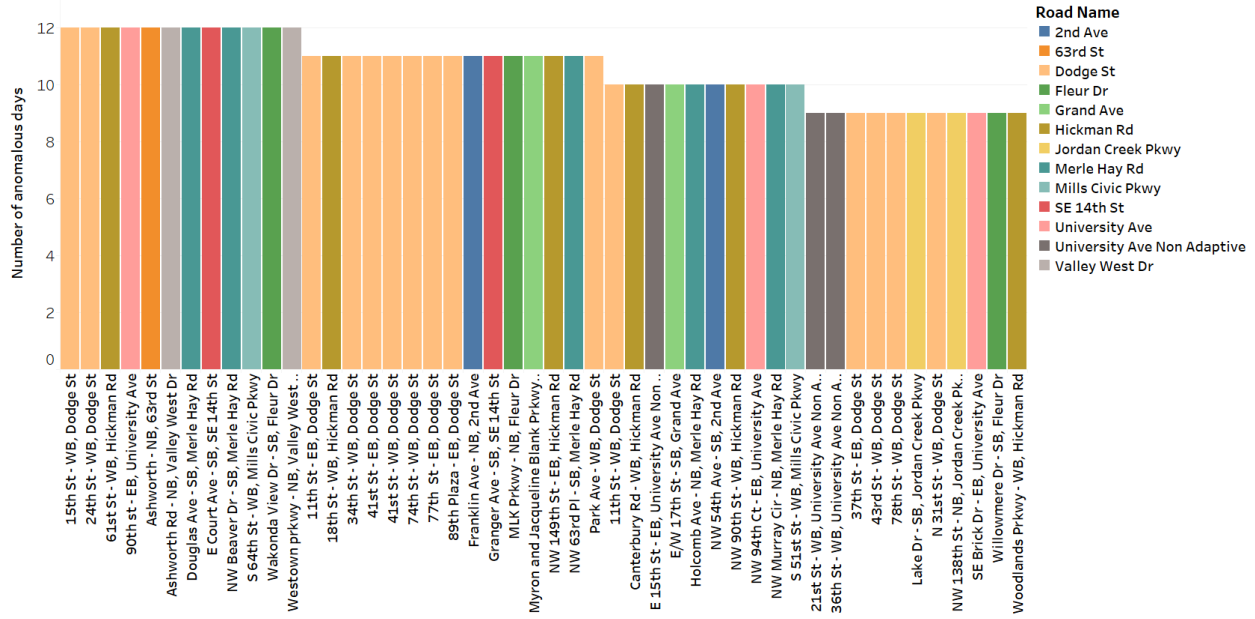
Figure C.9 shows the count of anomalous days for each segment.



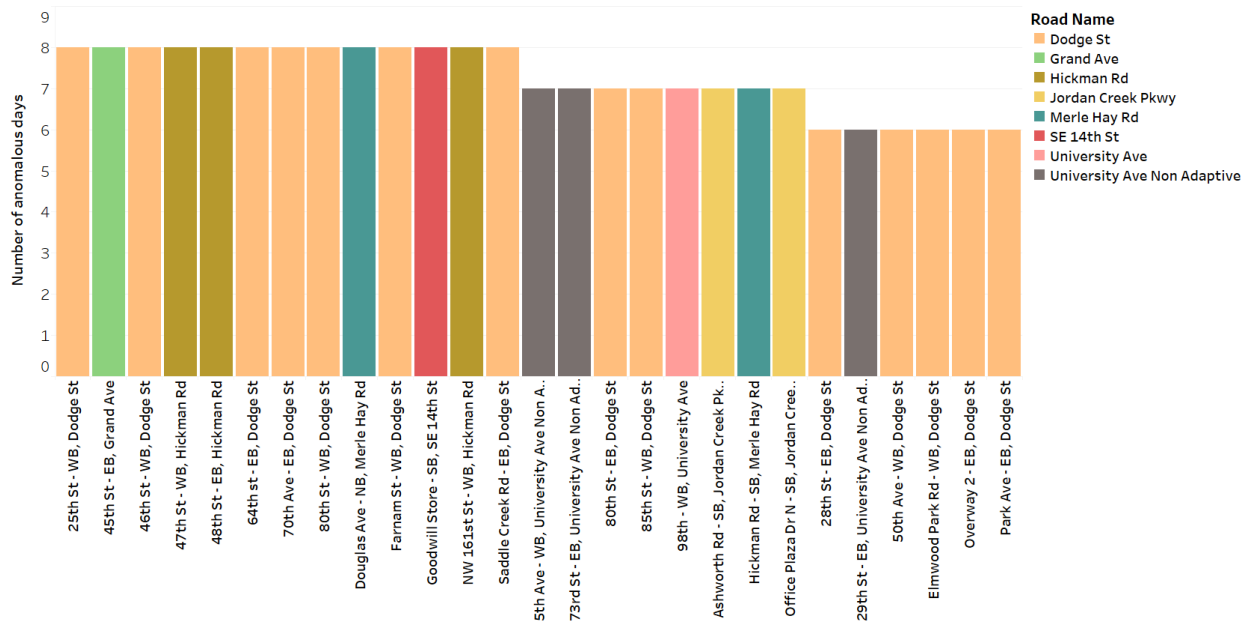
(a) Segments with 17 to 26 anomalous days in Des Moines and Omaha



(b) Segments with 13 to 16 anomalous days in Des Moines and Omaha

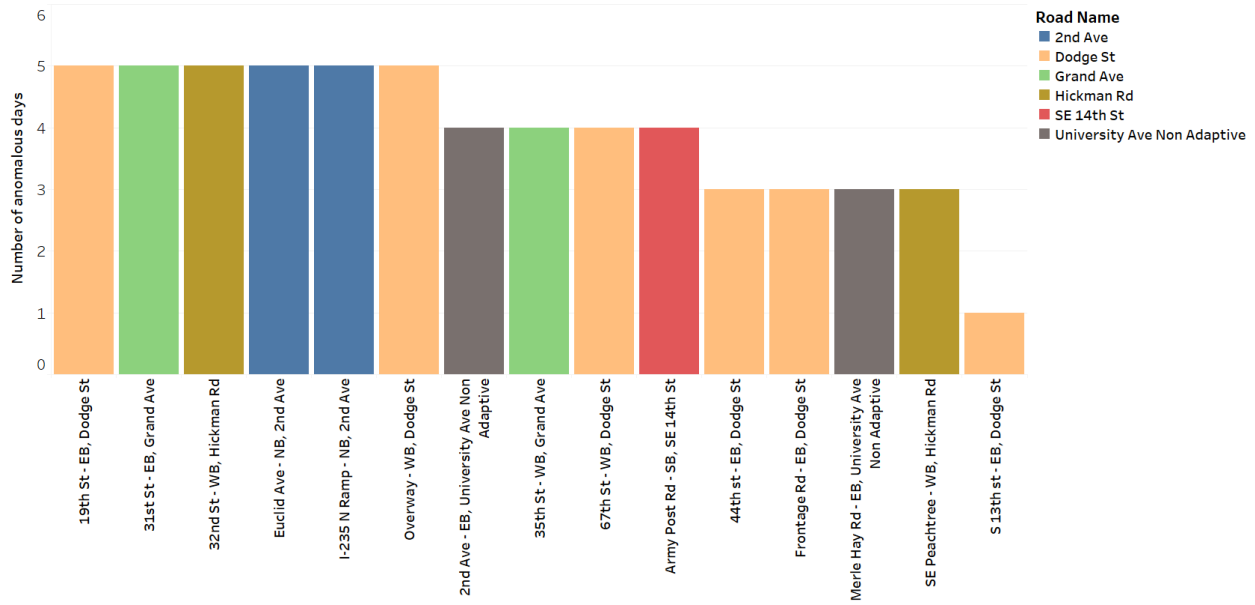


(c) Segments with 9 to 12 anomalous days in Des Moines and Omaha



(d) Segments with six to eight anomalous days in Des Moines and Omaha



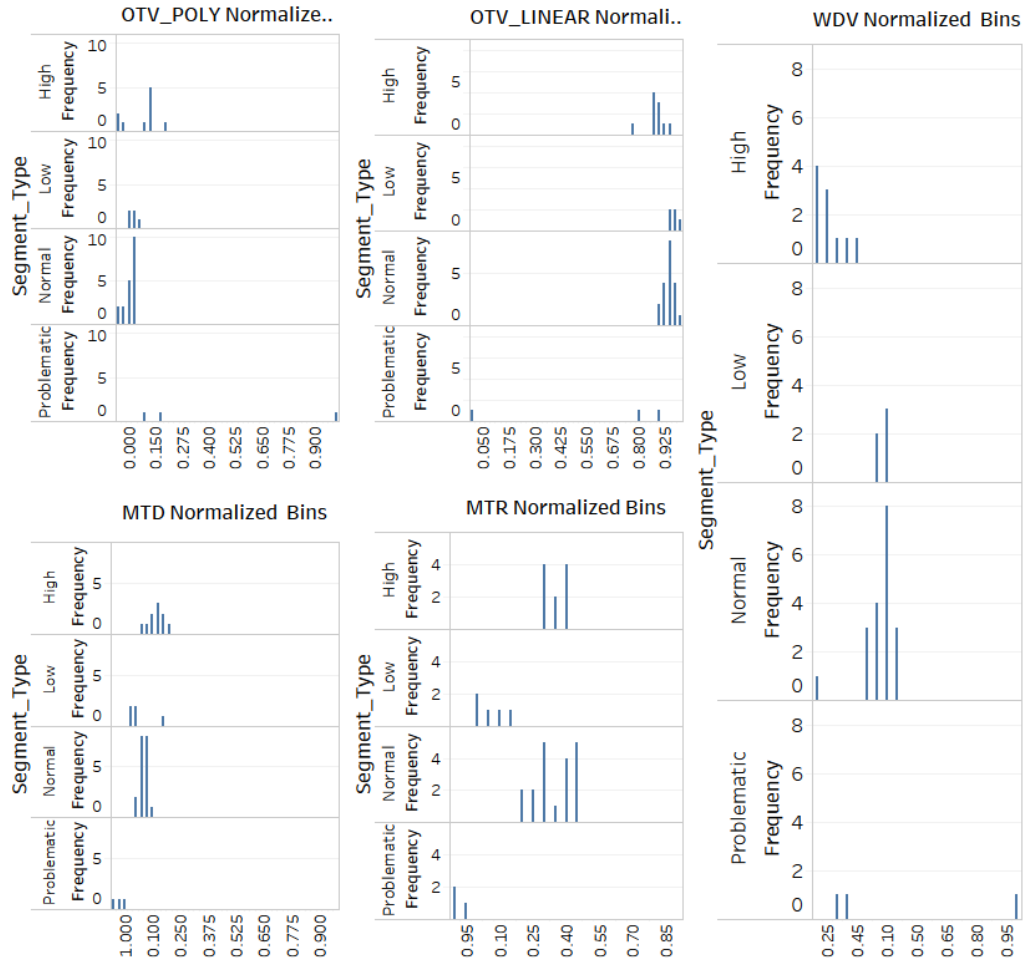


(e) Segments with one to five anomalous days in Des Moines and Omaha

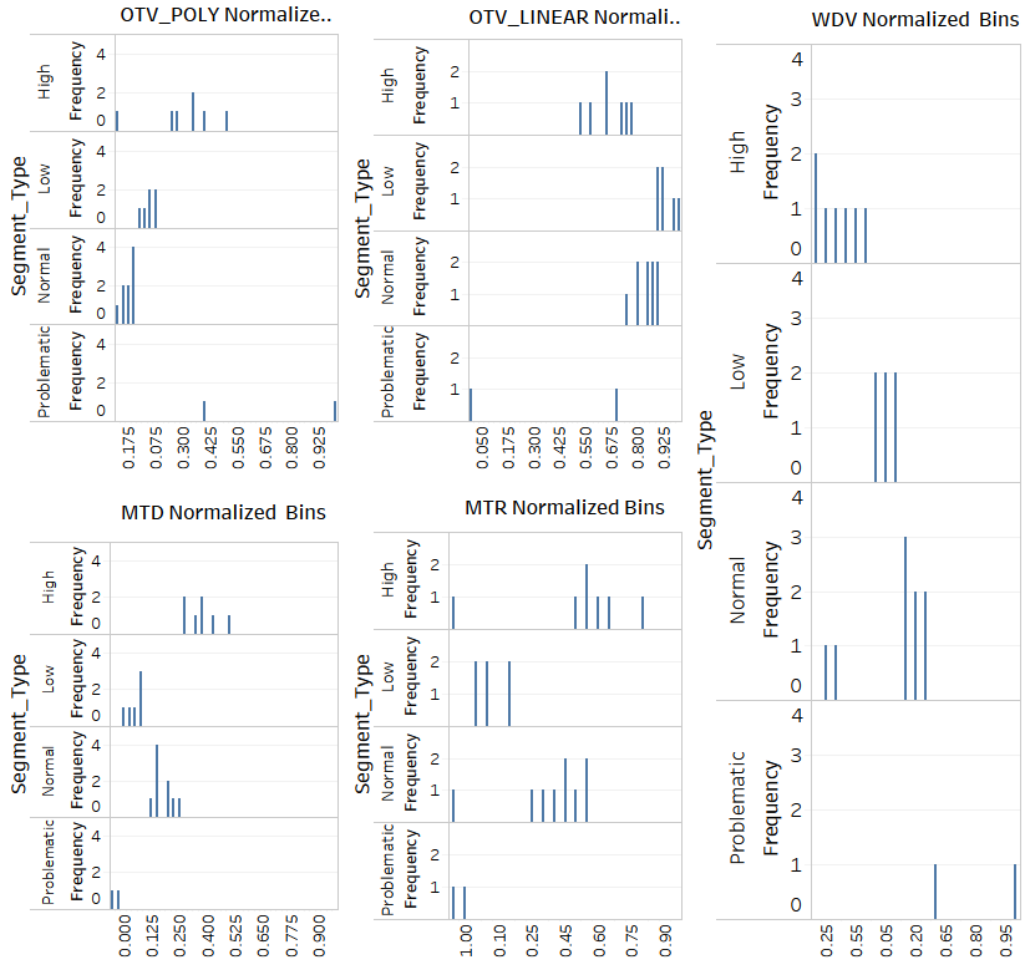
**Figure C.9. Number of anomalous days for each segment**

### Travel Rate and Travel Rate Variability

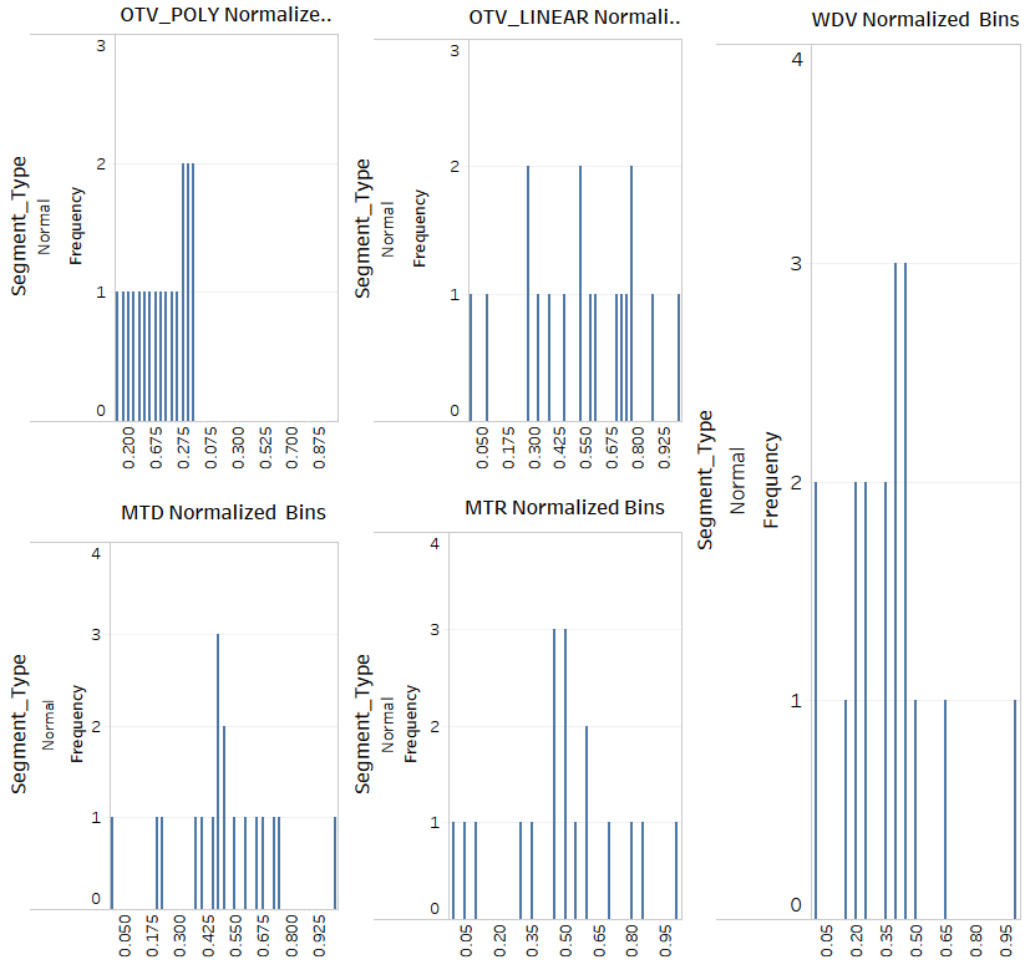
Variation of each of the parameters under the eight condition categories described in the results and discussion are shown below in Figure C.10. To find the effect of the parameters on the clustering, they are further normalized and plotted.



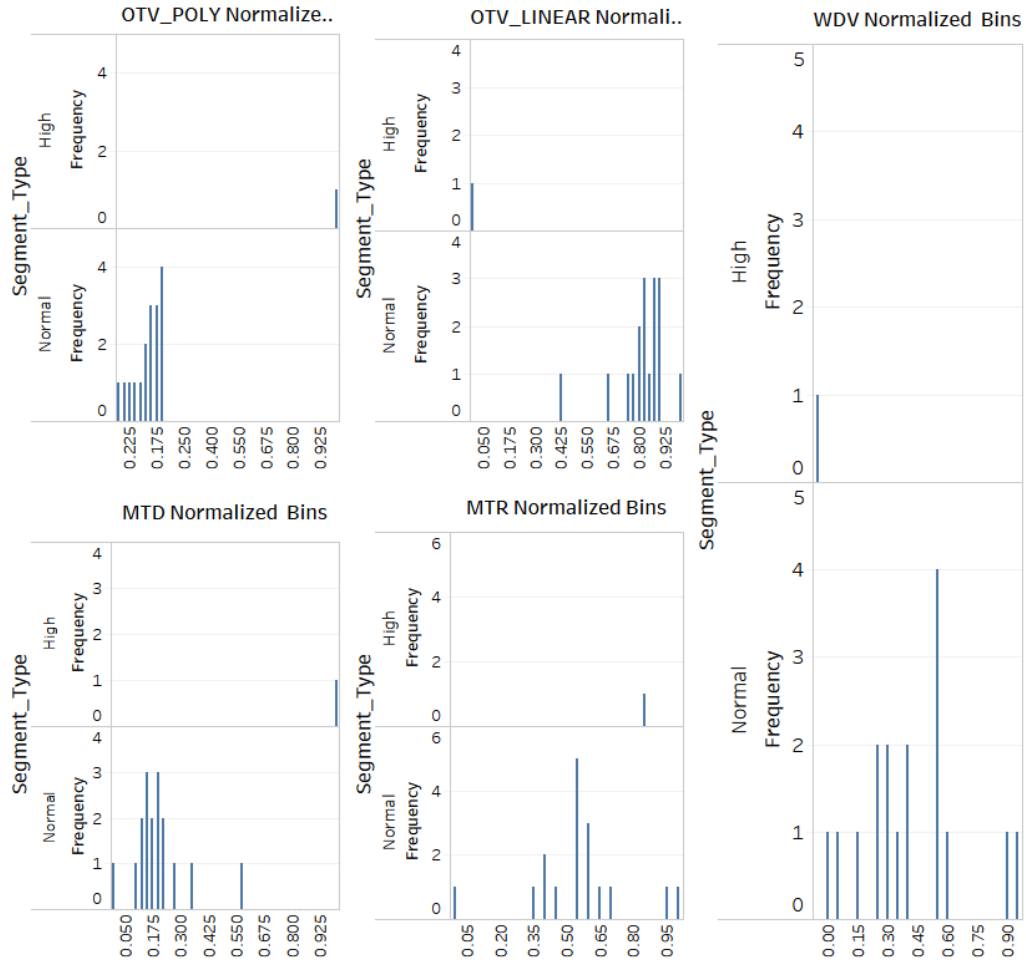
(a) Medium ID, low AADT



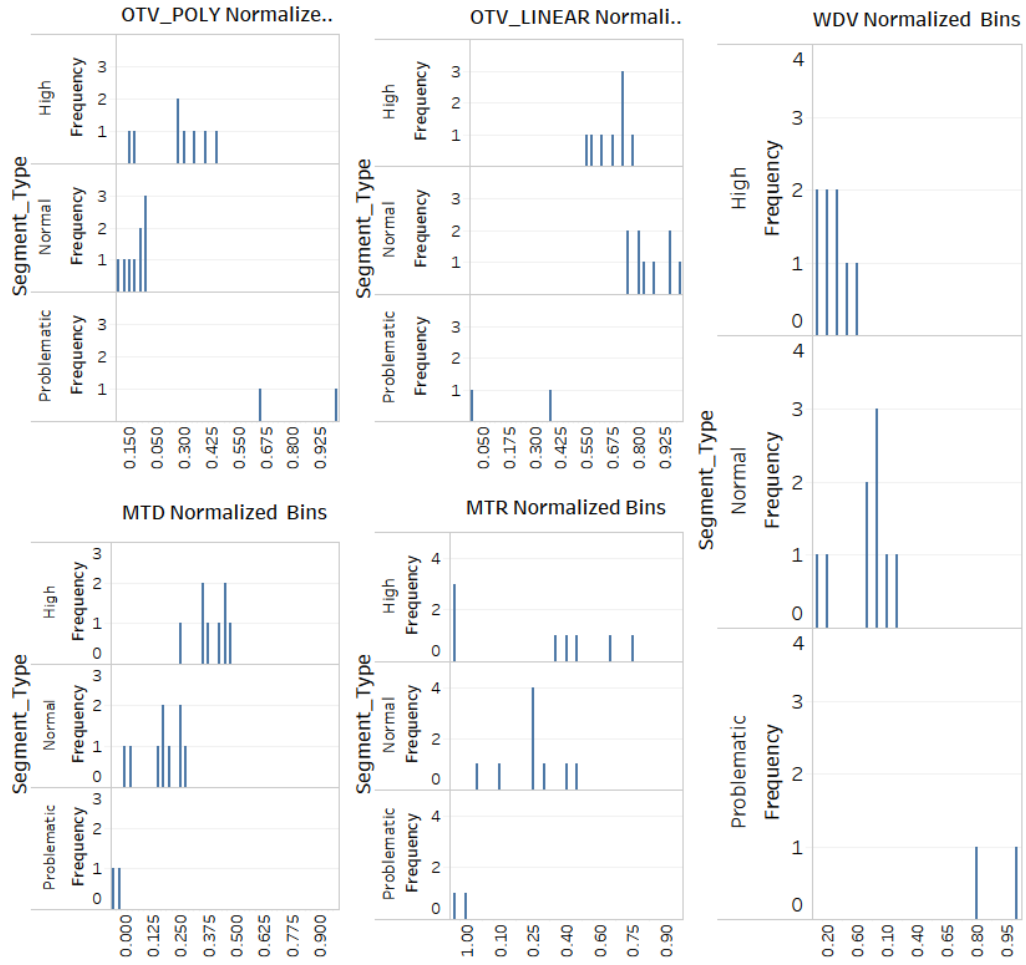
(b) Low ID, high AADT



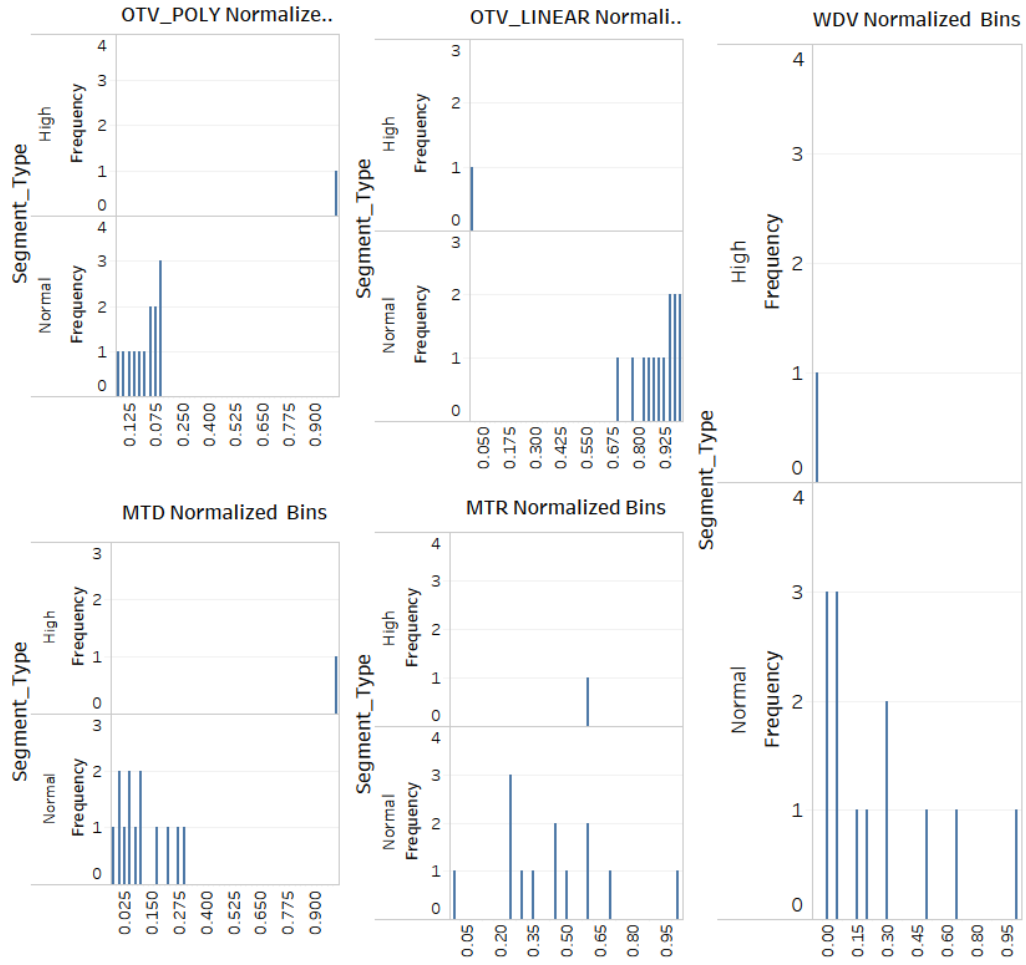
(c) Medium-high ID, medium AADT



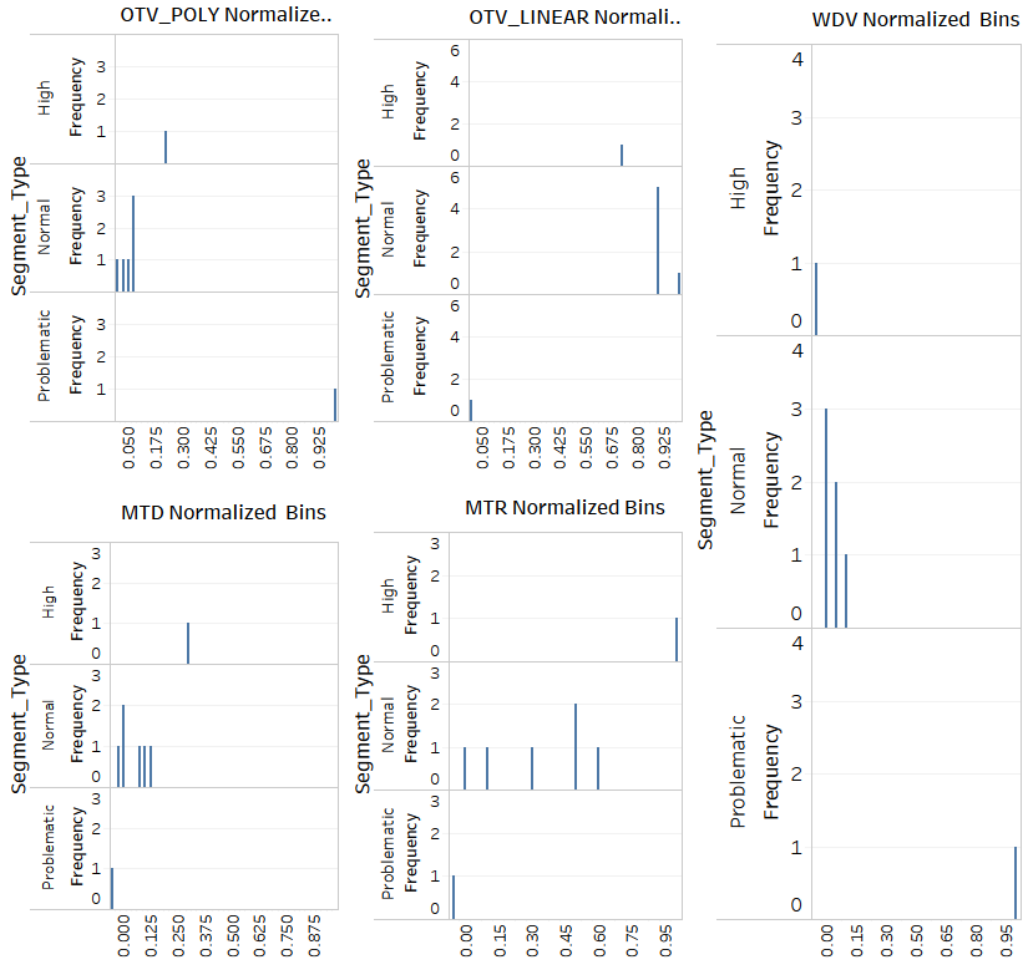
(d) Medium ID, high AADT



(e) Medium ID, medium AADT

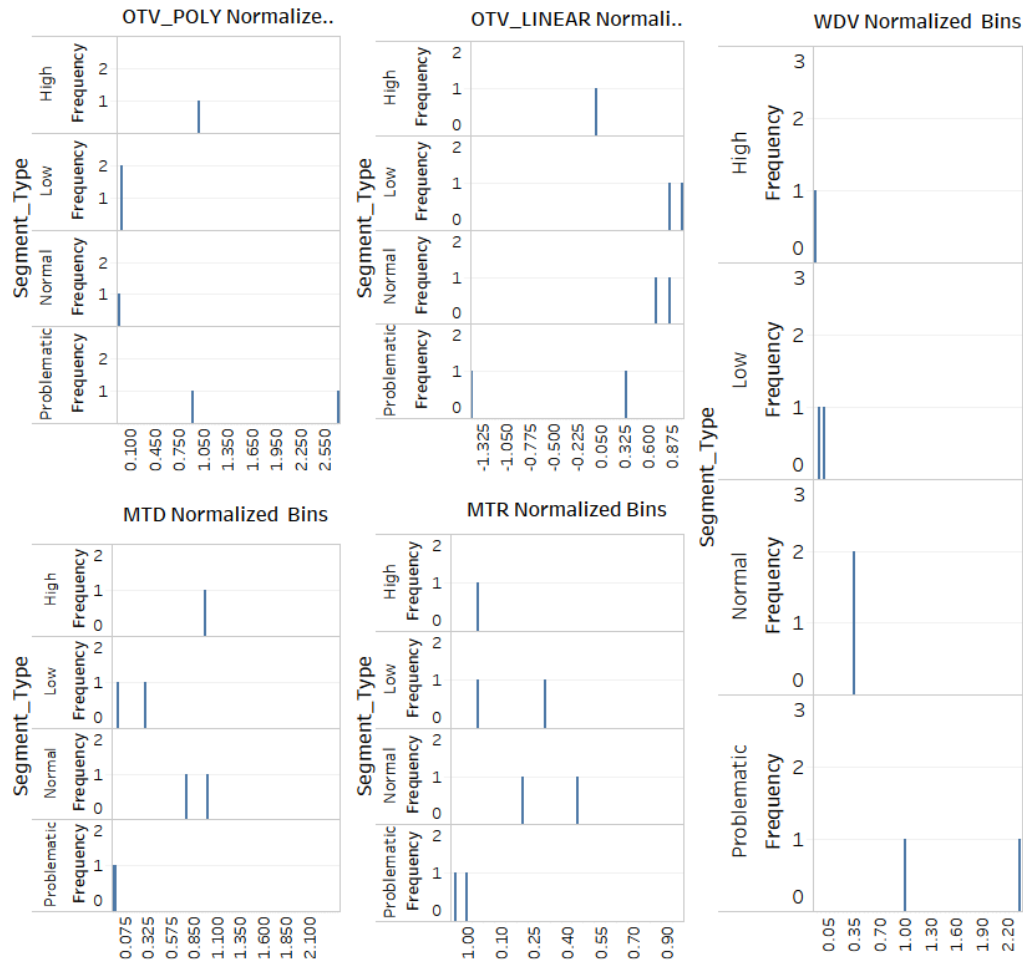


(f) Low ID, low AADT



(g) Medium-high ID, low AADT





(h) Low ID, high AADT

**Figure C.10. Comparison of the five parameters (median travel rate [MTR], within day variability [WDV], minimum travel rate dispersion [MTD], and two overall travel rate variabilities [OTV\_POLY and OTV\_LINEAR]) in the normalized form for the eight condition categories**

From Figure C.10, it seems that the overall travel rate variability parameters offer the best separation guidelines, and the minimum travel rate dispersion and variabilities seem to differentiate groups in most cases. The median travel rate and the within day variability do not separate the two groups as significantly.





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