Report No. UT-22.21

# DETECTING TRAFFIC DATA ANOMALIES IN LONGITUDINAL SIGNAL PERFORMANCE MEASURES

**Prepared For:**

Utah Department of Transportation
Research & Innovation Division

**Final Report**
**November 2022**

RESEARCH

Keeping Utah Moving

Utah Department of Transportation - Research Division
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16. Abstract

The Utah Department of Transportation (UDOT) has continuously invested in traffic signal performance evaluation in Utah. The Brigham Young University (BYU) transportation research team developed a high-level scoring system to evaluate signal performance using four Automated Traffic Signal Performance Measures (ATSPM), including platoon ratio, split failures, arrivals on green, and red-light actuations. The scoring system helps UDOT engineers and planners to evaluate the performance of each signal. However, there is still a need to understand how intersections and corridors perform over time. Therefore, the purpose of this research was to use the scoring system developed in the previous research to analyze the signal performance longitudinally. The method described in this research expanded the study area from 20 to 32 signalized intersections and the study period from 24 days to 2 years. One additional ATSPM (approach volume) was also included. The BYU research team developed an interactive data visualization tool to show the change in signal performance measures over time, and several data anomalies were discovered in the ATSPM datasets. The research team applied linear regression, moving average and standard deviation, and distribution comparison methods to identify the data anomalies. However, due to the various types of data anomalies, only the moving average and standard deviation method was successful in identifying most of the data anomalies. Future investigation is needed to address the data anomalies and improve the data accuracy.

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| | |
|---|---|
| ATSPM | Automated Traffic Signal Performance Measures |
| AOG | Arrivals on Green |
| AOR | Arrivals on Red |
| BYU | Brigham Young University |
| CCS | Continuous Count Station |
| GDOT | Georgia Department of Transportation |
| PCD | Purdue Coordination Diagram |
| PSF | Purdue Split Failure |
| PTI | Planning Time Index |
| SQL | Structured Query Language |
| SSAM | Surrogate Safety Assessment Model |
| TAC | Technical Advisory Committee |
| TTI | Travel Time Index |
| UDOT | Utah Department of Transportation |

## EXECUTIVE SUMMARY

The Utah Department of Transportation (UDOT) has developed an Automated Traffic Signal Performance Measures (ATSPM) system, which has played a crucial role in evaluating and monitoring signal performance throughout Utah since 2012. ATSPM aggregates high-resolution data collected from traffic signal detectors to create a real-time and historical performance of signalized intersections. The data are used in many capacities, including evaluating traffic progression along corridors, displaying unused green time, identifying vehicle and pedestrian detector malfunctions, and measuring key performance measures such as volume, travel time, and speed of vehicles. The UDOT ATSPM system aims to optimize mobility and manages traffic signal timing and maintenance to reduce congestion, save fuel costs, and improve safety (UDOT, 2022a). The Brigham Young University (BYU) transportation research team, in UDOT Report UT-20.08, developed a signal scoring system to evaluate signal performance using four performance measures: platoon ratio, split failures, arrivals on green (AOG), and red-light actuations. While this method was helpful in determining overall performance, there was still a need to evaluate signal performance over time, especially when signal retiming, detector malfunctioning, road construction, and other factors are present (Schultz et al., 2020; Wang et al., 2022).

The purpose of this research was to conduct a longitudinal analysis of traffic signal performance in the state of Utah using ATSPM data and the scoring system developed by the BYU transportation research team in UDOT Report UT-20.08 (Schultz et al., 2020). The BYU transportation research team applied the scoring system to generate continuous scores to monitor how the scores change over time for each signal. The research team added an additional performance measure (approach volume) in the longitudinal analysis, so the intersection scores can also be compared by traffic volume, which helps UDOT prioritize improvement to intersections with low scores and high traffic volume. To evaluate signal performance over time, the BYU transportation research team acquired 3 years of ATSPM data from 2017 to 2019 for a total of 89 signals from the UDOT ATSPM database. However, the study periods were reduced to 2 years, from 2018 to 2019, because the 2017 ATSPM data were archived in an inaccessible location. While 89 signals were initially chosen, a signal refinement process was applied to ensure that accurate and complete data were used for the analysis. All four performance measures mentioned in the scoring system were required to have valid values during the same period to create the intersection scores. The research team identified the number of missing values at each signal for each performance measure and narrowed the signal selection down to 32 signals with data for all performance measures.

During the longitudinal analysis, it became apparent that many data anomalies were present in all five performance measures, especially the approach volume measure, which could lead to inaccurate results in a longitudinal analysis. The approach volume is an element in both platoon ratio and AOG calculation and would therefore affect the results of the final scores. Consequently, the research focus was shifted to developing a method for identifying approach volume anomalies in longitudinal periods. A data visualizer was developed to display changes in performance measures over time. As the research progressed, it was determined that the data visualizer could also be used to identify data anomalies across multiple performance measures. Three statistical methods, including linear regression, moving average and standard deviation, and distribution comparison were chosen to determine if a method could be performed on the approach volume data to identify the locations of data anomalies. The research team found the moving average and standard deviation method to be most successful in identifying data anomalies. The findings and proposed method will allow UDOT to better identify data anomalies and help guide their continued efforts to improve ATSPM in future software releases.

# 1.0 INTRODUCTION

## 1.1 Problem Statement

The Utah Department of Transportation (UDOT) has taken an active role in evaluating and monitoring traffic signal performance throughout the state. Many Intelligent Transportation System technologies and innovations have been used and applied over the last 10 years. The Automated Traffic Signal Performance Measures (ATSPM) system is one of the innovations and technologies developed since 2012. ATSPM use data collected directly from traffic signal detectors to create a real-time and historical record of performance at signalized intersections. UDOT uses various measures to evaluate the quality of traffic progression along corridors while displaying unused green time that may be available from various movements. The information gained through ATSPM data helps to inform UDOT of vehicle and pedestrian detector malfunctions while also measuring vehicle delay and recording vehicle volume, speed, and travel time. UDOT uses the measure to optimize mobility and manage traffic signal timing and maintenance to reduce congestion, save fuel costs, and improve safety (UDOT, 2022a). UDOT has additionally expressed hope that the ATSPM system can provide strategic, longitudinal information to decision makers in the way that the Georgia Department of Transportation (GDOT) has done with its online ATSPM dashboard (GDOT, 2022a).

The Brigham Young University (BYU) transportation research team has been working on research to evaluate the quality of signal operations using ATSPM over the last 4 years. The objective of an initial research project (Schultz et al., 2020) was to assess performance measurement data collected through the ATSPM database that provides context to the historic quality of signal system operations across the state. This was done by developing an analysis procedure that establishes meaningful thresholds for various performance measures of signal system operations. The research created a statistical scoring system tool and interactive data visualizer using R (a language and environment for statistical computing and graphics) and the corresponding "Shiny" engine to evaluate intersections across a collection of individual performance measures. The performance measures assessed in the research included platoon ratio, split failures, percent arrivals on green (AOG), and red-light actuation, with threshold values determined by an expert panel consisting of Technical Advisory Committee (TAC) members and k-means cluster analysis. The four measures used high-resolution data for intersections and corridors in Utah from the UDOT ATSPM website. Based on the analysis results, threshold values were established to "score" the performance of an intersection or corridor. These threshold values were developed based on 2018 data for three corridors with a total of 20 intersections over 24 days (Schultz et al., 2020; Wang et al., 2022).

In the process of completing the previous research, it became apparent that the amount of data available for ATSPM analysis varies considerably from intersection to intersection across the state. For this reason, there was still a need to evaluate ATSPM data and refine the preliminary dashboard further. In particular, UDOT expressed a desire to further develop the intersection scoring methodology weights (platoon ratio, split failure, percent AOG, red-light actuation) and apply this methodology in a longitudinal analysis. This analysis would identify locations across the state that have been improving operational performance and those that have seen a decline. The analysis would aid UDOT as they pinpoint areas where ATSPM detectors could be fixed, and signal performance could be improved.

The purpose of this research was to conduct a longitudinal analysis of traffic signal performance in the state using ATSPM data by building upon the preliminary interactive data visualizer developed by the BYU transportation research team (Schultz et al., 2020; Wang et al., 2022) (https://atspmevaluation.shinyapps.io/ATSPM-Shiny/). The research also considered the inclusion of additional performance measures, such as approach volume, in the evaluation tool. The results of this research were anticipated to be implemented on the ATSPM website by the UDOT Traffic Management Division to monitor and evaluate signal system performance over time and to better understand how signalized intersections and corridors are operating, how their performance has improved (or declined) over time, and which intersections need to be prioritized. As the research progressed, however, it became apparent that data anomalies were present in the approach volume data and these anomalies could produce inaccurate results for a longitudinal analysis. Therefore, the focus was shifted to developing a method for identifying anomalies in approach volume data. With the change of focus for the research, the results will allow UDOT to better understand data anomalies that could help guide their continuous efforts to improve ATSPM in the future.

## 1.2 Objectives

The primary objective of this research was to utilize the UDOT ATSPM data as well as the results of UDOT Report UT-20.08 (Schultz et al., 2020) as a starting point to conduct a longitudinal analysis of traffic signal performance in the state by building upon the preliminary interactive data visualizer. That objective shifted partway through the research to evaluate data anomalies present in approach volume data that would assist UDOT in continuous efforts to improve ATSPM.

UDOT will benefit from this research by better understanding the overall performance of signalized intersections across the state and refining algorithms currently in use. Using the research results, traffic signal systems will be evaluated to determine which ATSPM detectors are returning inaccurate data (i.e., data anomalies) and where signal performance is improving or declining across the state.

## 1.3 Report Outline

This report is organized into the following chapters:

- Chapter 1 includes an introduction to the research, project objectives, and an outline of the report.
- Chapter 2 includes a literature review of existing ATSPM research, ATSPM use within UDOT, additional ATSPM data reports, and methods for ATSPM data analysis.
- Chapter 3 includes a discussion of the methodology used for this research including performance measures data selection, collection, and refinement. Statistical methods used in the development of a data anomaly detection tool are also summarized.
- Chapter 4 includes a discussion of the ATSPM data analysis, evaluation, and data validation.
- Chapter 5 includes conclusions from the research.

# 2.0 LITERATURE REVIEW

## 2.1 Overview

A literature review was performed to gain insight into the longitudinal analysis as well as the kinds of research conducted with longitudinal research in the transportation field that can be applied to evaluate ATSPM data over time. This chapter contains a summary of the literature review with a discussion on several key topics. First, the existing work of previous ATSPM research from the BYU transportation research team will be discussed. Second, ATSPM will be summarized, and new performance measures will be introduced. Third, additional ATSPM data resources and reports will be described. Finally, different types of data analysis methods for longitudinal data validation will be identified.

## 2.2 Previous ATSPM Research

Over the last 4 years, the BYU transportation research team has been working on research to evaluate the quality of signal operations using ATSPM data. The three objectives of the research included: evaluating performance measurement data collected through the UDOT ATSPM database and determining which performance measures could be used for evaluation of traffic signal maintenance and operation, developing threshold values for each selected performance measure, and providing a process for an overall evaluation to the historic quality of signal system operations across the state. The research results are documented in UDOT Report UT-20.08 (Schultz et al., 2020).

In UDOT Report UT-20.08, the BYU transportation research team identified 12 current performance measures used by UDOT. From these twelve, four performance measures were selected as the most useful for evaluating traffic signal maintenance and operations. The four performance measures chosen were platoon ratio, split failures, percent AOG, and red-light actuations. Once the performance measures were selected, 20 signals located on main arterials in Utah and Salt Lake counties were selected for application of the process. The signals included 10 on Fort Union Boulevard in Cottonwood Heights and Midvale, UT; five on 800 North in Orem, UT; and five on State Street in Orem, UT. The selected time periods for analysis were from 7:00

AM to 9:00 AM on Tuesdays and Wednesdays in March, July, and October 2018. The reason for choosing Tuesdays and Wednesdays is that they have similar traffic patterns to other weekdays. Three separate months were chosen to account for changes in weather and traffic demand.

Once the selected data were collected from the ATSPM, initial threshold values for each performance measure were determined using k-means cluster analysis. The threshold values were then adjusted based on industry standards and an expert panel when appropriate. For example, Day et al. (2018) used the Highway Capacity Manual (TRB, 2010) to determine threshold values for the data. Finally, the threshold values were supplemented by expert opinion from the TAC, a panel of engineers from UDOT overseeing the research. After threshold values were determined, an overall score based on the threshold values and scores of the individual performance measures was calculated for each intersection. An overall score based on the scores of the intersections in those corridors was calculated by averaging the scores of those intersections. Finally, the researchers provided a process and scoring system to evaluate the historic quality of signals and signal system operations across the state (Schultz et al., 2020; Wang et al., 2022).

During the previous research, there were several limitations and challenges discovered. The biggest challenge was that the ATSPM database was not as complete as the research team had expected. For multiple signals, data were missing or had extreme values for specific performance measures. This made data evaluation and analysis more challenging than expected. The amount of usable data was limited in constructing the scoring method because there were incomplete data (Schultz et al., 2020; Wang et al., 2022). Therefore, one of the goals of the current research effort documented in this report is to fine-tune the scoring method using more complete data from the UDOT ATSPM database.

### 2.3 Performance Measures Used by UDOT

As the benefits of ATSPM have become more well known, the technology has been adopted by more state departments of transportation. This uptick in use has also led to the creation and utilization of additional performance measures related to ATSPM technology. This section will mention the performance measures utilized in the previous research as well as introduce three new performance measures developed and implemented by UDOT, namely the timing and actuation measure, left-turn gap analysis, and wait time.

### 2.3.1 Performance Measures in Previous Research

The BYU transportation research team identified 12 performance measures used by UDOT in 2019 (details are found in Schultz et al., 2020). These performance measures included:

1. Purdue phase termination diagram.
2. Split monitor.
3. Pedestrian delay.
4. Preemption details.
5. Purdue split failure (PSF).
6. Yellow and red actuations.
7. Turning movement counts.
8. Approach volume.
9. Approach delay.
10. Arrivals on red (AOR).
11. Purdue coordination diagram (PCD).
12. Approach speed.

### 2.3.2 Timing and Actuation

The timing and actuation performance measure was created by UDOT. It depicts a detailed view of the vehicle and pedestrian cycles for each phase overlaid with detection actuation. In addition, it graphically displays the signal timing diagram for each phase and direction of an intersection over a period of time. The lengths of green, yellow, and red phases are shown in their respective colors, and blue bars are overlaid to show the lengths and timing of pedestrian walk intervals. Stop bar presence detector data is demonstrated by triangles representing when the detector was activated, a line representing the length of time the detector was active, and a square representing when the detector was deactivated. Lane-by-lane vehicle counts are also displayed, with individual vehicle counts represented by a single square. Due to the dense nature of the data, this metric is most useful for mesoscopic levels when viewed on a smaller time scale (60 minutes or less). The algorithm looks back at a user-specified period (5 minutes default) for green, yellow, and red data behind the specified start time. If no enumerations are found, it shows white or gray (GDOT, 2022b). Figure 2.1 shows an example of a timing and actuation diagram (UDOT, 2022a).

### 2.3.3 Left-Turn Gap Analysis

The left-turn gap analysis measure was created by GDOT to display the frequency of varying gap lengths of permissive left-turning vehicles for each through phase of an intersection. It also evaluates available gaps in opposing traffic for a left-turning vehicle to make a permissive movement. Because the gap time between vehicles varies, separate colors are used to represent different gap time spans. For example, red represents gap times of 1.0-3.3 seconds, light green for 3.3-3.7 seconds, dark green for 3.7-7.4 seconds, and teal for greater than 7.4 seconds.

The gap values were determined based on UDOT Report UT-19.05 (Schultz et al., 2019). The bar charts display the number of gaps of a certain length of time in each 15-minute bin. The left-turn gap analysis can be used to determine the capacity of permissive left turns for each through phase of an intersection, evaluate the left-turn phasing needs or improvements necessary for a particular through phase, or as a chart generator for left-turn gap analysis reports. Gap time spans for each color and bin time length can be adjusted if necessary. The left-turn gap analysis measure will only appear in the list of the available metrics if an intersection has lane-by-lane count or stop bar presence detection on an approach (GDOT, 2022b). Figure 2.2 shows an example of a left-turn gap analysis diagram (UDOT, 2022a).

### 2.3.4 Wait Time

The wait time measure was created by GDOT to calculate the average wait time for vehicles by approach and movements. The wait time measure calculates the time duration (in seconds) between the first detector call on a phase during red and the time the indication for that phase turns green. It also graphically represents how long vehicles using each phase wait between green indications, while data on the termination type of the previous phase and the volume per hour for the phase are also charted as references (GDOT, 2022b). Figure 2.3 shows an example of a wait time diagram (UDOT, 2022a).

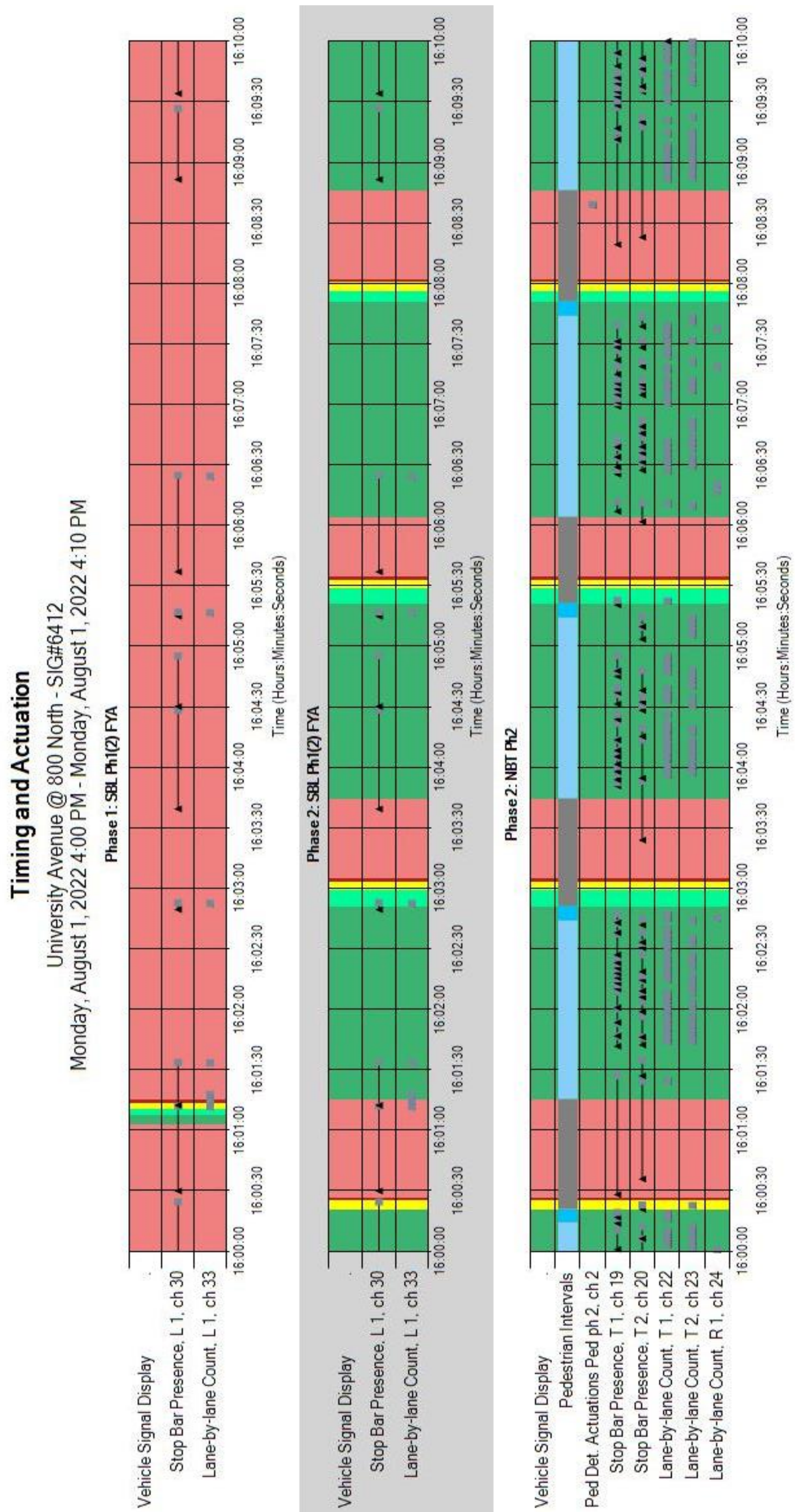



**Figure 2.1 Timing and Actuation for phase 1 & 2 at University Avenue and 800 North in Provo, UT (UDOT, 2022a).**

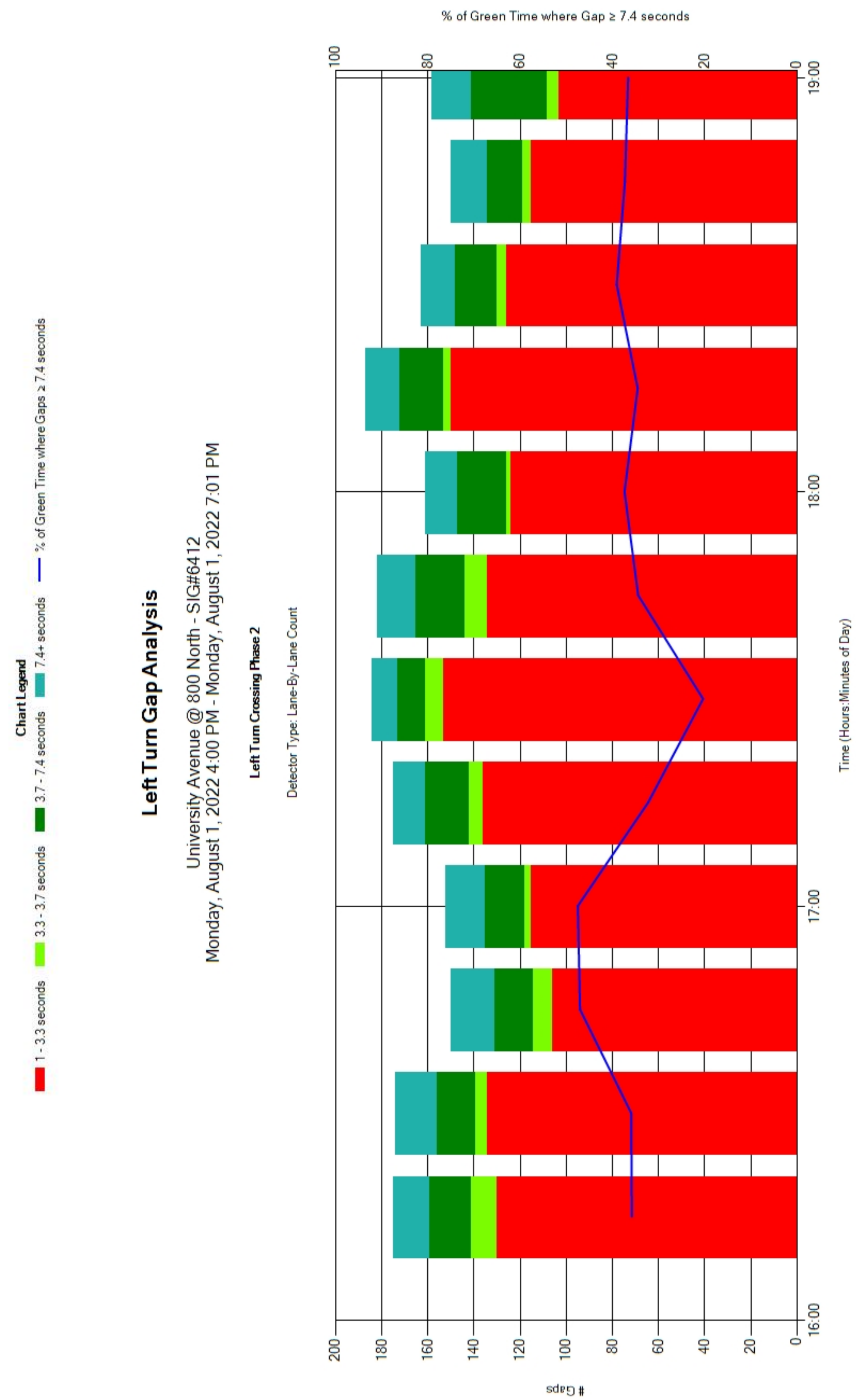



**Figure 2.2 Left-turn gap analysis for phase 2 at University Avenue and 800 North in Provo, UT (UDOT, 2022a).**

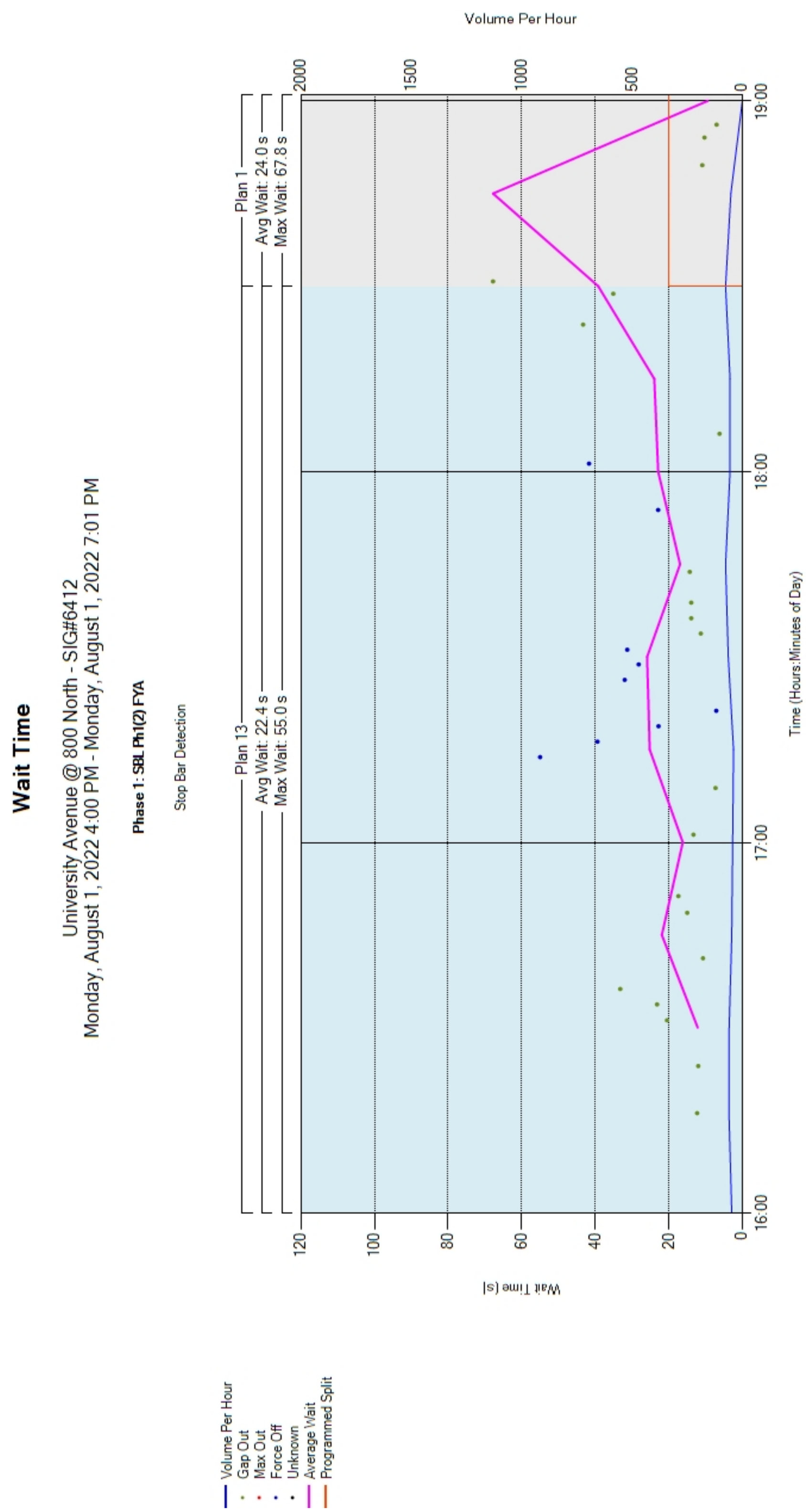



**Figure 2.3 Wait Time for phase 1 at University Avenue and 800 North in Provo, UT (UDOT, 2022a).**

## 2.4 Additional ATSPM Data Reports

To fully understand the changes that occur to the ATSPM datasets over time, additional data resources and reports related to ATSPM are included in the evaluation and analysis process. This section will discuss three other resources or reports: the GDOT SigOps metrics dashboard, the UDOT Watchdog reports, and the UDOT electronic logbook.

### 2.4.1 GDOT SigOps Metrics Dashboard

The GDOT SigOps metrics dashboard (http://sigopsmetrics.com/main/) (GDOT, 2022a) was created by GDOT to visualize ATSPM data longitudinally. Monthly, quarterly, and all-time summary tables are available with trending plots to compare changes in traffic-related performance measures over time. Separate tabs for metrics such as corridor performance, traffic volumes, and equipment reliability provide detailed graphics summarizing overall and corridor trends. In addition, a virtual statewide map displaying signal-specific monthly traffic volumes is provided for a system-wide longitudinal view. SigOps metrics are used to proactively manage and maintain traffic signals statewide by leveraging existing and emerging technologies through a data-filled, easy-to-use website.

In an effort to summarize crucial signal information, nine performance measure visualizations are available through the SigOps Metrics summary tables:

1. Throughput: a measure of efficiency representing the maximum number of vehicles served on all phases at an intersection.
2. AOG: a measure of coordination. A high percentage of arrivals on green would result in good offsets, fewer stops, and less delay.
3. Progression ratio: addresses the percent of vehicles arriving on green (which is highly correlated with the amount of green time given to each phase) by controlling for green time per cycle on each phase.
4. Queue spillback rate: an experimental measure of effectiveness. It measures unmet demand in a cycle as measured by setback detectors.
5. Split failures: identifies cycles where a phase has unserved demand.

6. Travel Time Index (TTI): a measure of delay on the corridor. It is the ratio of travel time to free flow travel time. The TTI for the day is calculated as the average hourly travel time weighted by the hourly volume for the corridor, which is the hourly volume averaged over all signals in the corridor.
7. Planning Time Index (PTI): a measure of delay on the corridor. It takes the $90^{th}$ percentile of the day over the Tuesdays, Wednesdays, and Thursdays for each hour. These $90^{th}$ percentile travel times are then averaged over the day, weighted by the average hourly volume from the main street through phases to get a PTI for the month.
8. Daily volume: a measure of demand on a corridor. Total volume on the main street through phases are summed over each Tuesday, Wednesday, and Thursday and then averaged over all days in the month.
9. Pedestrian activity: the total number of pedestrian pushbutton events recorded by hour and day.

These summary tables have data available from June 2020 to the present. They are customizable to view all signals across the GDOT system, specific signal zones and districts, and main corridors inside each zone or district. Figure 2.4 shows an example of a one-month summary of each performance metric and percent change from the previous month (GDOT, 2022a).

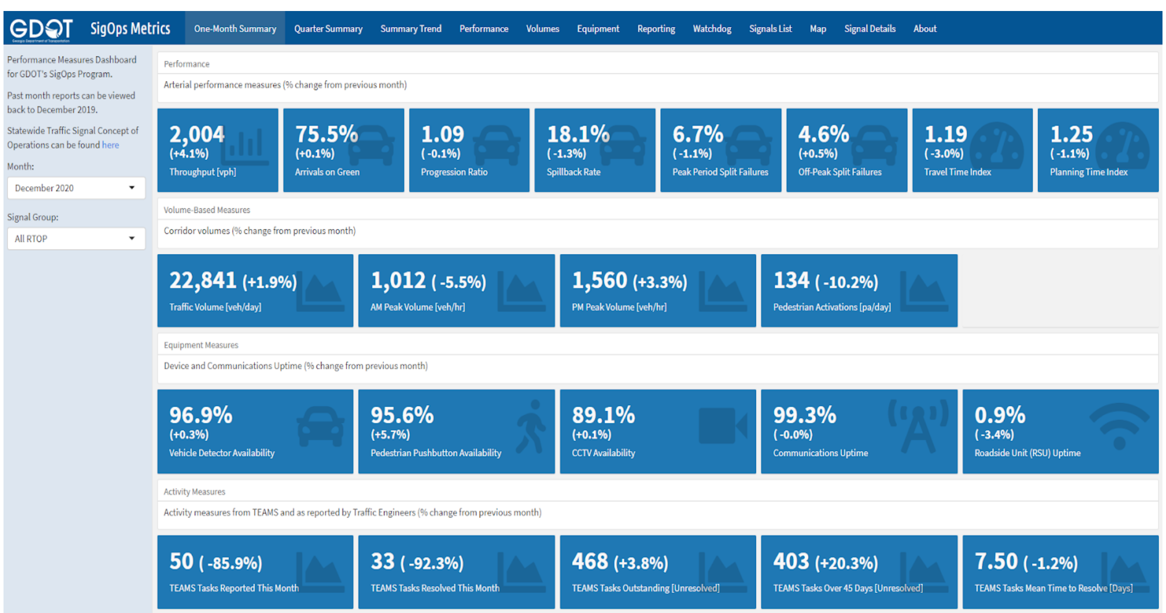



**Figure 2.4 GDOT SigOps Dashboard (GDOT, 2022a).**

### 2.4.2 UDOT Watchdog Reports

UDOT Watchdog reports are an automatically generated summary of data errors found in traffic signal controllers over the previous 24 hours, which are sent as an email to UDOT traffic engineers at 7:00 AM each weekday morning. These reports alert UDOT traffic engineers of detector issues that are manifested through inaccurate data. Watchdog reports enable UDOT to save money in maintenance costs by creating a more efficient way to detect malfunctions. They also help mitigate data errors in the ATSPM system and other data collection.

The Watchdog reports focus on five types of data errors. Each data error has a pre-set threshold which, if met, adds an alert for that specific signal to the Watchdog report for the next morning. The reports are sent to operators based on five conditions, where the numbering also represents the error code displayed for the particular alert in the data (GDOT, 2022c):

1. No data: reports phases with less than 500 records in the database between midnight and midnight the previous day.
2. Force offs: reports phases with more than 90 percent force offs in at least 50 activations between 1:00 AM and 5:00 AM the same day.
3. Max outs: reports signals with more than 90 percent max outs in at least 50 activations between 1:00 AM and 5:00 AM the same day.
4. Low advanced detector counts: reports phases with PCD detectors with less than 100 vehicles counted between 5:00 PM and 6:00 PM the previous day.
5. Stuck pedestrians: reports phases with more than 200 pedestrian activations between 1:00 AM and 5:00 AM the same day.

Figure 2.5 shows an example of the daily Watchdog report. Looking at the Watchdog reports will help the researchers to understand if the data are missing or if there are errors at specific time periods for particular signals, which will help to improve future data analysis and accuracy (Mark Taylor, personal communication).

--The following signals had too few records in the database on 3/2/2021:
7075 - 7200 South & I-15 SPUI (Missing Records - IP: 10.212.10.51)

--The following signals had too many force off occurrences between 1:00 and 5:00:
1097 - 700 East & 300 South - Phase 2 (Force Offs 100%)
1097 - 700 East & 300 South - Phase 6 (Force Offs 100%)
7128 - 300 West & 200 South - Phase 2 (Force Offs 100%)
7128 - 300 West & 200 South - Phase 6 (Force Offs 100%)

--The following signals had too many max out occurrences between 1:00 and 5:00:
5147 - Midland (3500 W) & 6000 South (Roy) - Phase 2 (Max Outs 100%)
5147 - Midland (3500 W) & 6000 South (Roy) - Phase 6 (Max Outs 100%)
6064 - US-89 (1200 West Lehi) & I-15 NB - Phase 4 (Max Outs 98.7%)
6461 - University Parkway & 2310 N (Plum Tree Plaza) - Phase 5 (Max Outs 96.1%)

--The following signals had unusually low advanced detection counts on 3/2/2021 between 17:00 and 18:00:
1056 - 600 South & 200 East - Phase 8 (CH: 57 - Count: 32)
4650 - 12600 S (Herriman Pkwy) & 4150 W - Phase 2 (CH: 2 - Count: 42)

--The following signals have high pedestrian activation occurrences between 1:00 and 5:00:
4845 - 13175 S & 3600 W - Phase 4 (554 Pedestrian Activations)

--The following signals have had FTP problems.  central was not able to delete the file on the controller between  1:00 and 5:00:
4119 - 5624 S & 4800 W (Cougar Ln) (FTPFromAllControllers could not download from Controller.  Number of attempts were: 0)
4771 - Old Bingham Hwy & 7040 W (FTPFromAllControllers could not download from Controller.  Number of attempts were: 1)

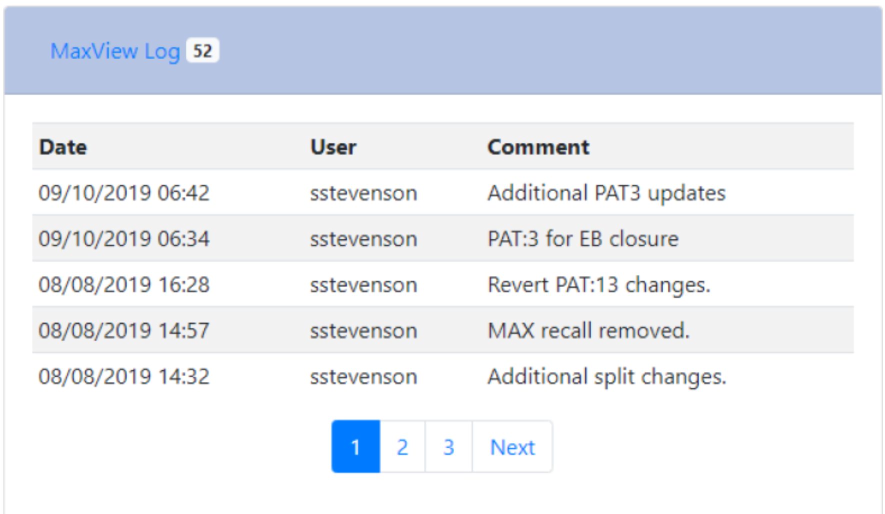
**Figure 2.5 Example daily Watchdog reports.**

### 2.4.3 UDOT Electronic Logbook

Historically, UDOT has used paper logbooks to record changes made to traffic signals. Each traffic operator who opens a traffic signal cabinet is required to record their name, what changes they made, and the reason for the changes. This provides UDOT with a reliable and detailed record that is used in many ways. If a traffic signal has problems, the logbook is used to give operators clues as to the root cause of the issue for faster and easier troubleshooting. Logbooks also show patterns of issues at a location and provide historical data for research studies. These logbooks are important for the long-term record keeping and integrity of traffic signals under the UDOT system.

In May 2020, UDOT implemented an electronic logbook system to be used statewide. This system provides a centralized digital repository to track and store changes made to traffic signals across Utah. With the electronic program, traffic operators can create logs digitally through a computer, tablet, or smartphone. These logs are used to track not only changes made physically in traffic signal cabinets but also changes made remotely that affect the traffic signals.

A log entry is required whenever a cabinet is opened, whether changes are made or not. This creates a record showing that operators are actively monitoring the signal system. Also, while paper logbooks are not used to create new logs, they remain in the cabinets for reference. The electronic logbook system is more consolidated, more flexible for the creation of logs, and provides remote access to statewide data that was not previously possible. Figure 2.6 shows the MaxView logbook that recorded the date and time, the users, and the comment on the changes (Mark Taylor, personal communication).



MaxView Log 52

| Date | User | Comment |
|---|---|---|
| 09/10/2019 06:42 | sstevenson | Additional PAT3 updates |
| 09/10/2019 06:34 | sstevenson | PAT:3 for EB closure |
| 08/08/2019 16:28 | sstevenson | Revert PAT:13 changes. |
| 08/08/2019 14:57 | sstevenson | MAX recall removed. |
| 08/08/2019 14:32 | sstevenson | Additional split changes. |

1 2 3 Next

**Figure 2.6 MaxView Logbook report.**

Because the electronic logbook was not implemented until 2020, and the data analyzed in this research are before 2020, the electronic logbook program will not be used in this research. It is still important to mention this important advancement and apply it to future research projects, enabling the researchers to compare signal performance before and after timing changes and measure the effectiveness of these timing changes on individual signal performance.

### 2.5 Data Analysis Methods

UDOT actively utilizes ATSPM as a monitoring and maintenance tool for traffic signals across the state. Still, the current ATSPM interface limits UDOT traffic engineers in their ability to view the effect of changes to signal timings over long periods of time. A goal of this research was to create an interface to view and analyze ATSPM data longitudinally. In terms of which data analysis method would be most appropriate for observing and measuring the trends of

ATSPM performance measures over time, many options are available, but it is crucial that a method most fitting to the type of problem given be chosen.

Perhaps the most basic method of data analysis is a before-and-after study. These studies use limited observations before and after an event occurred to observe any changes in the trend of the data in question as a result of the event. In the field of transportation, the structure of a before-and-after study is often used to answer questions about transit ridership. Busch-Geertsema et al. (2021) used a before-and-after survey distributed to Goethe University employees to find if the implementation of cost-free public transportation for state employees in the German state of Hesse had an effect on transit ridership. Goethe University is a state-run university, hence why the survey distributed to their staff would give insights into this question. The policy change occurred in December 2018.

Two very similar surveys were distributed to all full-time Goethe University employees, one in 2015 and one in 2019, providing a before-and-after observation for researchers to work with. The surveys included questions touching on the regular mode of transportation to work, attitudes on varying modes of transportation, distance traveled to work, and general socioeconomic information. The researchers found a substantial increase in employees commuting by public transit and the finding that employees only tend to move away from commuting by car when public transportation can fulfill their needs.

Seat et al. (2019) used a hierarchical Bayesian statistical before-after model to analyze locations where raised medians have been installed. The results show that installing a raised median gives an average reduction of 53 percent for all crashes. Kim et al. (2018) evaluated the safety impacts of access management alternatives with the Surrogate Safety Assessment Model (SSAM). The SSAM can save time and improve uncertainty in the crash data integrity and replaces traditional safety impact analysis. The study compared crash occurrences before and after a change in median treatment from a two-way left-turn lane to a raised median. The SSAM helped evaluate the physical and traffic characteristics for before-and-after analyses.

A before-and-after format fits this study well because the qualitative data collected through two surveys give the researchers sufficient information to answer their questions. While a before-and-after study may fit well for qualitative data, assumptions may not be as solid when working with two observations of quantitative data. There is also a concern that more variables may affect the data. In this case, a method that is more adept at parsing out the effects of multiple variables from the impact of a policy may be more appropriate.

In longitudinal studies, the effects of multiple variables can be controlled for, enabling a more accurate analysis of the impact of an event. Chamberlin and Fayyaz (2019) evaluated turning movement count accuracy in ATSPM datasets by comparing them with continuous count station (CCS) data in Utah. The ATSPM datasets had many data anomalies present, mainly in the form of jump discontinuities, where volume data shifted up multiple hundred units for a period of time and then shifted back down to regular levels. The researchers used the CCS data as ground truth for what the ATSPM dataset should be showing and utilized multiple statistical methods to clean the dataset. Interquartile range, k-means, and time-of-day methods were all used to identify and delete anomalies.

Liu et al. (2019) conducted a longitudinal analysis of the effect of California's handheld cell phone ban for drivers on the frequency of cell phone-related crashes. Crash data from 2002-2014, 6 years before and after the 2008 ban, was plotted longitudinally with monthly intervals, resulting in 144 data points across the analysis. A Negative Binomial regression model was built to measure the crash trends before and after implementation of the ban. The monthly vehicle miles traveled in the state were controlled for in the analysis, and the result showed that after the ban, there was a 66.7 percent drop in cell phone-related crashes in California.

Burger et al. (2014) conducted a similar study focusing on the same ban but controlled for more variables and used data from 6 months before and 6 months after implementing the ban. Daily crash counts on major California highways and a basic linear reduced-form model were used to find the marginal effect of the ban on crashes while controlling for rainfall, gas prices, day of the week, and other underlying factors. Those two research studies on California's handheld cell phone ban benefitted from longitudinal analysis by analyzing crash data and controlling for variables that may not have been readily visible in the data. Longitudinal analysis is a powerful method for discovering the actual effects of interventions, but it can be built upon. Some problems involve many moving parts over an extensive dataset to the point where it is impossible to determine causality conclusively.

A natural experiment arises when the researchers cannot control factors and create an experiment that mimics random selection. Brakewood et al. (2015) used a natural experiment brought on by a staggered release of real-time bus tracking information across New York City's multiple boroughs to study if real-time information affects bus ridership. From February 2011 to March 2014, the Metropolitan Transit Authority, which runs the subway and bus system in New York City, strategically released real-time information over time, which created the opportunity for the researchers to run multiple longitudinal studies, giving them the ability to control for variables such as changes in fares, local socioeconomic conditions, weather, and gas prices. Running multiple longitudinal analyses helps solve the issue of confidently assigning causality rather than simply correlation.

## 2.6 Chapter Summary

The purpose of this literature review is to provide valuable background information and limitations from previous research studies that will help researchers to expand existing work into a longitudinal analysis. The new performance measures and additional ATSPM data reports are discussed. The performance measures include timing and actuation, left-turn gap analysis, and wait time. The reports include the GDOT SigOps metrics dashboard, Watchdog reports, and electronic logbook. The GDOT SigOps metrics were discussed as an existing dashboard that provides longitudinal information on ATSPM signals. The Watchdog reports and electronic logbook are time-related data resources that will be valuable tools to aid in analysis. The data analysis methods applied to longitudinal analysis in the field of transportation were discussed as a foundation for this research.

Although evaluation methods and scoring systems were created in the previous research, limitations and challenges still need to be solved. This research aims to fine-tune the previous evaluation methods with an additional performance measure not analyzed in the previous research (approach volume), which helps to report intersection and corridor performance over time. The following chapters will outline the methods to analyze and evaluate ATSPM data longitudinally and to identify anomalies in the data.

# 3.0 METHODOLOGY

## 3.1 Overview

The methodology for this research will be explained in this chapter. First, the data collection process and selection of dates, times, and signals will be discussed. Second, the performance measures selected for analysis will be summarized. Third, a signal refinement process will be discussed to ensure the completeness and high quality of data used for analysis. Then, the signal refinement process will be explained including a discussion on the presence of data anomalies in the ATSPM database and their potential effects. Finally, because of data quality and availability issues, the decision to refine the focus of the project from an analysis of longitudinal trends in signal data to the development of a data anomaly detection tool will be outlined.

## 3.2 Collecting ATSPM Data

The aggregated data for this project were acquired through the UDOT ATSPM database. These data are located on a UDOT Traffic Operations Center server through their Structured Query Language (SQL) database. This SQL server database is the same Measures of Effectiveness server used in previous research and UDOT Report UT-20.08 (Schultz et al., 2020). The UDOT ATSPM database contains traffic data collected at intersections across the state with information on multiple performance measures. ATSPM data from January 1, 2017, to December 31, 2019, was organized in .csv format for this project. However, the first 10 months of data, from January 2017 to October 2017, were archived in the cloud and not usable. The data for all performance measures in this time range were shown as zeros in the ATSPM database due to the database not having direct access to the archived data. The BYU transportation research team did not have access to the archived data and due to the large amount of work needed to retrieve the archived data, the research team and the TAC decided to only use the data from January 1, 2018, to December 31, 2019.

To simplify and standardize the analysis, the times of the data collected were chosen to be the exact times as in UDOT Report UT-20.08, which selected the AM peak, or the hours of

7:00 AM to 9:00 AM, as the study hours. The AM peak provided a time period in which the presence of split failures would be more representative of overall signal performance. The PM peak was not selected because a large number of split failures during the PM peak are due to more cars being on the road. More roadway volume means fewer vehicles may move through an intersection, leading to more split failures during more heavily trafficked time periods. Moreover, the research team chose to analyze the AM peak because the intersection scoring system developed in UDOT Report UT-20.08 was based on data acquired from the AM peak (Schultz et al., 2020).

Tuesdays, Wednesdays, and Thursdays were selected as the days of the week to analyze because traffic patterns on the weekends tend to differ from those on the days closer to the middle of the week. Thursday was added to this research in addition to Tuesday and Wednesday from UDOT Report UT-20.08 (Schultz et al., 2020) because the research team wanted to include more data points for the longitudinal analysis. By selecting three days in the middle of the week, there was a higher probability that the traffic would act similarly across each day.

In addition, the research team decided to only evaluate through movements in Phases 2 and 6. These approaches contain the highest traffic volumes for each signal and hence, the most data to analyze. Choosing Phases 2 and 6 also simplified the analysis by eliminating permitted and protected left turns. Only the through movements were considered for developing the models in the research because turning movements can complicate the interpretation of performance measure data.

The initial signal selection was primarily based on the signals used in UDOT Report UT-20.08, where 21 signals from three major corridors were used. These three corridors were chosen because they had the type of detection required to capture the data needed to calculate the performance measures that would be analyzed. These corridors were 800 North and State Street in Orem, UT, and Fort Union Boulevard in Cottonwood Heights and Midvale, UT. In UDOT Report UT-20.08, the team stated that their research focused on ensuring that the ATSPM data were aggregated correctly, hence the low number of signals chosen. That research team indicated that it would be interesting to expand the number of signals in future research projects (Schultz et al., 2020).

In addition to the 21 signals from the previous research, five signals were added from Fort Union Boulevard, six signals from 800 North in Orem, four from State Street in Orem, 26 from University Avenue in Provo, and 27 more signals from downtown Provo. Overall, the team added 68 new signals for a total of 89 signals. A graphical representation of the signals included in the analysis will be provided in section 3.4.

## 3.3 Selecting Performance Measures

This section will summarize the performance measures used in UDOT Report UT-20.08 and discuss an additional performance measure to be considered in this research. The list of performance measures was provided in section 2.3.1, but a more thorough explanation of selected performance measures used in UDOT Report UT-20.08 will be given in this section. The performance measures included are AOG, split failures, platoon ratio, and red-light actuations. Approach volume will be added as an additional performance measure to fine-tune the scoring method and visualization tool, and a brief explanation will be provided. Threshold values that were used in conjunction with the signal scoring method developed in UDOT Report UT-20.08 will be listed for each measure (Schultz et al., 2020). These threshold values were developed so each performance measure could be evaluated separately, combining the score for each individual measure to form a single signal score.

### 3.3.1 Arrivals on Green

AOG was identified as a performance measure that would be useful for this research. It is a factor in measuring the coordination of signals. A higher percentage of AOG for a signal results in good offsets, fewer stops, and less delay, all of which are beneficial to signal performance. A low number of AOR is likewise preferred. Technically, either AOG or AOR can be used to measure coordination, as they are complements of each other, but AOG was chosen for this research because the UDOT ATSPM system already records raw AOG data. The data were available as the number of vehicles arriving on green for a particular signal in each 15-minute bin.

To effectively compare results between different signals, it was determined that AOG should be presented as percent AOG rather than the raw AOG. Calculating the percent AOG required the total volume of the movement, which was partly why approach volume was added as a performance measure. Equation 3.1 displays how percent AOG was calculated for intersection *i* in time period *t*. The threshold values for the percent AOG were set at 0.2, 0.4, 0.6, and 0.8 (Schultz et al., 2020; Wang et al., 2022).

$$aog_{it} = \frac{AOG_{it}+AOY_{it}}{Total\ Volume_{it}} \tag{3.1}$$

where, $aog_{it}$ = percent of vehicle arrivals on green in 15-minute bin,
$AOG_{it}$ = number of vehicle arrivals on green in 15-minute bin,
$AOY_{it}$ = number of vehicle arrivals on yellow in 15-minute bin,
$Total\ Volume_{it}$ = total number of vehicle arrivals in 15-minute bin.

### 3.3.2 Split Failures

Split failures are another performance measure used in this analysis. A split failure occurs when a vehicle fails to, or is not able to, pass an intersection on the first green light it is given. Split failure data are recorded using a stop bar presence detector. The detector calculates the amount of time during the green phase that the detector is occupied as well as the time during the first five seconds of the red phase. The time occupied during the green phase is converted into a percentage of time occupied and is referred to as the green occupancy ratio. The time occupied during the red phase is similarly converted to a percent and referred to as the red occupancy ratio. This information is then visualized in a PSF diagram (Schultz et al., 2020; Wang et al., 2022).

When the UDOT ATSPM database records a split failure, it is recorded as an event in the controller event log. These events are recorded for each signal approach and are aggregated into the ATSPM database in 15-minute bins. The aggregated number is divided by the total cycles during the 15-minute bin to produce the split failures per cycle. As with AOG, it was determined that this measure should be presented as a percentage to compare results between different signals effectively. Converting split failures to a percentage also required the total volume of the movement in addition to the number of split failures. Equation 3.2 displays how split failures per cycle were calculated. The threshold values for the percentage of split failures were set at 0.05, 0.30, 0.50, and 0.95 (Schultz et al., 2020; Wang et al., 2022).

$$sf_{it} = \frac{Split\ Failures_{it}}{Total\ Cycles_{it}} \tag{3.2}$$

where, $sf_{it}$ = number of vehicles that failed to pass the intersection in each cycle,

$Split\ Failures_{it}$ = number of vehicles that failed to pass the intersection in 15-minute bin,

$Total\ Cycles_{it}$ = number of signal cycles in 15-minute bin.

### 3.3.3 Platoon Ratio

The platoon ratio measures how effectively an intersection is utilizing the green portion of a cycle. It is also a measure of how well the corridor is progressing. Equation 3.3 displays how platoon ratio was calculated.

$$pr_{it} = \frac{PVG_{it}}{g_{it}/C_{it}} \tag{3.3}$$

where, $pr_{it}$ = platoon ratio,

$PVG_{it}$ = percentage of vehicles arriving during the effective green,

$g_{it}$ = effective green time,

$C_{it}$ = cycle length.

UDOT places great importance on this measure because it can quickly display whether a signal is performing well or poorly. A high platoon ratio signifies good performance, while a low platoon ratio signifies poor performance. Although there is no maximum value for a platoon ratio, any value higher than 1.5 is exceptional, and any value lower than 0.5 is considered poor (TRB, 2010). The threshold values for the platoon ratio were set at 0.50, 0.85, 1.15, and 1.5 (Schultz et al., 2020; Wang et al., 2022).

### 3.3.4 Red-Light Actuations

Red-light actuation is the only performance measure evaluated related to safety. This measure gives insight into which signals may have more or less red-light running vehicles and which intersections may have data quality issues. If the data shows a large number of red-light actuations in each 15-minute bin, it is a sign that there may be underlying issues in the data collection process. The threshold values for the red-light actuation were set at 0, 1-2, 3-4, 5-9, and 10 or greater (Schultz et al., 2020; Wang et al., 2022).

### 3.3.5 Approach Volume

Approach volume is a metric that measures the total number of vehicles per 15-minute bin passing a particular traffic signal detector over a specified unit of time. It is usually measured using advanced detection located 300-500 feet before the stop bar. Approach volume was added for this research study for multiple reasons.

First, approach volume is critical to the calculation of many of the previously mentioned performance measures. Percent AOG and percent split failures use approach volume in the denominator to convert AOG and split failures to percentages. For this reason, ensuring the accuracy of the approach volumes used was important.

Second, approach volume also can be used to prioritize the importance of signal scores. In UDOT Report UT-20.08, a signal scoring system was developed to give each signal a score based on the values of their performance measures. This scoring system then gave an aggregate score for the signal, and the priority for signal repair was determined by the aggregate score (Schultz et al., 2020). While the signal score is important, the number of vehicles that pass through the signal also provides an important insight into prioritization. A minor intersection with a lower signal score may be a lower priority than a major intersection (higher volume) with a slightly higher score. Including approach volume allows this important metric to also be part of the signal servicing prioritization process for UDOT.

Lastly, as this study focuses on creating a longitudinal analysis of performance measures at signals over time, it is important to consider whether the volume moving through an intersection has changed. Suppose an increase in volume over time is observed. In that case, UDOT will then have the ability to look into the reasons why an increase occurred, whether it be a holiday, a major event, weather, or a signal timing change. Including approach volume allows the research team and UDOT to observe and analyze increases or decreases over time.

### 3.3.6 Performance Measures and Threshold Summary

Overall, five performance measures will be used in this study. The data for each performance measure is collected and displayed in different ways to be most effective for the particular data type. Table 3.1 shows the visualization tool that is used to display each type of performance measure, as well as the type of detection equipment needed to collect the necessary data to calculate the performance measure.

**Table 3.1 Performance Measures by Tool and Detection Type**

| Visualization Tool | Detection Type | Performance Measure(s) |
|---|---|---|
| PCD | Advanced detection | Percent AOG, Platoon Ratio |
| PSF | Stop bar detection (lane by lane) | Split Failures per 15-minute bin |
| Yellow and Red Actuations | Lane by lane with speed restriction | Red-Light Actuations |
| Approach Volume | Stop bar detection (lane by lane) | Approach Volume |

The thresholds to calculate the intersection score are also needed and were developed in the UDOT Report UT-20.08 (Schultz et al., 2020; Wang et al., 2022). These threshold values were reported in the previous sections. Table 3.2 summarizes the thresholds of performance measures used to calculate the score.

**Table 3.2 Performance Measures Threshold Values**

| Threshold for Level Score | Platoon Ratio | Percent Arrivals on Green | Percent Split Failure | Red-Light Actuations |
|---|---|---|---|---|
| 5 (Exceptional) | > 1.50 | > 0.80 | ≤ 0.05 | 0 |
| 4 (Favorable) | 1.15 ≤ 1.50 | 0.60 ≤ 0.80 | 0.05 ≤ 0.30 | 1.0 - 2.0 |
| 3 (Average) | 0.85 ≤ 1.15 | 0.40 ≤ 0.60 | 0.30 ≤ 0.50 | 3.0 - 4.0 |
| 2 (Unfavorable) | 0.50 ≤ 0.85 | 0.20 ≤ 0.40 | 0.50 ≤ 0.95 | 5.0 - 9.0 |
| 1 (Poor) | ≤ 0.50 | ≤ 0.20 | > 0.95 | 10 + |

## 3.4 Signal Refinement Process

While 89 signals were initially chosen to be included in the longitudinal analysis, a signal refinement process was necessary to ensure that accurate and complete data were used for the analysis. The first stage of the signal refinement process was to determine the completeness of the signal data. Second, the data anomalies were determined and eliminated. Finally, the focus of the project was shifted to developing a method for identifying data anomalies in the signal data.

### 3.4.1 Determination of Data Completeness

For the ATSPM data at each signal selected for analysis, the BYU transportation research team needed to determine the percentage of data present. This was done to enable the research team to only select signals that had data for each performance measure. The research team used a count function in statistical computing and graphics tool R to identify the number of ‘NA’ values each signal had for its five performance measures and then determined which signals had ‘NA’ data for each performance measure. The team then narrowed the signal selection down to only the 32 signals that contained data for every performance measure (including ‘0’). This ended up being a reduction of 64 percent from the original 89 signals. The 32 signals selected had data for each performance measure, but the data were not always complete. Each signal only had partial data for each measure to be selected.

The percentage of complete data was calculated for each signal through two calculations. First, the number of ‘NA’ values for each signal was divided by the total number of observations to produce the percentage of ‘NA’ values for each signal. This percent was then subtracted from 100 to find the percent data values that were not ‘NA,’ or the percent complete data. The signals were divided into five categories: 100-75 percent complete data, 74-50 percent complete data, 49-25 percent complete data, 24-0 percent complete data, and no data. The signals were visualized through ArcGIS Pro, as shown in Figure 3.1 to Figure 3.4. Figure 3.1 and Figure 3.2 illustrate the signals in Provo used for analysis. Figure 3.3 illustrates the signals in Orem, while Figure 3.4 illustrates the location of the signals in Cottonwood Heights and Midvale.

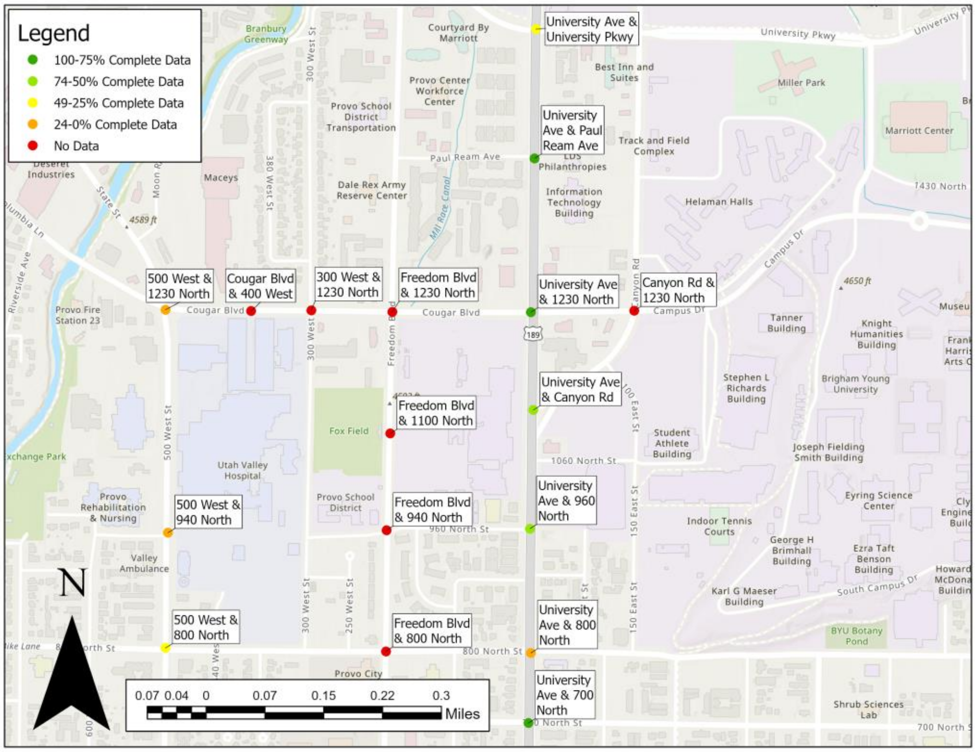



**Figure 3.1 Signals used for analysis in Provo, UT near BYU.**

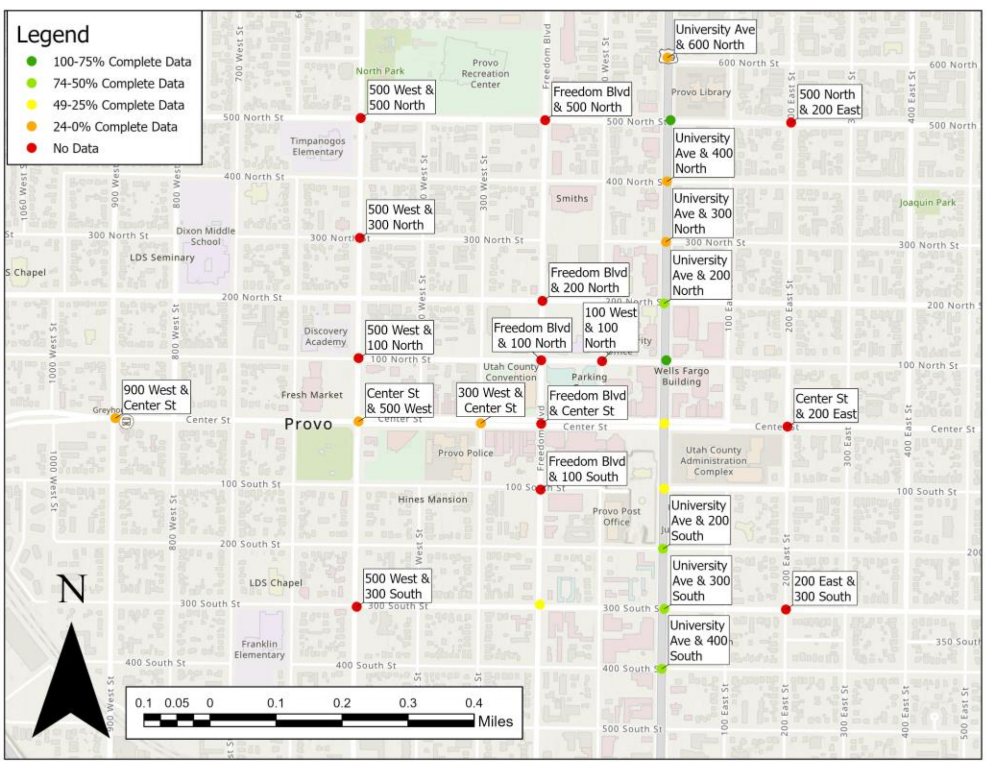



**Figure 3.2 Signals used for analysis in Provo, UT near Center Street.**

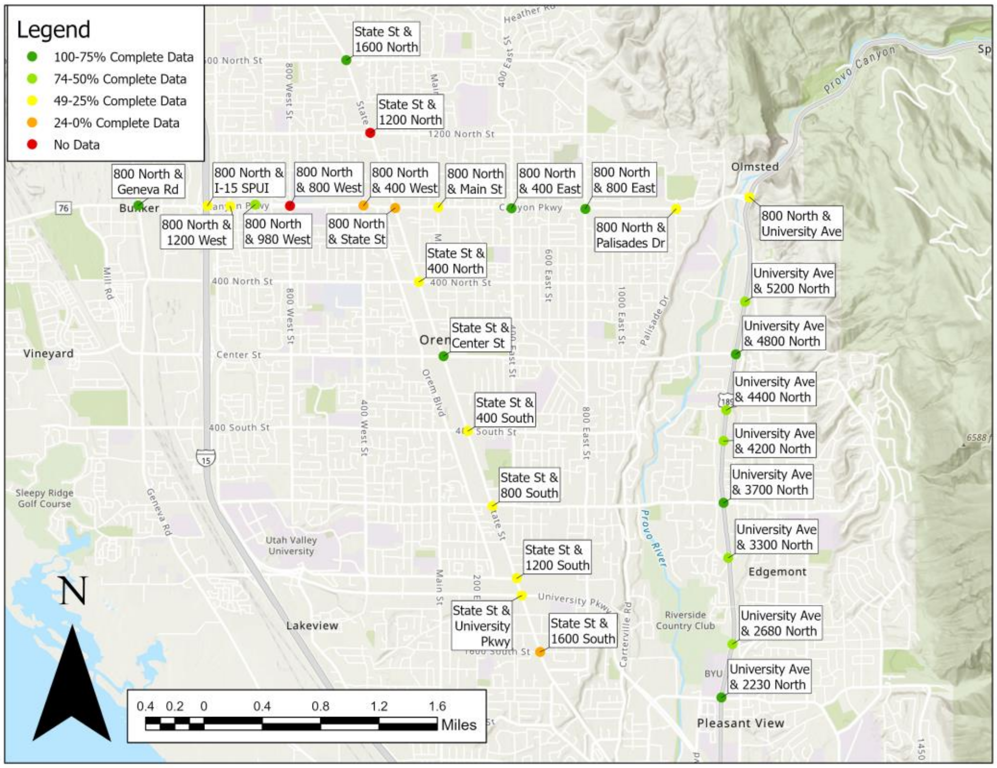



**Figure 3.3 Signals used for analysis in Orem, UT.**

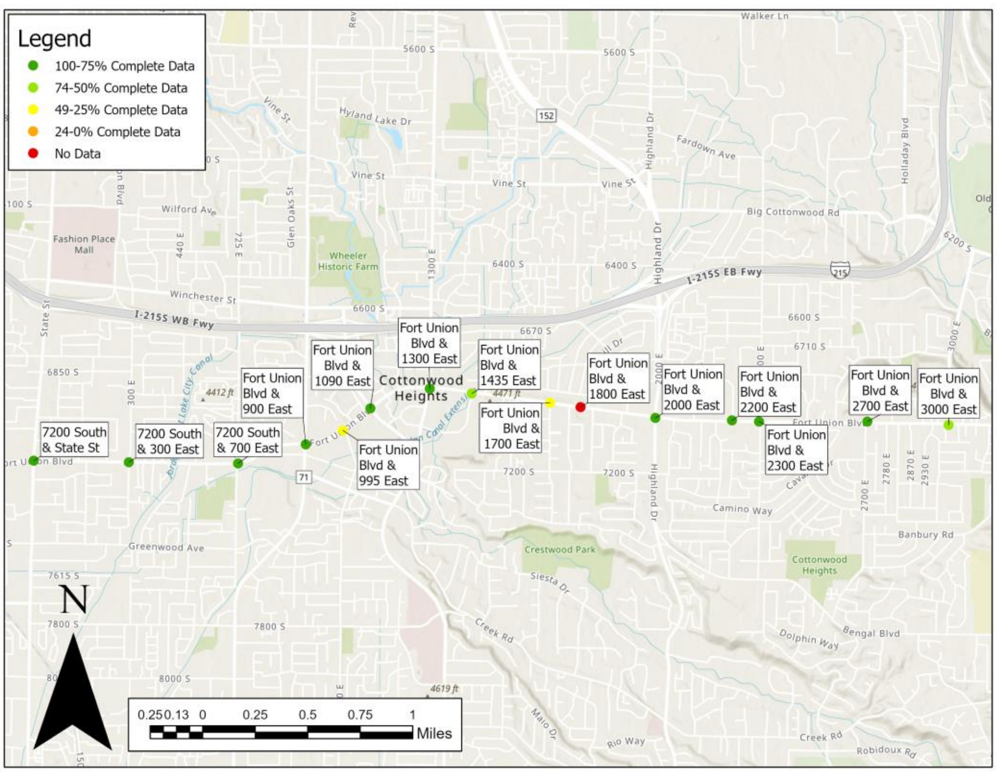



**Figure 3.4 Signals used for analysis in Cottonwood Heights and Midvale, UT.**

### 3.4.2 Determination of Data Anomalies

While data completeness was important to signal selection, data quality was also of concern to the research team. One of the main objectives of this research project was to measure the longitudinal trends found in signal data over time, but if major anomalies were present in the data, the accuracy of the longitudinal trends could be distorted. To classify and properly analyze anomalies present in the signal data, five types of anomaly categories were identified: data switching, data shifting, missing data under 6 months, missing data over 6 months, and irregular curves. The definitions of each anomaly are discussed in further detail in Table 3.3.

To view and identify the location of data anomalies in the signal data, the research team focused on using a data visualizer to graphically display data longitudinally for each signal. A more detailed explanation of the building and features of the data visualizer are provided in section 4.2 but for the anomaly analysis, the visualizer provided the ability to view and clearly identify anomalies. Suppose the data for a signal displayed volatile behavior, with irregular or drastic changes in value over a short period of time. In that case, the behavior could show a potential error in data continuity and should be flagged for UDOT to investigate. The visualizer was developed to graphically display signal data longitudinally, which gave the research team a direct view into possible anomalies that could impact longitudinal trends rather than initially detecting them through statistical means.

During the process of locating anomalies, the TAC informed the research team that any signal beginning with “4” is operated and controlled by a local government. This means that UDOT does not have control over the signal timing or phasing of these signals and that if data anomalies are present at these signals, UDOT does not have the ability to correct them. While analyzing these signals would be helpful for the research team to have access to more data, these signals do not provide UDOT with any information they have direct control over, thus providing inaccurate feedback for any improvements needed in the ATSPM system. However, 11 out of 12 signals on the Fort Union Boulevard corridor begin with a “4” and because the Fort Union Boulevard corridor is a main corridor in the study, signals starting with a “4” were still included in the analysis. These signals should be viewed with the understanding that UDOT does not have complete control over them.

**Table 3.3 Data Anomalies and Description**

| Data Issue | Issue Description |
|---|---|
| Data Switching | Data switching is characterized by offset phases that periodically switch positions. The approach volumes were switching between Phase 2 and Phase 6 in a time period. This issue was very rare and only occurred at signal 4029 – Fort Union Blvd. and 700 East. Neither the TAC nor the research team were able to discover the cause of this issue. |
| Data Shifting | Data shifting is characterized by the sudden and drastic upward shift of a phase or multiple phases where volume data would jump multiple hundred vehicles for a time period and then drop back down to an average level. This issue was found in 6 of the 32 signals (19 percent). Potential causes could include changes made in the Traffic Operations Center, systemic errors, or temporary detector issues. |
| Missing Data Under 6 Months | This issue is characterized by a gap of 1-6 months of missing data. Missing data is categorized as either a missing data point that is presented as an 'NA' value or as a missing value that is presented as a '0'. Data missing for fewer than 6 months would not become a major problem for the longitudinal analysis. This issue was found in 7 of the 32 signals (22 percent). The potential cause could be detector malfunction. |
| Missing Data Over 6 Months | This issue is characterized by a gap of 6 or more months of data missing. This issue was found in 12 of the 32 signals (38 percent). The potential cause could be detector malfunction. |
| Irregular Curves | This issue is characterized by data that follows curves with continuous jumps that cannot be explained by regular traffic patterns in time or seasonality. Many of these curves involve large, sudden increases or decreases in values or large and irregular trends. This issue was found in 7 of the 32 signals (22 percent). The potential cause could be long-term road construction. |
| Normal | Any signals that do not have data switching, data shifting, or irregular curves will count as normal signals. These signals may have missing data but are characterized as normal because they do not exhibit any anomalies that shift or manipulate the input data. For 19 of the 32 signals (59 percent), no issues were found. |

Overall, the 89 signals originally selected were reduced to 32 signals for the final analysis through the signal refinement process. This reduction is attributed to data availability and data quality issues. Figure 3.5 shows an example from the ATSPM datasets for each of the five data anomaly types identified by the research team. Table 3.4 displays an inventory of the data anomalies identified at each signal.

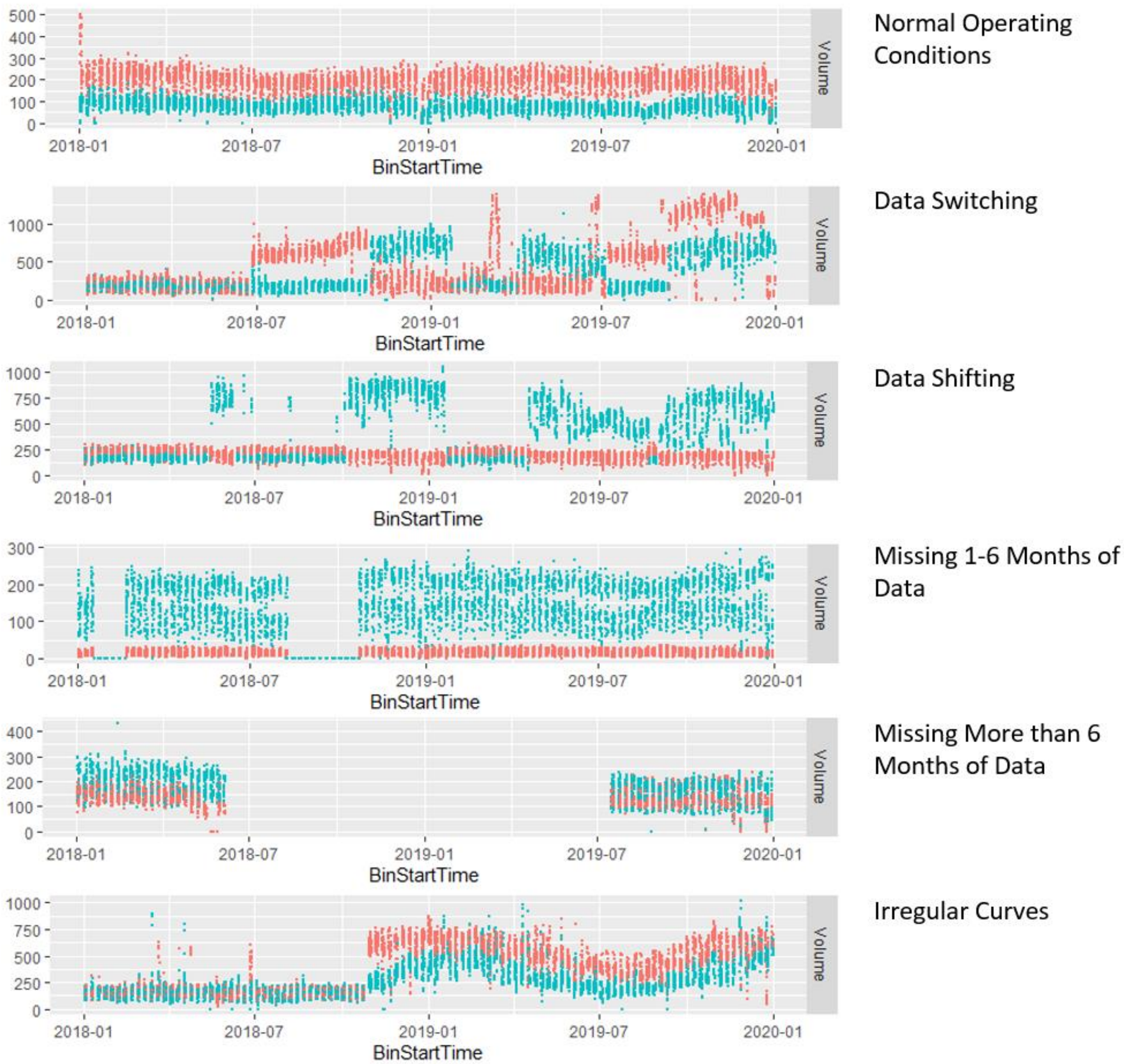



**Figure 3.5 Types of data anomalies example.**

**Table 3.4 Signal-Specific Data Issues**

| Signal ID | Major Street | Minor Street | Data Switching | Data Shifting | Missing Data Under 6 Months | Missing Data Over 6 Months | Irregular Curves | Normal |
|---|---|---|---|---|---|---|---|---|
| 4024 | Fort Union Blvd. | 1300 East | | | | | | X |
| 4028 | Fort Union Blvd. | 300 East | | | | | X | |
| 4029 | Fort Union Blvd. | 700 East | X | | | | | |
| 4090 | Fort Union Blvd. | 2000 East | | | | X | | X |
| 4165 | Fort Union Blvd. | 2200 East | | | X | | | X |
| 4301 | Fort Union Blvd. | 1090 East | | | | | | X |
| 4388 | Fort Union Blvd. | 1435 East | | | X | | | X |
| 4389 | Fort Union Blvd. | 995 East | | | | X | | X |
| 4704 | Fort Union Blvd. | 2300 East | | | X | | X | |
| 4705 | Fort Union Blvd. | 2700 East | | X | X | | | |
| 4706 | Fort Union Blvd. | 3000 East | | | X | | X | |
| 6305 | 800 North | 400 East | | | | | | X |
| 6306 | 800 North | 800 East | | X | | | X | |
| 6307 | 800 North | Palisade Drive | | | | X | X | |
| 6308 | State Street | 400 North | | | | X | X | |
| 6311 | State Street | Center Street | | | | | | X |
| 6313 | State Street | 400 South | | | | X | | X |
| 6395 | 800 North | Geneva Road | | X | | | | |
| 6405 | University Ave | 300 South | | | | X | | X |
| 6407 | University Ave. | Center Street | | | | X | | X |
| 6408 | University Ave. | 100 North | | | | | | X |
| 6409 | University Ave. | 200 North | | X | | X | | |
| 6410 | University Ave. | 500 North | | X | | X | | |
| 6411 | University Ave. | 700 North | | | | | | X |
| 6416 | University Ave. | Paul Ream Ave. | | | | | | X |
| 6417 | University Ave. | University Pkwy. | | | | X | | X |
| 6418 | University Ave. | 2230 North | | | | | | X |
| 6421 | University Ave. | 3700 North | | | | | | X |
| 6423 | University Ave. | 4800 North | | | | X | | X |
| 6427 | University Ave. | 200 South | | | | X | | X |
| 6465 | University Ave. | 400 South | | X | X | | | |
| 7207 | Fort Union Blvd. | 900 East | | | X | | X | |

### 3.4.3 Refinement of Project Focus

Throughout the signal refinement process, it became clear that there were many data quality issues. The initial goal of the research project was to identify and measure longitudinal trends throughout the signal data and to show the effect of signal retiming. Having data anomalies present would jeopardize the ability of the research team to find accurate trends in the data, making it very difficult to fulfill the purpose of the project. After careful discussion as a research team and with the TAC on the most valuable outcome of this project, the TAC decided to modify the focus.

The focus was shifted from conducting a longitudinal analysis of signal data to developing a method for identifying data anomalies in longitudinal signal data. UDOT asked the research team to evaluate statistical or mathematical methods that UDOT could use within the ATSPM system to produce a new performance measure relating to signal data quality. If data anomalies are identified in the signal data, the signal data quality performance measure would display a lower score than if no data anomalies were present. While the presence of data anomalies and missing data provided more challenges than currently anticipated, a new focus for the project would provide a useful tool for the future of the ATSPM system and ATSPM research.

Five performance measures were initially selected to be used in the analysis, but the TAC and research team decided to consolidate their focus from five performance measures to only one: approach volume. This was done for two main reasons. First, as stated in section 3.3.5, approach volume is involved in the calculation of two of the other four performance measures. With anomalies present in over 80 percent of the data, inaccuracies in approach volume would propagate to other performance measures. To be most effective in developing a data anomaly detection tool, it was important for the research team to focus their analysis effort only on approach volume. Second, selecting only approach volume to analyze simplifies and streamlines the process of creating the method. With only one input dataset, the method would be more consistent, and the team would only have to create a method for one performance measure instead of five.

## 3.5 Data Anomaly Detection Tool Development

With approach volume selected as the performance measure to focus on, multiple statistical and mathematical methods were investigated in an attempt to create a data anomaly detection tool. These methods vary, but all contribute to the development of the tool. The methods described in this section are linear regression, histogram distribution analysis, and moving average and standard deviation.

### 3.5.1 Linear Regression

Creating a linear regression model means estimating the values of the coefficients used in the representation with available data (Brownlee, 2020). The research team created a linear regression model to represent how the traffic volumes were related to the hour of the day, day of the week, day of the month, month of the year, phase number, Signal ID, and the 15-minute bin in which they were collected (e.g., 00:00, 00:15, 00:30, 00:45). The model was used to predict the general trend of the ATSPM data patterns over time. It was run against the ATSPM volume data to create a regression of predicted volumes for a typical day without data anomalies. This predicted volume regression was then used by the team as a baseline to compare against the actual ATSPM volume data to identify data anomalies that diverged from the predicted volumes.

Apronti et al. (2016) used linear and logistic regression methods to estimate traffic volume for low-volume roads. The variables in their linear regression model include pavement type, access to highways, land-use type, and population to estimate traffic volume. The result shows an $R^2$ value of 0.64 and a root-mean-square error of 73.4 percent, which shows high relevance between traffic volume for low-volume roads and the selected variables. Therefore, the linear and logistic regression methods were recommended for use in traffic volume estimation for low-volume roads.

The research team chose the seven variables outlined previously to develop the linear regression model. It was found that the 15-minute bin on the hour that they were created, day of the week, and day of the month variables had p-values that were greater than 0.05, meaning that there was no significant relationship with volume. Therefore, those three variables were removed from the linear regression model to reduce potential noise in the model from variables that did not have a significant effect. The simplified linear regression model is shown in Equation 3.4.

$$Volume_{predicted} = X + \beta_1 \cdot Signal\ ID + \beta_2 \cdot phase\ number + \beta_3 \cdot hour + \beta_4 \cdot month \tag{3.4}$$

where, $X$ = y-intercept

$\beta_1$ = coefficient for Signal ID,

$\beta_2$ = coefficient for phase number,

$\beta_3$ = coefficient for hour of the day,

$\beta_4$ = coefficient for month of the year.

By finding the intercept and coefficients for each variable, the research team can create a predicted volume to compare to the actual ATSPM data. The percentage difference between the prediction versus actual volume can then be calculated.

### 3.5.2 Histogram Distribution Analysis

Histograms are often used for distribution analysis and comparison. The research team aggregated the 15-minute bin volume data for each signal and created a histogram for each signal and phase. A normal signal without anomalies in the data should follow a normal distribution curve. For each histogram, the research team calculated the mean volume and standard deviation for anomaly detection. The data were considered an anomaly if any volume data point was found to be two standard deviations away from the mean or outside of a 95 percent confidence interval. Equation 3.5 shows the 95 percent confidence interval calculation. Figure 3.6 shows an example of a normally distributed histogram curve.

$$\mu = \overline{x} \pm 1.96 * \frac{\sigma}{\sqrt{N}} \tag{3.5}$$

where, $\mu$ = 95 percent confidence interval,

$\overline{x}$ = mean volume of each 15-minute bin,

$\sigma$ = standard deviation,

$N$ = number of observations.

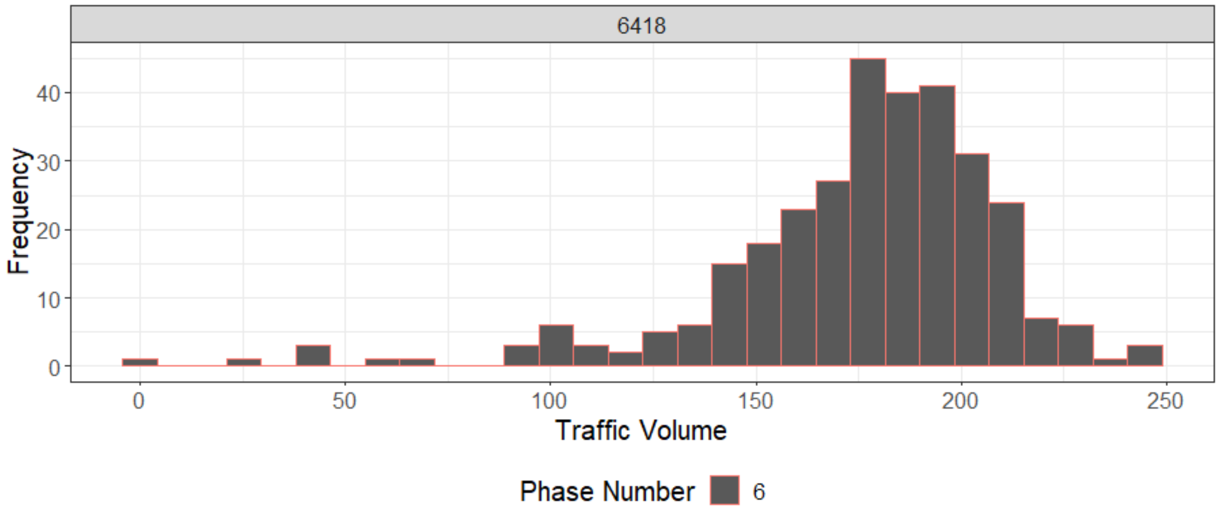



**Figure 3.6 Normally distributed histogram (Signal 6418 Phase 6).**

By finding and identifying a signal in which the traffic volume is normally distributed, the research team can use that signal as a baseline. Then, the research team can calculate the percentage difference or standard deviation of other signals to compare with the baseline signal to determine if those signals are normally distributed or have outliers as data anomalies.

### 3.5.3 Moving Average and Standard Deviation

The third method the research team attempted was to use a moving average and standard deviation. The team theorized that more significant shifts in data values would be easier to detect by using a method where the average and standard deviation of data points could be based on nearby data points rather than one blanket assumption for the entire signal and phase. The main benefit of this method was the ability to adjust the value of the moving window or the number of points to be included in the calculation of the average and standard deviation. A larger moving window would result in a more generalized average and standard deviation, whereas a smaller moving window would produce a more localized average and standard deviation.

The method developed in this section utilizes the moving window to identify the location of anomalies as well as a tool to calibrate the model. The length of the moving window is initially used in calculating the moving average and standard deviation. The moving average and standard deviation are then used to calculate a z-score for the data point, which is shown in Equation 3.6. The z-score value is crucial in determining when and where anomalies are occurring, as a high z-score value is likely correlated with a significant shift in data values. To ensure that the model was correctly adjusted, a sensitivity analysis was performed to optimize the moving window.

$$z = \frac{|x-\mu|}{s} \tag{3.6}$$

where, $z$ = z-score,

$x$ = volume of observation,

$\mu$ = moving average,

$s$ = moving standard deviation.

The research team conducted a sensitivity analysis of multiple window lengths to choose an appropriate moving window length. The volume data applied to this method was in 15-minute bins of the AM peak hours of 7:00 AM to 9:00 AM during Tuesdays, Wednesdays, and Thursdays from January 2018 to December 2019, which resulted in eight data points for each day and approximately 96 data points per month. The research team tested moving window lengths of 100, 200, and 300 data points, which are about 1 month, 2 months, and 3 months, respectively.

For the sensitivity analysis, the volume data were plotted for each signal and phase as a time series in the statistical computing and graphics tool R, as seen in Figure 3.7. Each data point was colored based on its z-score: blue for 0 to $1.9\overline{9}$ and red for 2.0 and greater. The moving window was optimized so that when a jump anomaly occurred in the data, the data points directly before the data points shifted had a z-score of 2 or greater. A z-score of 2 was chosen as the cutoff as any points within two standard deviations are within a 95 percent confidence interval. This sensitivity analysis was done graphically, and the results of the sensitivity analysis will be presented in section 4.3.5.

The moving average and standard deviation method was chosen to identify jump discontinuities within the ATSPM data. The theory was that the standard deviation between points should be slight when the signal generally operates with no data anomalies. However, the standard deviation between points would dramatically increase when a jump discontinuity occurred, providing a momentary spike identifying the location of a jump discontinuity.

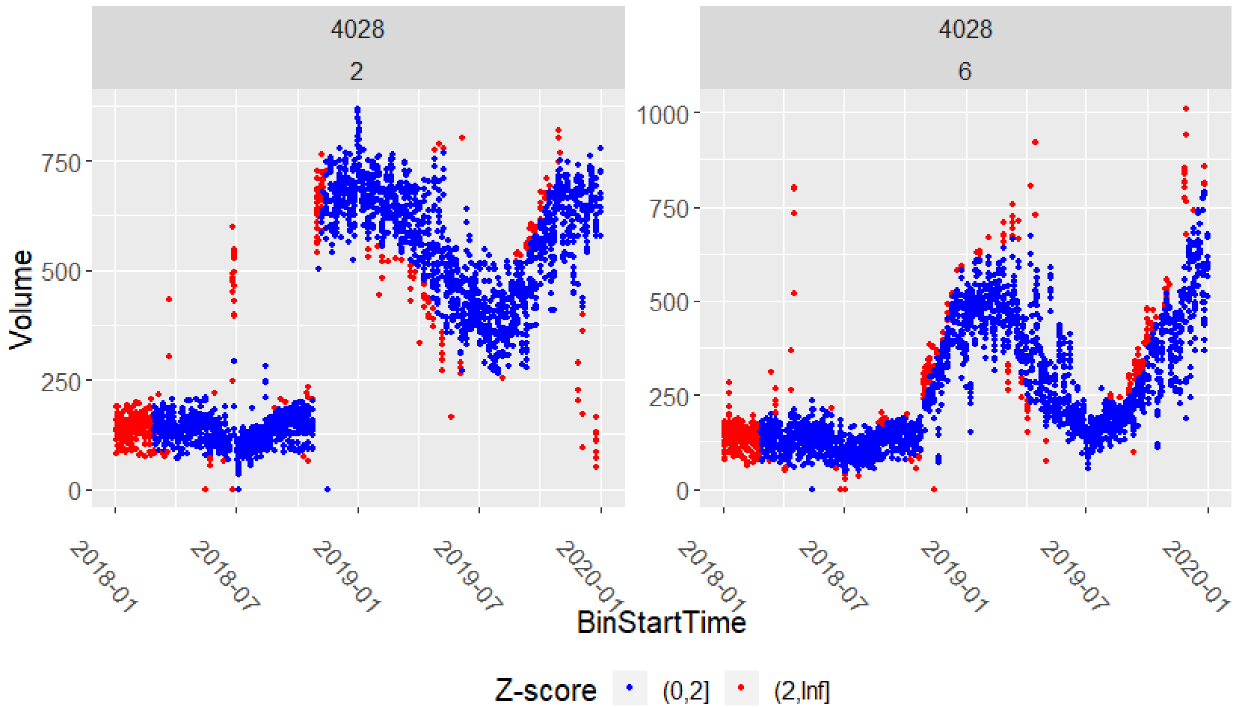



**Figure 3.7 Example of color code Z-score for data anomalies (Signal 4028).**

### 3.6 Chapter Summary

The purpose of this chapter was to explain the methodology for this research. Data from Tuesdays, Wednesdays, and Thursdays of the AM peak for Phases 2 and 6 were collected from UDOT's ATSPM database. Five performance measures were selected for this research and discussed. The initial signal selection from UDOT Report UT-20.08 was built upon and refined based on data completeness and quality. After a signal refinement process was completed, 32 of the initial 89 signals were selected for application in the data anomaly detection tool analysis. Five data anomalies were identified, and each of the 32 signals was analyzed for the presence of these anomalies. Because of the presence of many data anomalies, the focus of the project was shifted to the development of a data anomaly detection tool. Linear regression, histogram distribution analysis, and moving average and standard deviation techniques were selected and outlined in the development of the data anomaly detection tool that UDOT can utilize to detect anomalies in ATSPM data automatically.

# 4.0 RESULT EVALUATION

## 4.1 Overview

The BYU transportation research team used the statistical computing and graphics tool R as the means of analysis for this project. This chapter summarizes the results of the data analysis. First, a new ATSPM data visualizer to help users to see how the performance measures and overall scores for each intersection changed over time is explained. The approach volume validation for data anomalies is discussed, followed by the approach volume evaluation.

## 4.2 Data Visualizer

The research team created a data visualization tool to help UDOT understand the change in performance measures over time. This tool was modeled after a previous data visualization tool designed through UDOT Report UT-20.08 (Schultz et al., 2020). The previous data visualizer generated a k-means cluster analysis and calculated weighted overall performance scores for individual intersections from UDOT ATSPM data. This data contained multiple performance measures that were discussed in section 3.3. The new visualizer displays the aggregated data from the previous visualizer in a longitudinal format. Figure 4.1 shows the interface of the longitudinal ATSPM data visualizer.

In the data visualizer sidebar panel displayed in Figure 4.2, the research team created a selection tool that allows the user to select the performance measures, intersection (SignalID), time of day, day of the week, date range, and time period change. A check box is provided, which allows the user to facet the graphs by the time of day or day of the week. Selecting these boxes separates the final visualizations by the facet schema chosen.

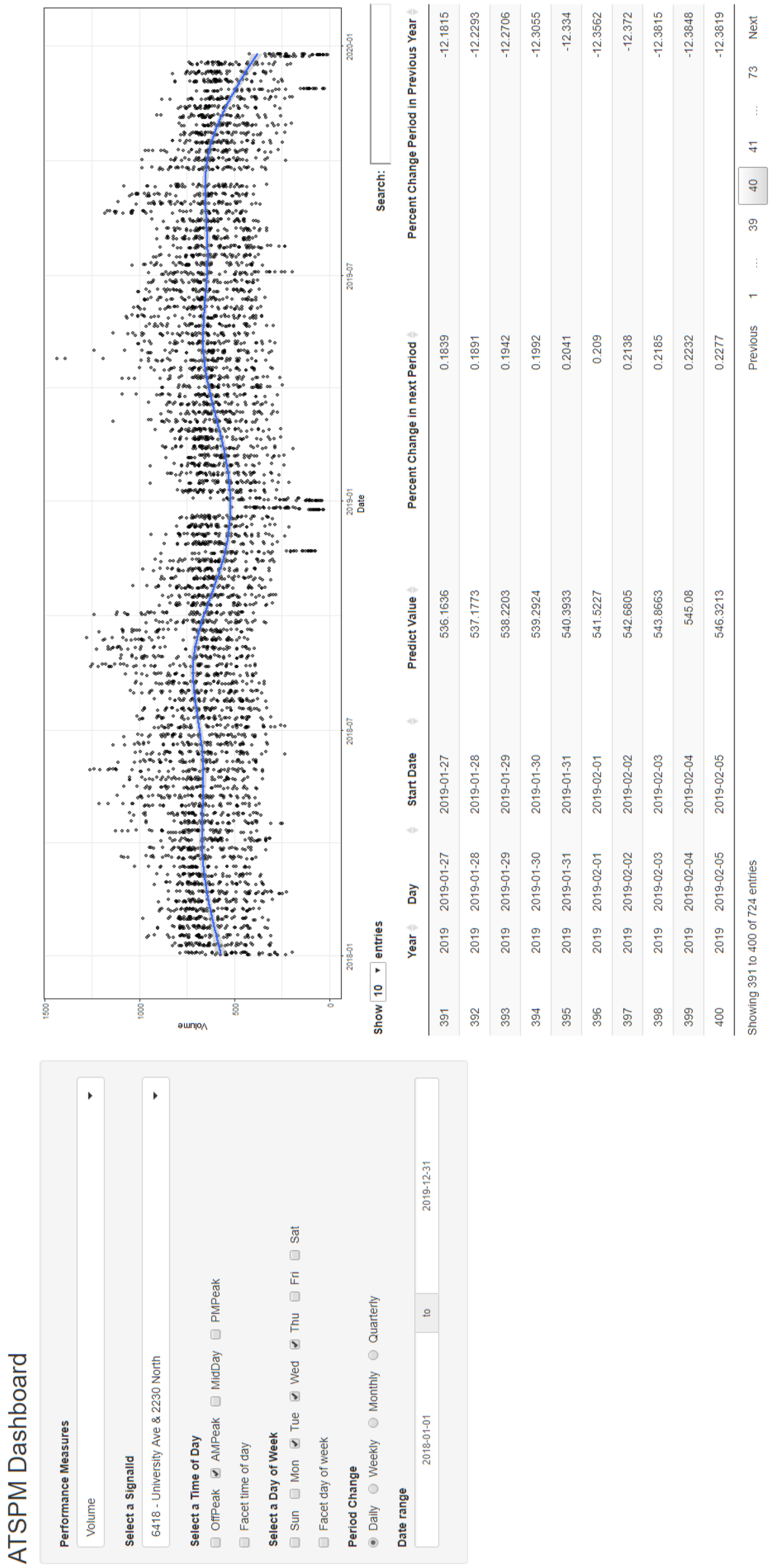



**Figure 4.1 ATSPM longitudinal data visualizer.**

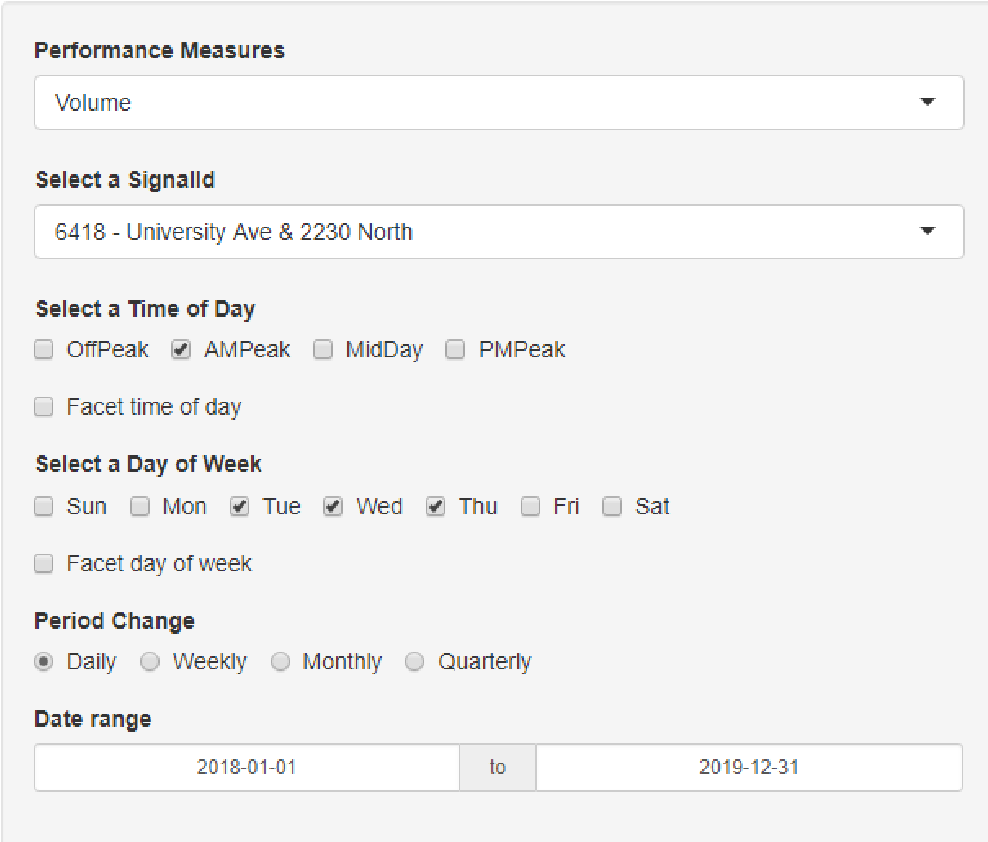



**Figure 4.2 Data visualizer sidebar panel.**

Figure 4.3 shows an example of the graphs provided by the data visualizer. The figure shows the overall score data points computed for all 15-minute bins on Tuesday, Wednesday, and Thursday during the AM Peak for Signal 6418 (University Avenue and 2230 North) from January 1, 2018, to December 31, 2019. The blue line displayed over the data points is a daily average trend line of the 15-minute bin scores.

Figure 4.4 displays an example of the score table in the data visualizer. The score table calculates the average value of the data points based on the period change option selected. The visualizer can be used to calculate and display the daily average value, weekly average value, monthly average value, and quarterly average value. It also shows the percent change between the current period (day, week, month, or quarter) versus the previous period (day, week, month, or quarter) based on the period selected in the period change option, and the percent change between the current period (day, week, month, or quarter) versus the same period during the last year (day, week, month, or quarter).

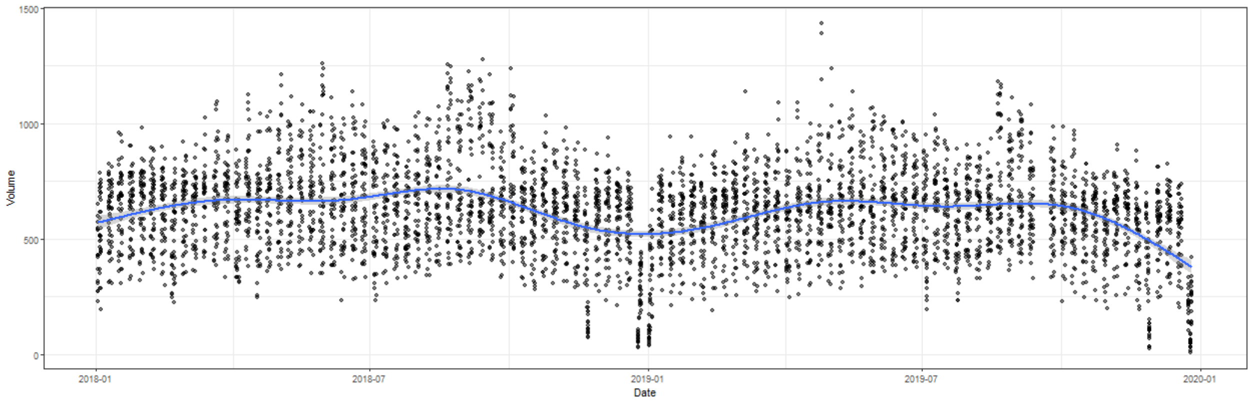



**Figure 4.3 Overall score visualization (Signal 6418).**

| | Year | Day | Start Date | Predict Value | Percent Change in next Period | Percent Change Period in Previous Year |
|---|---|---|---|---|---|---|
| 391 | 2019 | 2019-01-27 | 2019-01-27 | 536.1636 | 0.1839 | -12.1815 |
| 392 | 2019 | 2019-01-28 | 2019-01-28 | 537.1773 | 0.1891 | -12.2293 |
| 393 | 2019 | 2019-01-29 | 2019-01-29 | 538.2203 | 0.1942 | -12.2706 |
| 394 | 2019 | 2019-01-30 | 2019-01-30 | 539.2924 | 0.1992 | -12.3055 |
| 395 | 2019 | 2019-01-31 | 2019-01-31 | 540.3933 | 0.2041 | -12.334 |
| 396 | 2019 | 2019-02-01 | 2019-02-01 | 541.5227 | 0.209 | -12.3562 |
| 397 | 2019 | 2019-02-02 | 2019-02-02 | 542.6805 | 0.2138 | -12.372 |
| 398 | 2019 | 2019-02-03 | 2019-02-03 | 543.8663 | 0.2185 | -12.3815 |
| 399 | 2019 | 2019-02-04 | 2019-02-04 | 545.08 | 0.2232 | -12.3848 |
| 400 | 2019 | 2019-02-05 | 2019-02-05 | 546.3213 | 0.2277 | -12.3819 |

Showing 391 to 400 of 724 entries    Previous 1 … 39 40 41 … 73 Next

**Figure 4.4 Data visualizer score table (Signal 6418).**

Once the data visualizer was built in the statistical computing and graphics tool R, it was used to display the aggregated ATSPM data. The research team was able to understand how the performance measures changed over time by observing the volatility of the data. To understand how the performance measures and overall scores for each intersection change over time, the values in each 15-minute bin were averaged into an average daily value. Figure 4.5 shows the average daily value in all studied performance measures for five signals from January 2018 to December 2019. The complete signal results for the average daily value can be found in Appendix A.

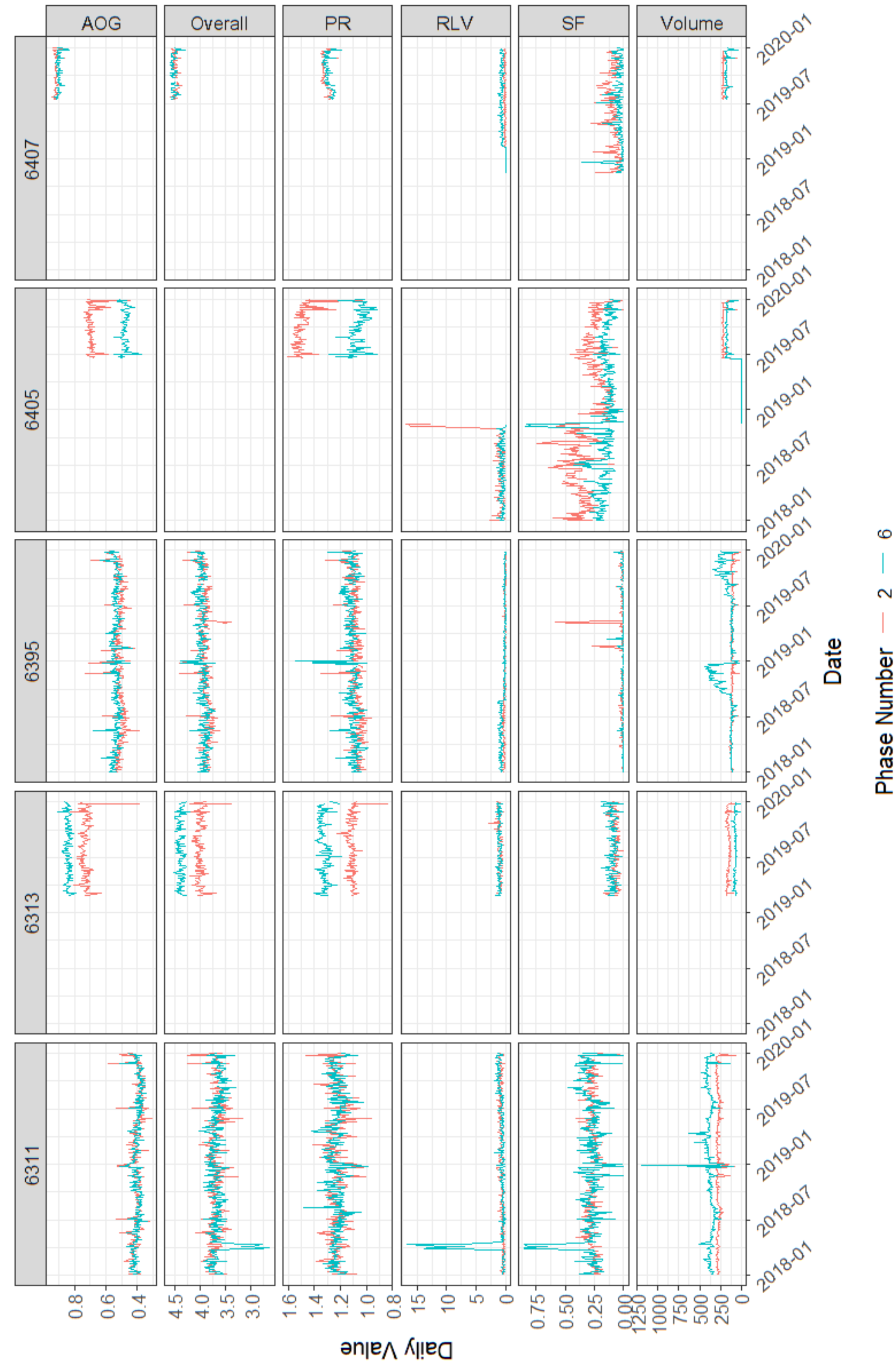



**Figure 4.5 Visualization of the average daily value for all performance measures (Signals 6311, 6313, 6395, 6405, 6407).**

## 4.3 Approach Volume Validation

The research team applied two validation methods to verify the data accuracy and to help UDOT identify data anomalies. The data validation methods include comparing the ATSPM data with Watchdog reports and CCS data.

### 4.3.1 Watchdog Report Analysis

Before the Watchdog reports introduced in section 2.4.2 were implemented, UDOT maintenance teams were responsible for discovering errors in traffic signals as they came across them in the field. This method was time consuming, expensive, and while proactive in nature, very inefficient. The innovation of the Watchdog reports has given UDOT the ability to be reactionary in their response to detector errors in a way that wasn’t possible previously.

With the Watchdog reports, the process for maintaining and monitoring traffic signal health has become streamlined and simplified. UDOT traffic engineers receive the Watchdog reports from the previous 24-hour period each weekday morning. They use the ATSPM system, construction updates, maintenance records, or work order histories to determine the primary cause of the issues presented. Many alerts are found to be part of normal operation, like having low advanced detection counts on a minor road. Still, a large number are caused by ongoing road construction or detector issues with the controller. If traffic engineers can fix the error remotely, they will. If the error requires on-site maintenance engineers, a work order will be submitted for the traffic controller to be evaluated and resolved. Through this process, data errors are investigated and fixed efficiently and effectively.

The Watchdog reports are also crucial to UDOT preventing data errors for the ATSPM system. The UDOT ATSPM system records traffic data from across the state to help optimize mobility, manage traffic signal timing and maintenance to reduce congestion, save fuel costs, and improve safety (UDOT, 2022a). It is important that the data collected from traffic controllers be accurate and consistent, and the Watchdog reports are one tool to ensure that this happens. Through this process, data errors can be observed and resolved in a timely manner to maintain the integrity of the data.

Watchdog reports are anticipated to be helpful in two ways. First, in determining which detectors may have been malfunctioning at the time of data collection and second, in potentially explaining anomalies found in the ATSPM data. To analyze the Watchdog reports, a combination of ATSPM data and email reports was used to identify pertinent issues. Watchdog report information was obtained using UDOT's SQL database. The data were exported in .csv files, which contained the time stamp of the Watchdog observation, Signal ID, Detector ID, Phase, Error Code, and the Watchdog message, which are shown in Figure 4.6. The error codes and Watchdog messages are correlated, and information on their pairings can be found in section 2.4.2. The Watchdog messages were analyzed for the signals chosen in the overall analysis, and only a few Watchdog messages were applied to the analysis.

| ï..ID | TimeStamp | SignalID | DetectorID | Direction | Phase | ErrorCode | Message |
|---|---|---|---|---|---|---|---|
| 1 | 2018-08-06 | 9701 | 0 | | 0 | 1 | Missing Records - IP: 10.209.2.123 |
| 2 | 2018-08-06 | 6083 | 0 | | 0 | 1 | Missing Records - IP: 10.10.10.10 |
| 3 | 2018-08-06 | 6055 | 0 | | 0 | 1 | Missing Records - IP: 10.162.9.27 |
| 4 | 2018-08-06 | 6051 | 0 | | 0 | 1 | Missing Records - IP: 10.169.5.155 |
| 5 | 2018-08-06 | 4897 | 0 | | 0 | 1 | Missing Records - IP: 10.210.8.227 |
| 6 | 2018-08-06 | 4896 | 0 | | 0 | 1 | Missing Records - IP: 10.210.8.215 |
| 7 | 2018-08-06 | 4894 | 0 | | 0 | 1 | Missing Records - IP: 10.10.10.10 |
| 8 | 2018-08-06 | 4893 | 0 | | 0 | 1 | Missing Records - IP: 10.10.10.10 |
| 9 | 2018-08-06 | 4892 | 0 | | 0 | 1 | Missing Records - IP: 10.10.10.10 |
| 10 | 2018-08-06 | 4879 | 0 | | 0 | 1 | Missing Records - IP: 10.10.10.10 |
| 11 | 2018-08-06 | 4874 | 0 | | 0 | 1 | Missing Records - IP: 10.207.5.203 |
| 12 | 2018-08-06 | 4872 | 0 | | 0 | 1 | Missing Records - IP: 10.210.9.27 |

**Figure 4.6 Watchdog report data obtained from UDOT's SQL server.**

Five types of alerts are sent out by the Watchdog daily report: "no data," "force offs," "max outs," "low advanced detector counts," and "stuck pedestrians." A description of each of these alerts is provided in section 2.4.2. In addition to the five alerts sent out in the daily report, two additional alerts are available through Watchdog data found in UDOT's SQL server: "could not download" and "FTP not able to delete file on controller." Of these seven total alerts, four were of most interest to the research team: "no data," "low advanced detector count," "could not download," and "FTP not able to delete file on controller."

The “no data” alert provides insight into detectors that did not detect 500 vehicles in the previous 24-hour cycle. In comparison, the “low advanced detector count” alert similarly counts the lack of vehicles recorded but is only triggered when fewer than 100 vehicles are counted between 5:00 PM and 6:00 PM of the previous day.

The “could not download” and “FTP not able to delete file on controller” alerts refer to the main system not being able to delete the most recent 24-hr file on the controller between 1:00 AM and 5:00 AM. These categories give the research team an idea of which detectors may have been malfunctioning and if some of the anomalies in the data can be explained in some part by the information given in the Watchdog reports.

Data from the Watchdog reports were visualized and evaluated using the statistical and graphics tool R. Figure 4.7 displays signals containing Watchdog alert categories and the day on which the Watchdog alerts were reported between July 2018 and December 2019. This figure uncovered potentially systemic issues in the ATSPM and an unclear determination whether the Watchdog reports could conclusively explain the inconsistencies found in the data.

The most common type of alert in the Watchdog reports was the “low advanced detection counts” alert. Under proper operating conditions, this alert is only reported when low numbers of vehicles are detected, which may occur at different times for each signal. The data showed that there were multiple days where nearly all 30 signals on the Watchdog reports had the “low advanced detection counts” report. This occurrence happened for one day in mid-November 2018 and 14 days between September 2019 and December 2019. The frequency and simultaneous occurrence of this alert suggest an internal issue in the ATSPM system. It is unclear whether this was an effect of an adjustment made in the system manually or an internal bug that simultaneously affected every signal, but it is too coincidental to suggest that every signal had the same issue on the same day across 30 signals.

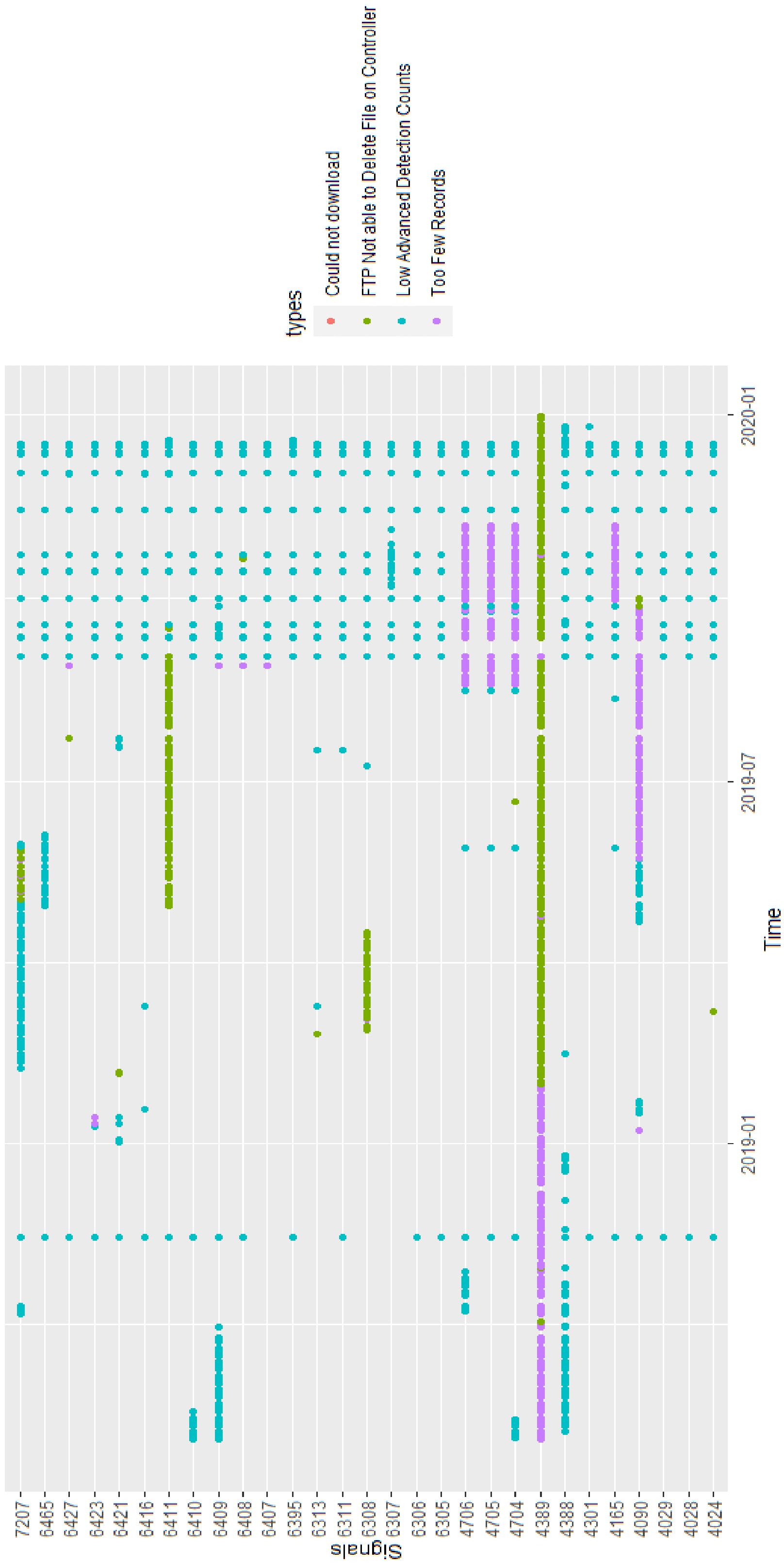



**Figure 4.7 Watchdog reports by Signal from July 2018 to December 2019.**

The research team found that the Watchdog reports might not wholly explain the discontinuities found in the data. They compared the dates of Watchdog alerts to the dates when anomalies occurred in the ATSPM volume data and found that while many of the alert dates are close to the anomaly dates, the two do not line up directly and no clear patterns exist between the two datasets. Another issue that the research team discovered was that the “too few records” alert was reactionary to the data trends rather than explanatory about detector issues. While many of the alerts were focused on detector or controller issues that could potentially affect what data came in, the “too few records” alert was directly generated when under 500 records were made. This made it less useful for the research team, as it did not help explain why the volumes may have been low or irregular on a particular day. In addition, many of the reports did not correlate with discontinuities in the data. While the “low advanced detection counts” alert was found across the system, it also occurred at unique positions for different signals rather than only at the same places for every signal. The research team assumed that it would be one of the most likely Watchdog alerts to influence the data, but there was not a strong correlation between the dates of the “low advanced detection counts” alerts and the discontinuities in the data.

### 4.3.2 Continuous Count Station

The research team used the UDOT CCS data as a baseline for validating the ATSPM volume data. Chamberlin and Fayyaz (2019) used the same approach to check the accuracy of ATSPM volume data for AADT reporting to the Federal Highway Administration. The researchers lined up the CCS and ATSPM data by hour, day, and month and compared data lane by lane. They found that 67 percent of Matrix detectors, or ATSPM volume data collectors, systematically undercounted hourly volumes compared to their nearest CCS data collection site. The Matrix detector AADT counts were within -21 percent to +7 percent (with an average of -9 percent) range of the CCS AADTs, but with the addition of an adjustment factor, the estimated AADTs from Matrix detectors were within -9 percent to 0 percent (with an average of -2 percent).

Similar to the research conducted by Chamberlin and Fayyaz (2019), the BYU research team found CCS stations near ATSPM volume data collection sites and aligned the data graphically to compare the through daily volumes. The CCS data were downloaded from the

UDOT data portal (UDOT, 2022b). Four CCS stations were selected due to their proximity to ATSPM-enabled signals and given names based on their relative locations: 800 East Orem station, 800 North Orem station, North University Avenue Provo station, and South University Avenue Provo station. Traffic volumes were selected for the AM Peak hours of 7:00 AM to 9:00 AM on Tuesday, Wednesday, and Thursday and for all through lanes within both Phases 2 and 6. For simplicity, volumes for Phases 2 and 6 were combined and all individual lane volumes were separately combined.

Figure 4.8 and Figure 4.9 display two of the results found in the comparison of CCS volume data and ATSPM volume data. Figure 4.8 shows that while the ATSPM data are undercounted, supporting the findings from Chamberlin and Fayyaz (2019), the trends in the volume data are very similar. In contrast, Figure 4.9 shows a problematic example where the ATSPM data do not match the CCS count and where data anomalies may be present in the ATSPM data.

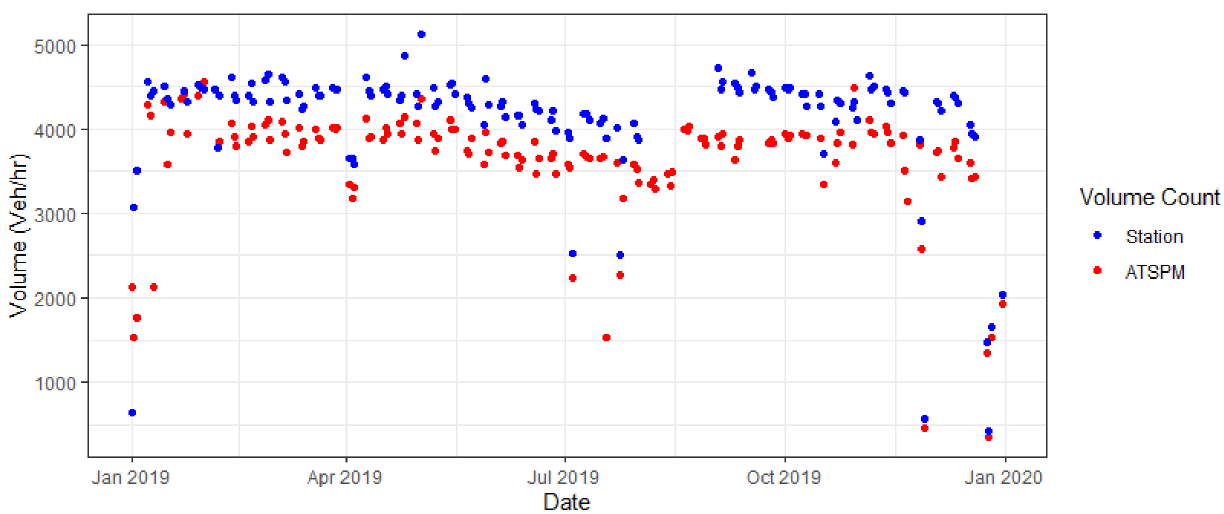



**Figure 4.8 Signal 6421 vs. North University Avenue station.**

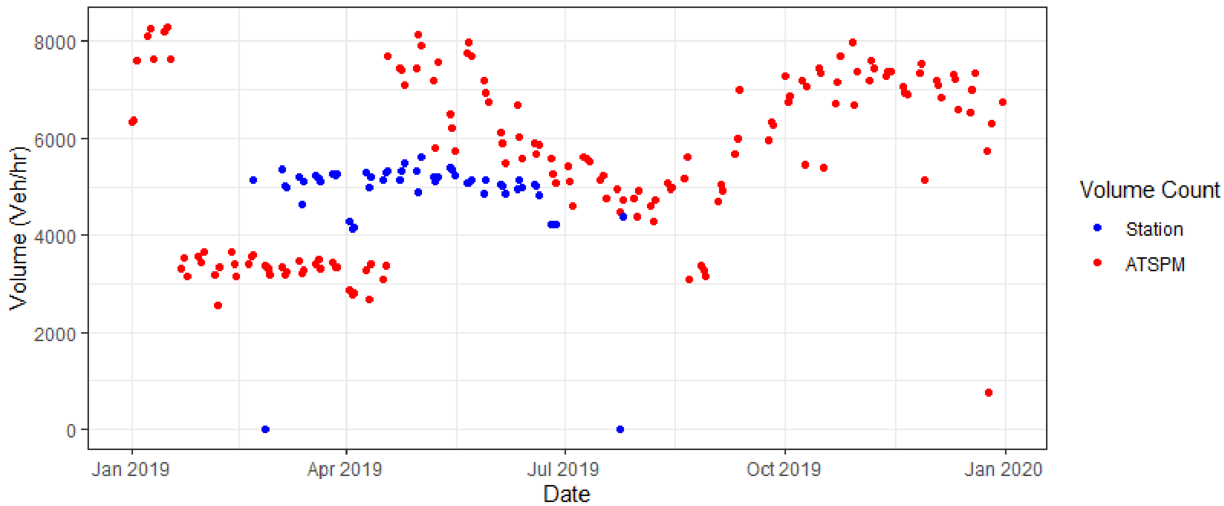



**Figure 4.9 Signal 6306 vs. 800 East station.**

Not all 32 signals that were selected for this research are in a corridor that has CCS. This made it difficult to compare the ATSPM data to the CCS data because the farther an intersection is from a CCS station, the less accurate the comparison becomes. This method was not as comprehensive as originally expected because of the signals selected and the infrequency of CCS stations along the chosen corridors. As shown by Chamberlin and Fayyaz (2019), CCS data is effective in validating ATSPM volume counts but cannot be effectively used in the case of this research due to the proximity of CCS and the study intersections.

## 4.4 Approach Volume Evaluation

The research team explored three evaluation methods to help UDOT find anomalies automatically. The data evaluation methods include linear regression evaluation, group distribution comparison, and moving average and standard deviation evaluation.

### 4.4.1 Linear Regression Evaluation

Section 3.5.1 introduced linear regression and discussed how to use it to predict traffic volumes. Figure 4.10 shows the results of the linear regression model discussed in that section. The results in Figure 4.10 show that the p-values are greater than 0.05 for Signal 4704, Signal 4706, Signal 6409, and month 9. This means that these four factors are not statistically significant and are similar to the signal 4024 and month 1. All other factor variables show significant differences with p-values less than 0.05. The $R^2$ is 0.3442, meaning the ATSPM data do not fit in the linear regression well, and different signals have their own identification variables.

Figure 4.11 and Figure 4.12 plot the ATSPM volume (blue data points) against the predicted volumes (red data points). The results show that with the linear regression method, most of the predicted signal volumes are stable with low volatility and only minor changes over time. While the comparison between the actual volume and the predicted volume did not end up being completely accurate for many signals, such as Phase 2 of Signal 6306, Signal 6308, Signal 6405, and Signal 6410 as seen in Figure 4.11, the linear regression was able to create a curve similar to what an average volume should look like. While the constant and consistent linear regression helped identify significant data anomalies like data shifting or irregular curves, the method was not as sensitive to sudden, brief shifts in data values. A more flexible method that allowed for the detection of anomalies and would display the location of an anomaly was needed. The complete signal results for the predicted volume versus real traffic volume can be found in Appendix B.

### 4.4.2 Group Distribution Comparison

In the group distribution comparison method, the research team grouped the average daily volume into histograms to see how the volumes are distributed for each signal, as described previously in section 3.5.2. Figure 4.13 shows the sample group of average daily volume by signal ID. Assuming the traffic volumes are normally distributed, all the values that are two standard deviations from the mean are counted as outliers. This grouping method is the most direct way to identify the outliers, but there are still some limitations. For example, signal 6306 phase 6 is not normally distributed, the distribution has long tails with another two peaks, and it is hard to identify a 95 percent confidence interval. Additionally, signals 6405 and 6410 have a high number of zero volumes during the AM Peak period, which is highly suspect. Therefore, the distribution comparison method does not apply to some signals and phases. The complete signal results for the histogram grouping of average daily volume can be found in Appendix C.

```
lm(formula = value ~ factor(SignalId) + factor(PhaseNumber) +
    factor(Times) + factor(month), data = x)

Residuals:
    Min      1Q  Median      3Q     Max
-442.24  -55.59   -8.14   39.93 1072.53

Coefficients:
                      Estimate Std. Error t value Pr(>|t|)
(Intercept)           108.5861     2.0842  52.100  < 2e-16 ***
factor(SignalId)4028 211.2526     2.4309  86.902  < 2e-16 ***
factor(SignalId)4029 282.0022     2.4309 116.007  < 2e-16 ***
factor(SignalId)4090   8.3492     2.5198   3.313 0.000922 ***
factor(SignalId)4165  15.8804     2.4309   6.533 6.48e-11 ***
factor(SignalId)4301  24.3281     2.4309  10.008  < 2e-16 ***
factor(SignalId)4388 -59.2576     2.4309 -24.377  < 2e-16 ***
factor(SignalId)4389 -93.2402     2.4309 -38.356  < 2e-16 ***
factor(SignalId)4704  -1.6258     2.4309  -0.669 0.503624
factor(SignalId)4705  -5.1410     2.4309  -2.115 0.034446 *
factor(SignalId)4706  -4.1012     2.4309  -1.687 0.091583 .
factor(SignalId)6305 105.6558     2.4309  43.463  < 2e-16 ***
factor(SignalId)6306 210.7969     2.4309  86.715  < 2e-16 ***
factor(SignalId)6307  74.9318     3.4131  21.954  < 2e-16 ***
factor(SignalId)6308  52.7393     3.3660  15.668  < 2e-16 ***
factor(SignalId)6311 157.2500     2.4309  64.688  < 2e-16 ***
factor(SignalId)6313 -11.8451     3.1507  -3.760 0.000170 ***
factor(SignalId)6395  29.9451     2.4309  12.318  < 2e-16 ***
factor(SignalId)6405 -33.7385     2.8716 -11.749  < 2e-16 ***
factor(SignalId)6407  48.4361     3.9676  12.208  < 2e-16 ***
factor(SignalId)6408  43.3043     2.4309  17.814  < 2e-16 ***
factor(SignalId)6409   1.2783     2.5960   0.492 0.622424
factor(SignalId)6410 126.3085     2.4309  51.959  < 2e-16 ***
factor(SignalId)6411 -18.8554     2.4309  -7.757 8.79e-15 ***
factor(SignalId)6416  21.1903     2.4309   8.717  < 2e-16 ***
factor(SignalId)6417  17.5405     3.4255   5.121 3.05e-07 ***
factor(SignalId)6418  42.5457     2.4309  17.502  < 2e-16 ***
factor(SignalId)6421 127.0887     2.4309  52.280  < 2e-16 ***
factor(SignalId)6423  78.1179     2.7469  28.439  < 2e-16 ***
factor(SignalId)6427  26.1849     3.0936   8.464  < 2e-16 ***
factor(SignalId)6465  48.0570     2.8269  17.000  < 2e-16 ***
factor(SignalId)7207  53.5294     2.4309  22.020  < 2e-16 ***
factor(PhaseNumber)6  -7.7157     0.6675 -11.559  < 2e-16 ***
factor(Times)8        22.6056     0.6667  33.906  < 2e-16 ***
factor(month)2        -4.7062     1.6839  -2.795 0.005193 **
factor(month)3        -6.2294     1.6607  -3.751 0.000176 ***
factor(month)4       -17.6214     1.6525 -10.664  < 2e-16 ***
factor(month)5       -16.6601     1.5796 -10.547  < 2e-16 ***
factor(month)6       -22.1959     1.6633 -13.345  < 2e-16 ***
factor(month)7       -31.9830     1.6034 -19.947  < 2e-16 ***
factor(month)8       -19.6083     1.6022 -12.238  < 2e-16 ***
factor(month)9        -0.6227     1.6444  -0.379 0.704912
factor(month)10       14.7323     1.5711   9.377  < 2e-16 ***
factor(month)11       29.0492     1.6203  17.928  < 2e-16 ***
factor(month)12       25.3515     1.6130  15.717  < 2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 121.6 on 133107 degrees of freedom
Multiple R-squared:  0.3442,    Adjusted R-squared:  0.344
F-statistic:  1588 on 44 and 133107 DF,  p-value: < 2.2e-16
```

**Figure 4.10 Linear regression results.**

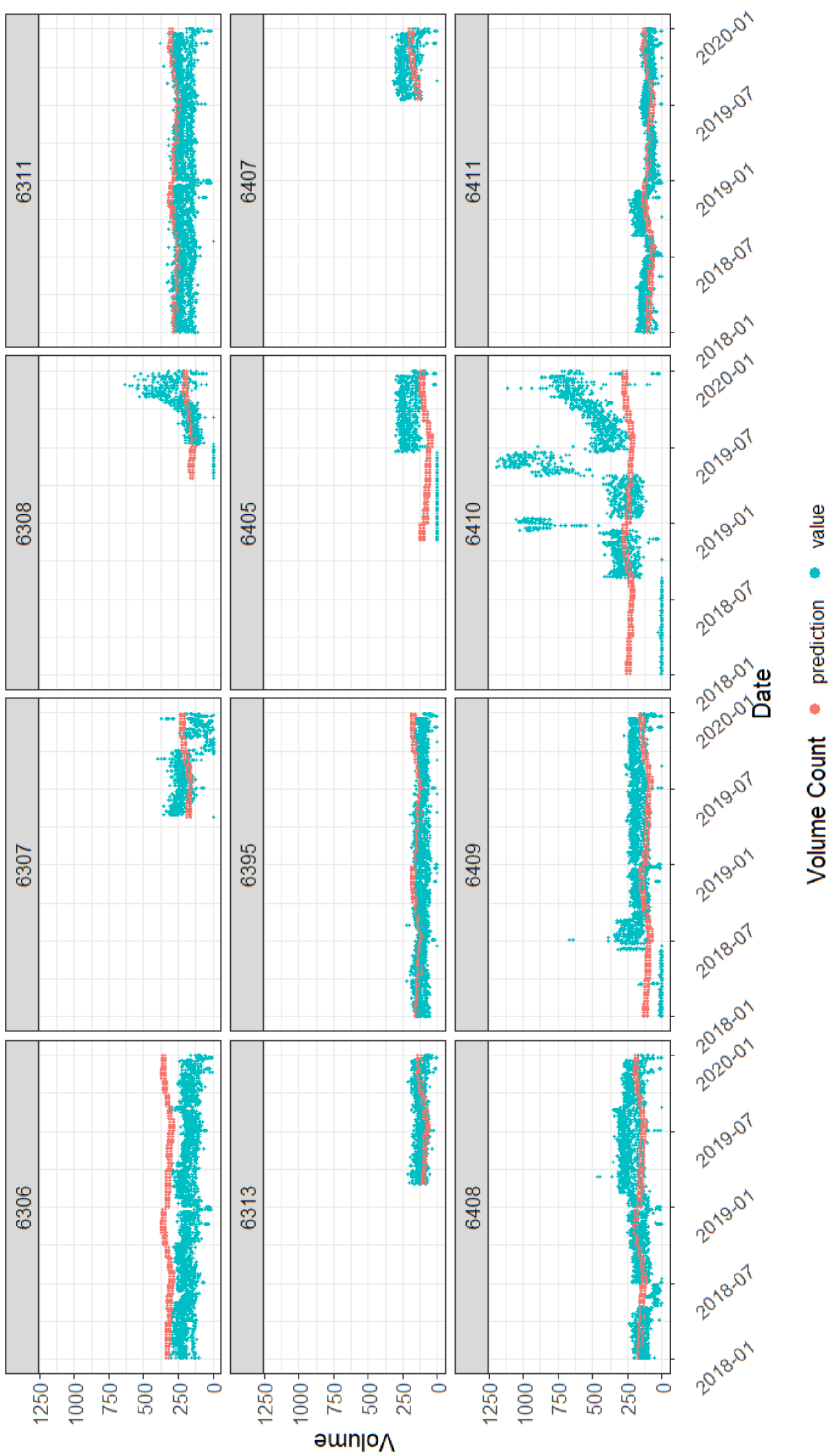



**Figure 4.11 Predicted vs. actual traffic volume (value) - phase 2 (Signal 6306, 6307, 6308, 6311, 6313, 6395, 6405, 6407, 6408, 6409, 6410, 6411).**

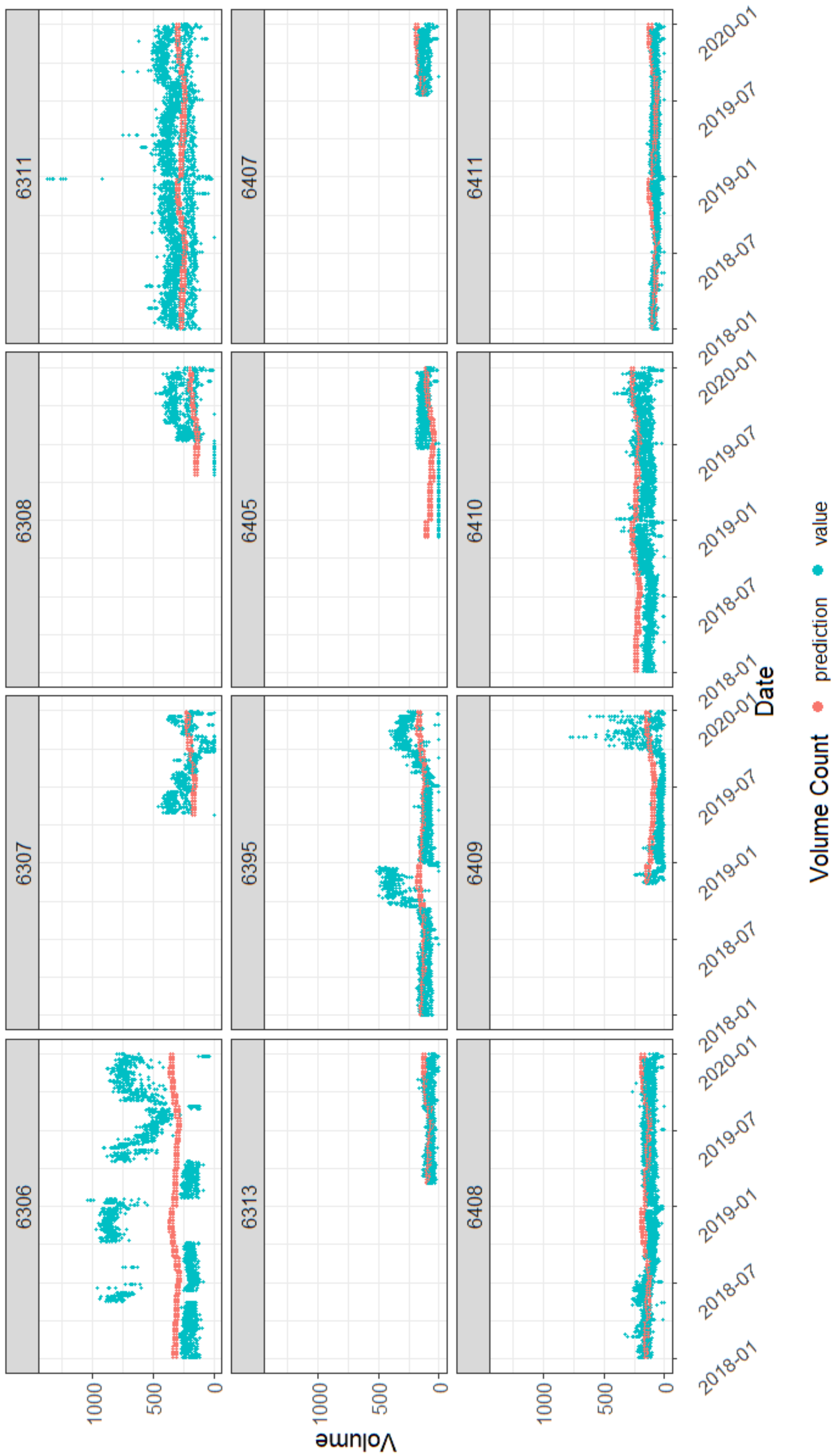



**Figure 4.12 Predicted vs. actual traffic volume (value) - phase 2 (Signal 6306, 6307, 6308, 6311, 6313, 6395, 6405, 6407, 6408, 6409, 6410, 6411).**

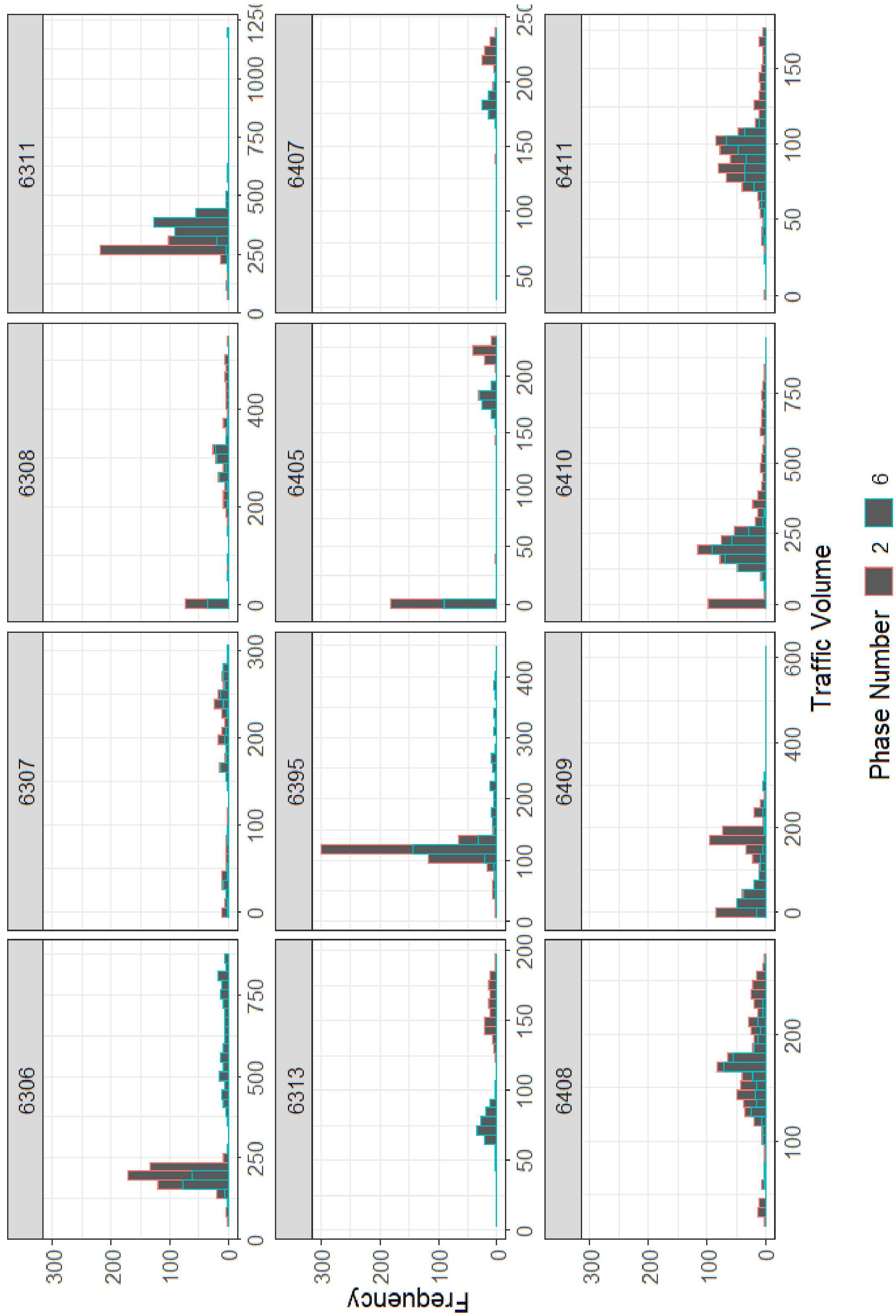



**Figure 4.13 Group of average daily volume (Signals 6306, 6307, 6308, 6311, 6313, 6395, 6405, 6407, 6408, 6409, 6410, 6411).**

### 4.4.3 Moving Average and Standard Deviation Evaluation

The moving average and standard deviation method was intended to create clear distinctions where data anomalies such as data shifting and irregular curve were present, as outlined in section 3.5.3. Following an extensive sensitivity analysis process, a moving window of 200 data points was used, with a moving average and standard deviation calculated from the moving window. Figure 4.14 shows the visualization of the z-score for phases 2 and 6 at five signals over 2 years. The blue dots represent a z-score less than 2, and the red dots represent a z-score greater than or equal to 2. The first 200 data points are shown in red because there is no previous data to calculate the moving average and standard deviation. After the first 200 points, the red dots were detected and displayed in the graph when there was a significant shift in the volume of data. In a few cases, the red dot only appeared one or a few times continuously in a short period. Those data can be considered noise and can be ignored because the data returns quickly to normal.

To find data anomalies signifying any potential issue that UDOT should be aware of, the research team determined that any eight continuous red dots should be flagged because eight data points would represent anomalies that occur for more than 1 day. Therefore, this method can help UDOT automatically identify when data anomalies occur. The complete signal results for the moving average and standard deviation evaluation can be found in Appendix D.

## 4.5 Chapter Summary

In this chapter, the performance measures and overall scores for selected intersections were evaluated and displayed in the new data visualizer. The research team discovered six different data anomalies in the ATSPM datasets, which would decrease the quality of the ATSPM data and make the longitudinal analysis difficult. Two validation and three evaluation methods were used to help UDOT identify the data anomalies. The results showed the moving average and standard deviation method works best to identify the data anomalies.

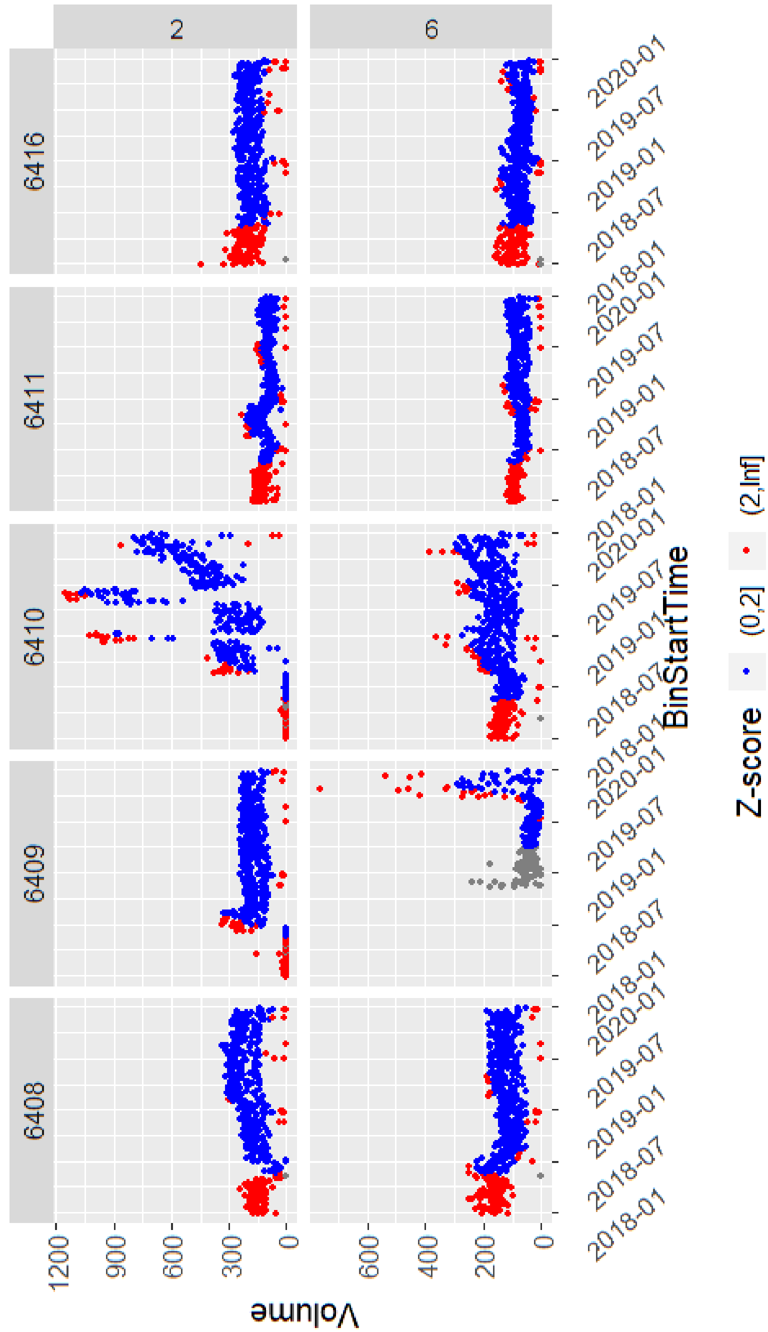



**Figure 4.14 Moving average and standard deviation with z-score (Signal 6408, 6409, 6410, 6411, 6416).**

# 5.0 CONCLUSIONS

## 5.1 Overview

The primary objective of the research was to conduct a longitudinal analysis of traffic signal performance in the state, building upon previous research results (Schultz et al., 2020). That objective shifted partway through the research to instead evaluate data anomalies present in approach volume data that would assist UDOT in its efforts to improve the utility of ATSPM. This chapter summarizes the research methodology and findings, outlines limitations, suggests associated future research, and presents limited recommendations and conclusions.

## 5.2 Methodology Summary

The data workflow for this project is shown in Figure 5.1. ATSPM datasets were retrieved from the SQL server at BYU, which was connected to UDOT's Measures of Effectiveness database. Signals were initially selected based on the type of data available at each intersection. The performance measures of AOG, split failures, platoon ratio, and red-light actuations were used to calculate the scores longitudinally. The research team then combined the data into a single table and filtered out missing values using the statistical computing and graphics tool R. The signal refinement process was conducted to ensure data quality and accuracy. Once the final signals were selected, longitudinal intersection scores were calculated using the signal scoring method developed in UDOT Report UT-20.08 (Schultz et al., 2020). The ATSPM performance measures data were then visualized using graphs and charts in ArcGIS Pro and R. Data anomalies for approach volume were identified in each of the signals using the CCS and Watchdog reports. Lastly, statistical methods including linear regression, distribution comparison, and moving average and standard deviation were applied to approach volume data to create a data anomaly detection tool.

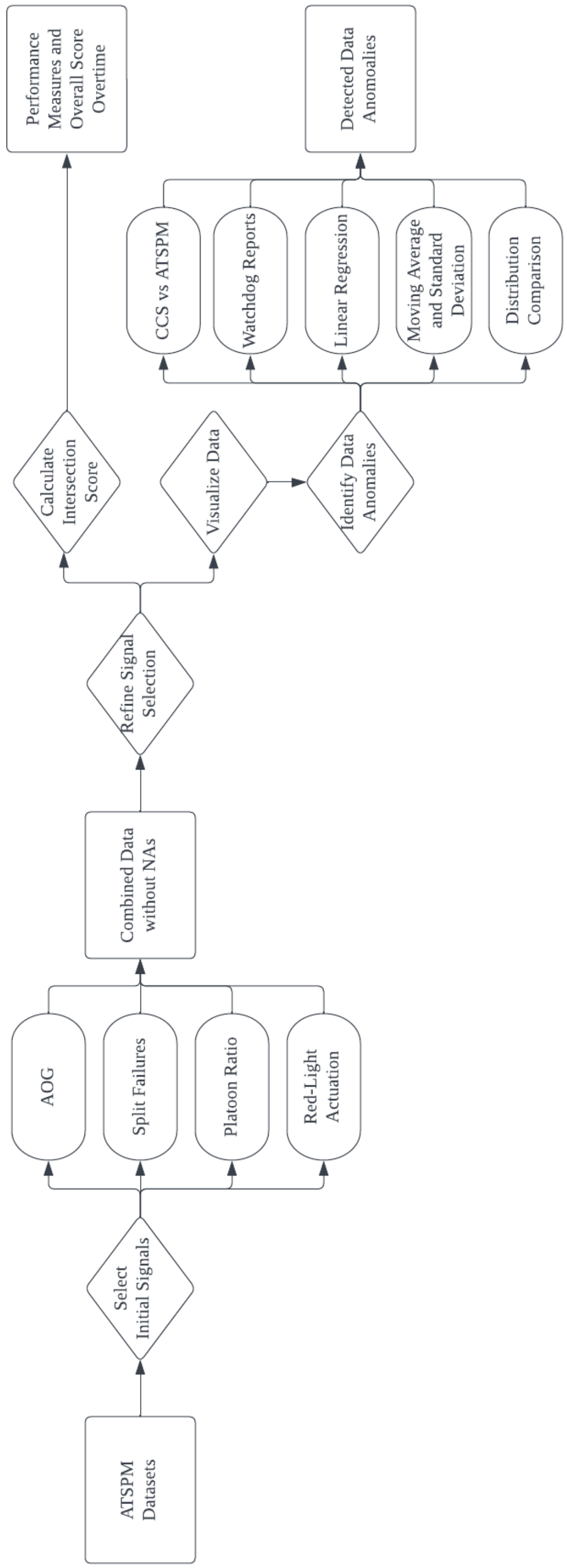



**Figure 5.1 Data workflow.**

## 5.3 Limitations and Future Research

The primary limitation faced in this research surrounded issues with data completeness and apparent accuracy. These issues were prevalent enough to cause a shift in focus of the project from an analysis of longitudinal trends to identifying data anomalies. Initially, the research team selected 89 signals to analyze, but 57 signals were missing data ('NA') for at least one necessary performance measure. Because the signal scoring method requires all data for each performance measure, these 57 signals were not able to be used in the final analysis, reducing the total number of usable signals to 32, or approximately one-third of the initial signals selected.

Even for the signals containing some data for all performance measures, missing data was a widespread issue across all signals. For 19 out of 32 signals (or nearly 60 percent), missing data values were found for more than 1 month of data. Thirteen signals were missing more than 6 months of data, making the potential for a longitudinal analysis much more limited in scope for almost half of the signals. In addition, other data anomalies were present, which caused further challenges to an accurate longitudinal analysis. Data shifting occurred in nine signals, which inherently prevented simple linear regressions from outputting reliable and accurate trend predictions. Irregular curves were also common, with 11 signals presenting data curves that did not match normal trends for approach volume data. Each of these data anomalies causes challenges, and with 26 out of 32 signals containing data anomalies and 10 of those with more than one, a longitudinal trend analysis was much more complicated than initially expected.

While each of the methods attempted by the research team had its strengths, only the moving average and standard deviation method was robust enough to identify different types of data anomalies for each signal. At this point, the data visualization tool allows for the most flexible and comprehensive data anomaly detection out of all the tools. With the data visualization tool, UDOT traffic engineers might be able to view the ATSPM data longitudinally and quickly identify when and where data anomalies appear.

Future research could be conducted to investigate data anomalies for other performance measures. The research could also study how the data anomalies may affect transportation decision making and policy. Once UDOT has completed the current round of software advancements (Version 5 is under development at the time of this research), the research team would like to use the developed methodologies to re-evaluate the intersection performance longitudinally and do a before-after study to see if the intersection performance improved.

### 5.4 Recommendations and Conclusions

The primary recommendation to UDOT is to investigate the cause of data anomalies and missing data presented in the ATSPM database. A thorough analysis into the potential reasons for these issues will lead to more usable data. It is noteworthy that because of the discoveries of missing and erroneous data found by the research team, UDOT traffic engineers have reached out to consulting firms and coding technicians to help fix and debug the data issues.

To improve data accuracy and quality, several steps to assist in this data remediation process are suggested. This study identified multiple steps that UDOT can take to ensure the consistent accuracy of their ATSPM data. First, data detectors at intersections with unusually high numbers of data anomalies should be inspected. Chang et al. (2016) found that properly installing microwave sensors to detect traffic volumes and speeds is paramount to data accuracy. If the sensors are poorly aimed, the accuracy of the resulting data can be severely limited. Second, if no issues are present on the data detector level, the controller event log should be compared with the aggregated performance measure data at data anomaly timestamps. This step will show if any discrepancies are present between the raw data and the aggregated data. Third, the methodology and coding for each performance measure should be evaluated to ensure that the calculations and aggregation performed will generate the correct data.

Two main purposes of the ATSPM system are to provide accurate data to UDOT traffic engineers to make engineering decisions and to provide UDOT and government leadership with information to produce policy decisions. Given the potentially large role of the ATSPM system in system-wide dashboards, it is felt that the data quality of the system needs refinement. With consistent monitoring for anomalies, detector calibration at signals with anomalies present, controller event log inspection, and confirmation of accurate calculation in the coding of performance measures, the team believes that the ATSPM system could achieve higher accuracy and produce even more informed decisions.

# REFERENCES

Apronti, D., Ksaibati, K., Gerow, K., & Hepner, J. J. (2016). "Estimating traffic volume on Wyoming low volume roads using linear and logistic regression methods." *Journal of Traffic and Transportation Engineering (English edition)*, 3(6), 493-506.

Brakewood, C., Macfarlane, G. S., and Watkins, K. (2015). "The Impact of Real-time Information on Bus Ridership in New York City." *Transportation Research Part C: Emerging Technologies*, 53, 59-75.

Brownlee, J. (2020). "Linear Regression for Machine Learning." Machine Learning Mastery <https://machinelearningmastery.com/linear-regression-for-machine-learning/> (Apr. 5, 2022).

Busch-Geertsema, A., Lanzendorf, M., and Klinner, N. (2021). "Making Public Transport Irresistible? The Introduction of a Free Public Transport Ticket for State Employees and Its Effects on Mode Use." *Transport Policy,* 106, 2449-261.

Burger, N. E., Kaffine, D. T., and Yu, B. (2014). "Did California's Hand-Held Cell Phone Ban Reduce Accidents?" *Transportation Research Part A: Policy and Practice*, 66, 162-172.

Chamberlin, R., and Fayyaz, K. (2019). "Using ATSPM Data for Traffic Data Analytics." Report No. UT-19.22. Utah Department of Transportation. Research and Innovation Division, Salt Lake City, UT.

Chang, D. K., Saito, M., Schultz, G. G., and Eggett, D. (2016). "How Accurate Are Turning Volume Counts Collected by Microwave Sensors?" *International Conference on Transportation and Development 2016,* Reston, VA: American Society of Civil Engineers, 945-956.

Day, C. M., Li, H., Sturdevant, J. R., and Bullock, D. M. (2018). "Data-Driven Ranking of Coordinated Traffic Signal Systems for Maintenance and Retiming." *Transportation Research Record,* 2672(18), 167-178.

Georgia Department of Transportation (GDOT). (2022a). “SigOps Metrics” <http://sigopsmetrics.com/main/> (Jul. 7, 2019).

Georgia Department of Transportation (GDOT). (2022b). “Automated Traffic Signal Performance Measures Reporting Details.” <https://traffic.dot.ga.gov/ATSPM/Images/ATSPM_Reporting_Details.pdf> (Aug. 31, 2022).

Georgia Department of Transportation (GDOT). (2022c). “Automated Traffic Signal Performance Measures Component Details.” <https://traffic.dot.ga.gov/ATSPM/Images/ATSPM_Component_Details.pdf > (Aug. 31, 2022).

Kim, K. M., Saito, M., Schultz, G. G., and Eggett, D. L. (2018). “Evaluating Safety Impacts of Access Management Alternatives with the Surrogate Safety Assessment Model.” *Transportation Research Record*, 2672(17), 120-128.

Liu, C., Lu, C., Wang, S., Sharma, A., and Shaw, J. (2019). “A Longitudinal Analysis of the Effectiveness of California's Ban on Cellphone Use While Driving.” *Transportation Research Part A: Policy and Practice*, 124, 456-467.

Schultz, G. G., Macfarlane, G. S., Wang, B., and McCuen, S. (2020). “Evaluating the Quality of Signal Operations Using Signal Performance Measures.” Report No. UT-20.08. Utah Department of Transportation. Research and Innovation, Salt Lake City, UT.

Schultz, G. G., Adamson, M. L., Stevens, M. D., and Saito, M. (2019). “An Analysis of Decision Boundaries for Left-Turn Treatments.” Report No. UT-19.05. Utah Department of Transportation. Research and Innovation Division, Salt Lake City, UT.

Seat, M. L., Schultz, G. G., Clegg, B. W., and Saito, M. (2019). “Analyzing the Safety Impacts of Raised Medians.” *International Conference on Transportation and Development 2019: Smarter and Safer Mobility and Cities.* Reston, VA: American Society of Civil Engineers, 84-95.

Transportation Research Board (TRB). (2010). “Highway Capacity Manual.” Washington, DC.

Utah Department of Transportation (UDOT). (2022a). “Automated Traffic Signal Performance Measures (ATSPM).” <https://udottraffic.utah.gov/ATSPM> (Aug. 27, 2021).

Utah Department of Transportation (UDOT). (2022b). “Continuous Count Station.” <https://data-uplan.opendata.arcgis.com/datasets/uplan::continuous-count-stations > (May 12, 2022).

Wang, B., Schultz, G. G., Macfarlane, G. S., and McCuen, S. (2022). “Evaluating Signal Systems Using Automated Traffic Signal Performance Measures.” *Future Transportation*, 2(3), 659-674.

## APPENDIX A: AVERAGE DAILY VALUE FOR ALL PERFORMANCE MEASURES

This appendix contains the visualization of the average daily value for all performance measures for all signals not described in Section 4.2.

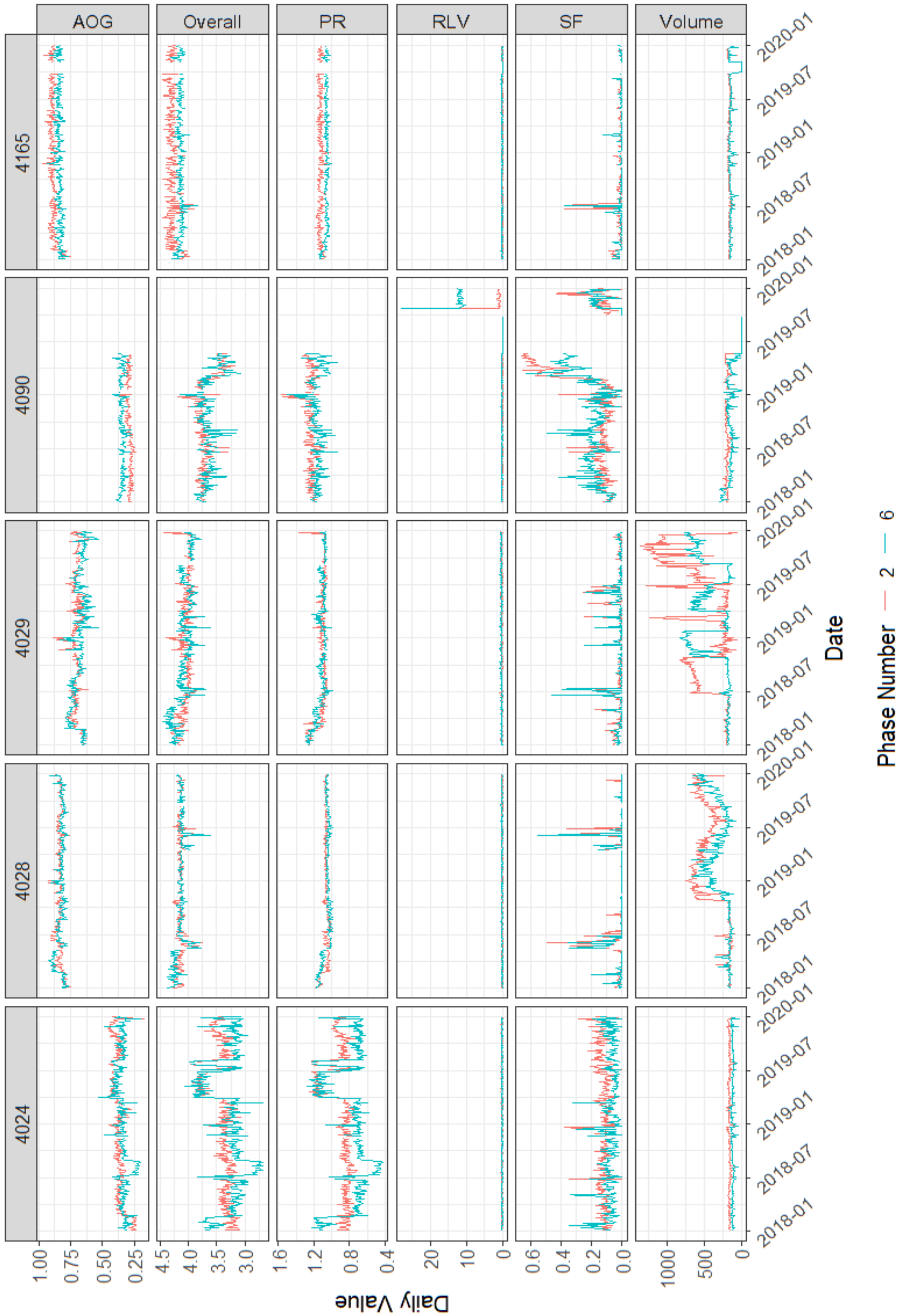



**Figure A.1 Visualization of the average daily value for all performance measures (Signals 4024, 4028, 4029, 4090, 4165).**

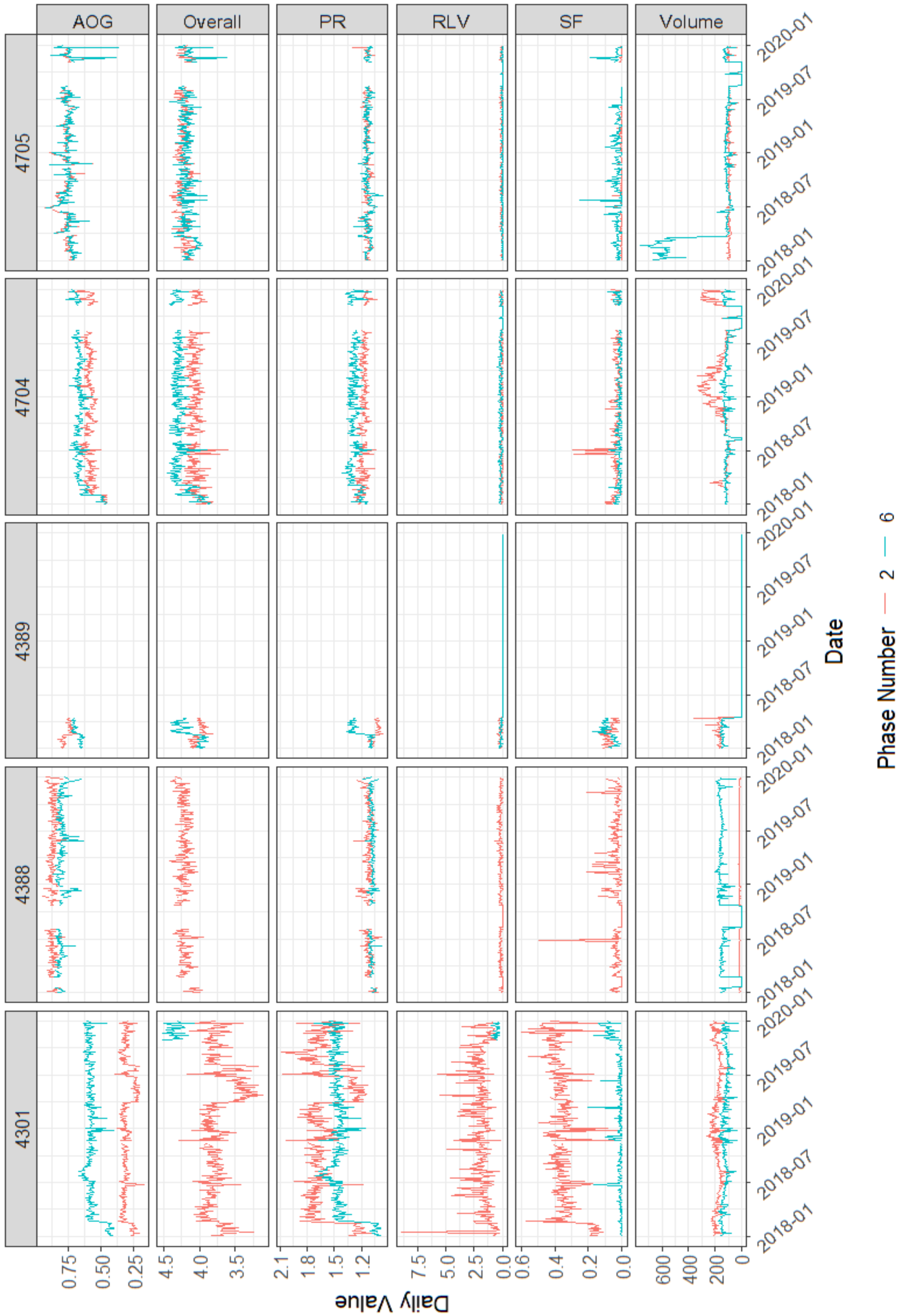



**Figure A.2 Visualization of the average daily value for all performance measures (Signals 4301, 4388, 4389, 4704, 4705).**

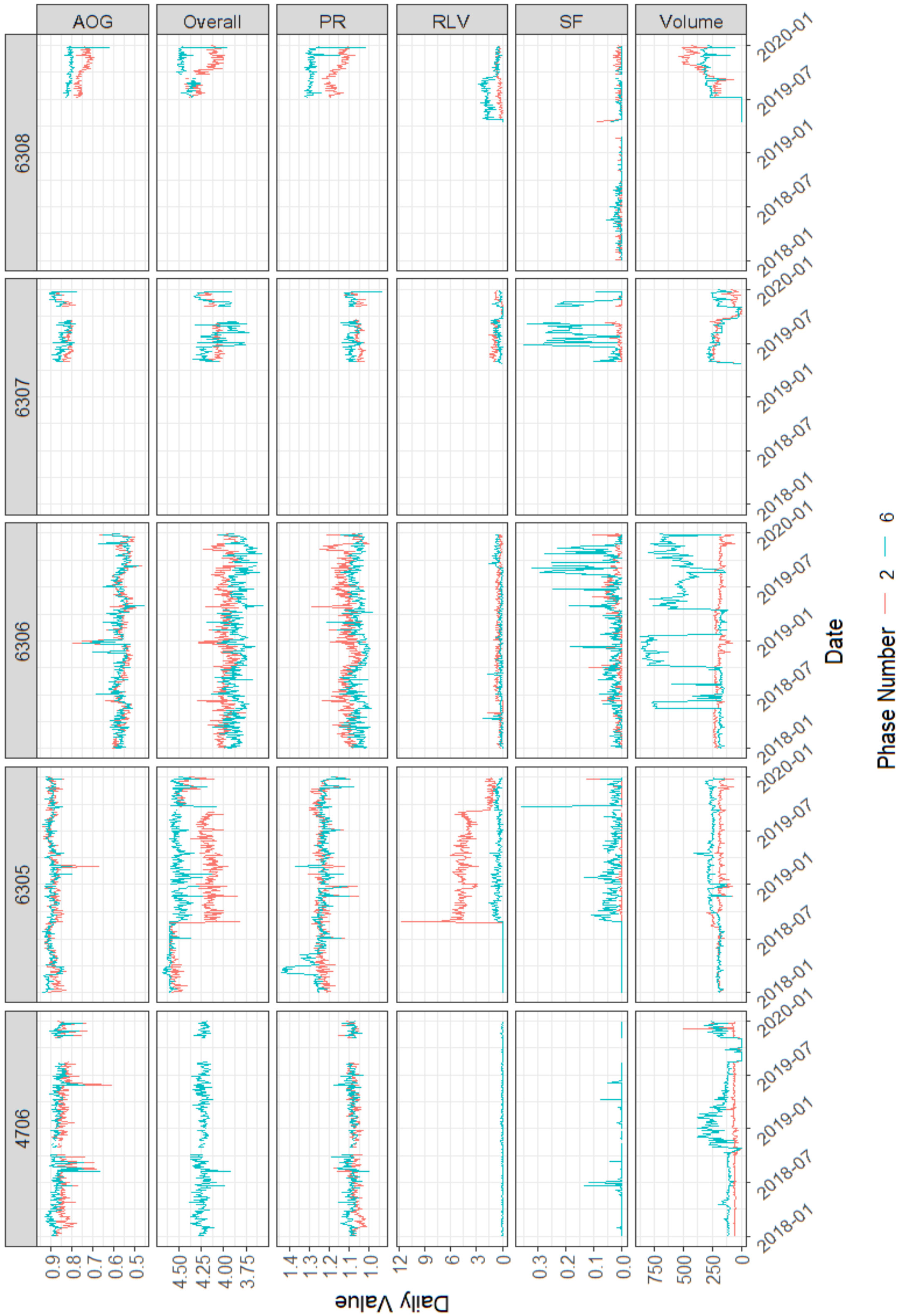



**Figure A.3 Visualization of the average daily value for all performance measures (Signals 4706, 6305, 6306, 6307, 6308).**

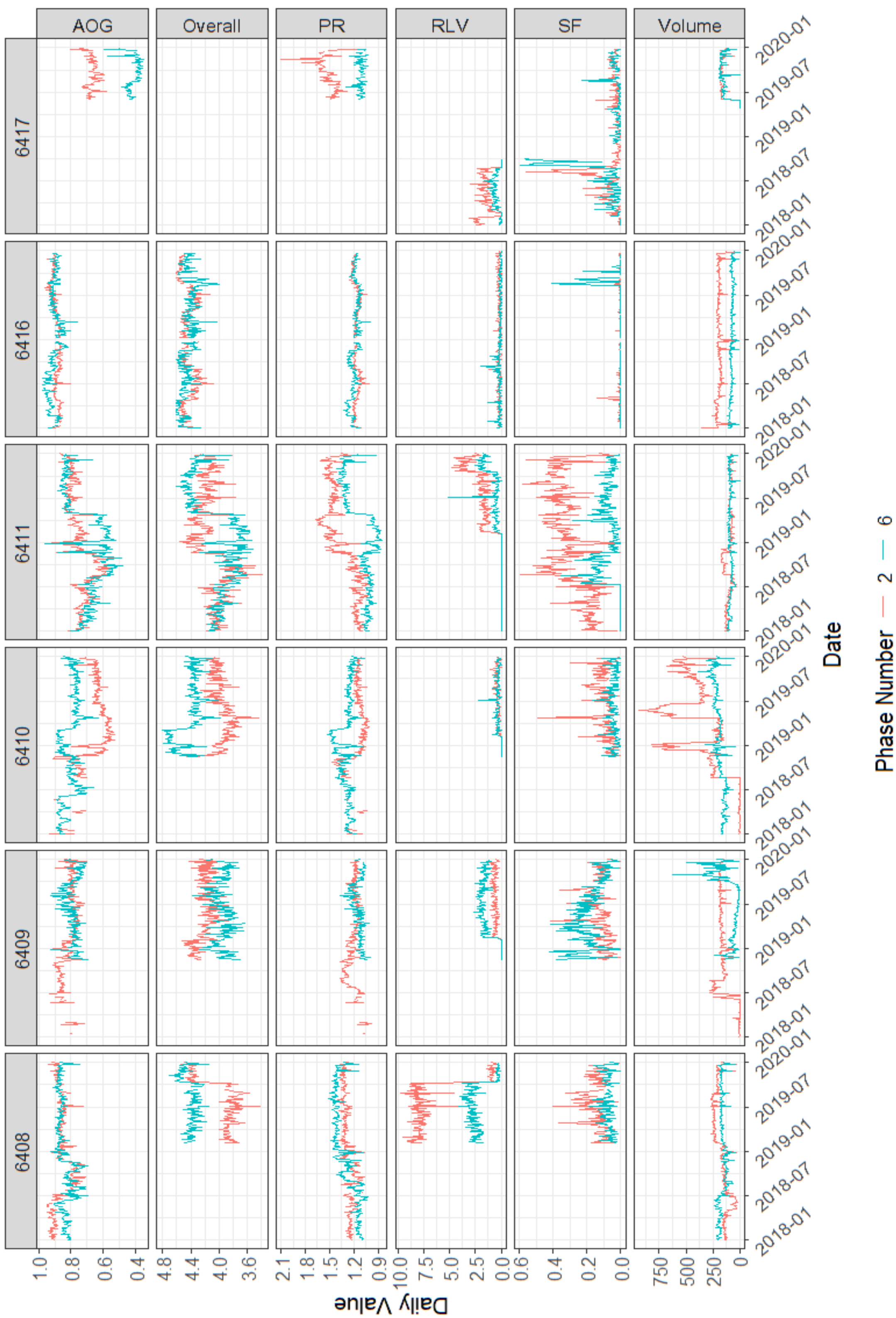



**Figure A.4 Visualization of the average daily value for all performance measures (Signals 6408, 6409, 6410, 6411, 6416, 6417).**

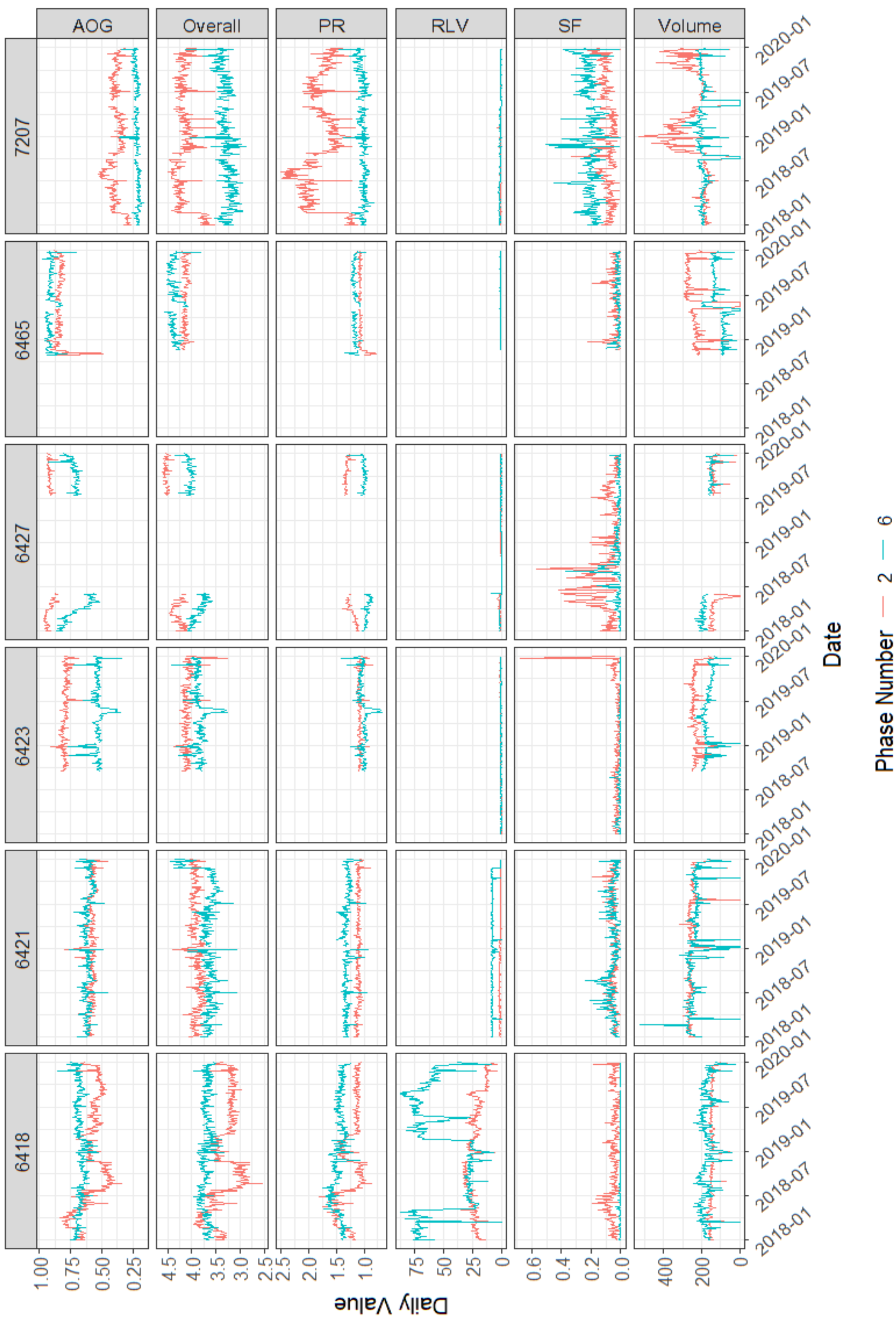



**Figure A.5 Visualization of the average daily value for all performance measures (Signals 6418, 6421, 6423, 6427, 6465, 7207).**

# APPENDIX B: LINEAR REGRESSION PREDICTION VERSUS REAL TRAFFIC VOLUME

This appendix contains the additional graphs for the linear regression prediction versus real traffic volume in ATSPM for those signals not previously reported in Section 4.4.1.

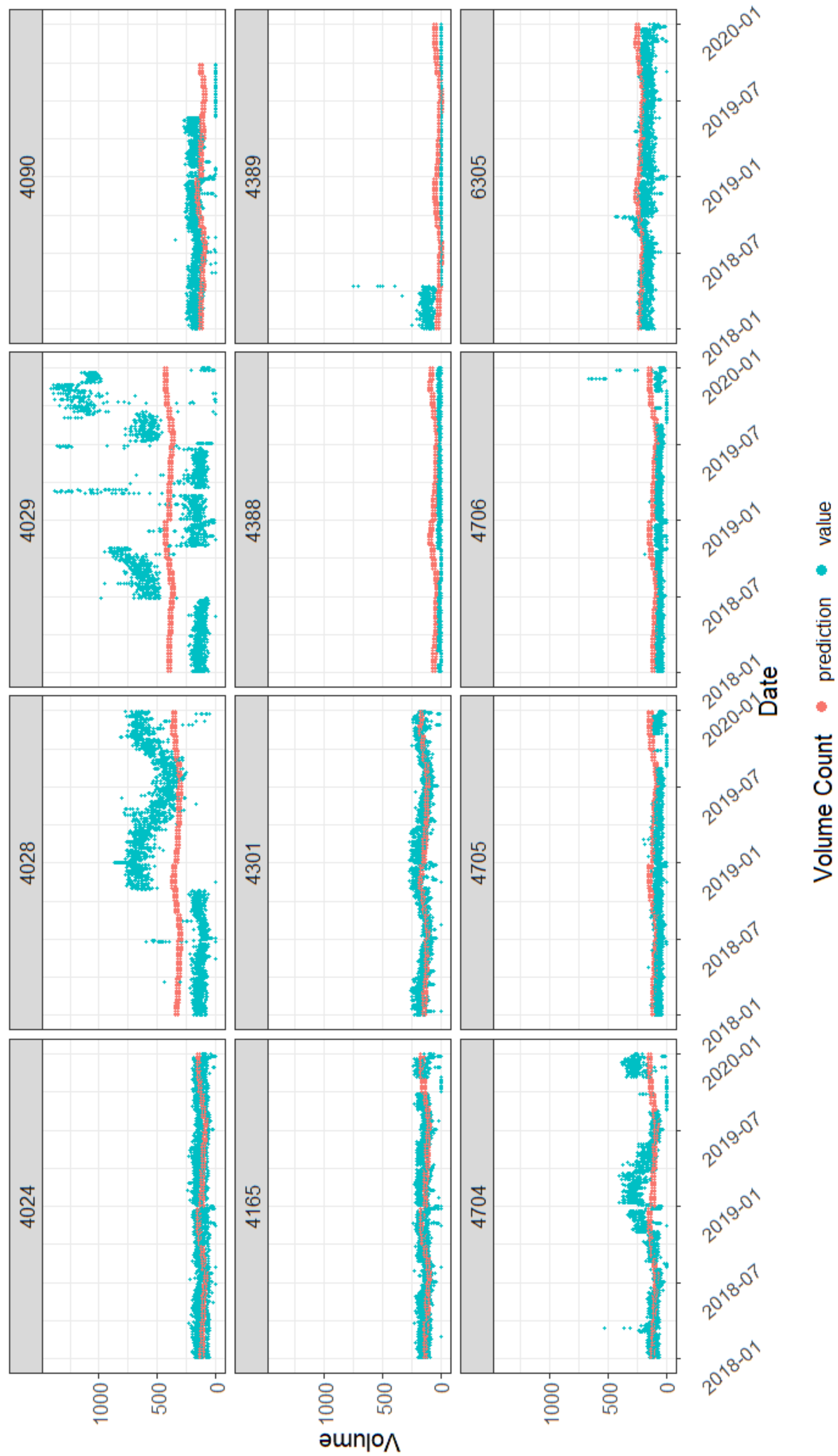



**Figure B.1 Predicted vs. real traffic volume - Phase 2 (Signal 4024, 4028, 4029, 4090, 4165, 4301, 4388, 4389, 4704, 4705, 4706, 6305).**

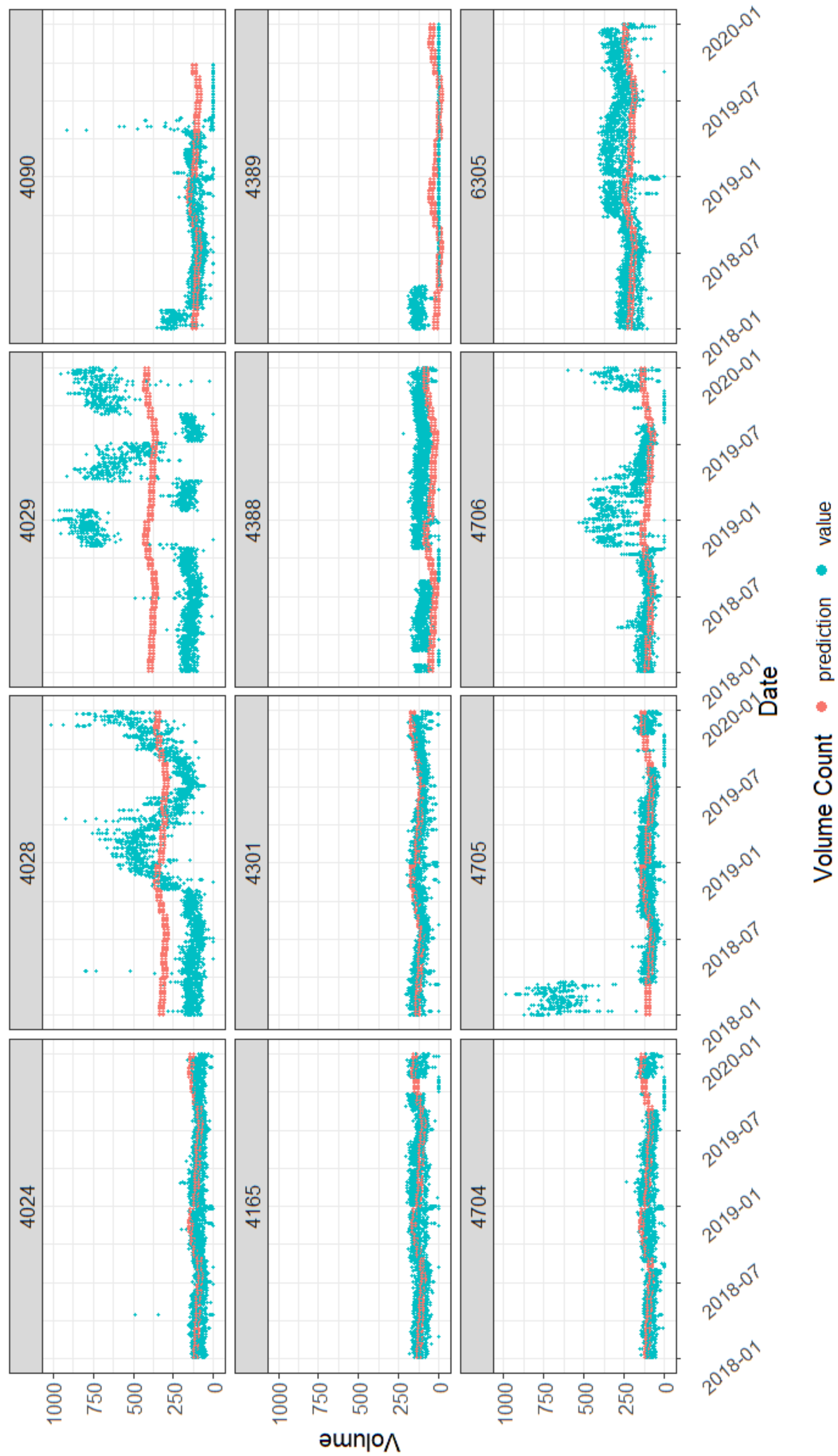



**Figure B.2 Predicted vs. real traffic volume - Phase 6 (Signal 4024, 4028, 4029, 4090, 4165, 4301, 4388, 4389, 4704, 4705, 4706, 6305).**

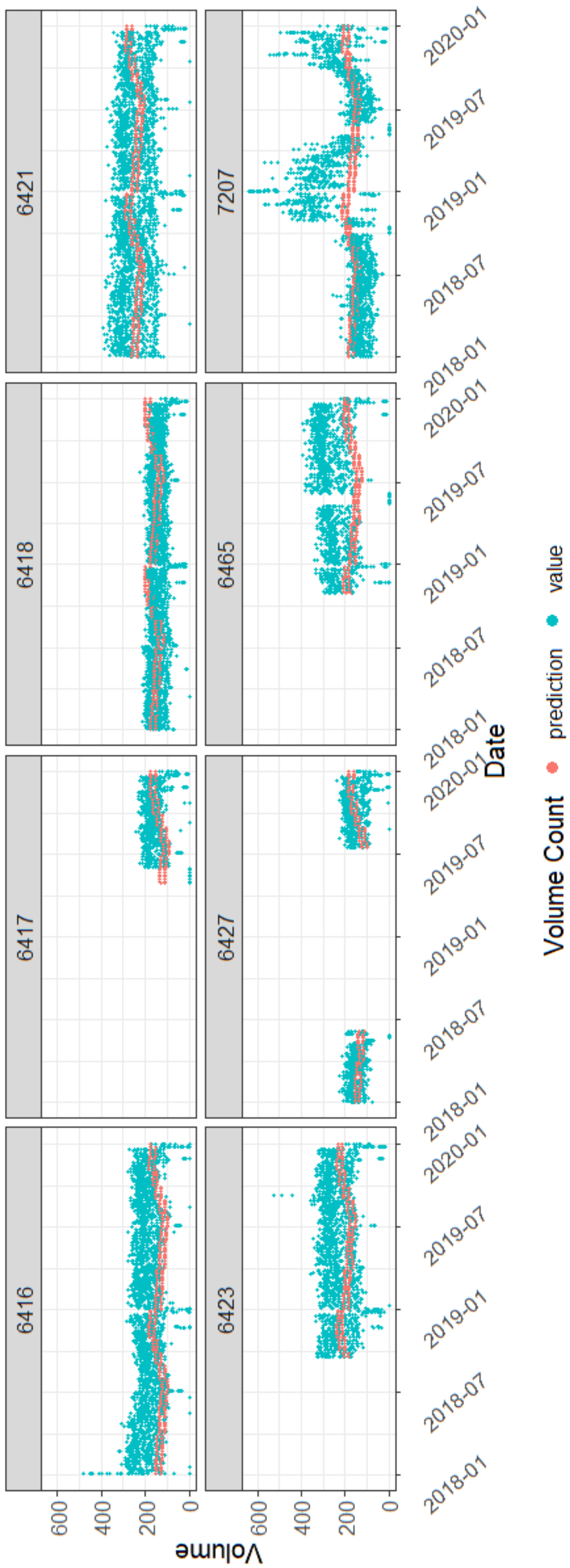



**Figure B.3 Predicted vs. real traffic volume - Phase 2 (Signal 6416, 6417, 6418, 6421, 6423, 6427, 6465, 7207).**

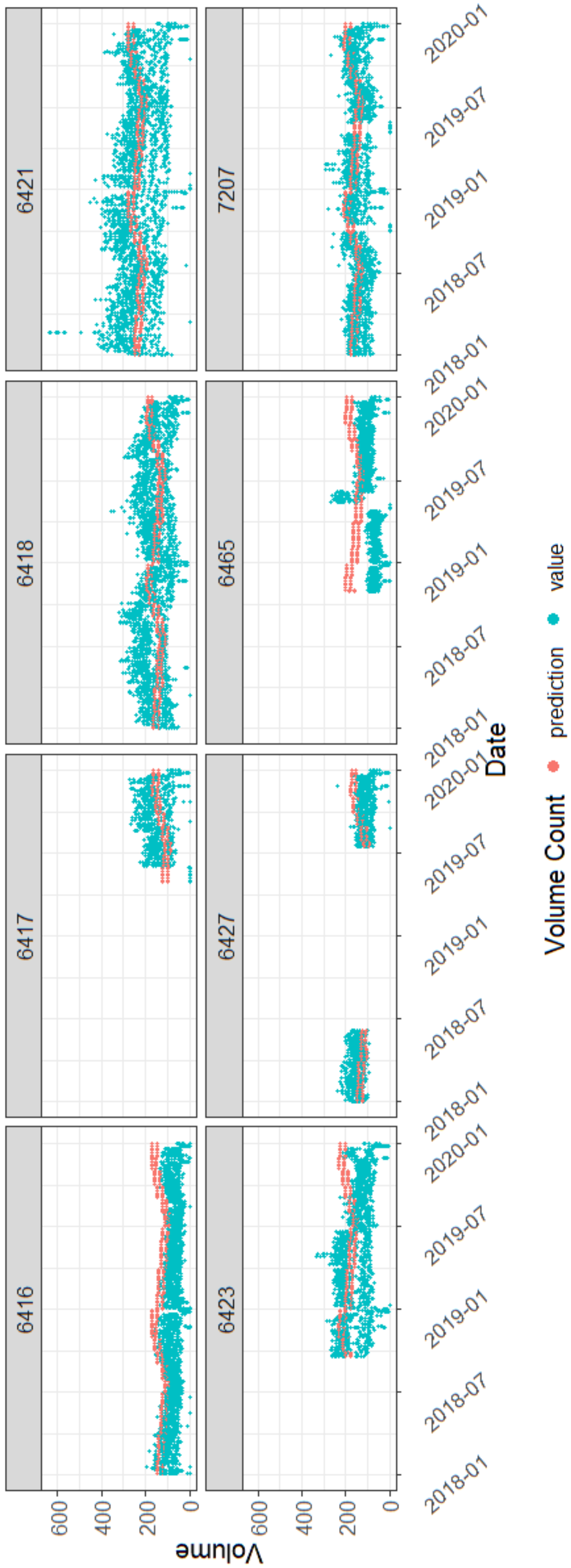



**Figure B.4 Predicted vs. real traffic volume - Phase 6 (Signal 6416, 6417, 6418, 6421, 6423, 6427, 6465, 7207).**

# APPENDIX C: GROUP DISTRIBUTION COMPARISON

This appendix contains the visualization of the group distribution comparison for all signals not previously included in Section 4.4.2.

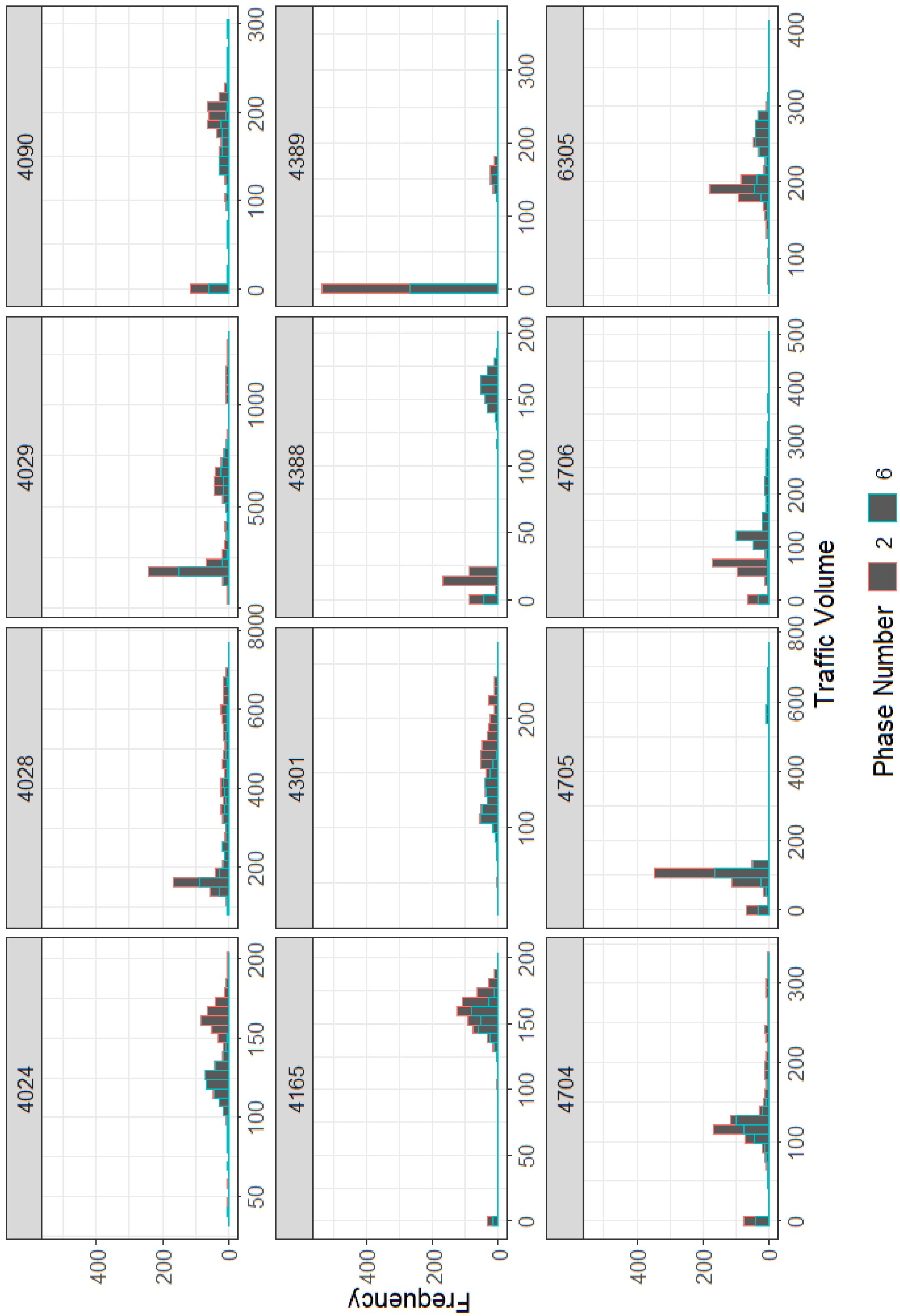



**Figure C.1 Group of average daily volume (Signals 4024, 4028, 4029, 4090, 4165, 4301, 4388, 4389, 4704, 4705, 4706, 6305).**

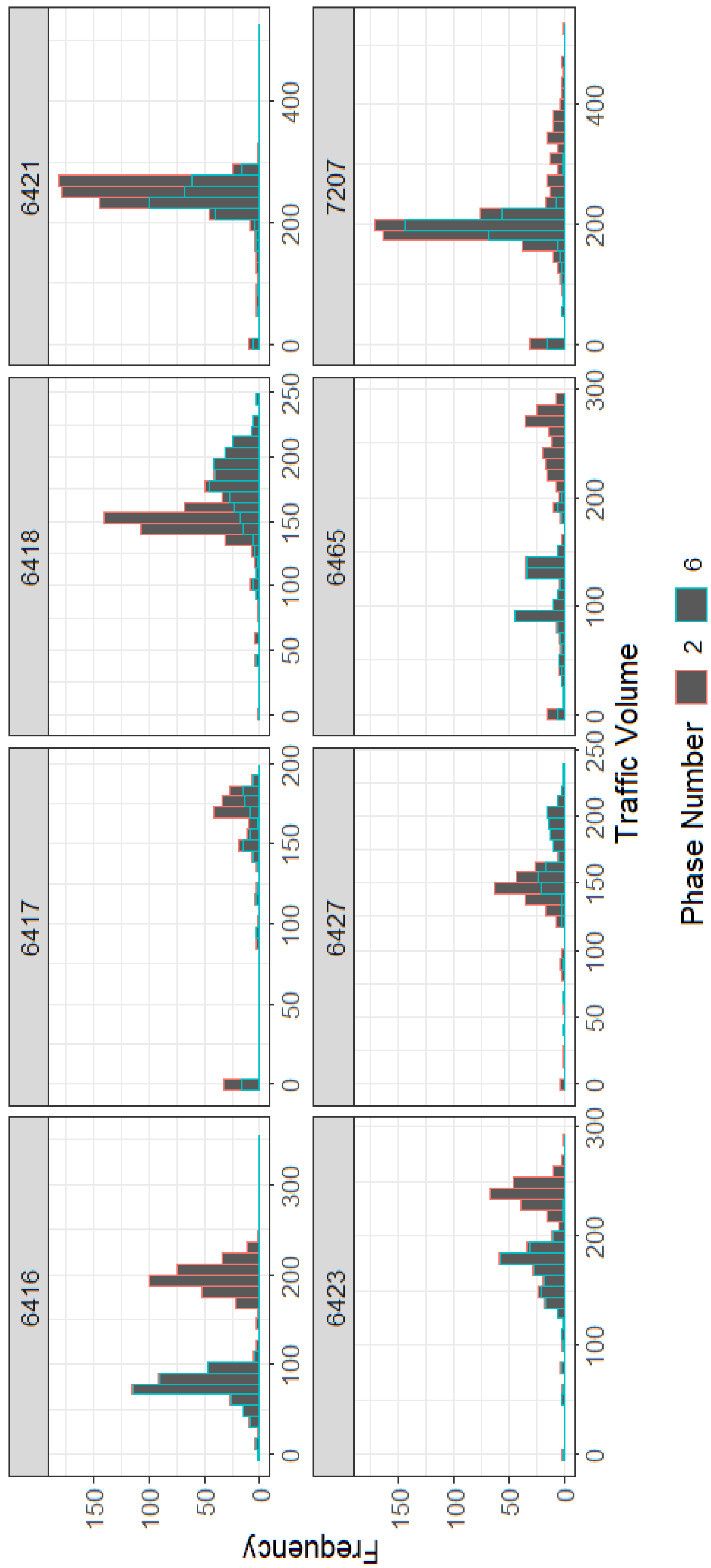



**Figure C.2 Group of average daily volume (Signals 6416, 6417, 6418, 6421, 6423, 6427, 6465, 7207).**

# APPENDIX D: MOVING AVERAGE AND STANDARD DEVIATION

This appendix contains the visualization of moving average and standard deviation for all signals not previously described in Section 4.4.3.

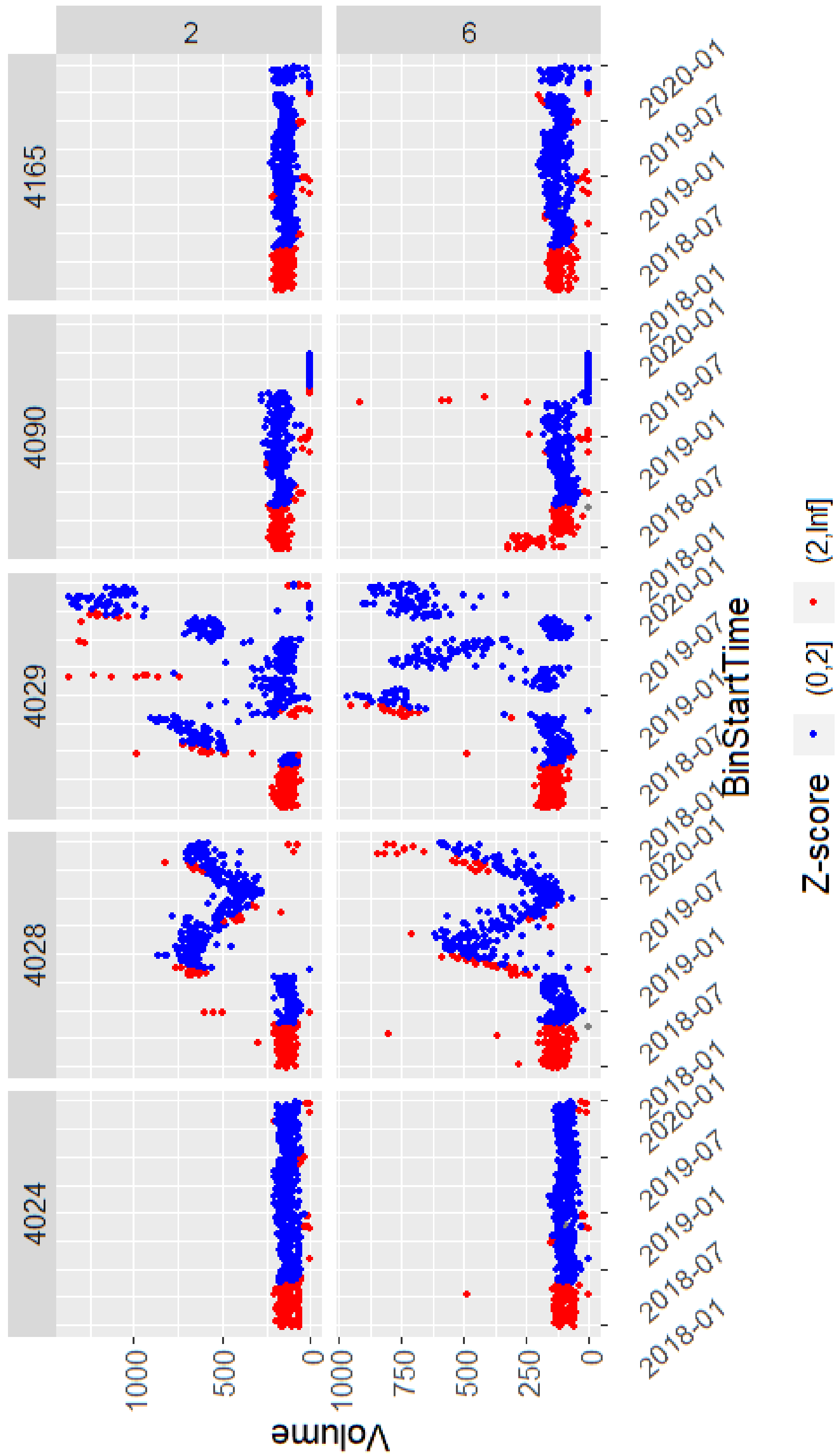



**Figure D.1 Moving average and standard deviation with Z-score (Signal 4024, 4028, 4029, 4090, 4165).**

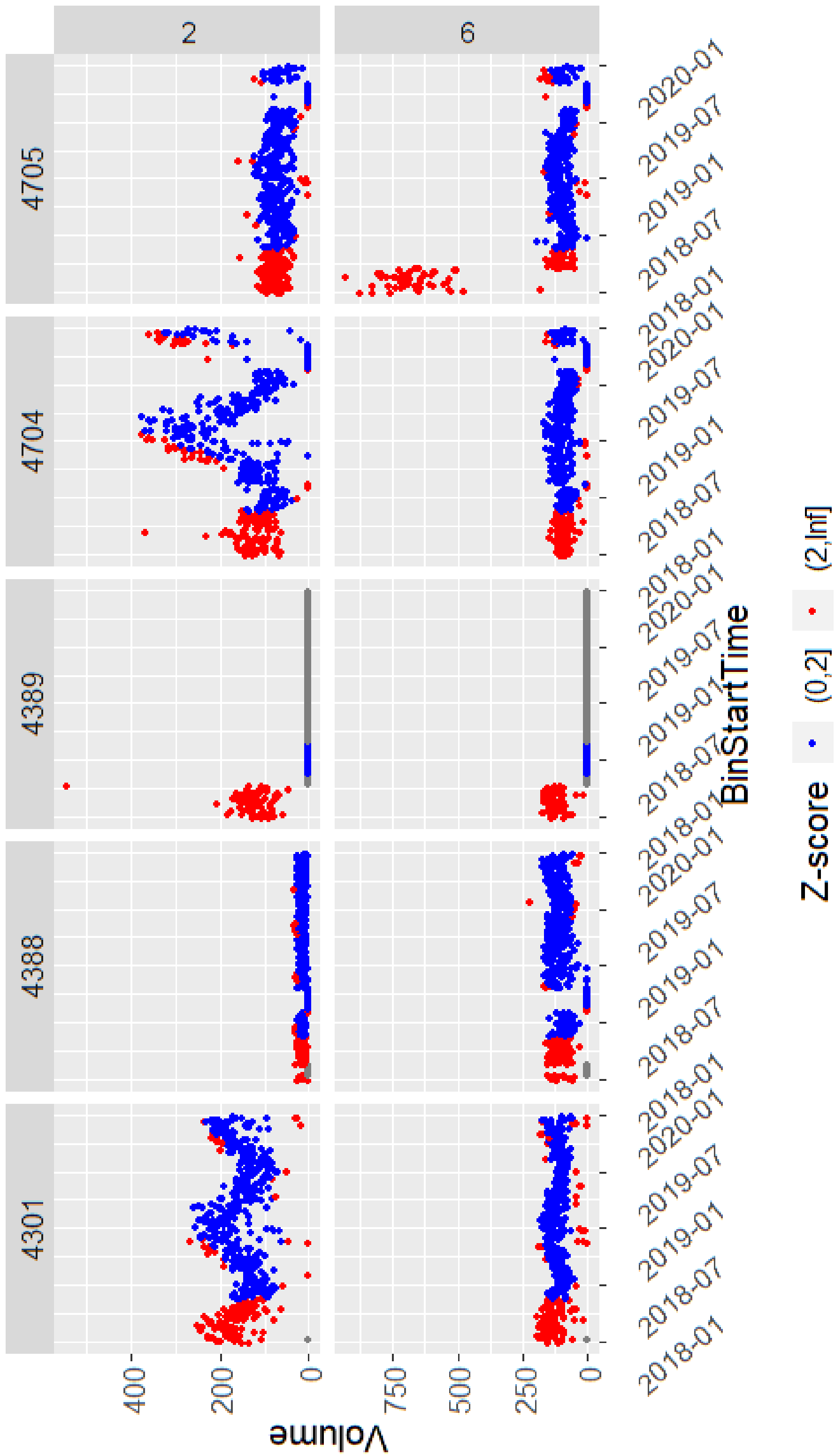



**Figure D.2 Moving average and standard deviation with Z-score (Signal 4301, 4388, 4389, 4704, 4705).**

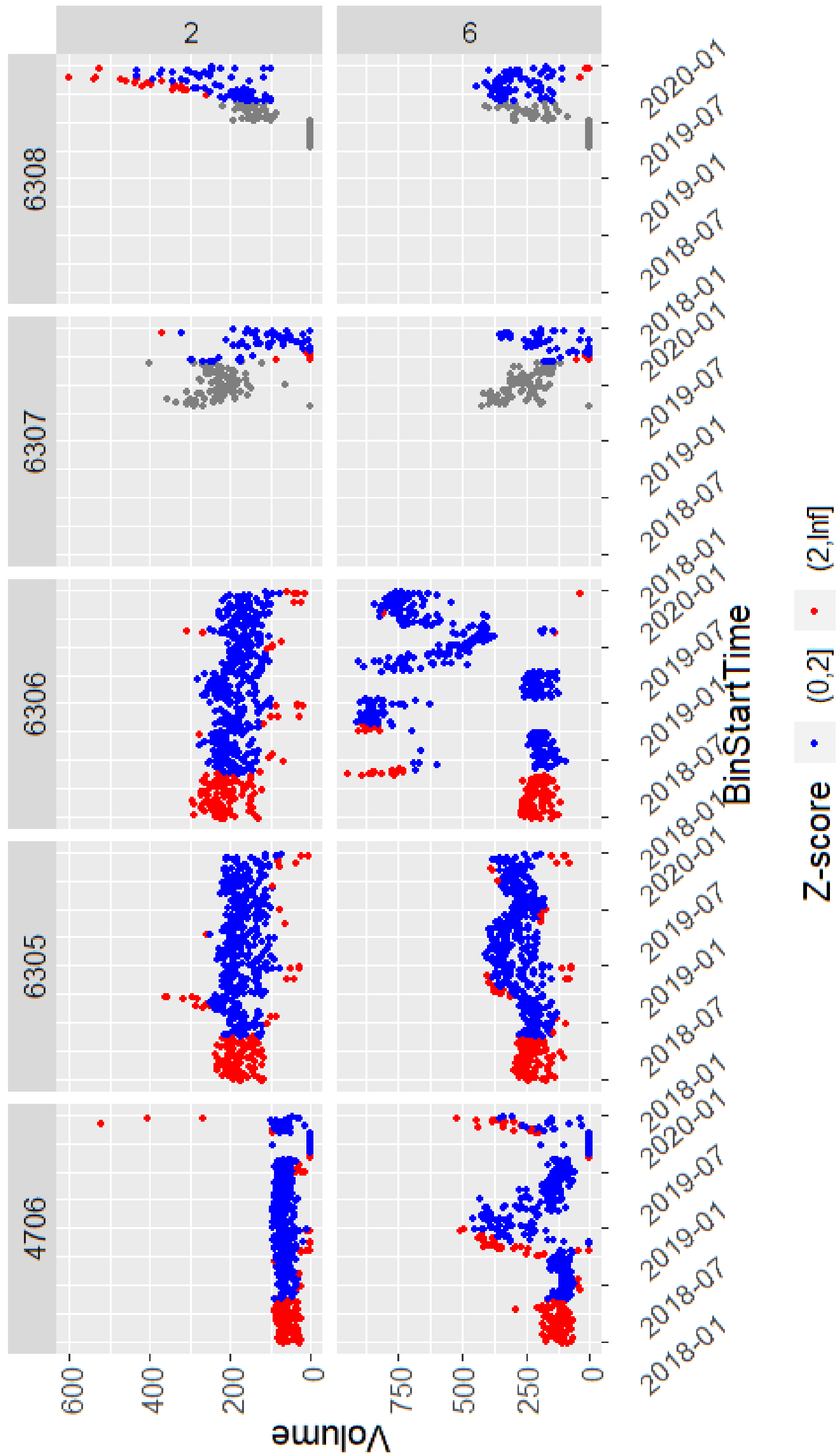



**Figure D.3 Moving average and standard deviation with Z-score (Signal 4706, 6305, 6306, 6307, 6308).**

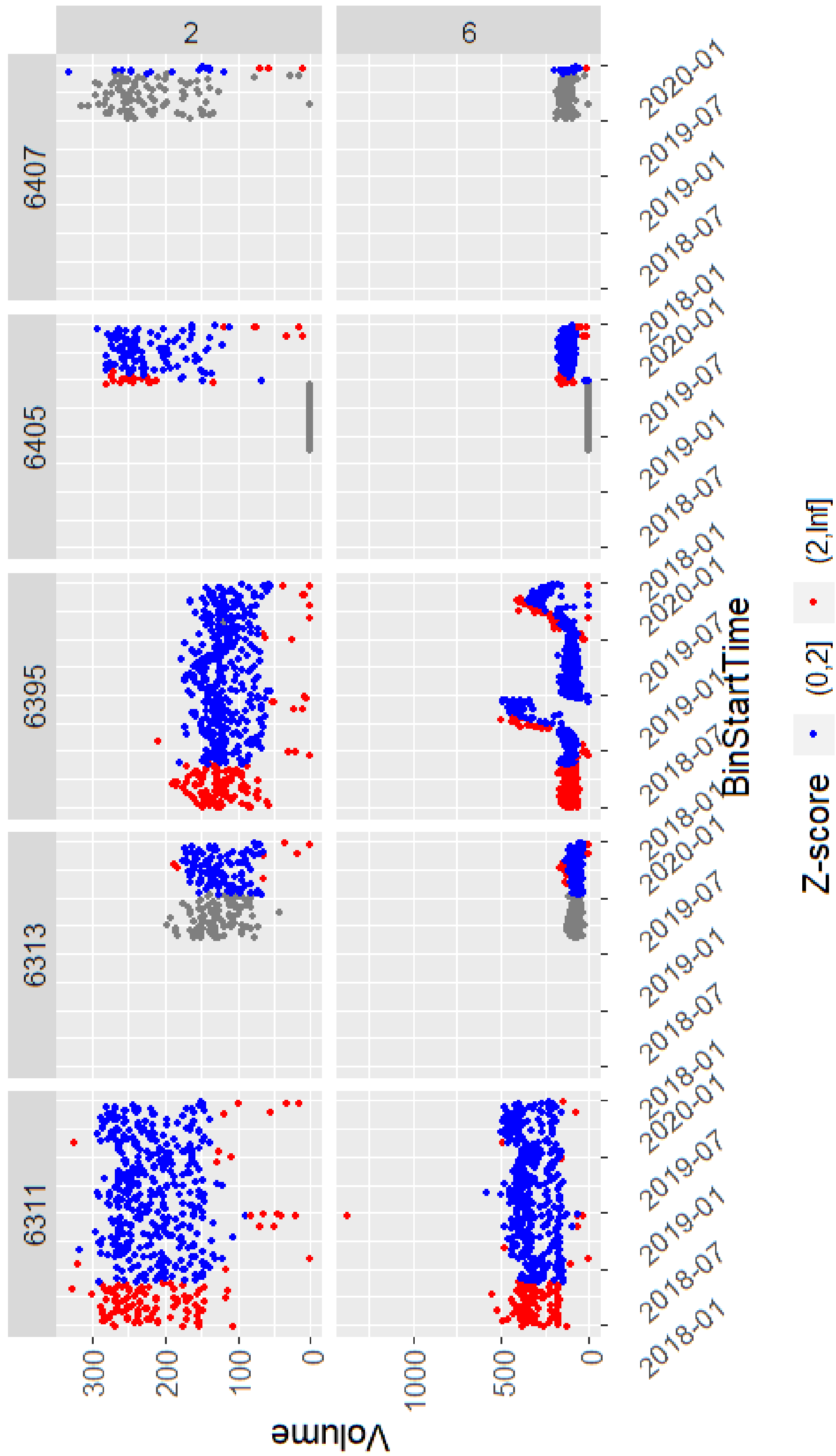



**Figure D.4 Moving average and standard deviation with Z-score (Signal 6311, 6313, 6395, 6405, 6407).**

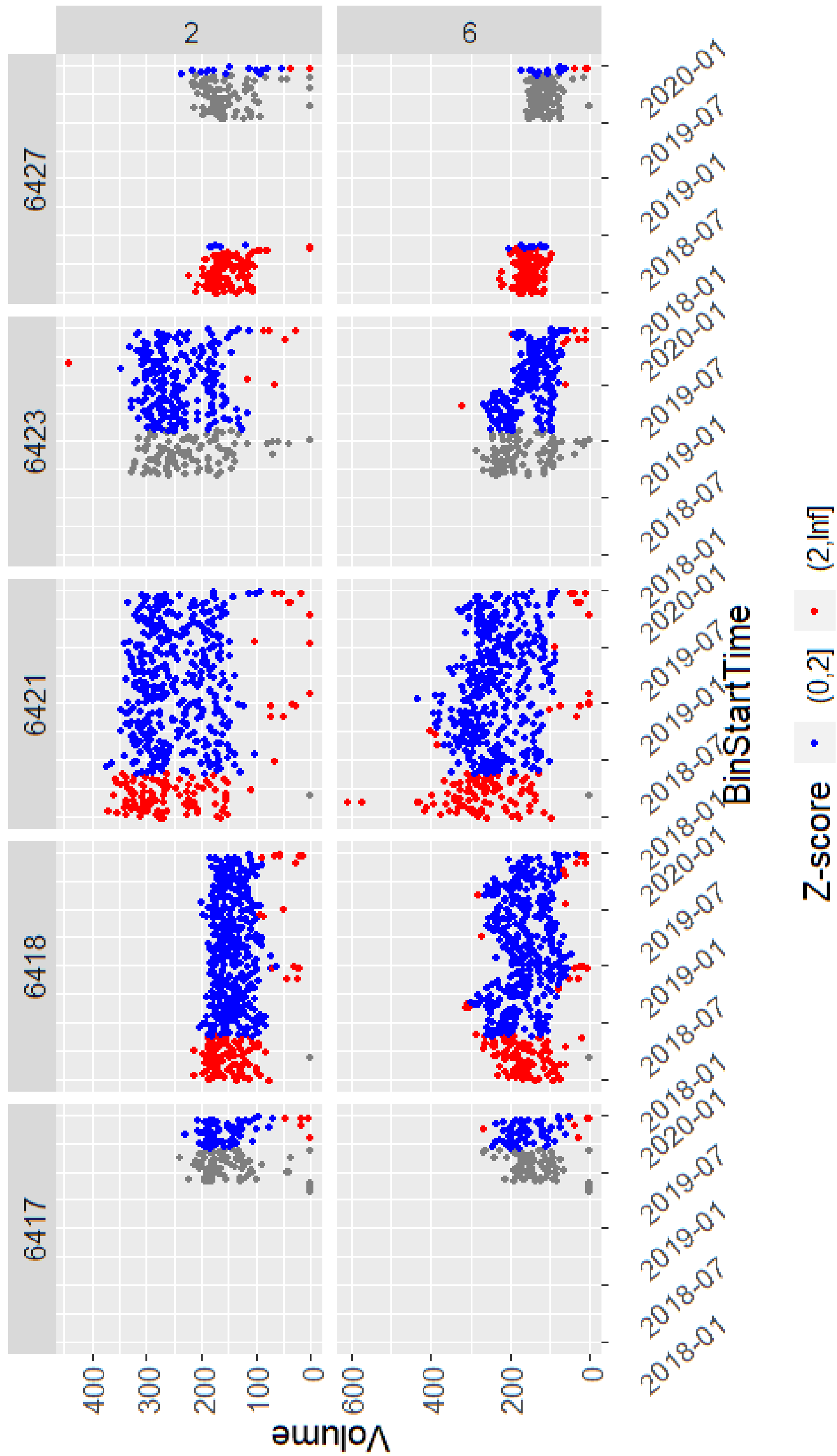



**Figure D.5 Moving average and standard deviation with Z-score (Signal 6417, 6418, 6421, 6423, 6427).**

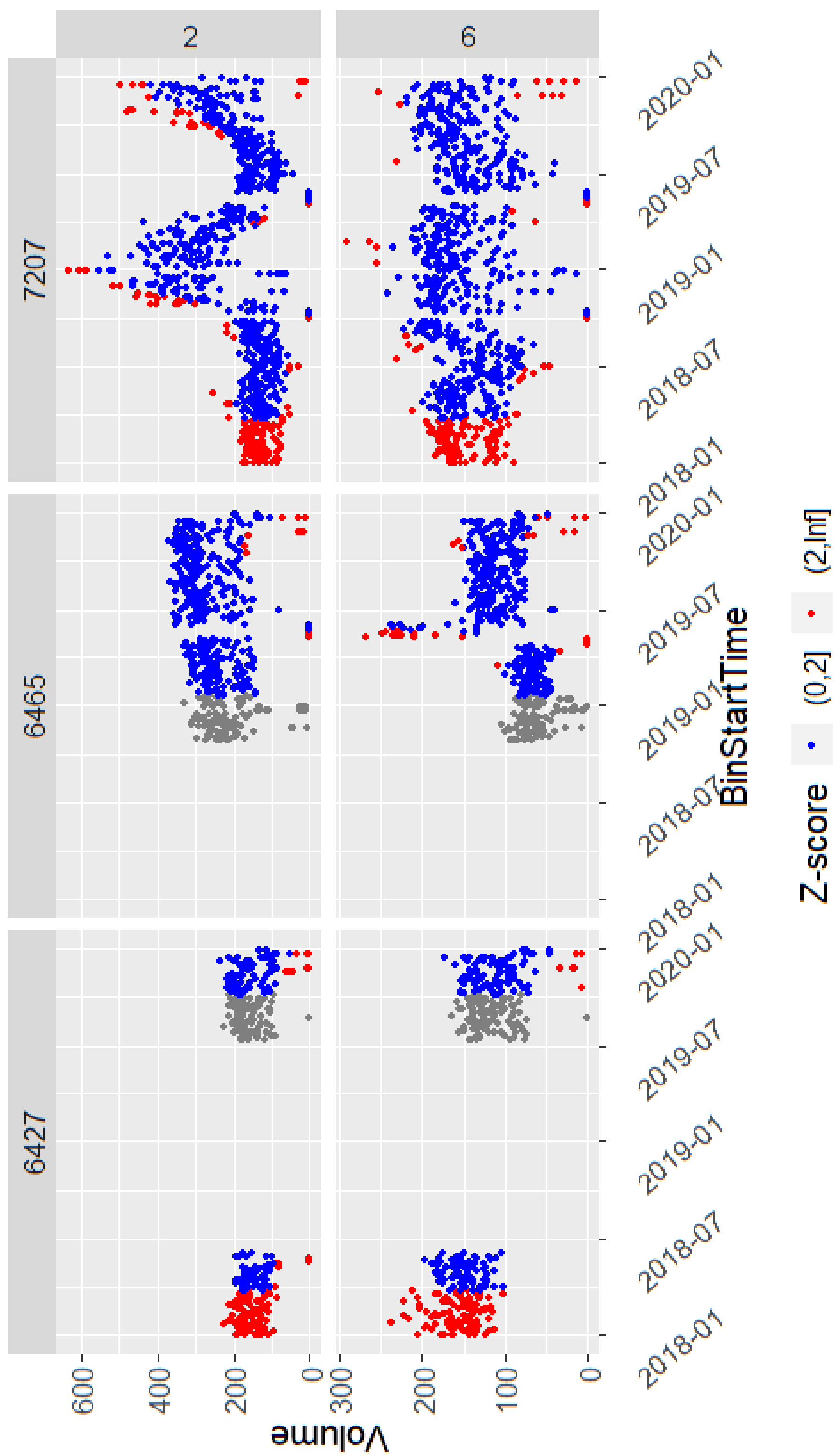



**Figure D.6 Moving average and standard deviation with Z-score (Signal 6427, 6465, 7207).**