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Building Intelligence in the Automated Traffic Signal Performance Measures with Advanced Data Analytics

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Building Intelligence in the Automated Traffic Signal Performance Measures with Advanced Data Analytics

Abstract

Automated traffic signal performance measures (ATSPMs) are an effort to equip traffic signal controllers with high-resolution data-logging capabilities and utilize this data to generate performance measures. These measures allow practitioners to improve operations as well as to maintain and operate their systems in a safe and efficient manner. Although these measures have changed the way that operators manage their systems, several shortcomings of the tool, identified by talking with signal operators, are a lack of data quality control and the extent of resources required to properly use the tool for system-wide management. To address these shortcomings, intelligent traffic signal performance measurements (ITSPMs) are presented in this paper, using the concepts of machine learning, traffic flow theory, and data visualization to reduce the operator resources needed for overseeing data-driven traffic signal management systems. In applying these concepts,

Ms provide graphical tools to identify and remove logging errors and data from bad sensors, intelligently determine trends in demand, and address the question of whether or not coordination may be needed at an intersection. The focus of ATSPMs and ITSPMs on performance measures for multimodal users is identified as a pressing need for future research.

Disciplines

Civil Engineering | Computer-Aided Engineering and Design | Transportation Engineering

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1 **Building intelligence in the automated traffic signal performance measures**
2 **with advanced data analytics**

3

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1 ABSTRACT

2 Automated traffic signal performance measures (ATSPMs) are an effort to equip traffic signal
3 controllers with high-resolution data-logging capabilities and utilize this data to generate
4 performance measures. These measures allow practitioners to improve operations as well as to
5 maintain and operate their systems in a safe and efficient manner. Although these measures have
6 changed the way that operators manage their systems, several shortcomings of the tool, identified
7 by talking with signal operators, are a lack of data quality control and the extent of resources
8 required to properly use the tool for system-wide management. To address these shortcomings,
9 in this paper intelligent traffic signal performance measurements (ITSPMs) are presented, using
10 the concepts of machine learning, traffic flow theory, and data visualization to reduce the
11 operator resources needed for overseeing data-driven traffic signal management systems. In
12 applying these concepts, ITSPMs provide graphical tools to identify and remove logging errors
13 and data from bad sensors, intelligently determine trends in demand, and address the question of
14 whether or not coordination may be needed at an intersection. The focus of ATSPMs and
15 ITSPMs on performance measures for multimodal users is identified as a pressing need for future
16 research.

1 INTRODUCTION

2 In the United States, more than 300,000 traffic signals are currently in operation. According to
3 the Federal Highway Administration, the operation and performance of most of these signals is
4 assessed through citizen complaints (1). In these settings, agencies are forced to rely on software
5 and simulation models to develop timings, with the presumption that if there are no complaints,
6 everything is working acceptably, often compromising on performance and efficiency.

7 Automated traffic signal performance measures (ATSPMs) are an effort to equip traffic
8 signal controllers with high-resolution data-logging capabilities and to utilize these to generate
9 performance measures. These measures allow practitioners to improve operations and to
10 maintain and operate their systems in a safe and efficient manner (1). State-of-the-art ATSPM
11 systems primarily present raw data in graphic representations with the goal of providing tools for
12 visual queries to traffic signal experts. The tool has been very useful for data-driven management
13 of traffic signal systems and has been adopted and modified by several agencies. From
14 conversations with several practitioners who use them, the three main shortcomings of the tool
15 are: (i) The tool currently uses raw data feeds but has very little data quality control or quality
16 checks in place, (ii) using the tool for system-wide management is resource intensive, and (iii)
17 the tool's primary focus is automobile traffic, and it fails to address multi-modal aspects of signal
18 operation.

19 In this study, the current state of the art is extended by the creation of a new tool called
20 the Intelligent Traffic Signal Performance Measurement System (ITSPM). Instead of primarily
21 automating the signal performance calculation from a raw data stream, this tool uses machine
22 learning techniques, traffic flow theory, and data-driven intelligence to provide additional
23 insights to decision makers. In this paper, three primary enhancements are provided to address
24 the above-reported shortcomings of the existing state-of-the-art tool, namely:

- 25 a. Additional measures for data quality control are provided;
- 26 b. Machine learning-based intelligence is provided to deliver initial insights into the data,
27 thus reducing the visual querying time, which results in more efficient utilization of
28 personnel resources;
- 29 c. Some of the current graphics in ATSPM are improved to better represent operations at
30 different spatial and temporal resolutions.

31 Although noted as a shortcoming, multi-modal aspects are not addressed in this paper and
32 will be the focus of future research. The remainder of the paper is presented in the following
33 manner. A literature review and the state of practice are presented next, followed by
34 methodology, data used, and results. The paper then wraps up with conclusions and
35 recommendations.
36

37 LITERATURE REVIEW

38 The development of ATSPMs began with the collection of event-based data by researchers at
39 Purdue University in the mid-2000s (2) and the identification of tactical methods to control
40 traffic within NCHRP 3-66 (3). Since these original works, researchers have emphasized the
41 development of event-based data acquisition systems that have the capability of generating high-
42 level performance measures as well as enough data resolution capable of being used for fault
43 recreation and signal fine tuning (4). Researchers at Purdue University as well as practitioners at

1 the Indiana and Utah Departments of Transportation spearheaded the effort to move Highway
2 Capacity Manual operational parameters from the post-processed environment to real-time
3 performance measures in a mainstream operational environment (5). Whereas historical
4 performance measure data were limited to hourly volumes, peak hour factors, and v/c values
5 over long analysis periods, these measures use event-based data to empower an agency with the
6 ability to make data-driven decisions regarding detector and communication health, traffic signal
7 coordination, and split efficiency (6–9). Although this work has been a game changer in the
8 operation and management of traffic signal systems, thus far it has focused mostly on vehicular
9 performance measures with limited investigation into multimodal performance. The natural
10 platform for this would be an extension of ATSPMs from a multimodal perspective, perhaps
11 incorporating visualization techniques by the nationally renowned author Edward Tufte (10).
12 Existing vehicular ATSPMs may also benefit from improved visualization techniques, although
13 the Purdue researchers responsible for much of the ATSPM development work have already
14 spent much effort on visualization (11, 12).

15 The state-of-practice with respect to ATSPMs involves the use of open source software
16 and continued improvements to visualizations and metrics using advances in data analytics.
17 From conversations with several practitioners who use them, ATSPMs are most often used for
18 troubleshooting, operations, and planning. The AASHTO innovation initiative led by the Utah
19 DOT has led to the adoption of ATSPMs by 26 transportation agencies across the country (1).
20 The open source software used by the Utah DOT produces chart usage reports to track which
21 performance measures and visualizations are most used by agency personnel. A usage report for
22 from Jan 1 – July 23, 2017 in Utah showed that the Purdue phase termination (18000 queries),
23 split monitor (8000 queries), and Purdue Coordination Diagram (PCD; ~ 6000 queries) are the
24 most used metrics. Conversations with engineers at the Utah DOT and Georgia DOT
25 corroborated this report. Turning movement counts and approach volumes are additional metrics
26 that are used frequently by planners for simulation and modeling purposes.

27 According to agency personnel at the Utah DOT, the Purdue phase termination metric is
28 used from an operations standpoint to address complaints. The split monitor is used for
29 troubleshooting, retiming, and general operations, whereas the PCD is used for assessing if cycle
30 lengths are optimal as well as the need for general retiming. Currently, with the open source
31 software pioneered by Utah DOT, presentation of the PCD is not optimized. However, planned
32 improvements in the near future involve linking the PCD with the link-pivot diagram to study
33 progression quality and improve operations. The link-pivot algorithm was developed by
34 researchers at Purdue University to optimize offsets along signalized arterials (13). Additional
35 improvements involve the addition of transit signal priority (TSP) metrics to evaluate transit
36 delays and to study the transition status of the controller when TSP is implemented. According to
37 agency personnel, least useful measures currently are approach delay, arrivals on red, and
38 pedestrian delay. With respect to improvements, engineers expressed interest in improving ways
39 to measure delays, which could then be used in decision making. They also wanted the ability to
40 examine the operational performance at the corridor and network levels, when currently they can
41 only do so at the intersection level.

42 **METHODOLOGY**

43 The objective of this study was to improve the current state-of-the-art ATSPMs by providing
44 enhancements in diagnosing sensor errors and assessing demands. The paper also emphasizes the
45 need to associate each graphic with a given spatial and temporal resolution as described below:

- 1 1. Stream analytic measures – These performance measures are used to quickly detect any
2 anomalous behavior at any intersection during the course of a day.
- 3 2. Batch analytic measures – This historical chart serves to provide trends over time, and
4 individual day's information can be retrieved for anomaly detection.
- 5 3. Spatial resolution – Spatial resolution can be either at the phase/approach level for a
6 given intersection or at a network level, depending on the desired objective. The decision
7 makers might want to use ITSPMs to compare different corridors or to focus on a given
8 intersection.

9 The graphic used for each resolution should be carefully planned to avoid any visual
10 overload of information and to provide the users with the ability to identify the information that
11 needs to be conveyed. In this paper, an attempt is made to use appropriate graphics to convey
12 information suitable to a given resolution. The designed graphics and alerts in ITSPM are tied to
13 decision support queries, as shown in Table 1. A comparison of how these decision support
14 queries are answered by Utah ATSPM 4.0.1 is also shown in the table (14). Decision support for
15 traffic signals can be divided into four broad categories, namely: (a) data quality, (b) demand
16 assessment, (c) traffic control, and (d) level of service. The focus of this paper is on major
17 improvement in assessing the first three categories.

18 **DATA USED**

19 The data used for this study were obtained from the City of Portland, which recently started the
20 implementation of ATSPMs at five intersections. For the visualizations in this paper, data were
21 obtained from two specific intersections: NE Sandy Blvd. @ 57th Ave. and SE Division St. @
22 122nd Ave. Data were available for February, May, and June of 2017. In this paper, the results
23 are demonstrated based on data from different time frames. The Sensor and Communication
24 Health section and the Control Support section used data from June 18 to June 24 (one week of
25 data), whereas the Demand Assessment section used data from May 1 to June 24 for a better
26 demand pattern extraction. The database contains the high resolution logs from each
27 intersection's controller. The high resolution logs record events, such as phase changes, detector
28 calls, power failures, etc. at a 10th of a second resolution.

29 **RESULTS**

30 The enhancements proposed in this paper are divided into three sections: Sensor and
31 Communication Health, Demand Assessment, and Control Support. In the Sensor and
32 Communication Health section, data logging and sensor errors are discussed. Next, demand is
33 analyzed to find the typical patterns that can be used to identify variation in demand and need for
34 coordination. In the last section, enhancement of the PCD for adaptation to a multi-day display is
35 discussed. The improved version is called the Aggregate Platoon Coordination Diagram
36 (APCD). It should be noted that existing ATSPMs are very strong in the visualizing control and
37 level-of-service parameters, and the measures proposed here are not intended to substitute all the
38 graphics in the ATSPM system but, rather, to further augment the existing set of tools.

1 **Table 1: Traffic signal decision support queries that could be better addressed by ITSPM**

Operator Queries	Utah Automated Traffic Signal Performance Monitoring (ATSPM 4.0.1)	Proposed Intelligent Traffic Signal Performance Monitoring (ITSPM)
<i>Sensor and Communication Health</i>		
<i>Are there any failures in logging?</i>	Utah DOT uses email alerts (not a generated report) for the following items: 1. No data 2. Too many ped calls 3. Too many max outs 4. Too many force-offs 5. Low detector count 6. High detector count Georgia DOT is working on an extension that will allow users to query the database to see how long these errors have been occurring	New performance measure proposed (shown in Figure 1 and Figure 2)
<i>Are there any sensor failures?</i>	Utah DOT uses the Purdue phase termination plot to determine if sensor failures exist. The phase termination plot is used to identify data gaps, too many max-outs (which can occur due to constant calls), too many force-offs and too many ped calls (which can occur due to constant calls due to a malfunctioning detector).	New performance measure proposed (shown in Figure 3)
<i>Demand Assessment</i>		
<i>What days have similar demand patterns?</i>	Manually observed from approach volume graphic that has plot for each day with the x axis as time of day and the y axis as volume in vph	Machine learning (ML)-based algorithms designed (described in Figure 4 and Figure 5)
<i>How many days were abnormal in a specified historical range?</i>	Not available	
<i>What was the potential cause of an anomaly?</i>	Not available	
<i>Is today a typical day?</i>	Manually observed by comparing today's approach volume graphic with the historical volumes	
<i>What are the temporal variations for timing plan settings</i>	Not available	Not addressed in this paper
<i>Is the demand randomly distributed or is there a need for coordination</i>	Not available	New performance measure proposed based on ML-based algorithm (described in Figure 6)
<i>Control Support</i>		
<i>Are the coordination parameters ideal?</i>	Can be manually identified by visually exploring the Purdue Coordination Diagram	Aggregate Platoon Coordination Diagram (APCD) proposed (Figure 7)

1 **Sensor and Communication Health**

2 Data quality is important to assure that decisions are being made using accurate information.
3 ITSPMs are intended to monitor two sources of problem: (a) problems occurring due to incorrect
4 logging of the data and (b) sensor errors involving false and stuck calls. It should be noted that
5 issues of missed calls are not observable using high-resolution logs unless a redundant sensor is
6 present to validate the missed calls.

7 *Logging Failures*

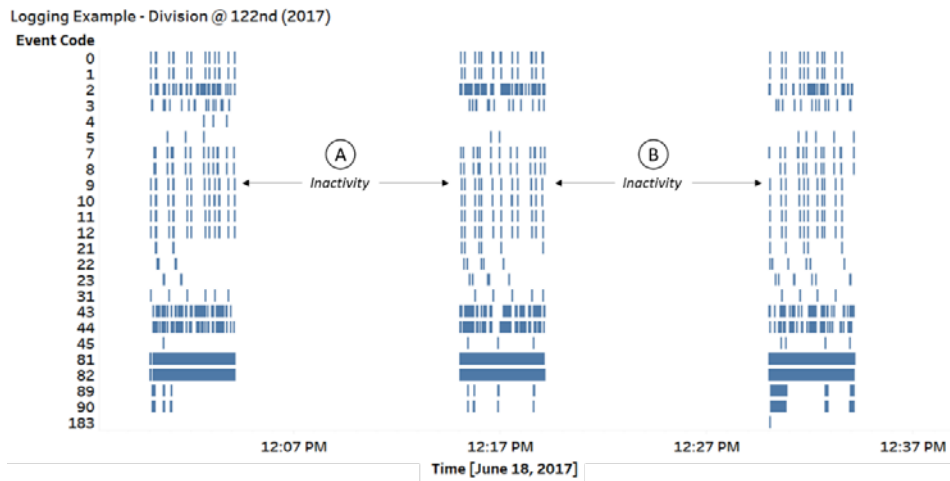
8 In high resolution logging, it is recommended that a logging flag that triggers a log entry at a
9 known interval (every 10–15 sec) be added. This will ensure that any logging failures can be
10 directly measured by counting the number of missing logging flags. In the absence of such a
11 feature, ITSPMs propose to use surrogate measures to monitor logging failures.

12 **a. Spurious Inactivity Period** – This is defined as a period during which the controller
13 records no entries for any of the event codes. A tick mark appears for each time one of the event
14 codes is logged during a 30-minute period, as illustrated in Figure 1a. The periods of inactivity,
15 annotated by “A” and “B,” could be due to an absence of any activity at the intersection or some
16 spurious behavior of the logging program. To use a data-driven technique to find a threshold that
17 separates spurious inactivity from normal inactivity, we explored logging gap distributions,
18 which show the duration of time interval between two events observed over a week on the x axis
19 and the number of times they were observed on the y axis, as displayed in Figure 1b. It can be
20 seen that for the distributions observed at both Sandy @ 57th and Division @ 122nd, most of the
21 entries are shorter than 300 seconds and then there is a sudden burst of activity after a long gap,
22 at around 450 seconds (annotated by “C”) and near 660 seconds (annotated by “D”). For this
23 work, we used 300 sec as the threshold for detecting spurious vs. normal inactivity.

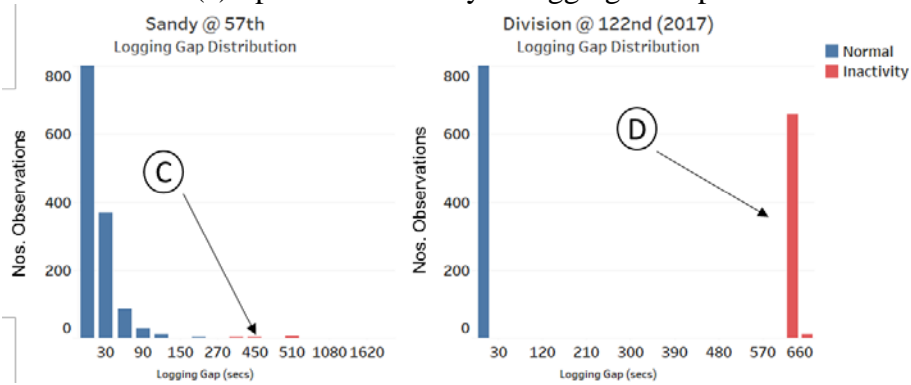
24 For the study intersections, a spurious inactivity period was defined as any period of time
25 greater than 300 seconds during which no event was recorded in the database. The average
26 spurious inactivity period versus time-of-day plot is presented in Figure 1c. The y axis represents
27 the percentage of time during an hour when there was missing data, classified to be spurious
28 activity, and the x axis represents the hour of the day. It can be observed that the performance of
29 Division @ 122nd was poor over the entire day with approximately 70% of the data not being
30 recorded in any given hour. If a dataset with 70% missing values were to be used for
31 performance evaluation, the results would be misguided. The volume distribution reported for a
32 Friday (6-23-2017) by the Portland ATSPM and the volume observed for a Friday (10-23-2015)
33 using another data collection program (15) are presented in Figure 1d. The stark contrast
34 between 2015 and 2017 volumes highlight the importance of using data quality checks prior to
35 making decisions using automated performance measures.

36 **b. Missing Event Error** – A second form of logging error can occur if only a single
37 event code is spuriously missed for some period of time. In general, the phase status of “green-
38 start” should be followed by “green-end,” and these events should repeat in pairs. After
39 removing the spurious logging failures, if there are still instances when such pairings are
40 violated, a missing event status error will then be recorded. A missing event status can be
41 recorded for phases or detector calls or for any event that is bound to have occurrences in pairs.
42 Tick marks for each time green and a detector turned on and off is shown in Figure 2a. An
43 example with phase 2 of Sandy @ 57th, for which the green indication started twice

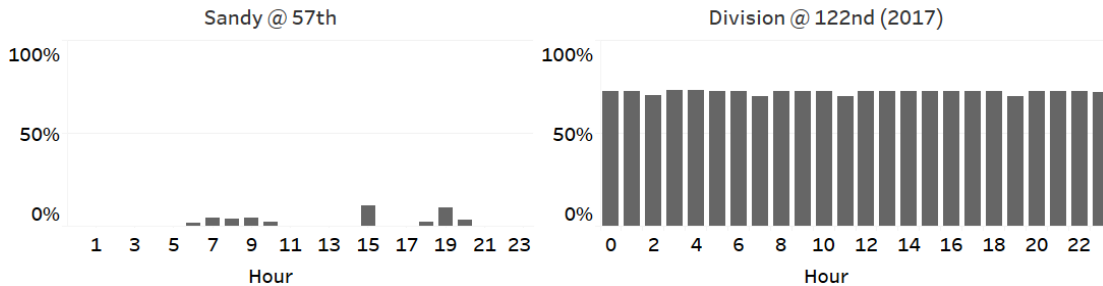
1



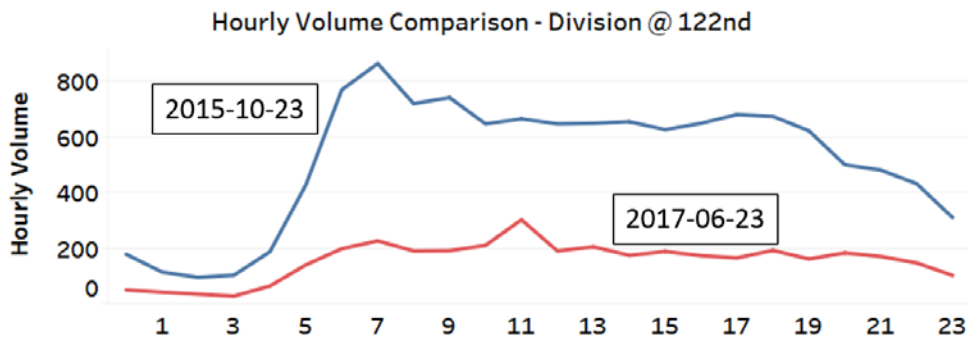
(a) Spurious Inactivity in logging example



(b) Logging gap distribution

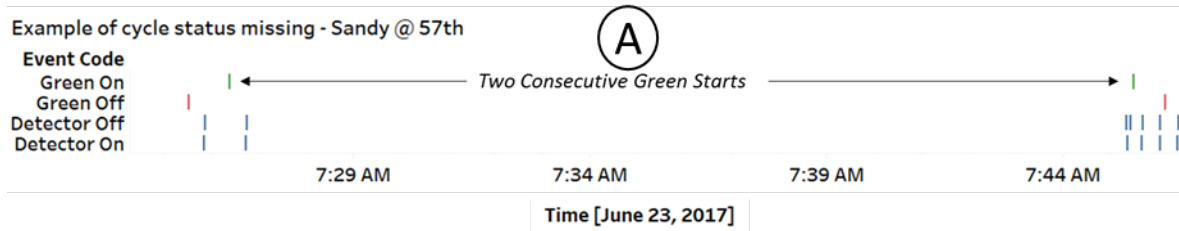


(c) Summary of spurious inactivity for Sandy @ 57 and Division @ 122nd

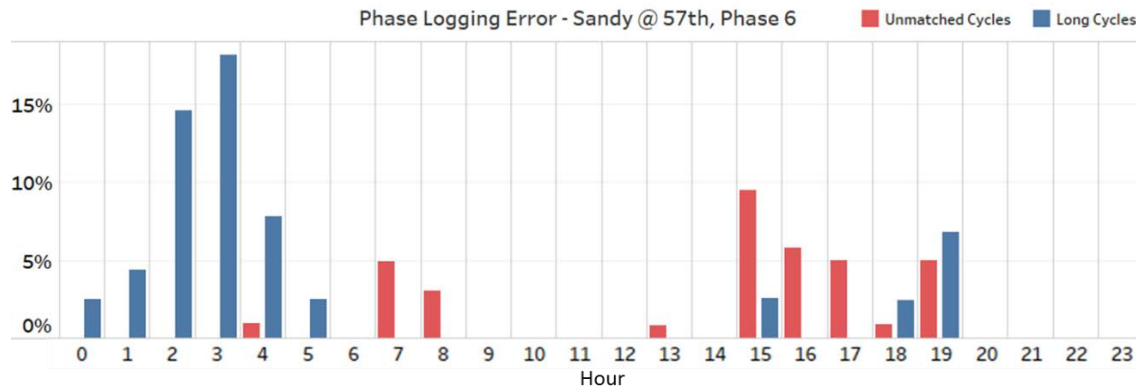


(d) Impact on volume distribution (Friday 6-23-2017) vs. Friday (10-23-2015)

Figure 1: Spurious inactivity assessment



(a) Missing phase status example



(b) Summary of missing phase 6 status for Sandy @ 57

Figure 2: Missing event assessment

1
 2
 3 consecutively with no green termination was recorded in between, is annotated with “A.” In
 4 Figure 2b, this data is shown aggregated into a histogram of missing phase 6 status over time of
 5 day. Also displayed are the long cycles (greater than 5 minutes) observed for phase 6.

6 The red bars indicate the percentage of time that phase logging was unmatched, and the
 7 blue bars indicate the percentage of time that the cycle length was greater than 5 minutes in
 8 through movements. The long cycles are shown because it is possible that the whole phase pair
 9 could be missed because of this logging error. Plotting of very long cycles along with unmatched
 10 pairs over time of day can give an indication of how often this might be occurring. Typically,
 11 very long cycles are acceptable during night times, but a red flag should be raised if a lot of them
 12 are observed during the daytime for movement on a main street. This type of aggregation could
 13 also be compiled for detector statuses, as there is an expectation of a certain level of volume by
 14 time of day.

15 *Sensor Errors*

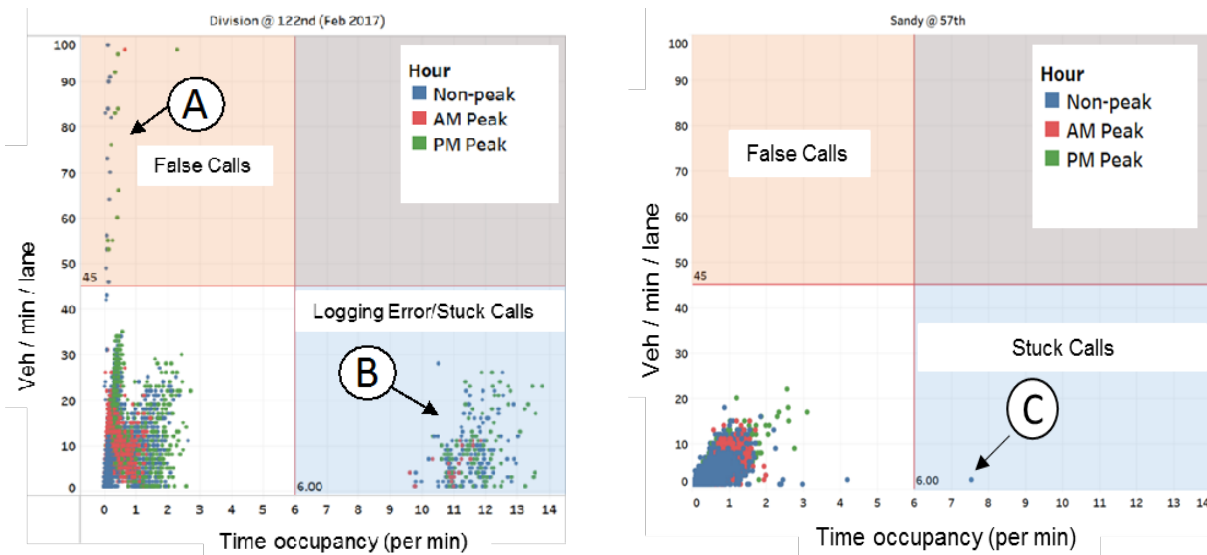
16 Stuck call errors can be calculated using Equation 1 with the threshold set as a user-defined
 17 parameter. Six minutes implies that a detector was occupied for two or more consecutive cycles
 18 (with 180 seconds chosen as a conservatively high cycle length for most jurisdictions), which is
 19 highly improbable, especially during non-peak hours.

20
 21
$$Stuck\ Call = \begin{cases} 1, & \sum_{1min} Occupied\ Time > 6\ min \\ 0, & otherwise \end{cases} \quad \text{Equation 1}$$

22

1 A false call error refers to the count that one detector per lane during 1 minute should not
 2 exceed, which would be the saturation flow rate. Although the exact saturation flow rate of that
 3 approach is not known, a threshold determined from experience can be used. Here we used 45
 4 counts per minute (2700 vphpln) as a threshold, and any records exceeding that were coded as
 5 false call errors.

6 To identify sensor errors, a scatter plot of the vehicle count per lane per minute is plotted
 7 against time occupancy in 1-minute bins. A detector example with 1 month of data is shown in
 8 Figure 3a. The two shaded regions represent different potential sources of errors: false call errors
 9 (annotated by “A”) and stuck call errors (annotated by “B”). If the logging error is not removed
 10 from the data, the number of stuck call errors will drastically change the data distribution, as in
 11 the case of Figure 3a. A case of a sensor performing reasonably well is shown in Figure 3b. Only
 12 one stuck call, annotated by “C,” is observed in a period spanning one week. It should be noted
 13 that sensor health statistics should be calculated after eliminating the time periods with
 14 significantly high logging errors.
 15



(a) Detector count vs. total occupied time in 1-min aggregations (diagnostic figure)

(b) Detector errors after removing spurious inactivity errors

Figure 3: Sensor quality performance

16 **Demand Assessment**

17 *Traffic Pattern Estimation*

18 Identifying traffic patterns is critical in designing optimal traffic signal control strategies. Some
 19 of the questions that need to be answered by a traffic signal manager include:

- 20 a. What does a typical day look like? This is needed to ascertain the base set of timing
 21 plans that are designed to meet these conditions
- 22 b. On which days of the week do similar traffic patterns exist? This helps in assigning a
 23 given time-of-day plan to certain days of week. The traffic manager can use ATSPMs to
 24 look at the volume distribution of different days of the week and make an engineering
 25 judgment.

- 1 c. How many days deviate from the traffic pattern of a typical day? An intersection with a
2 significant number of non-typical days and greater deviation among a typical day may
3 show a greater need for an adaptive control or other unique timing solutions.
- 4 d. Are there any intersections today exhibiting an atypical demand? This might help the
5 traffic managers detect an issue and respond to it in a timely fashion.

6 Here, an intelligent method of detecting demand patterns to answer the four above
7 questions is presented. As shown in Figure 4, the process uses cumulative demand (the sum of
8 advance detector volume on all the approaches) to determine the days of the week that have
9 similar demand patterns, separates out anomalous demand patterns days, and then aggregates the
10 days of the week having similar demand patterns into groups. This process involves four steps.

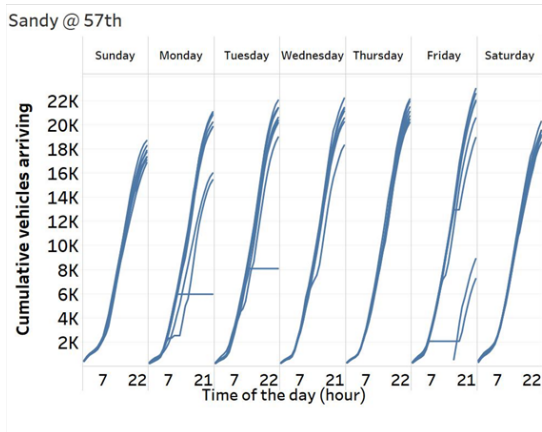
- 11 • **Step A** involves creating cumulative arrival plots for the total approach volume at the
12 intersection.
- 13 • **Step B** entails identifying days with missing data, determined by instances for which the
14 cumulative volume shows no change over any 1-hour period. One such example is shown
15 by annotation “A” in Figure 4. The horizontal bar indicates this missing data, with the
16 volume remaining fixed at 6,000 after 7 AM in the morning. After such missing data days
17 are identified, they are removed from further analysis. These horizontal lines can also be
18 used to identify detector issues.
- 19 • In **Step C**, after removing the missing data days, typical and atypical days for each day of
20 the week are found. This is done by computing a representative base curve for that day
21 and then computing the deviation of the other curves from the base curve. The base curve
22 is obtained by averaging the demand data points for every hour of the day. These
23 deviation values (means and standard deviations) are clustered by a mean-shift clustering
24 algorithm, and the largest group is identified to be the typical pattern for that day of the
25 week. The mean-shift algorithm works on the following principle:
 - 26 ○ First, assume each feature point is a cluster center.
 - 27 ○ Then, take all the points within the bandwidth or radius of the feature center and
28 recalculate the mean of these feature points as the new center.
 - 29 ○ Repeat this for all the points until convergence is achieved; that is, the center
30 points remain unchanged. Further details about mean-shift clustering algorithms
31 can be found elsewhere (16–19).

32 The curve marked by annotation “B” in Figure 4 was selected by the algorithm as an
33 atypical day. It can be seen that the daily arrivals on that day were much lower than for
34 the rest of the cluster.

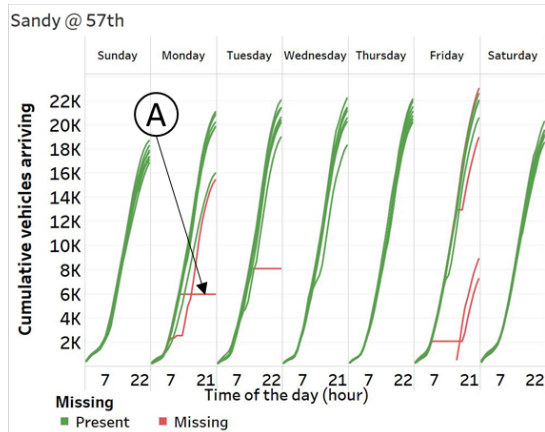
- 35 • After removing the anomalous days obtained in Step C, **Step D** is to group the days of the
36 week with similar demand patterns into one cluster. First, the base day for each day of the
37 week is determined. For example, curves for all the Sundays are combined to form one
38 curve for a Sunday and so on. This grouping is similar to that of Step C. After this, the
39 representative curves are clustered to obtain the groups of similar days. For example, as
40 shown by annotation “C” in Figure 4, weekdays show as one cluster and weekends make
41 up another.

42
43

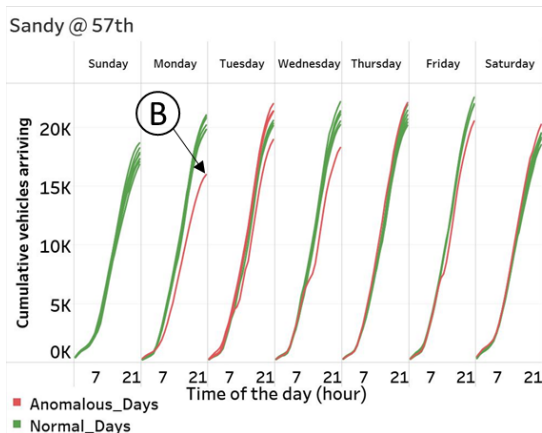
Step A: Create cumulative arrival plots grouped by day of week



Step B: Remove days with missing data



Step C: Use mean shift algorithm to determine typical and atypical days for a given day of week



Step D: Within a week, find days are similar

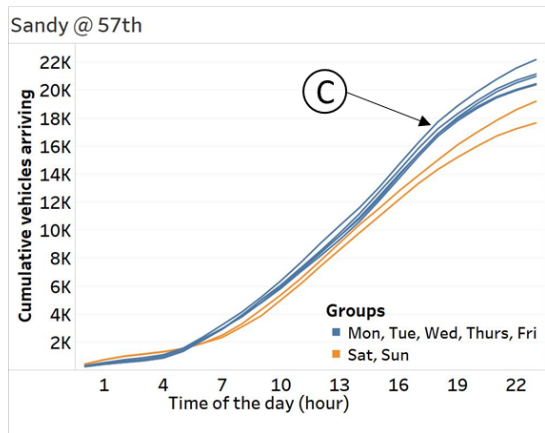
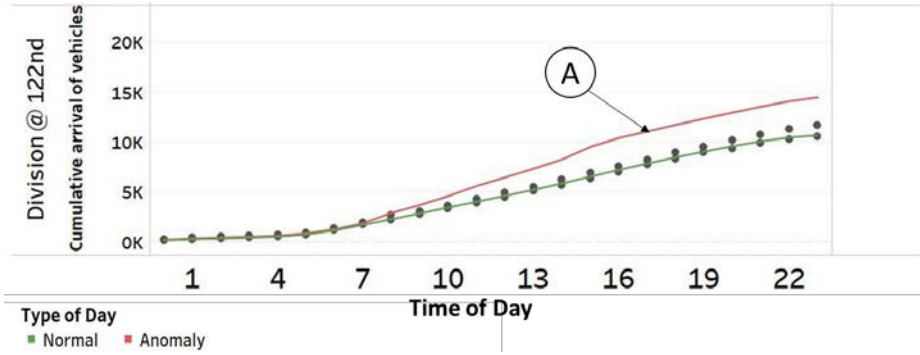


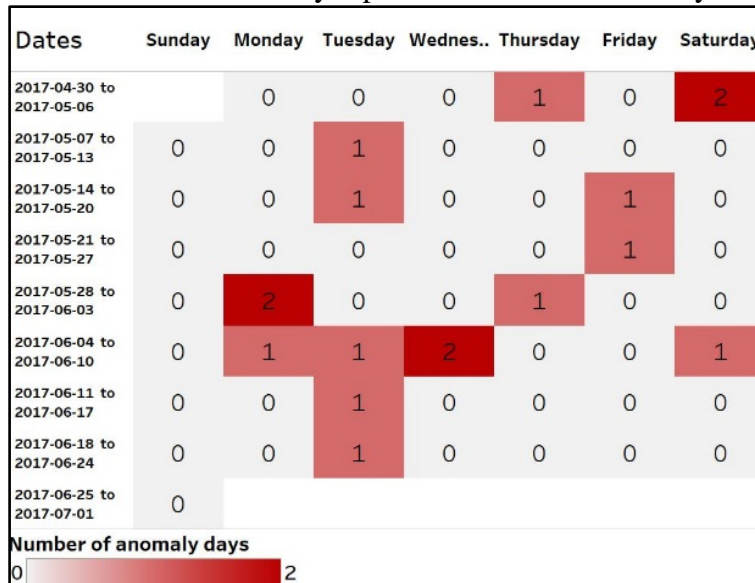
Figure 4: Demand trend analysis

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It is important to identify anomalous data in real time as well as to present an overview at the network level. After estimating the group of typical days, a 90% confidence bound is generated, and a curve departing from the confidence bound can trigger alarms in real time. An example of such a day is shown in Figure 5a, as annotated by the “A.” In addition to identifying an anomalous day in real time, other such days can also be identified at a network level over a period of time, as shown in Figure 5b, with the shading of each cell indicating the level of anomalous days.



a. Real-time or daily representation of an anomaly



b. Weekly number of anomalies seen on the network

Figure 5: Anomalous day overview

1 *Need for Coordination*

2 Whether or not to provide signal coordination for a given time-period is a challenging question
 3 for traffic operators to answer. This section provides a data-driven methodology to address the
 4 following problems:

- 5 a. Are there bunches/platoons arriving at an intersection? This provides evidence that the
 6 arrivals are not completely random and that the upstream intersection is impacting the
 7 arrival pattern at the subject intersection. This in turn points toward exploring the impact
 8 of providing coordination.
- 9 b. What is the time period for which coordination should be explored? The proximity of an
 10 upstream intersection shows only the possibility of creating tightly packed platoons. For
 11 coordination to be beneficial, there needs to be enough platoons for enough cycles. The
 12 percentage of cycles showing platoons during a given time period and the average
 13 platoon length can be good measures for answering the question of the appropriate time
 14 period to be explored.

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1 Steps used to identify the presence of platoons and calculate surrogate measures to
2 identify a good time period to explore coordination options are presented in Figure 6.

- 3 • In **Step A**, the arrivals that will be classified as a platoon of vehicles are identified. To
4 cluster those arrivals, a machine learning technique was applied. Density-based Spatial
5 Clustering of Applications with Noise (DBSCAN), a data-clustering algorithm (20), was
6 used to identify the group of vehicles in a single cycle. To categorize vehicles into
7 platoons, the following rule was used: A platoon should contain a minimum of 5 vehicles
8 and not be separated by average headway greater than 1.6 seconds. It results in a
9 parameter setting of 5 as minimum samples and 4 seconds as epsilon in DBSCAN
10 algorithm. These parameters were user-defined and can be chosen as deemed appropriate
11 by the operator. In Figure 6, an example using data from Sandy @ 57th St. and Division
12 @ 122nd St. for a given day is shown in Step A. The black dots are random arrivals that
13 are not clustered into any potential platoons, and the red dots show vehicles classified as
14 platoons.
- 15 • In **Step B**, the percentage of cycles in a given hour that have platoons is identified. An
16 example distribution of percentage of cycles containing platoons is shown in Step B of
17 Figure 6. The blue line indicates the median cycle percentages by time of day; the gray
18 shading implies the range from the 25th and 75th percentiles of the data by time of day.
- 19 • In **Step C**, the distribution of average platoon lengths by number of vehicles is calculated.
20 The average platoon length distributed by time of day is shown in Figure 6, Step C. The
21 blue line and gray shading represent the median and the range from the 25th to the 75th
22 percentile of each distribution, respectively.
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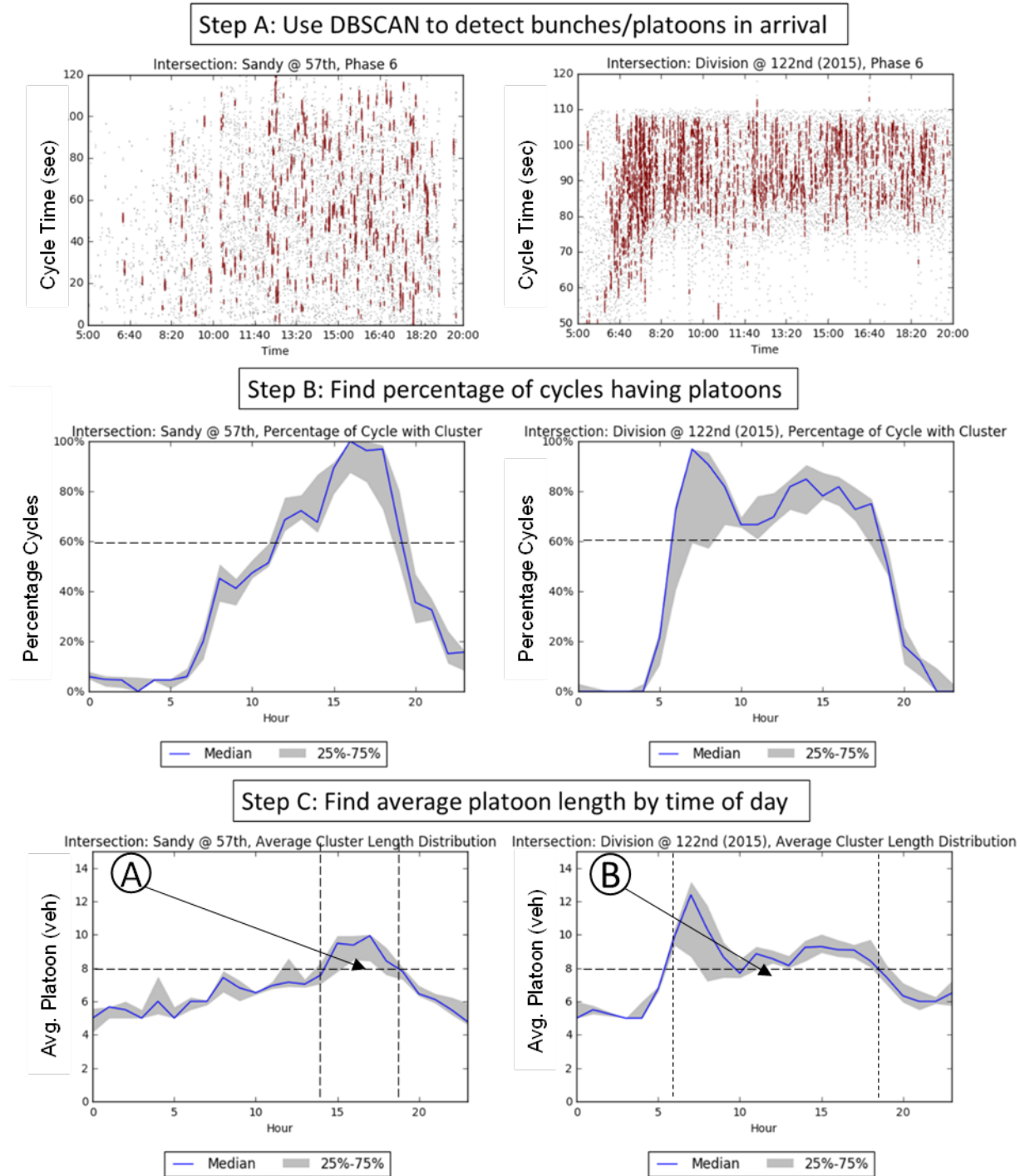


Figure 6: Procedures for determining the need of coordination

The percentage of cycles with a platoon and average platoon length by time of day are needed to identify the time period for which the impact of providing coordination should be explored. A predefined threshold can be used to identify the time periods to explore. As an example, if a threshold of 60% was chosen for percentage of cycles exhibiting platoons with platoon length greater than 8 vehicles then, as annotated by “A” and “B” in Figure 6, the PM peak for Sandy @ 57th might be explored for impacts of coordination.

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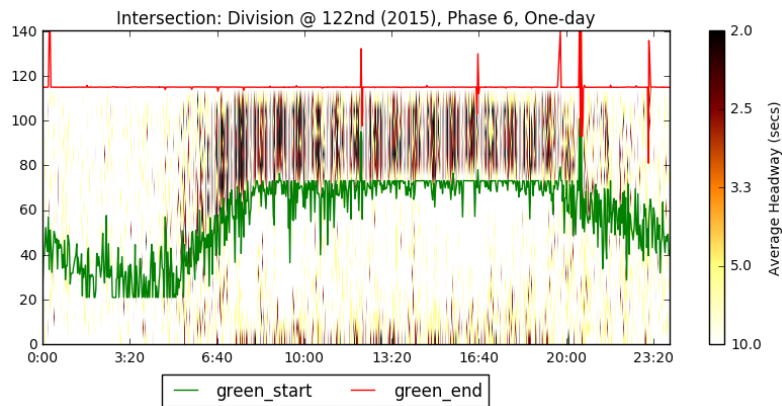
1 **Control Support**

2 *Aggregate Platoon Coordination Diagram (APCD)*

3 The PCD is currently used by a number of agencies to identify if most arrivals occur during the
 4 green band, among other items. It is an effective tool to identify if there are any occurrences of
 5 platoon incursions happening during the start or end of green times. Despite being a very useful
 6 tool at a single-day resolution level, the PCD in its current form is not extendable to longer time
 7 durations. When given a month as a time range, UTAH ATSPM 4.01 generates one PCD per
 8 intersection per day. Here, a new tool named Aggregate Platoon Coordination Diagram (APCD)
 9 is proposed. Please note that the term “Platoon” instead of “Purdue” is used to avoid any claims
 10 that this measure has been supported or recommended by Purdue University personnel.

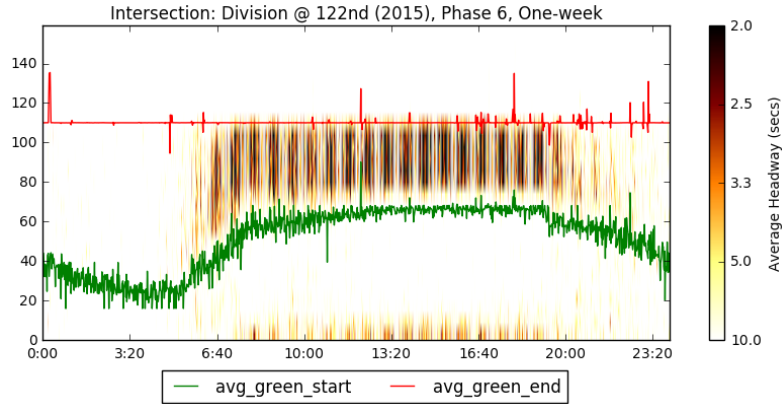
11 Vehicle distributions using one day and one week of data, respectively, are shown in
 12 Figure 7a and 7b. In Figure 7b, the green and red lines show average red time and average cycle
 13 time, respectively. The color map indicates the density of arrivals, which is the average number
 14 vehicle arrivals for each 5-sec period per cycle. The darker color indicates higher density and,
 15 thus, shorter headways. The color threshold was chosen to populate only densities that can be
 16 considered as platoons.

17 How to use the APCD to find the potential platoon bandwidth is demonstrated in Figure
 18 7c, annotated by “A.” For each time slot (along the y axis), if over 10% of vehicles arrive within
 19 a 2-second headway, this slot would be considered as part of the platoon band. Taking the lowest
 20 and highest values from all the time slots, which are the band boundaries, the platoon bandwidth
 21 can be determined. Here, the intersection of Division @ 122nd St. (2015) shows a 29.5 second
 22 platoon bandwidth.
 23

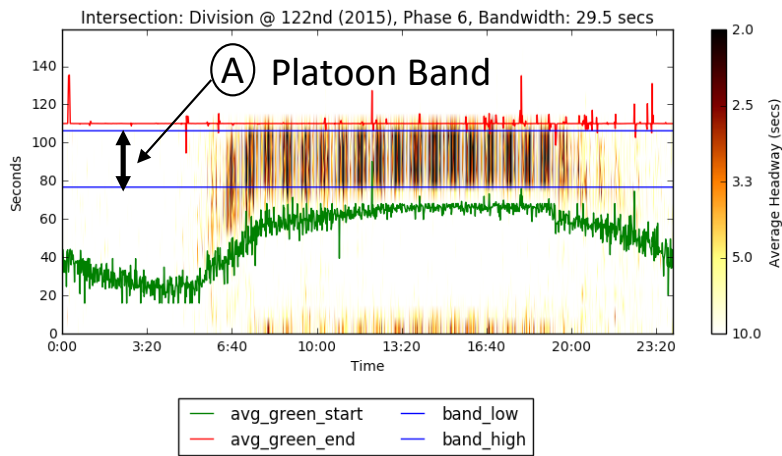


(a) Single day PCD example

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(b) APCD over one week



(c) APCD with bandwidth detected

Figure 7: Proposed APCD features.

This example of an APCD is presented with an average of one week of data. It should be noted that the APCD can aggregate similar days, as identified in the Demand Trend Analysis section.

CONCLUSION

The ITSPM presented in this paper builds on the concepts of machine learning, traffic flow theory, and data visualization to minimize the human time needed for data-driven traffic signal management systems. From talking with practitioners intimately familiar with ATSPMs, the existing state-of-the-art systems were reported to have three primary limitations: (a) limited data quality control, b) intensive resource requirements, and (c) falling short in addressing the multi-modal aspect of the operations. This paper addressed the first two of these shortcomings.

In this paper, a methodology to identify and remove data-logging errors as well as to identify bad sensors was presented. Eliminating these errors improves the quality of data, which leads to more precise decision making and also results in more efficient human asset management. After providing the methodology for data quality control, machine learning principles, which include intelligence in demand trend identification, were used. The use of machine intelligence will reduce the time taken by human operators, who would otherwise have to detect the same patterns manually, and will allow them to allocate their time more efficiently making decisions rather than identifying patterns. In addition, ITSPM also includes an intelligent

1 method for identifying whether or not coordination may be needed at an intersection. This can be
2 achieved using two surrogate measures defined in this paper, namely, percentage of cycles
3 exhibiting platoons per hour and average platoon sizes. Finally, in this paper the Aggregate
4 Platoon Coordination Diagram (APCD), which is an advancement over the current PCD, was
5 proposed. The APCD can be used to minimize visual clutter by removing any vehicle that is not
6 in a platoon and can be scaled to include multiple days of data, thus eliminating the need for the
7 traffic signal managers to browse through multiple individual PCDs when looking to improve
8 coordination.

9 Future work could emphasize on two aspects. In regards to sensor and communication
10 health, besides the proposed methods in this paper, future research direction would be integrating
11 more data sources like crash and weather data to conduct a causation analysis. In addition,
12 shortcomings in the ATSPM outputs in addressing the multi-modal aspect of traffic signal
13 operations were identified, and the authors recommend that efforts be focused on designing these
14 performance measures in future research. The availability of multi-modal information through
15 high resolution logs is also limited. At a minimum, there is a need to integrate more multi-modal
16 sensors on the roadways to provide approach volumes and delays for all modes. New surrogate
17 measures can be calculated to investigate if phase allocations are equitable.

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