# Using AlgoTraffic Data to Improve Traffic Incident Management 

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## Project Background

Traffic crashes are key contributors to non-recurrent congestion. The Federal Highway Administration estimated that Traffic Incident Management (TIM) efforts in the USA are credited with reducing annual delay by 129.9 million hours with an associated cost savings of $\$ 2.5$ billion (U.S. Department of Transportation. Federal Highway Administration, Dec 2008). Traffic incidents are frequent and lifethreatening to motorists and responders, particularly secondary crashes. A secondary crash is one which occurs at the tail end of a queue caused by an initial event, such as a crash or construction. Despite the fact that traffic crashes are heavy contributors to non-recurrent congestion, the interface between crashes, incidents, and congestion has not been fully explored in context with new data sources.

Over the past few years, ALDOT has taken a transportation systems management and operations (TSMO) approach to manage intelligent transportation system (ITS) assets and monitor congestion across their road network. Regional Traffic Management Centers (RTMCs) have been established in four of the five regions to monitor data and information from a newly developed ALGO Traffic web interface. The ALGO Traffic platform provides real-time feeds for cameras, speed sensors, and other pieces of infrastructure. This platform and data are used by RTMC operators to monitor and log crashes and other various types of incidents (disabled vehicles, construction, queues, etc.). The University of Alabama (UA) through the Center for Advanced Public Safety (CAPS) has recently begun working on phase-II of the ALGO Traffic Platform, which will continue to add functionality for TMC operators.


Figure 1 First Regional Traffic Management Center in West Central Region

Also, in an effort to monitor congestion, ALDOT currently purchases state-wide crowdsourced mobility data from HERE. These data are included in the ALGO Traffic Platform for real-time speed observation, and in Iteris iPeMS / ClearGuide. The data are also continuously collected and stored and can be used to generate performance metrics that provide a stronger quantitative assessment of mobility. These metrics will enable Alabama to meet compliance with a recent FHWA ruling that supports the Fixing America's Surface Transportation (FAST) Act by measuring and assessing system performance (Federal Highway Administration, 2017).


Figure 2 Iteris iPeMS dashboard showing example historical speed information

To further leverage the benefits of both the ALGO Traffic incident data and the state-wide HERE data, these datasets have been synthesized together to understand factors affecting safety and congestion. Each incident has been collected and documented in the ALGO Traffic platform for quantification based on its impact to traffic flow using the crowdsourced mobility data. By looking at the incident type, location, response, and other variables, improvements to traffic safety and congestion can be considered.

## Organization of this Report

Following the above background and introduction, the tasks of the project are reviewed in the next section. There are two main groups of tasks: (1) incident analysis and (2) dashboards for presenting the speed data. The second task group was conducted first to setup the data storage and retrieval processes. The data component for this project is very key and described after the tasks recap. After the data sources section, the dashboards are described, and a case study is shown for each. Finally, the incident analysis task group is discussed. The table of contents is a useful guide to follow each component.

## Tasks for the Incident Analysis

1. Gather Incident Data - Incident data was gathered from the Center for Advanced Public Safety's (CAPS) Critical Analysis Reporting Environment (CARE). Also, other non-crash information that is stored by the Alabama Traffic Management Centers was collected. This was synthesized using modeling techniques.
2. Generate Per-Incident Reports - Each crash and incident has been quantified based on the mobility impact. Every incident is available here (https://sdmh.aladata.com/) and will be discussed in this report.
3. Summarize Per-Incident Reports - Again, all crashes and incidents have been quantified, and the results have been used to identify and summarize significant factors.
4. Modeling of Mobility Impact from Incidents - The crash and incident data were analyzed using duration models to determine key factors based on the attributes listed in each report. This allowed multiple factors to be considered simultaneously, providing additional insight beyond single-factor analysis.
5. Interpretation and Write-Up of Model Findings - The significant parameters are discussed at the end of this report (and fully discussed in attached white paper).

## Tasks for the Traffic Ticker and Delta Speed Map Dashboards

6. Collecting TMC-level Shapefiles - Shapefiles for TMC segments were obtained and sanitized to include only mainline interstate segments. These were joined with other data to classify what ALDOT region and county each segment lies in.
7. Downloading Existing Speed Data - The HERE bulk download interface was be used to download CSV files of historical speed data for the interstates. These data have been stored in a database that can be queried to provide the basis of the dashboards.
8. Livestream of Speed Data - An automated service was developed to automatically download and import speed data into the database as it becomes available.
9. Preliminary Dashboard Integration with ALGO Traffic and ALGO Reports - An interface based on the Traffic Ticker will be designed for Alabama and integrated into existing tools for ease of access (https://reports.algotraffic.com/dashboard). Information from ALGO Reports has been integrated with the Traffic Ticker view to streamline identification of the sources of congestion.
10. Implement Live-Data Dashboard - The Traffic Ticker dashboard uses the data accessed by the livestream automated service, allowing it to display the most up-to-date information available to ALDOT (https://reports.algotraffic.com/here-charts).
11. Prototype Incident Report Generation Tool - The integration of traffic and incident data now creates automated incident reports that can summarize delay, queuing, and other traffic factors for after-action review (https://sdmh.aladata.com/).

## Data Sources

The main sources of data for this project were speed data obtained from HERE and volume data obtained through Highway Performance Monitoring System (HPMS). This data was combined with crash data and TMC incident data for specific analyses.

## HERE Speed Data

The speed data provided by HERE is reported every minute for stretches of road called Traffic Message Channels (TMCs), which can range in length from under a mile to several. These data are provided in a live XML feed (see Figure 3), which is downloaded and ingested into a database for use in reporting dashboards and other tools. These data are available from April 2018 onwards.

```
C:\Users\ahainen.UA-NET\AppData\Loca\\Temp\7zO42AFC418\RealtimeFlowA0101.xml (1)
(<)}\mathrm{ C:\Userslahainen.UA-NET\Ap... }\times\square
<?xml version="1.0" encoding="UTF-8" standalone="true"?>
<TRAFFICML_REALTIME UNITS="imperial" VERSION="3.2.2" CREATED_TIMESTAMP="2018-09-13T21:44:51Z" TMC_TABLE_VERSION="6.0" MAP_VERSION
    - <FEATURES>
        <FEATURE>LANES</FEATURE>
        <FEATURE>FORM_OF_WAY</FEATURE>
        <FEATURE>EXPRESS</FEATURE>
        <FEATURE>OPEN_LR</FEATURE>
        <FEATURE>DLR_AGGREGATION </FEATURE>
    </FEATURES>
    <RWS MAP_VERSION="201803" TABLE_ID="1" EXTENDED_COUNTRY_CODE="AO" EBU_COUNTRY_CODE="1" TY="TMC">
        <RW mid="dd104fe3-70a4-48d7-993e-db2b8793d749|" PBT="2018-09-13T21:44:06Z" DE="I-75/I-85" LI="101+00067">
            - <FIS>
                - <FI>
                    <TMC DE="I-85 Split/Exit 242" LE="0.11486" QD="-" PC="4115"/>
                    <CF TY="TR" TS="O" CN="0.99" JF="0.0" FF="55.30" SU="70.56" SP="55.30"/>
                </FI>
                <FI>
                    <TMC DE="GA-166/Lakewood Fwy/Exit 243" LE="0.66244" QD="-" PC="4116"/>
                    <CF TY="TR" TS="O" CN="0.99" JF="0.0" FF="54.68" SU="76.86" SP="55.30"/>
                </FI>
                <FI>
                    <TMC DE="University Ave/Exit 244" LE="1.56059" QD="-" PC="4117"/>
                    _ <CF TY="TR" TS="O" CN="0.99" JF="0.97850" FF="54.68" SU="51.03" SP="51.03">
                            - <SSS>
                    <SS LE="1.09972" TS="O" JF="0.0" FF="54.68" SU="66.49" SP="55.30"/>
                    <SS LE="0.46087" TS="O" JF="5.29652" FF="54.75" SU="32.83" SP="32.83"/>
                    </SSS>
                    </CF>
                </FI>
                <FI>
                    <TMC DE="Pryor St/Exit 245" LE="0.27719" QD="-" PC="4118"/>
                    <CF TY="TR" TS="O" CN="0.99" JF="8.37818" FF="54.68" SU="15.10" SP="15.10"/>
                </FI>
                    <TMC DE="Fulton St/Central Ave/Exit 246" LE="0.38015" QD="-" PC="4119"/>
                    <CF TY="TR" TS="O" CN="0.99" JF="8.68736" FF="55.05" SU="12.64" SP="12.64">
                    <CF TY="TR
                            <SS LE="0.22497" TS="O" JF="8.68736" FF="55.05" SU="12.64" SP="12.64">
                        <LN JF="7.80230" SU="19.42" NM="7"/>
                            <LN JF="8.85509" SU="11.24" NM="1,2,3,4,5,6"/>
                    </SS>
                    <SS LE="0.15517" TS="O" JF="8.68736" FF="55.05" SU="12.64" SP="12.64"/>
```

Figure 3 Sample XML feed of live HERE data

Archive data are available in the iPeMS bulk data download back to 2017. These data are available as a GZ files for each day. A stored procedure was created for ingesting and storing this data. The fields and example download interface are shown in Figure 4.


## Data Summary

This dataset is the here traffic ml samples.
Months with data are indicated by a gray rectangle. Click a rectangle to view a listing of files available for download.

Field Specification

| Name | Comment | $\wedge$ |
| :---: | :---: | :---: |
| utc_time_id | Time UTC |  |
| feed_id | Source data feed |  |
| Roadway Type | Road class |  |
| Linear Id |  |  |
| fis_num |  |  |
| source_id | The item being mapped (e.g. TMC Code) |  |
| recv_time |  |  |
| Total Length Km | Length of segment in km |  |
| Offset Km | Subsegment offset relative to the start of the segment |  |
| Subsegment Flag | Indicates whether this records belongs to the main segment (flag=0) or a subsegment (flag=1) |  |
| Subsegment Length Km | Length of sub-segment in km |  |
| Point Code |  |  |
| Queuing Direction |  |  |
| Flow Item Type |  |  |
| Current Avg Speed Capped | Average speed ( $\mathrm{km} / \mathrm{h}$ ) that traffic is traveling capped to the speed limit |  |
| Current Avg Speed | Average speed ( $\mathrm{km} / \mathrm{h}$ ) that traffic is traveling. |  |
| Freeflow Speed | 80th percentile of observed speeds during non-rush hour periods. |  |
| Jam Factor | a number between 0 and 10 | * |

## Available Files

| File_Name | Bytes |
| :--- | :--- |
| state_prov-AL_text_here_trafficml_raw_2020_01_01.txt.gz | $322,438,463$ |
| state_prov-AL_text_here_trafficml_raw_2020_01_02.txt.gz | $346,095,351$ |
| state_prov-AL_text_here_trafficml_raw_2020_01_03.txt.gz | $351,064,059$ |
| state_prov-AL_text_here_trafficml_raw_2020_01_04.txt.gz | $331,352,786$ |
| state_prov-AL_text_here_trafficml_raw_2020_01_05.txt.gz | $325,195,230$ |
| state_prov-AL_text_here_trafficml_raw_2020_01_06.txt.gz | $350,724,848$ |
| state_prov-AL_text_here_trafficml_raw_2020_01_07.txt.gz | $354,715,597$ |
| state_prov-AL_text_here_trafficml_raw_2020_01_08.txt.gz | $354,142,695$ |
| state_prov-AL_text_here_trafficml_raw_2020_01_09.txt.gz | $354,326,675$ |
| state_prov-AL_text_here_trafficml_raw_2020_01_10.txt.gz | $350,699,410$ |
| state_prov-AL_text_here_trafficml_raw_2020_01_11.txt.gz | $320,274,660$ |
| state_prov-AL_text_here_trafficml_raw_2020_01_12.txt.gz | $323,057,753$ |
| state_prov-AL_text_here_trafficml_raw_2020_01_13.txt.gz | $351,880,468$ |
| state_prov-AL_text_here_trafficml_raw_2020_01_14.txt.gz | $354,068,329$ |
| state_prov-AL_text_here_trafficml_raw_2020_01_15.txt.gz | $353,574,688$ |
| state_prov-AL_text_here_trafficml_raw_2020_01_16.txt.gz | $354,944,743$ |
| state_prov-AL_text_here_trafficml_raw_2020_01_17.txt.gz | $356,612,207$ |
| state_prov-AL_text_here_trafficml_raw_2020_01_18.txt.gz | $332,015,511$ |
| state_prov-AL_text_here_trafficml_raw_2020_01_19.txt.gz | $322,412,683$ |
| state_prov-AL_text_here_trafficml_raw_2020_01_20.txt.gz | $342,488,915$ |
| state_prov-AL_text_here_trafficml_raw_2020_01_21.txt.gz | $364,297,278$ |
| state_prov-AL_text_here_trafficml_raw_2020_01_22.txt.gz | $358,143,824$ |

Figure 4 HERE Bulk Data Download

## Speed Subsegments

One very challenging aspect with the HERE data is the dynamic subsegment data. Historically, TMC segments have been the standard segment regime used for reporting aggregated speed information. Usually, TMCs span between nodes on road networks. In urban areas, the distance between nodes I usually reasonable ( 0.25 mile to 1 mile). In rural areas, these TMCs can span several miles. Trying to detect incidents over these longer distances is challenging and vague.

To improve on this segmentation scheme, two different systems have been used: fixed subsegments and dynamic subsegments. With fixed subsegments, short ( 0.1 mile to 0.5 mile) segments are created to split TMCs into smaller stretches. For Alabama, there are approximately 10,000 TMC segments for the freeways. With fixed subsegments, this could be over 100,000 subsegments. Reporting for each subsegment produces a tremendous amount of information each minute. This is especially unnecessary when none of the fixed subsegments are significantly different from the parent TMC. With dynamics subsegments, TMCs can be split on-the-fly to report only portions of a TMC that vary significantly. This cuts down on the amount of data generated for each interval, but issues arise when each minute features a different segmentation.

The ways that HERE spatially segments the data are shown in Figure 5. The main segment is the TMC, shown at the top. These are usually several miles long, often broken at interchanges with a short segment between the on and off ramp. The next level is the LinkID, which are very small segments, often only a few hundred feet, which are available in the shapefiles. The third is the dynamic subsegments. This is how sub-TMC speeds are represented in the data. They are only used when the speed on a subsegment is substantially different from the average of the whole TMC. They are assigned dynamically, and as the two examples show, can change minute to minute in both length and number.


Figure 5 HERE Data Segmentation

Subsegments are made up of one or more LinkIDs, though they are not referred to in that manner in the XML document. They are instead defined by their offset from the beginning of the TMC and recorded in order with the flow of traffic. Therefore, the data for the segments in Figure 5 may look like Table 1, with the direction of travel being left-to-right. In this constructed example, the importance of subsegments can be seen in comparing the speed column, which is a weighted average for the TMC, with the subsegment speeds.

Table 1 Subsegment Speed Example

| Timestamp | TMC | Speed | Sub. Length | Sub. Speed |
| :---: | :---: | :---: | :---: | :---: |
| $9: 00$ | $101+01559$ | 61.5 | 0.6 | 65 |
| $9: 00$ | $101+01559$ | 61.5 | 0.5 | 45 |
| $9: 00$ | $101+01560$ | 65 | 0.3 | 45 |
| $9: 00$ | $101+01560$ | 65 | 1.5 | 25 |
| $9: 00$ | $101+01560$ | 65 | 0.2 | 70 |
| $9: 00$ | $101+01561$ | 70 | NULL | NULL |
| $9: 01$ | $101+01559$ | 52 | 0.4 | 60 |
| $9: 01$ | $101+01559$ | 52 | 0.7 | 40 |
| $9: 01$ | $101+01560$ | 57 | 0.3 | 35 |
| $9: 01$ | $101+01560$ | 57 | 1.0 | 25 |
| $9: 01$ | $101+01560$ | 57 | 0.5 | 15 |
| $9: 01$ | $101+01560$ | 57 | 0.2 | 70 |
| $9: 01$ | $101+01561$ | 70 | NULL | NULL |

## Data Storage and Access

The data are stored in a SQL database with an ingestion process that adds new data as it becomes available. This allows for the dashboard tools and other users to query data in real-time. The HERE bulk data was stored in a Microsoft SQL Server database for easy retrieval. The database stores several billion records and has grown to several terabytes. A sample of the data is shown in Figure 6. In Figure 6, there are three rows highlighted showing the dynamic subsegmentation. The main TMC (row 5) has a measured average speed of 34.44997 mph (see the "speed" column of row 5). However, the average is a poor representation of the conditions on this 0.8235736 mile segment (note: the unreasonable number of significant digits is used for the reader to be able to connect this narrative with the data shown in Figure 6). The proprietary methods used by HERE split the TMC into two subsegments (row 6 and row 7). The first subsegment (row 6) is 0.5249348 miles long and has an average speed of 68.37166 mph . The following subsegment (row 7) is 0.3389435 miles long and has an average speed of 19.47172 mph . From this information, it would be reasonable to expect some anomaly at the 0.52 mile mark of this TMC. Additional information about this TMC (route, direction, etc.) would be available in another table to properly locate the specific location.


Figure 6 SQL retrieval of HERE bulk data (highlighted rows showing dynamic subsegmentation)

## HPMS Volume Data

The Highway Performance Monitoring System (HPMS) data was used to attribute volumes for segments and analysis. Mostly, the annual average daily traffic was used as an independent variable in models. Shapefiles were used in GIS for the conflation process.

## RTMC Incident Data

Another new dataset used in this project was the incident data logged by the RTMCs. For each incident that the RTMCs handle, detailed notes are included. These notes were combined with crash data and used for modeling and understanding impacts from the response. Approximately 7,000 incidents were included in the study. A sample dataset for three incidents is shown in Table 2.

Table 2 Sample RTMC incident data

| EVENTID | 48235 | 48312 | 48488 |
| :---: | :---: | :---: | :---: |
| EVENTTYPE | Accident | Accident | Accident |
| EVENTSUBTYPE | Crash | Crash | Crash |
| LASTSEVERITY | 1 | 1 | 2 |
| LASTLANEPATTERN | tzzzs | tzzs | tzzs |
| CREATEDBY | floydkb | adams | harrisg |
| LATITUDE | 32.367825 | 31.679459 | 31.58355 |
| LONGITUDE | -86.121147 | -86.754379 | -86.839966 |
| MILEMARKER | 12 | 116 | 107 |
| ROADTYPE | Interstate | Interstate | Interstate |
| PRIMARYROAD | I-85 | I-65 | 1-65 |
| CROSSROAD | Exit 11: Atlanta Hwy | Bolling Road | Exit 107: CR 7; Hank Williams Rd |
| DIRECTION | N | N | N |
| COUNTY | Montgomery | Butler | Butler |
| CITY | Montgomery |  |  |
| DISTRICT | Montgomery | Montgomery | Montgomery |
| DETECTIONMETHOD | Operator-detected | Operator-detected | Operator-detected |
| DATE | 2018/01/02 08:40:00 | 2018/01/02 10:51:17 | 2018/01/02 15:34:19 |
| CREATEDDATE | 1/2/18 8:40 AM | 1/2/18 10:51 AM | 1/2/18 3:34 PM |
| VERIFIEDTIME | 1/2/18 8:40 AM | 1/2/18 10:51 AM | 1/2/18 3:34 PM |
| DISPATCHEDTIME | 1/2/18 8:40 AM | -- | -- |
| FIRSTRESPONDERTIME | 1/2/18 9:00 AM | -- | -- |
| ALLLANESOPENTIME | 1/2/18 9:57 AM | 1/2/18 11:32 AM | 1/2/18 4:48 PM |
| RESPONDERDEPARTTIME | 1/2/18 9:57 AM | 1/2/18 11:32 AM | 1/2/18 4:56 PM |
| NORMALFLOWTIME | -- | -- | -- |
| POLICEARRIVETIME | 1/2/18 9:00 AM | -- | -- |
| POLICEDEPARTTIME | 1/2/18 9:57 AM | -- | -- |
| AMBULANCEARRIVETIME | -- | -- | -- |
| AMBULANCEDEPARTTIME | -- | -- | -- |
| FIREARRIVETIME | -- | -- | -- |
| FIREDEPARTTIME | -- | -- | -- |
| HAZMATARRIVETIME | -- | -- | -- |
| HAZMATDEPARTTIME | -- | -- | -- |
| CORONERARRIVETIME | -- | -- | -- |
| CORONERDEPARTTIME | -- | -- | -- |
| TOWARRIVETIME | -- | -- | -- |
| TOWDEPARTTIME | -- | -- | -- |
| PROCESSEDTIME | 4/10/19 10:29 AM | 4/10/19 10:29 AM | 4/10/19 10:29 AM |
| AGENCY | ALDOT | ALDOT | ALDOT |

For reference, a sample of the RTMC incident data in the Advanced Traffic Management System (ATMS) is shown in Figure 7. The RTMC operators monitor each incident and note any key changes in incident status.


Figure 7 Sample RTMC data as it's being handled in the ATMS

## Data Conflation

When working with multiple linear datasets (HERE dynamic subsegments, freeway mileposts, HPMS segments, etc.), combining these datasets in a logical manner to fully describe the road network is important. Ideally, and specific location on the road network (either a latitude/longitude point or a milepost and direction on a specific freeway) would have a full set of information, including route, direction, AADT, speed, geometry characteristics, and other pertinent information. One major problem is that each dataset usually has different break points. As an example, the TMC shapefile provided by HERE is shown with the HPMS volume shapefile in Figure 8. While both of these files chart the roads of Alabama, they do not directly match.


Figure 8 Conflation example where two different linear systems feature different break points

To overcome the varying break points of each dataset and properly assemble the data for all freeways in Alabama, conflation of the multiple datasets was conducted. Conflation is a process developed at the Texas Transportation Institute at Texas A\&M to join two maps such that data can be used from both. The conflation process is done in a GIS system such as ArcMap and is described in the steps below:

1. Select one map as the "Join Map" and the other as the "Base Map." We used the HPMS data set as the base map.
2. Extract the segment endpoints from the Join Map
3. Create a buffer around each of the endpoints
4. Merge overlapping or adjacent points and extract the centroid to create a clean endpoint file
5. Break the Base Map features at each endpoint
6. Create a buffer around each Join Map segment
7. Spatially join the Base Map links to the Join Map by giving each the attributes of the buffer polygon it falls completely inside.
8. Repeat the process on unmatched links
9. Merge all layers
10. Perform quality control checks

At the end of the process, the conflated segment is broken at both the TMC and HPMS endpoints, and so for a given segment of road both the speed and volume records may be retrieved. These data can be combined with a weighted average so that the volume of a TMC segment or the speed of an HPMS segment may be calculated. This allows for the calculation of more robust delay metrics that account for both speed and volume. The conflation process is challenging, particularly in the quality control step, and many lessons were learned along the way to adapt to continual changes with datasets.

## Data Dashboards

Dashboards are used to display the speed data in meaningful ways, allowing the user to select the areas or time periods of interest. These tools can be used for real-time monitoring of the road or after-action review. Already, the RTMCs have been using speed dashboards in their existing ATMS (Figure 9).


Figure 9 West Central RTMC speed dashboard (upper right) in existing ATMS

In the next sections, the development of two additional dashboards will be discussed. These dashboards will summarize and use the HERE speed data in new ways as described in the original proposal.

## Traffic Ticker

The traffic ticker dashboard displays the miles of roadway that are operating under a certain speed threshold (usually 45 mph ). This dashboard is useful for looking at an entire state or region and breaking down speed records by facility, direction, and speed. The early prototype traffic ticker dashboard is shown in Figure 10.


Figure 10 Prototype traffic ticker

In this dashboard, a date is first selected. Usually a 24 -hour period for a single day is most useful for reviewing the speed data and how the network was operating. Next, a speed threshold is set for when congestion is likely to have occurred. While 45 mph is the standard threshold, a lower value (e.g. 25 mph ) would provide more certainty about congestion or anomalies happening. Recalling the speed records (see Table 1), when the median observations for a segment are under the threshold, then that segment length is included in the miles of congestion (miles affected in Figure 11 through Figure 15). These charts can be used daily to track freeways across the state and gauge how congestion is doing. Perhaps one of the most interesting uses will be for winter weather conditions. In the next section, a case study is shown for a special event traffic scenario.

Case Study - The University of Alabama vs Louisiana State University (11/9/19) To demonstrate the final traffic ticker product, November 9, 2019 will be used as a case study. This Saturday was a special event football game at the University of Alabama. In Figure 11, the traffic ticker is used to show all freeways in Alabama across all regions. The worst time of the day was 20:15 when over 30 miles of freeway was below the congestion speed threshold of 45 mph . Note that the colors in this graph represent different speed intervals below the congestion level.


Figure 11 Traffic ticker (all freeways, all regions, varying congestion thresholds by speed)

In Figure 12, the data is divided by region. East Central Region had a steady portion (approximately 3 miles) of freeway that remained below 45 mph due to the Central Business District project. More to the point of the case study, West Central Region had congestion conditions during the AM period from 8:3011:45 and the PM period from 18:00-22:30.


Figure 12 Traffic ticker (all freeways, grouped by region, congestion threshold set at 45 mph )

Selecting just the West Central Region, these two periods are very clearly shown in Figure 13. This information is very useful to the West Central Region, the RTMC, and the RTOP program to monitor how special event traffic control was handled.


Figure 13 Traffic ticker (West Central Region only, all freeways, congestion threshold set at 45 mph )

The traffic ticker also allows for the data to be grouped by freeway. Figure 14 shows the breakout of each freeway and when there is congestion for each facility and direction.


Figure 14 Traffic ticker (all regions, grouped by freeway \& direction, congestion threshold set at 45 mph )

When only the freeways and directions handled in Tuscaloosa County are shown, the directional anomalies and characteristics can be observed for this particular event (Figure 15).


Figure 15 Traffic ticker (WCR only, grouped by freeway \& direction, congestion threshold set at 45 mph )

This insight is, again, especially useful for reviewing management strategies of special events.

## Delta Speed Map Dashboard

This delta speed tool is designed to detect areas of speed differential on the interstate system, which usually signals a building queue that can lead to dangerous back-of-queue crashes. The delta speed between two segments is the difference in speeds between the downstream and upstream segments. If this difference is greater than 15 mph , it is shown on the map. Delta speed events are shown as circles placed between the two segments. Recent events have a large circle, which gets smaller as the speed recovers. The color of the circle points to the severity of the speed drop. The map makes use of subsegments where available, to better locate a queue within a TMC segment. One other feature with this dashboard is the ability to playback historical data. For all of the HERE speed data stored, this tool is able to review historical incidents as shown in the following case study.

Case Study - The University of Alabama vs Louisiana State University (11/9/19)
Following the previous case study for the traffic ticker, November 9,2019 will be used as a case study. During this special event day, there was a small spike in congestion on I-20/59 westbound (see Figure 15). At 1:56PM, a speed differential occurs. Something happened on I-20/59 westbound where speeds drop on a downstream segment and the upstream segment remains high (favorable conditions for queuing and secondary crashes). Figure 16 shows where these conditions first occur.


Figure 16 Delta speed playback tool: speed differential occurs

Looking at the measured speeds for each of the two segments, the upstream speed is 59.1 mph and the downstream speed is 28.2 mph . This speed differential is approximately 31 mph as shown in Figure 17.


Figure 17 Delta speed playback tool: measuring the speed differential

After the next data interval of two minutes, an incident is automatically established for tracking. Figure 18 shows the speed differential located on the map for tracking as long as the speed differential persists.


Figure 18 Delta speed playback tool: tracking the speed differential

For the 1:58 observation, the speed differential is measured to be approximately 43 mph based upon the upstream speed of 60.1 mph and downstream speed of 16.8 mph as shown in Figure 19.


Figure 19 Delta speed playback tool: continue tracking and measuring the speed differential

Details of this speed differential incident are stored as shown in Figure 20 and can be reviewed to see specific information for more accurate measurements and understanding.


Figure 20 Delta speed playback tool: looking at speed differential detail data

## FHWA EDC Presentation and Interest

After reviewing these dashboards with the project advisory committee (PAC) and maintenance bureau, this work was presented at an FHWA EDC-5 Vehicle Probe Data Peer Exchange on March 12 in St. Louis, MO. The presentation was shared with 11 peer states and very-well received, with follow-up from several states. The full presentation is included in the appendix and the highlight from FHWA is shown below in Figure 21.


Figure 21 FHWA Newsletter about Alabama Probe Data Work

## Incident Analysis

After the dashboards were developed, the data storage procedures were in place to start analyzing each incident. One key component was a way to measure the impact of each incident, including the duration of the incident, the queuing distance of the incident, and the severity of the drop in speed. A new scoring system was used and called the Speed Differential Mile Hours (SDMH).

## Speed Differential Mile Hours

The SDMH concept was previously described by Hainen, Jones, and Zephaniah. This measure is consistent with what other researchers have used (Wang Z. et al., 2018). It is computed using historical speed data to estimate the SDMH as defined by Equation 1.

SDMH $=\left\{\frac{\sum_{m_{i}}^{m_{f}} \Sigma_{t_{i}}^{t_{f}}\left(\text { FFS }_{i}-\text { Speed }_{m_{t}}\right)}{60}\right\} *$ miles
Where $m_{i}$ and $m_{f}$ indicate start and end milepost over a specific segment, $t_{i}$ and $t_{f}$ are the initial and end time stamps over a specific duration, and $F F S_{i}$ is the free flow speed at road segment $i$. The SDMH is calculated by analyzing a segment upstream of a crash location following a crash event using six-step process described below:

- Step 1 - collect traffic speed data for the segment where the crash event occured.
- Step 2 - estimate reduction in free flow speed (per mile per minute ).
- Step 3 - sum the reduction in free flow speed over time and space (for each minute and segment length).
- Step 4 - divide the reduction in free flow speed per mile per minute by 60 to obtain the reduction in speed per mile per hour per segment.
- Step 5 - sum up the values obtained in Step 3 which gives the speed differential mile minute.
- Step 6 - divide value obtained in Step 5 by 60 to obtain the SDMH (in hours).

The methodology discussed above is consistent with shockwave propagation approach for estimating the spatiotemporal impact of traffic incidents (Wang Z. et al., 2018) which describes the gradual propagation of traffic speed through the shockwaves. To illustrate the process, Figure 1 depicts two typical applications of this this process. Figure 1a shows how the process is followed step-by-step to calculate an SDMH of 0.5 and provides a visual image of the time-space domain. Figure 1b, then illustrates how a more intense speed reduction upstream results in a larger SDMH being calculated - in this case and SDMH of 13.


Segment Speed (Miles per Hour) Sampled each minute over 1-mile segments



(a) NB Crash at 8:02AM ( $\mathrm{SDMH}=0.5$ )

(b) NB Crash at 9:02AM (SDMH = 13)

Figure 1 Estimation of the SDMH for a crash event

## SDMH Tool

With a systematic and qualitative scoring methodology in place, a tool was developed to retrieve this information for each incident and crash. This tool is available at the following location:
https://sdmh.aladata.com/.

Month: 8 マ Year: 2020 Get Crashes
2020-08-06T11:53:16-1-10 at Exit 35/Daphne (Crash | Overturned Vehicle) $\quad \vee$
Hours before (scoring): $\square$ Miles after (scoring): $\qquad$

Refresh
1216270: I-10 (E) at Exit 35/Daphne at MP 35.07
Score: 8101.8 (11906.7) | Crash Time: 2020-08-06T11:53:16 | Sequence ID: 1


Figure 22 SDMH tool showing an example incident with an SDMH score of 8101.8

## Modeling Incident Duration and Assessing Incident Clearance Times

With all the data previously discussed, the final tasks included the modeling of mobility impact from incidents and then the interpretation and write-up of model findings. The following work is a paper led by N. Islam and A. Hainen which examines the TIMs clearance times for incidents on Alabama freeways.

Traffic congestion caused by incidents is a major problem in the freeways (Hou, et al., Modeling freeway incident response time: A mechanism-based approach, 2013). As the duration of a freeway incident increases, it increases the probability of secondary accidents, severity of traffic congestion levels, traveler delays, travel time variability, negative social and economic impacts, air pollution and fuel consumption (Alkaabi, Dissanayake, \& Bird, 2011; Ghosh, Savolainen, \& Gates, 2014; Hojati, Ferreiraa, Washington, Charles, \& Shobeirinejad, 2014). Traffic Management Centers (TMCs) are often tasked with monitoring and responding appropriately to minimize the incident duration and to alleviate the impact of traffic incidents (Hou, et al., 2014; Ding, Ma, Wang, \& Wang, 2015). To achieve this goal, it is important for the TMCs to understand the impact of incidents on traffic congestion and the contributing factors that effects the incident duration. A better understanding of the influential factors on incident duration can help the TMCs in assigning suitable incident management resources to a certain incident. Also, operational changes in current incident management procedure can be identified to improve incident response and clearance times (Hojati, Ferreiraa, Washington, Charles, \& Shobeirinejad, 2014; Hou, et al., 2014).

The Highway Capacity Manual has divided the incident response timeline into four phases. These phases include (1) detection time: the time between the incident occurrence and incident reporting time, (2) response time: the time between the incident reporting time and the time that the first responder arrives on the scene, (3) clearance time: the time between the arrival of the first responder on the scene and the moment when the incident has been cleared from the highway, and (4) recovery time: the time taken for traffic flow to return to normal after the incident has been cleared (Manual, 1994). These phases are illustrated in Figure 23. Among these phases, the incident clearance time is the focus of this paper, as it is a critical phase which can be directly controlled by the Traffic Management Centers (TMCs).


Figure 23 Phases of Incident Duration.

Over the last few decades, several researchers analyzed incident duration and explored the affecting factors using different statistical models. (Nam \& Mannering, 2000) used hazard-based duration models to analyze the incident duration in terms of detection/reporting time, response time, and clearance time by using freeway incident data of Washington State. Their analysis proved that hazard-based duration models are appropriate in analyzing incident duration data. The study showed that incident type, day of the week, month of the year, weather condition, location of the incident, peak time, and presence of shoulder had significant effect on incident duration times. (Alkaabi, Dissanayake, \& Bird, 2011) examined incident duration by using fully parametric accelerated failure time (AFT) hazard-based duration model by using data from the city of Abu Dhabi, UAE. The results of this study showed that various incident characteristics significantly affect incident clearance time, including incident type, severity of incident, weather condition, location, month of the year, number of vehicles involved and so on. The authors also used the fully parametric AFT hazard-based duration models to analyze effect of the influential factor on incident response time in their further research work (Alkaabi, Dissanayake, \& Bird, 2012). They found that incident type, location of the incident, day of the week, and month of the year had significant influence on incident response time.
(Hojati, Ferreira, Washington, \& Charles, 2013) explored the effects of various factors related with the type of incidents on incident duration. Twelve months of Austrian freeway incident data were analyzed by developing parametric accelerated failure time (AFT) survival models for incident duration, which included log-logistic, lognormal, fixed and random parameters Weibull and Weibull model with gamma heterogeneity. The results showed that incident severity, incident type, towing requirements, location, time of day, and traffic characteristics of the incident had significant impact on incident duration. The authors expanded their analysis further by using the parametric AFT survival model with fixed and random parameters specifications to analyze the unobserved heterogeneity of the incident detection and response time (Hojati, Ferreiraa, Washington, Charles, \& Shobeirinejad, 2014). The study showed that incident characteristics (i.e., severity of the incident, type of the incident), infrastructure characteristics (i.e., presence of shoulder), temporal characteristics (i.e., time of the day) and traffic characteristics (i.e., peak time) significantly affected the incident detection and response time.
(Hou, et al., 2013) proposed a mechanism-based approach to model incident response time and to explore the influential factors of incident response time based on the performance of the incident response truck (IRT). Using the Washington State Incident Tracking System (WITS) data and dual-loop detector data, the authors found that injury involved, shoulder/medial involved, heavy truck involved, disabled vehicles involved, weekends, and debris were factors associated with longer response time. However, collision, work zone involved, HOV lane involved, fire involved, abandoned vehicles involved, all travel lanes blocked, winter, summer, AM peak, PM peak, and average annual daily traffic (AADT) were identified to shorten incident response time. The authors also developed a non-proportional hazard-based duration model to analyze the incident clearance time and the time-varying effects of contributing factors on incident clearance time (Hou, et al., 2014). The authors found that five factors (Washington State Patrol involved, average annual daily traffic, fire involved, injury involved, and summer) had significant constant impact on the incident clearance time. Seven variables (disabled vehicles involved, single lane blocked, multiple lanes blocked, collision, short response time, medium response time, and long response time)
were found to have significant time-increasing influence and six variables (abandoned vehicles involved, heavy truck involved, debris, traffic control, weekends and night time) were observed to have timedecreasing effects on incident clearance time.
(Ghosh, Savolainen, \& Gates, 2014) examined freeway incident clearance time taken by the Michigan Department of Transportation Freeway Courtesy Patrol and the effects of the influential factors by using the southeastern Michigan freeway incident duration data. The authors used a series of fully parametric hazard-based duration models to explore the factors affecting the freeway incident clearance time. The results showed that time of the day, month of the year, seasonal variation, traffic characteristics, geometric characteristics, and incident characteristics were significantly impacting the incident clearance time. (Ding, Ma, Wang, \& Wang, 2015) used a switching regression model and a binary probit model to analyze the influential factors in incident response and clearance time. Using the Washington State freeway incident data, the authors conclude that incident type, geographical, temporal, environmental, operational and traffic characteristics had significant impact on incident response and clearance time.

Over the course of these studies, freeway incident management programs have become more common in managing freeway incidents. Traffic Management Centers (TMCs) have shown their dependency on these programs to respond quickly and safely as possible to incidents. Many previous studies had identified various factors, including incident types, temporal factors, environmental characteristics, infrastructure or geometry of the roadway, traffic condition and operational characteristics, impacting incident duration in terms of detection time, response time and clearance time. As for operational characteristics, the freeway service patrol area coverage has yet to be examined as an important influential factor affecting incident clearance time. In this paper, the existing coverage of the Alabama Service and Assistance Patrol (ASAP) program has been considered as an important influential factor on freeway incident clearance time.

## Goals and Objectives

The goal of this paper is to measure and understand the impact of Alabama Service and Assistance Patrol (ASAP) on incident clearance time. The objectives of this paper include (1) to pair and analyze TMC incident data with crash data, (2) estimate a duration model for incident clearance time, and (3) assess the factors that contribute to incident clearance time. This study uses a fully parametric hazard-based duration model to statistically analyze the factors that affect the incident clearance time. The novelty of this paper is the inclusion of additional ASAP coverage area information in the duration models. The contribution of this paper is to provide a better understanding of the factors that contribute to the incident clearance time and to provide a quantitative estimate of the impact of ASAP programs.

## Data

Four different datasets were used to achieve the goal and objectives of this paper. The first dataset includes 18,275 highway crashes collected from the Center for Advanced Public Safety (CAPS), an interdisciplinary research center at The University of Alabama for the calendar year 2018. The second dataset comprises 7,323 highway incidents recorded by Traffic Management Centers (TMCs) for the year of 2018. These two datasets were joined using the attributes date, time, road name, direction of travel and location, which linked 2,206 crashes and incidents. The third dataset includes the average annual daily
traffic (AADT) data for the calendar year 2018 collected from ALDOT. The final dataset contains the existing Alabama Service and Assistance Patrol (ASAP) information gathered from ALDOT, which is the key attribute in this paper (Figure 24). Each incident was determined whether the location occurred within the service patrol region (Figure 25) or not. It should be noted that incidents within the ASAP area may not have necessarily had the ASAP arrive to the location first or at all. In the future, additional logs and records will further help to understand the impact.


Figure 24 Flowchart of Data Processing.

After joining these four datasets, 88 potential independent variables were created to analyze and assess the effects of these variables on the incident clearance time. These variables can be divided based on incident types and characteristics, environmental effects, traffic characteristics, operational characteristics, temporal effects and geographic characteristics. The final sample included 2,206 crashes and incidents occurring on freeways in Alabama.


Figure 25 Alabama Service and Assistance Patrol Area Coverage.

## Methodology

Considering the large variance in the incident clearance time, a statistical method is warranted to understand the duration problem. Hazard-based duration models are statistical models which are well suited for modeling duration data. The models are used to analyze the conditional probability of a time duration that continued until time t , given that the duration has ended at the time $t$ (Washington, Karlaftis, \& Mannering, 2011). Hazard-based duration models are extensively used in biostatistics, economics, engineering, and social sciences for analyzing the duration of a specific event (Hensher \& Mannering, 1994; Nam \& Mannering, 2000; Washington, Karlaftis, \& Mannering, 2011). In this paper, a hazard-based duration model was used to understand the additional information of the underlying duration of incidents.

In studying incident duration data, the variable of interest is the length of time between the arrival of the first responder at the scene and the opening of all lanes, which is defined as the incident clearance time. The incident clearance time in hazard-based model is a continuous random variable $T$, with a cumulative distribution function $F(t)$, which is called the failure function, probability density function $f(t)$, survival function $S(t)$, and hazard function $h(t)$. The cumulative distribution function $F(t)$ for the incident clearance time $(T)$ is defined in the following equation, where $P$ is the probability that the incident clearance duration being greater than some specified time $t$.

$$
\begin{equation*}
F(t)=P(T<t) \tag{1}
\end{equation*}
$$

The probability density function $f(t)$, which is the derivative value of the cumulative distribution function $F(t)$, is defines as

$$
\begin{equation*}
f(t)=\frac{d F(t)}{d t} \tag{2}
\end{equation*}
$$

The hazard function $h(t)$ gives the rate at which the incident clearance times are ending at time $t$, given that they have not ended prior to time $t$ (Washington, Karlaftis, \& Mannering, 2011).

$$
\begin{equation*}
h(t)=\frac{f(t)}{1-F(t)} \tag{3}
\end{equation*}
$$

Conversely, the survival function, $S(t)$, is the probability of the duration being greater than or equal to some specific time $t$.

$$
\begin{equation*}
S(t)=P(T \geq t)=1-F(t) \tag{4}
\end{equation*}
$$

The derivative of $h(t)$ will indicate if the probability of an incident clearance time is increasing, decreasing or remain constant as $t$ changes which can depend on the incident types and other attributes of the incident. Proportional-hazard model have been popular in accounting for the attributes which are influential to the incident clearance time (Washington, Karlaftis, \& Mannering, 2011). Therefore, a statistical model can be incorporated using the proportional-hazard approach:

$$
\begin{equation*}
h(t \mid X)=h_{0}(t) e^{\beta X} \tag{5}
\end{equation*}
$$

where $h_{0}(t)$ indicates the baseline hazard function and $e^{\beta X}$ represents the effect of explanatory factors on the hazard. $X$ is the vector of external influential factors and $B$ is the vector of estimable parameters.

In estimating Eq. (5) with fully parametric model, a variety of parametric forms of the underlying hazard function can be used, which includes exponential, log-logistic, Weibull, and so on (Nam \& Mannering, 2000; Washington, Karlaftis, \& Mannering, 2011). The Weibull distribution allows the hazard function to be monotonically increasing or decreasing (indicating the probability of an incident clearance-time duration ending increases or decreases over time) (Washington, Karlaftis, \& Mannering, 2011; Hainen, Remias, Bullock, \& Mannering, 2013). With parameters I > 0 and $\mathrm{P}>0$, the Weibull distribution has the hazard function,

$$
\begin{equation*}
h(t)=(\lambda P)(\lambda t)^{P-1} \tag{6}
\end{equation*}
$$

The original proportional-hazard approach assumes that the baseline hazard function $h_{0}(t)$ is homogeneous for each observation. However, there is a possibility of unobserved heterogeneity in analyzing the incident clearance time using hazard-based duration model. (Washington, Karlaftis, \& Mannering, 2011) showed that the most popular approach to examine heterogeneity in fully parametric models, is to introduce a heterogeneity term, gamma over the population. Therefore, the Weibull model with gamma heterogeneity with mean 1 and variance $\theta$ is:

$$
\begin{equation*}
h(t)=\frac{(\lambda P)(\lambda t)^{P-1}}{1+\theta(\lambda t)^{P}} \tag{7}
\end{equation*}
$$

In this study, the Weibull model with gamma heterogeneity is used to analyze the incident clearance time on 2,206 crashes on Alabama highways. Numeral previous studies have been used this statistical model to assess the incident duration data and therefore, is used in this paper for direct comparison. All statistical analyses are performed using NLOGIT 5.

## Results

The parameter estimates of the Weibull model with gamma heterogeneity on highway incident clearance time are provided in Table 3. The $t$-statistic is included in the table to indicate the statistical significance. All the variables are statistically significant at $95 \%$ level of confidence. The positive value of the parameter estimate indicates the decrease in the hazard function and the increase in the incident clearance time. Eighty-eight potential independent variables were examined on 2,206 highway incidents, including incident types and characteristics, environmental effects, traffic characteristics, operational characteristics, temporal effects and geographic characteristics. Seventeen variables are found to have significant effect on the duration of the incident clearance time. The effects of such significant variables are discussed in detail in the following discussion section and will be compared with previous findings.

Table 3 Weibull model with gamma heterogeneity estimation results for incident clearance time

| Variables | Estimated <br> Parameter | $\boldsymbol{t}$-statistic |
| :--- | :---: | :---: |
| Constant | 3.593 | 33.97 |
|  |  |  |
| Incident characteristics | 0.196 | 5.44 |
| Fire response (1 if yes, 0 otherwise) | 0.917 | 3.11 |
| Hazardous materials response (1 if yes, 0 otherwise) | 0.388 | 6.77 |
| Commercial motor vehicle (CMV) involved (1 if yes, 0 | 0.689 | 5.23 |
| otherwise) | -0.144 | -3.41 |
| Fatality involved (1 if yes, 0 otherwise) | 0.161 | 6.77 |
| Seat belt involved (1 if yes, 0 otherwise) | 0.373 | 11.06 |
| Number of vehicle(s) involved | -0.195 | -4.30 |
| Vehicle towed (1 if yes, 0 otherwise) | 0.201 | 2.24 |
| On-road (1 if yes, 0 otherwise) |  |  |
| Overturn (1 if yes, 0 otherwise) | 0.081 | 2.33 |
| Temporal characteristics | 0.073 | 1.96 |
| Nighttime (1 if yes, 0 otherwise) | -0.085 | -2.74 |
| Winter (December, January, February) |  |  |
| Peak hours (1 if incident occurred between 7 AM -9 AM |  |  |
| and 4 PM - 6 PM, 0 otherwise) | -0.005 | -8.66 |
| Traffic characteristics | 0.044 | 3.91 |
| Average annual daily traffic (AADT) |  |  |
| Number of lanes in the trafficway (1 - 6) | 0.495 | 37.93 |
| Operational characteristics | 0.405 | 8.72 |
| Detection Time (in minutes) | -2280.013 | -0.010 |
| Police involved (1 if yes, 0 otherwise) | 2206 | 2.67 |
| ASAP area (1 if yes, 0 otherwise) | 0.264 | 4.44 |
| Model structure parameters | -0.218 | -10 |
| Sigma (distribution parameter) |  |  |
| Theta (heterogeneity) |  |  |
| Log-likelihood at convergence |  |  |
| Number of observations |  |  |

Figure 26 represents various functions for the incident clearance time. The blue solid line indicates the survival function for the raw data, whereas the red short-dotted line shows the survival function for the estimated model. From Figure 26, it is found that the raw and estimated survival functions are very close to each other, indicating that the model fits the data quite well. The green long-dotted line shows the estimated hazard function for the incident clearance time. The estimated value of $t$ at the inflection point is 76 minutes for the hazard function, which indicates that the incident duration is likely to be increased after 76 minutes. In other words, the P value greater than one for the hazard function of the analyzed incident clearance time suggests that the rate of incident ending decreases after 76 minutes.


Figure 26 Survival and Hazard Functions for Incident Clearance Time.

## Discussion

Incident characteristics
The variables which are grouped in the incident characteristics includes involvement of fire, hazardous material, presence of coroner, severity types (injury, fatality, property damage), number of vehicle(s) and person(s) involvement, incident types (collision with vehicle, overturn, barrier involvement, on road or off road incidents) and so on. Looking at the model results using 2018 highway incident data, if fire response (coef $=0.196, t=5.44$ ) was involved in the incident, this variable was found to have increased incident clearance time. The involvement of the fire truck response to incidents usually requires more time to clear the incident as traffic across all lanes is stopped. This finding of increased clearance time is consistent with the research works conducted by (Hou, et al., 2014) and (Ding, Ma, Wang, \& Wang, 2015). Incidents involving hazardous material response ( $c o e f=0.917, t=3.11$ ) were found to be associated with longer incident clearance times, which is consistent with the previous research works from (Nam \& Mannering, 2000) and (Hojati, Ferreira, Washington, \& Charles, 2013). Fuel spills, hazardous material spills, and other types of incidents which require additional care will require additional time. While these findings are intuitive, this modeling methodology serves as a valuable and holistic tool to identify these key factors
and which should be considered in response plans as parameters that may provide opportunity to reduce incident clearance times.

The variable for commercial motor vehicle involved (CMV) (coef $=0.388 . t=6.77$ ) was found to have a positive parameter estimate, which indicates an increase in the incident clearance time. This is expected as incidents involved with CMV are complex and often require time-consuming recoveries. If the incident is involved with any fatality (coef $=0.689, t=5.23$ ), it was found to significantly increase the incident clearance time. The incidents with fatality tend to be more severe and require more time to document and process as the response teams have to work with different agencies such as police and EMS. This finding agrees with the many previous research works (Nam \& Mannering, 2000; Lee \& Fazio, 2005; Chung, 2010; Alkaabi, Dissanayake, \& Bird, 2011).

The parameter estimate for seat belt (coef $=-0.144, t=-3.41$ ) was found to be associated with shorter clearance time. Seat belt use tends to reduce the severity of an incident which results shorter clearance time (Kashani, Shariat-Mohaymany, \& Ranjbari, 2012). The parameter estimate for the number of vehicle(s) (coef $=0.161, t=6.77$ ) was found positive, which indicates that as the number of vehicle(s) increases, the duration of clearing the incident also increases. This result is expected as additional vehicles involved leads to longer incident clearance time. The variable indicating that a vehicle was towed (coef = $0.373, t=11.06$ ) was found to have positive parameter estimate, which indicates an increase in clearance time. This finding is consistent with the previous research (Nam \& Mannering, 2000; Hojati, Ferreira, Washington, \& Charles, 2013).

Incidents occurring on-road (coef $=-0.195, t=-4.30$ ) as opposed to the shoulder or off of the roadway were found to have a negative parameter estimate, which indicates a decrease in clearance time. The incidents occurring on the roadway (as opposed to incidents which ended up outside of the travel lanes) is more likely to cause one or more lanes to be closed. Therefore, the traffic incident management agencies provide rapid response to these types of incidents to reduce the possibility of more intense congestion. The blocking of traffic is more quickly detected and increases the probability of drivers reporting the incident. If overturning (coef $=0.201, t=2.24$ ) of a vehicle occurred in the incident, it was found to be associated with longer clearance time. The incidents involving overturned vehicles tend to have higher severities and require substantial effort in removal or up-righting of the overturned vehicles. The traffic incident management agencies have to work with police and first responder departments, which results longer clearance time.

## Temporal characteristics

The temporal characteristics in the model include the time of the incident (daytime or nighttime), the seasonal variations, different peak and off-peak time, day of the week, month of the year, weekdays, weekends and so on. If the incident occurred at nighttime (coef $=0.081, t=2.33$ ), it was found to be associated with longer clearance time. This might be because of the lower availability of the response team and additional complications with working at night. This result is consistent with the research works conducted by (Nam \& Mannering, 2000), (Ghosh, Savolainen, \& Gates, 2014), but inconsistent with the works conducted by (Hou, et al., 2014) and (Ghosh, Savolainen, \& Gates, 2014).

The incidents which occurred in winter ( $c o e f=0.073, t=1.96$ ) was found to have positive parameter estimate which indicates increased clearance time. This might be because of the inclement weather or buildup snow on the shoulder (Ghosh, Savolainen, \& Gates, 2014), therefore, it takes more time to clear the incident. The peak hours parameter estimate ( $\operatorname{coef}=-0.085, t=-2.74$ ) was found to be associated with shorter clearance time. Daily traffic peak hours are important and therefore for the traffic management agencies respond to incidents as quickly to alleviate the any additional traffic congestion. This finding coincides with the research works conducted by (Alkaabi, Dissanayake, \& Bird, 2011; Ding, Ma, Wang, \& Wang, 2015; Hojati, Ferreiraa, Washington, Charles, \& Shobeirinejad, 2014; Hou, et al., Modeling freeway incident response time: A mechanism-based approach, 2013; Jones, Janssen, \& Mannering, 1991).

## Traffic characteristics

For traffic characteristics, average annual daily traffic (AADT), truck annual daily traffic (TADT), percent truck annual daily traffic (PTADT), number of lanes in the trafficway, etc. were analyzed to measure their effects on the incident clearance time. The factor of average annual daily traffic (AADT) (coef $=-0.005, t=$ -8.66) was associated with decreased clearance time. The freeways with higher AADT indicates the importance of the freeway with higher traffic demand. Therefore, the traffic incident management agencies seem to appropriately provide response priority to the freeways with higher AADT to avoid more traffic congestion which results shorter incident clearance time. This finding is consistent with many previous research works (Jones, Janssen, \& Mannering, 1991; Hou, et al., 2013; Ding, Ma, Wang, \& Wang, 2015). The infrastructure characteristic for number of trafficway lanes (coef $=0.044, t=3.91$ ) was found to have positive parameter estimate which indicates increased clearance time. This indicates that if the number of lanes in the trafficway increases, it increases the clearance time. More lanes may complicate temporary traffic control and therefore takes more time to clear the incident.

## Operational characteristics

Detection time, verification time, response time, police involvement, and existing Alabama Service and Assistance Patrol (ASAP) area were examined to assess the influence of operational characteristics on the incident clearance time. As for operational characteristics, the variable for detection time in minutes (coef $=0.010, t=2.67$ ) was found to be associated with longer clearance time. This is expected as any blockage causing queuing for a longer time will take more time for the traffic incident management agencies to respond to the incident which leads to longer clearance time. The factor for police involved (coef $=0.264$, $t=4.44)$ was found to have a positive parameter estimate. This is likely reflecting the nature of police responding to relatively severe incidents which would naturally require police attending to the scene. This finding is consistent with the research conducted by (Hou, et al., 2014), which showed that police involvement tends to increase the clearance time.

Lastly, the inclusion of the freeway service patrol is a major emphasis and novelty for this work. The variable ASAP (coef $=-0.21845, t=-5.10$ ) was found to be associated with shorter clearance time. If an incident occurs in the ASAP patrol area, the ASAP can quickly detect it. Therefore, the traffic incident management agencies get informed fast resulting lower response time, which leads to decreased clearance time. This finding is consistent with the research work performed by (Hou, et al., 2014). This is very encouraging for the agency freeway service patrol and demonstrates how to appropriately measure the effectiveness of these programs. If crashes were analyzed with a simpler approach (for example, a
traditional $t$-test for incidents in the patrol area compared to incidents outside the patrol area), a potential omitted variable bias could lead to false conclusions. A holistic model appropriately includes all attributes as shown in this work.

## Incident Analysis Conclusions

In the past, many research efforts have gone into staying incident clearance time. With the increasing use of highway service and assistance patrol, this paper is an extension to include additional information regarding these programs. This paper describes the analysis of the incident duration data of the state of Alabama highways during the period January 1, 2018 to December 31, 2018. Four different datasets were collected from CAPS, TMCs and ALDOT including ASAP area coverage information for the highways. A fully parametric hazard-based duration model has been analyzed and was demonstrated to be an appropriate methodology for this type of data. To address the heterogeneity problem, a Weibull model with gamma heterogeneity has been examined.

In this incident analysis, the model findings indicate that a total of seventeen variables significantly effects the incident clearance time. For this study, four groups of conclusions were found. First, for the incident characteristics, seven factors (fire, hazardous materials, commercial motor vehicle, fatality, number of driver(s), vehicle towed, and overturn) are found to be significantly associated with longer incident clearance time. Meanwhile, two variables (seat belt and on-road) tend to decrease the incident clearance time. Second, for the temporal group, both the variables (night and winter) are found to significantly influence the longer incident clearance time. Third, two factors (AADT and peak hour) in the traffic group, are identified to be significantly associated with shorter incident clearance time, whereas only one factor (number of lanes) is captured to responsible for longer clearance time. Fourth, for the operational characteristics, the two factors (detection time and police involvement) are found to be associated with longer clearance time. The only variable (ASAP) tends to significantly decrease the incident clearance time.

It should be encouraging this point to see the beneficial impacts of Alabama's Highway Service and Assistance Patrol coverage. A next step should be to explore similar analyses in other states, perhaps with additional or alternative modelling frameworks. Also, changes with spatial coverage, operational hours, and/or the size and quantity of crews should be monitored and examined over time.

## Project Conclusions

Crowdsourced probe data is rapidly becoming a viable dataset for a variety of transportation applications. Improvements over the traditional TMC 5-minute records continue to develop in the ways of shorter segments, travel patterns, and signal analytics. In the distant future, connected vehicle data will provide completely disaggregated probe data. For now, this data is a highly-scalable dataset that will help operators understand and assess how their systems are working.

For this project, an initial set of dashboards was developed. With data collection, storage, and retrieval procedures in place, additional dashboards could be developed according to agency needs and interests. As more data becomes available, combining datasets to gain more insight will help to provide further insights about travel patterns and operations. A few challenges certainly exist with combining information. First, the conflation process to combine data is extremely challenging. Whether the data needs to be combined in a GIS platform or through other linkages, this process is tedious and requires a high level of error checking. Once the data is combined, analyzing the data also requires careful approaches. Simply filtering incidents or crashes or other observations on a single variable (e.g. urban vs. rural or night vs. day) is insufficient compared to developing appropriate models. Storing the data is also quite challenging, both with the collection processes and the database size and management.

While all of these challenges were successfully mitigated in this research project, there are commercial products which may be better alternatives. The Iteris ClearGuide platform has much promise. The University of Maryland's / CATT Lab's RITIS platform is certainly a mature product. The maintenance bureau has been investigating these alternatives, and further exploration should be continued. The tradeoff between customized research project-oriented dashboards or more widely-available offerings from vendors will be an involved decision to make.

In the future, while additional transportation systems hardware will continue to be deployed, commercially available crowdsourced probe data will certainly augment any analyses or reports. The crash data and RTMC incident data will be key in providing independent variables to understand each incident on the roadways. Ultimately, combining all of this data with volume data to quantify the costs to travelers will help with benefit-cost ratios for programmatic and operational decisions.

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Appendix A - Slides from FHWA EDC-5 Vehicle Probe Data Peer Exchange


## Agenda - Alabama DOT Probe Data

- Procuring Data
- INRIX 2014 - HERE 2016
- Statewide Mobility Report
- Processing and Managing Data
- Real-time XML storage
- TTI Conflation Process
- Using Data

1. Football Traffic Ticker (McNamara)
2. Tracking Incidents (Li)
3. Scoring incidents
4. I-10 Cost of Doing Nothing (ATI)
5. Signal Work (Not great...)

- Next Steps
- Signal BSM (...but this is awesome!)
- Inrix Signal Analytics?
- ADT from Probe Data?

| Section \#1 - Procurement <br> FHWA Every Day Counts |  |
| :--- | :--- |
| Qound 5 - Crowdsourcing for Operations Program |  |
| Qehicle probe data source | Possible Response Elements |
| What facilities / how many miles? | All highways and major arterials |
| Purchasing real time data, only <br> archived data, or both? | Real time since 2016 |
| What is the duration of the <br> commitment with the probe provider? | Annual with renewals |
| Have you used other sources in the <br> past? Why switch? | Yes, INRIX for select counties. Price. |
| Any lessons on data procurement? | Difficult to switch platforms from one to another with <br> proprietary data (HERE dynamic subsegments vs. INRIXXD) |

Alabama Crowdsourced Data (2014)
Old; ALDOT currently has state-wide coverage of HERE data




## Section \#2 - Data Processing, Management, and Access

| Questions | Possible Response Elements |
| :--- | :--- |
| Who processes the data? | Center for Advanced Public Safety |
| Who stores the data? Is the real- <br> time data archived? | Center for Advanced Public Safety at the University of Alabama <br> The real-time data is archived |
| What is your data verification <br> process and scope? | - Some checks with intersection information <br> What have you found, what has <br> Changed over time? |
| - Blyncsy SensMetrics and SensID (Wifi / Bluetoth / WiFi |  |

Section \#2 - Data Processing, Management, and Access
FHWA Every Day Counts Round 5 - Crowdsourcing for Operations Program

| Questions | Possible Response Elements |
| :--- | :--- |
| What other data is integrated with vehicle probe data? | TMC operator data, Waze, crash data, signal <br> data |
| Is the integration in real time post-processed? | Both |
| Are there processes in place to trace the "provenance" <br> of processed data? | Logs of each insertion (one-minute) |
| Who can access the data? | State DOT, Local Agencies, Support <br> contractors/consultants |
| Have you hosted any formal or informal training on use <br> of the data? | We share peer-to-peer, we held workshops <br> when the data became "live" and invited local <br> agencies, etc. |



Live XML Feed of HERE Data (2017)
Capturing once a minute and storing in SQL (64GB/day)

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        <FEATURES>
            <FEATURE>LANES</FEATURE>
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            <FEATURE>EXPRESS</FEATURE>
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                    </FI>
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                    <TMC DE="University Ave/Exit 244" LE="1.56059" QD="-" PC="4117"/>
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                    </CF>
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                </FI>
                    <TMC DE="Fulton St/Central Ave/Exit 246" LE="0.38015" QD="-" PC="4119"/>
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                    <SS LE="0.15517" TS="O" JF="8.68736" FF="55.05" SU="12.64" SP="12.64"/>
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# Section \#3 - Using the Vehicle Probe Data <br> $\mathcal{A}$ <br> FHWA Every Day Counts Round 5 - Crowdsourcing for Operations Program 

| Questions | Possible Response Elements |
| :---: | :---: |
| How are you using the data in real-time? Please describe what and its effectiveness and user feedback. | - Traveler information (web 511, travel time on DMS, etc.) [Yes] <br> - Traffic incident management (TIM) detection, back of queue, [Delta] <br> - Arterial management (dynamic signal progression) [RTOP] <br> - Road weather or work zone management [Winter Weather] |
| How are you using the archived data? Please describe what and its effectiveness and user feedback. | - Performance reporting (reliability, delay, etc.) [SPM / RTOP] <br> - Project prioritization (estimating cost of delay) [l-10] <br> - Modifying arterial management - need versus time-based retiming <br> - More complete before/after assessments [RTOP] <br> - Work zone planning or contract compliance [Smart Work Zone] <br> - Planning or simulation model verification [RTOP / Vissim] |
| How do you justify investment? | - Are there any reports/documents? [Mobility Report / Quarterlies] <br> - How was your agency able to overcome resistance to investment? |














|  | Sample of Extracted Data for Researchers AScores for Each Incident $\rightarrow$ Link to Crash / Response Attributes (TIMS) |  |  |  |  |  |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  | Column Row Timestamp Segment |  | Direction | Speed [fFs so | so from |  | length |
|  |  | ${ }_{\mid-10}^{1-10}$ | Eastbound | 74.47 <br> 67.69 <br> 0.03 <br> 99.73 |  | 16.00023 |  |
|  |  | ${ }_{1-10}^{10}$ | Eastbound |  | ${ }_{28.28}^{20.0 .372723}$ | 317.55506 | 1.32183 |
|  | 4 9/12/20190080:00:00 1.65/Exit 20 | -10 | Eastbound | 33.7565 .0633 | 33.3117 .55907 | 18.91788 | 1.25881 |
|  | $59 / 12 / 201909890000001.65 /$ /Exit 20 | ${ }^{\text {I-10 }}$ | Eastbound | 61.54 59.83 | 018.97788 | 20.75878 | 1.8409 |
|  | $69 / 12 / 20190808000000 \mathrm{Al}$-163/Dauphin Sland Pky/Exit 22 | 1.10 | Eastbound | 75.16 | - 20.7588 | 22.52957 |  |
|  |  | $\stackrel{\mid}{\mathrm{r}} \mathrm{\mid} 10$ | Eastbound | 716.65 .24 70.85 | 022.52957 023.5089 | ${ }^{23.5098985}$ | ${ }^{0.98832}$ |
|  | 9 9/12/2019080:00:000 s broad st/xitit 24 | ${ }^{\text {P/ }} 10$ | Eastbound | $71.71 \quad 65$ | - 24.0385 | 24.86102 | 0.82252 |
|  | 10 9/12/2019098000:00 Virginia 5 /fexit 25 | $t \cdot 10$ | Eastbound | ${ }^{68.24} 64.75$ | - 24.868102 | 25.56456 |  |
|  | 11 9/12/2019080:000:000 Texas St/Exit 25 | ${ }^{\text {-10 }}$ | Eastbound |  | 0.4425 .56656 | 526.08946 | 0.52491 |
|  | $129 / 12 / 2 / 20190808000000$ Canal 5 st// Water 5 //Exit 26 | ${ }^{\text {P10 }}$ | Eastbound | ${ }_{5}^{52.295} 53.75$ | 1.4626 .08946 |  |  |
|  |  | ${ }_{\mid-10}^{1-10}$ | Eastbound | ${ }_{5}^{42.21} 50.75$ | 3.2126.74826 1.54 27.4795 | 27,489711 | -0.123179 |
|  |  | ${ }^{\text {b }} 10$ | Eastbound | 67.2465 .24 | - 27.89111 | 30.99135 | 2.60024 |
|  |  | $t \cdot 10$ | Eastbound | ${ }^{68.57}$ 65.43 | $\bigcirc 030.99135$ | 35.688053 |  |
|  | $1179917 / 2 / 2010080000000 \mathrm{AL}-181 /$ /xxit 38 | $t \cdot 10$ | Eastbound | 63.6569 .59 | 5.9435 .68053 |  |  |
|  | 1 9/12/2001908:00:100 US.90/AL-16/Govermment Elv//Exit 15 |  | Eastbound | 73.3170 .03 | 16 |  |  |
|  |  | ${ }_{\mathrm{l}}^{1-10}$ | Eastbound Eastbound | 67.999 .9973 <br> 34.865 .24 <br> 20 | ${ }^{2.0416 .00023} 30.414 .3723$ | 11.33723 | ${ }_{\text {c.32183 }}^{0.337}$ |
|  | 4 9/12/2019008:01:001.65/xxit 20 | ${ }^{1} 10$ | Eastbound | 33.2865 .0631 | 31.7817 .58597 | 18.91788 | 1.25881 |
|  | $59 / 12 / 2 / 21908080101001$ 1.65/Exit 20 | ${ }^{\text {-10 }}$ | Eastbound | 57.72 59.83 | 2.11 18.91788 | 20.75878 |  |
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|  | $99 / 12 / 2019080801000$ S Braad St/Exit 24 |  | Eastbound | 72.1465 | - 24.0385 | 24.86102 | 0.8225 |
|  |  |  | Easthound | 67096475 | 02488610 | 25.5655 |  |











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|  | Delay costs: $\$ 13.17$ for cars and $\$ 47.59$ for trucks, $7 \%$ discounting rate (2021 to 2040) in Million \$ |  |  |  |  |  |  |
|  | $\begin{array}{ll}\text { す. } \\ 0 & 0 \\ 0 & 0 \\ 0 \\ \text { E } \\ 0 & 0 \\ 0 & 0 \\ 0 & 0\end{array}$ |  | Percent Trucks |  |  |  |  |
|  |  |  | 5\% | 10\% | 13\% | 15\% | 20\% |
|  |  | 3.0\% | 426.24 | 448.92 | 462.57 | 471.65 | 494.34 |
|  |  | 3.5\% | 450.26 | 474.24 | 488.63 | 498.25 | 522.21 |
|  |  | 4.0\% | 475.87 | 501.25 | 516.43 | 526.60 | 551.93 |
|  |  | 4.2\% | 486.59 | 512.51 | 528.06 | 538.44 | 564.35 |
|  |  | 4.7\% | 623.00 | 656.25 | 676.14 | 689.41 | 722.60 |
| Assumptions: <br> 1) 1.7 occupancy for passenger cars (the average vehicle occupancy factor provided by the Federal Highway Administration: https://www.fhwa.dot.gov/tpm/guidance/avo_factors.pdf) <br> 2) $7 \%$ discounting factor (recommended by the federal Office of Management and Budget for the analysis of federal programs: https://www.wbdg.org/FFC/FED/OMB/OMB-Circular-A94.pdf and http://www.sfu.ca/~heaps/483/discounting.htm) |  |  |  |  |  |  |  |
| https://www.fhwa.dot.gov/tpm/guidance/avo_factors.pdf) <br> 2) 7\% discounting factor (recommended by the federal Office of Management and Budget for the analysis of federal programs: https://www.wbdg.org/FFC/FED/OMB/OMB-Circular-A94.pdf and http://www.sfu.ca/~heaps/483/discounting.htm) |  |  |  |  |  |  |  |
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| $\begin{aligned} & 0 \\ & 0 \\ & 8 \end{aligned}$ |  |  |  |  |  |  |  |





EB TMC Segment: Intersection US-82 @ SR-69

02/14/2019 - Thursday





## ATSPM: Oversaturation? or Crash?

Signal data collected for intersection US-82 @ SR-69, February 4, 2019

Advance Detector Data (~500ft upstream of EB US-82 @ SR-69)


Time of the Day






[^0]
[^0]:    A
    Conclusions - Alabama DOT Probe Data

    - Procuring Data
    -INRIX $2014 \rightarrow$ HERE 2016
    -Statewide Mobility Report
    - Processing and Managing Data
    - Real-time XML storage
    -TTI Conflation Process
    - Using Data

    1. Football Traffic Ticker (McNamara)
    2. Tracking Incidents (Li)
    3. Scoring incidents
    4. I-10 Cost of Doing Nothing (ATI)
    5. Signal Work (Not great...)
