Developing an Architecture to Integrate Safety, Mobility, and Traffic Data

Final Report
June 2021

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16. Abstract

The Iowa Department of Transportation (DOT) consumes data from multiple streams that are stored to assist in better decision-making. Despite access to unprecedented amounts of data, decision-makers are often restricted in their ability to explore multiple data sets. This research demonstrated a simple proof-of-concept architecture that addresses some of the constraints on decision-makers but also opens up additional data sets for the Iowa DOT or other researchers to explore without the additional time and effort needed to integrate the data. Users can spend additional time analyzing the data rather than interpreting and processing the raw data. Three data sets used for this demonstration include crash, INRIX probe, and weather data for the past five years.

The data integration methodology developed for both the weather and probe data is a multistep process with intermediate outputs created along the way that are needed for later steps in the integration. Seven outputs were created that are all related back to the crash data. The research team considered any potential output that may be beneficial for future integration efforts and outputted those as separate tables for future use. The primary outputs of the integration process are the weather and probe data at the time of the crash, which allow for the data to be joined directly with the crash data similar to other attributes collected or derived within the crash data. For advanced analysis, a Python script was also developed that allows the probe and weather data to be extracted for a configurable amount of time before and after each crash.

The Iowa DOT views this project as an initial effort to develop a system that enhances crash data reports by integrating additional data sources. The ultimate goal is to have a system that allows any pertinent data sets to be readily available when evaluating crashes and to be utilized within any safety and mobility decision-making. The work in this study has established a foundation to simplify the efforts to integrate additional data sources by associating the crash data to the Iowa DOT's linear referencing system (LRS).

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Principal Investigator
Skylar Knickerbocker, Research Engineer
Center for Transportation Research and Education, Iowa State University

Research Assistant
Sudesh Bhagat

Authors
Skylar Knickerbocker, Sudesh Bhagat, Zach Hans, and Anuj Sharma

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A report from
Institute for Transportation
Iowa State University
2711 South Loop Drive, Suite 4700
Ames, IA 50010-8664
Phone: 515-294-8103 / Fax: 515-294-0467
https://intrans.iastate.edu/

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EXECUTIVE SUMMARY

Purpose and Background

The Iowa Department of Transportation (DOT) consumes data from multiple streams that are stored to assist in better decision-making. Despite access to unprecedented amounts of data, decision-makers are often restricted in their ability to explore multiple data sets. In general, pre-canned reports are serially produced from individual sources of data and circulated to decision-makers without providing a comprehensive picture of the issue. Under the present setup, a simple query, such as how many crashes occur during congested conditions, cannot be answered easily and requires a dedicated research project. There are three main reasons for the inability of decision-makers to easily query mobility and safety trends, which are as follows:

- Current data architecture restricts queries across data sources.
- Data manipulation is not distributed and hence takes a significant amount of time for even a simple aggregate query, such as average snowfall per county for a given year.
- Lack of easy to visualize or natural-language based querying tool. It requires an expert to create complex programs to answer these simple questions, thus restricting decision-makers to answering a few critical questions rather than having an ability to query the whole database

This research demonstrated a simple proof-of-concept architecture that addresses some of the constraints on decision-makers but also opens up additional data sets for the Iowa DOT or other researchers to explore without the additional time and effort needed to integrate the data. Users can spend additional time analyzing the data rather than interpreting and processing the raw data. Three data sets were used for this demonstration that include crash, INRIX probe, and weather data for the past five years. The weather data utilized expands current capabilities beyond the existing research by using a grid across the entire state, allowing weather estimates statewide rather than the localized area surrounding a weather station. The demonstration architecture includes the following benefits over the existing system:

- Data from multiple sources are saved in a format that leads to extended ability to query across these data sources. Thus, queries, such as how many crashes occurred during snow and congested conditions, should be easy to perform.
- High-performance computing systems are used to store and manipulate the data, and hence the data processing time will be significantly reduced.
- The data set is available for visual queries. Decision-makers can visually filter and explore the data using a dashboard developed for the project.

Findings

The size of the weather and probe data can potentially exceed 20 TB in size over the five-year period analyzed for this project. The weather data consists of 61,395,552 records a day, while the probe data can reach over 72,000,000 records a day. With the size of data available, it is critical to develop systems that can automate the process of integrating and extracting the appropriate data. By implementing the processes described in this report, data can be made available to a larger user group that may not have the ability to extract the data themselves or do not regularly use the data to understand the nuances that must be considered when integrating the data.

The data integration methodology developed for both the weather and probe data is a multistep process with intermediate outputs created along the way that are needed for later steps in the integration. Seven outputs were created that are all related back to the crash data. The research team considered any potential output that may be beneficial for future integration efforts and outputted those as separate tables for future use. The primary outputs of the integration process are the weather and probe data at the time of the crash, which allow for the data to be joined directly with the crash data similar to other attributes collected or derived within the crash data. For advanced analysis, a Python script was also developed that allows the probe and weather data to be extracted for a configurable amount of time before and after each crash.

Crash and Weather Data Integration Process

The process of integrating crash and weather data focused on reporting weather conditions based on radar, weather models, and weather networks that can better estimate the conditions at the time of the crash. The weather data also introduced quantitative variables that can be utilized as compared to the existing qualitative variables in the crash data. The weather data provided a simple integration using a 0.01 decimal degree grid across the state to associate with each crash. Additional effort was needed to develop a storage and extraction system that allowed for fast and cost-effective querying. To achieve this, the size of the data was reduced through multiple methods: the data were partitioned to allow for better grouping of the data, and a big data querying service was utilized in Amazon Athena.

Crash and Probe Data Integration Process

Crash data are further limited in the ability to report traffic conditions at the time of a crash as compared to the weather data. Only a handful of fields are available in the crash data, which allow reporting traffic impacts with no single field directly reporting the traffic conditions. Probe data allow for expanded access to speed data that can be utilized with crash data to understand the speed at the time of a crash.

The crash and probe data integration required additional consideration as compared to the weather data due to the nature of how crashes occur on roadways and how probe data contains data for both directions of travel. In addition to these challenges, additional consideration was given to creating an integration method that can be utilized for other future integration. Instead of a simple spatial analysis identifying the nearest probe data segment to the crash, the crash and probe data segments were both related to the linear referencing system (LRS) for integration. This will simplify the process for integrating the crash data with other data related to the Iowa DOT Roadway Asset Management System (RAMS) in the future.

Crash Safety Tool

After developing the integration engine, a prototype online safety and operations evaluation tool was developed to explore the interactions between the crash, weather, and probe data. Methods of analyzing the data were explored to show the potential benefits of using the integration engine, but it is expected that future research efforts will be utilized to further explore and understand these relationships.

The online safety tool was developed similar to other safety data visualization at the Institute for Transportation (InTrans). The tool was developed in Tableau, which allows users to explore the data interactively by selecting charts and filtering the data to understand relationships between the various attributes. In total, 16 pages were created as part of the dashboard that includes commonly utilized attributes from the crash, weather, and probe data. The data utilized in the dashboard included the weather integration output and probe data integration output described in the previous section. The before/after crash outputs were also evaluated as part of a separate tool.

Conclusions

The current research literature shows that there is value in using weather and traffic data within safety analysis due to the impact these factors have on crashes. However, most literature shows that researchers often had to aggregate data sets, used a variety of different integration processes, and likely spent a considerable amount of time integrating the data. The architecture in this report identified the various data sets needed to support crash, weather, and traffic analysis and then developed a process to extract the data. The considerable size of the data required developing a pipeline that allowed the data to be stored cost-effectively while also reducing the time to query the data sets. The created outputs from these processes assign the attributes for the related weather and probe data to each crash, which can then be treated like all other crash data within Iowa.

The Iowa DOT views this project as an initial effort to develop a system that enhances crash data reports by integrating additional data sources. The ultimate goal is to have a system that allows any pertinent data sets to be readily available when evaluating crashes and to be utilized within any safety and mobility decision-making. The work in this study has established a foundation to simplify the efforts to integrate additional data sources by associating the crash data to the Iowa DOT’s LRS.

Additional data sets that can be used to enhance the crash data or used in future research based on input from the Iowa DOT and other relevant stakeholders include the following:

- Advanced Traffic Management System
- Snowplow automatic vehicle location (AVL)
- Winter road conditions
- Traffic and road weather snapshot and videos
- Pavement condition data

- Intersections
- Work zones

Future enhancements can be made to the architecture developed in this project to allow for additional summary statistics to be created for each crash as well as the ability to extract additional data for nearby road segments or weather grids. The summary statistics can include information such as the amount of precipitation for a defined amount of time before the crash, whether speeds were trending up or down before the crash, and whether speeds were impacted after the crash. The summary statistics can provide additional attributes but would require additional workflows to extract and summarize these data for other users. Limitations also exist within the architecture for understanding the impacts on traffic upstream and downstream of the crash. The current process can be modified to support extracting additional probe data for nearby segments. Finally, the weather data provided by the Iowa Environmental Mesonet also includes weather forecasts every six hours based on the same grid and attributes. The forecast data have not been explored fully and may have benefits in some applications.

Overall, the proof-of-concept architecture that was developed provides an initial step in integrating crash, weather, and traffic data for more widespread use within Iowa. It is expected that the integration of data will continue to expand in Iowa, opening up the use of additional data for more users.

INTRODUCTION

The Iowa Department of Transportation (DOT) consumes data from multiple streams that are stored to assist in better decision-making. The ideal scenario would be to have all of the data easily integrated so that users have all the information at their fingertips to make decisions that can improve safety or mobility. However, this is often not the case due to the storage of data in silos across an agency. The effort is compounded by the size and availability of different data sources. Most users do not have the time or resources to dig through the amounts of data that are available to find the relevant information that is needed.

Table 1 gives an example of some traffic operations related data sources including the amount of data that are available for each.

Table 1. Different traffic operations related data sources

Data	Memory	Per month
INRIX probe data	3.4 GB/day	102 GB
Wavetronix sensor data	1 GB/day	30 GB
Waze data	330 MB/day	10 GB
Work zone events	1 MB/day	0.03 GB
Weather data	17.9 GB/day	537 GB
Total	22.6 GB/day	678 GB

In addition to these sources, the Iowa DOT maintains a state-of-the-art crash repository as well as access to very detailed weather data through the Iowa Environmental Mesonet (IEM) at Iowa State University. The data archive of all these sources extends back for several years with the cumulative data size for the past five years of data in the range of 20 TB or more.

Despite access to an unprecedented amount of data, decision-makers are often restricted in their ability to explore these data sets. In general, pre-canned reports are serially produced from each of these individual sources of data and circulated to decision-makers without providing a comprehensive picture of the issue. Under the present setup, a simple query, such as how many crashes happen during congested conditions, cannot be answered easily and requires a dedicated research project. There are three main reasons for the inability of decision-makers to easily query mobility and safety trends, which are as follows:

- Current data architecture restricts queries across data sources.
- Data manipulation is not distributed, and hence takes a significant amount of time for even a simple aggregate query, such as average snowfall per county for a given year.
- Lack of easy to visualize or natural-language based querying tool. It requires an expert to create complex programs to answer these simple questions, thus restricting decision-makers to answering a few critical questions rather than having an ability to query the whole database

This research demonstrates a simple proof-of-concept architecture that addresses some of the constraints on decision-makers but also opens up additional data sets for the Iowa DOT or other researchers to explore without the additional time and effort it takes to integrate the data. Users can spend additional time analyzing the data rather than interpreting and processing the raw data. Three data sets were used for this demonstration that include crash, INRIX probe, and weather data for the past five years. The demonstration architecture includes the following benefits over the existing system:

- Data from multiple sources are saved in a format that leads to an extended ability to query across these data sources. Thus, queries, such as how many crashes occurred during snow and congested conditions, should be easy to perform.
- High-performance computing systems are used to store and manipulate the data, and hence the data processing time will be significantly reduced.
- The data set is available for visual queries. Decision-makers can visually filter and explore the data using a dashboard developed for the project.

Objectives

This project focused on enhancing the available crash data by developing a proof-of-concept architecture to integrate mobility and weather data. Processes were developed that allow for easy integration of weather and probe data with crash information that can support the determination of what role weather and traffic play in vehicle crashes. The processes allow for weather conditions at the time of the crash to be reported including quantitative variables, such as the amount of precipitation, road temperatures, and rainfall rates. Traffic conditions at the time of the crash are also available including the speed along the roadway, the speed in the opposite direction of travel, and the historical average speed at the crash location. For advanced analysis, the processes are customizable, which allows users to dynamically enter durations before and after the crash to extract the relevant probe and weather data. To support future efforts, the project team also integrated crash data with the Iowa DOT’s linear referencing system (LRS). This additional work allows for easier integration of data sets across the Iowa DOT using a common network for associating data sets. This research is expected to serve as the foundation for integrating additional data sets with historical crash data and a concept that can be implemented for additional data sets.

Once the architecture was developed, possible uses of the data were explored, including calculating the amount of precipitation on the roadway directly before the crash, the traffic conditions leading up to the crash, and estimating the impacts the crash had on traffic. A basic analysis was also completed to compare the existing weather data reported from the crash report to the additional detailed information in the weather data.

LITERATURE REVIEW

Crash data are typically self-contained and don’t incorporate data from other sources natively. In Iowa, crash data are limited to the information reported by law enforcement officers in crash reports as well as some roadway information based on how the crash is geo-located, including speed limit, system type, and rural/urban. Additional enhancements can be made to crash data to incorporate other data sources. Multiple research efforts have shown the value of integrating additional data sets including weather and probe data, which are described in this chapter.

However, integrating the data presents multiple challenges and barriers that many agencies and researchers face. Das et al. (2021) stated, “Key challenges include simplified models are preferred for ease of interpretation and usability, access to quality data of the type and quantity needed for a robust study is expensive, and sufficient analytical expertise for both the analyst and user may not be present.” Efforts are needed within an agency to improve data integration processes to reduce the cost of using quality data and allow users to focus on the analytical expertise needed for more robust analysis. Without these improved efforts, Das et al. (2021) described how simplified data can produce fundamentally flawed model predictions because critically important variables are omitted or only partially captured. This can lead to decisions with good intentions but based on insufficient information.

Weather and Traffic Data Integration Efforts

Various other research efforts have integrated weather and traffic data to support safety related research. Malin et al. (2019) integrated weather data with crash data in Finland. The research team purchased weather data that included variables, such as road surface temperature, wind direction, and road weather code. The weather reported was based on weather stations near each of the crashes.

In Kansas, Tobin et al. (2021) also related crash data to Automated Surface Observing System (ASOS) and Automated Weather Observing System (AWOS) stations but were limited by the number of counties with sites providing the precipitation type data needed for the study. The team found105 counties in Kansas had precipitation type crashes identified but only 42 counties had an ASOS/AWOS station, with varying levels of accuracy.

In Florida, AWOS data were evaluated to provide real-time visibility by Ahmed et al. (2014). The weather station data reported hourly were identified as a good predictor to assess safety on a highway but was limited to 5 nautical miles from the station. Chung et al. (2018) expanded on this effort to assess the viability of using Quality Controlled Climatological Data (QCLCD) by relating fatality crashes to weather stations within 20 mi nationwide. The study validated the reliability of the weather data for up to 20 mi from the station. Fatal crashes were the focus of the analysis, with 75% of crashes occurring within 20 mi of a weather station.

Cheng et al. (2017) utilized weather data for evaluating motorcycle crashes using Weather Underground, which obtains data from a variety of weather stations including personal weather stations. The data provided daily summaries of the weather data but were limited to a single city.

One suggestion from Theofilatos and Yannis (2014) about the gaps in weather and safety research was a recommendation on using interpolation methods with weather data for evaluating quantitative weather parameters, which can reduce the need to associate crashes with a specific sensor.

Benefits of Integrating Additional Weather Data

The research shows there are potential benefits to integrating additional weather data outside of what are reported in the crash data. Weather data have the ability to provide quantitative variables as well as more descriptive attributes about the weather conditions. In a majority of the research, individual weather stations were the typical method of identifying weather related data to supplement crash data. The limitation of this approach is the influence area of the station in representing the weather conditions at the location of the crash.

Additionally, based on the research, it appears that the data for a single sensor are typically associated to a crash based on proximity. In locations equidistant from two sensors, there does not appear to be any consideration of interpolating between the sensors or analyzing which station most likely represents the weather conditions at the crash location. Research efforts to integrate weather data and crash data were either developed or completed as part of individual projects, meaning they were not derived based on an existing system for extracting the data. Because of this, most of the research was limited to feasibility studies and/or assessments or were only completed for a subset of the data due to the limited availability of weather stations.

The final limitation with the existing research is based on the granularity of weather data. All research efforts utilized hourly or greater aggregations of weather data. Localized or quick-moving weather events may not be captured accurately based on hourly or daily level summaries. Crashes directly before a winter storm or a heavy rainfall event may be aggregated with data that are summarized over an hour or day and that do not capture the actual conditions at the time of the crash.

This research project attempts to address some of the limitations uncovered in previous research by extracting weather data for all crashes based on weather data sources, reducing the effort to obtain the weather data by aggregating data from various sources and providing five-minute aggregates of the data.

Benefits of Integrating Traffic Data

Using traffic data, such as probe data, to get operating speeds at the time of a crash is limited, and to date most research evaluating speed has used point detectors or other data collection methods. The increased availability of probe data has allowed for additional usage of these data into safety analysis, which in turn allows for more widespread analysis due to the greater coverage probe data provides in comparison to traditional data collection methods.

Ederer et al. (2020) used network conflation to relate data together based on a common network. A traffic message channel (TMC) network was used as the base network, with roadway features and crashes assigned to a given TMC segment. This was completed for a 72 mi stretch of roadway. The conflation process included validating the data based on route names. The crash data would be assigned a TMC if it was within 100 ft of the corridor and was verified as occurring on the route. This process is fairly comprehensive but provides limited future integration, as it is defined based on a network that may change over time instead of relating to a state DOT network, which has greater control over managing network-level changes.

Dutta and Fontaine (2019) discussed the difficulty in matching crash data with traffic data and evaluated the relationship various traffic data sources and aggregation levels have on crashes. The study found that using probe data increased the rural model performance by 10% and the urban model by 20%. Although the results are lower than using a continuous count station, the increased availability of probe data can be utilized on a larger scale for future efforts. Dutta and Fontaine (2020) also integrated probe vehicle data into their crash analysis and found that their model accuracy improved when speed attributes were added. Both efforts by Dutta and Fontaine utilized hourly and 15 minute speed aggregations for developing the crash models.

Hans et al. (2018) incorporated both traffic speed and weather data when evaluating winter weather crashes. The study investigated the potential use of other data sets, such as camera images and probe data, when evaluating winter weather events. When evaluating the probe data, each crash was associated with a TMC segment based on the crash timestamp. The 1 minute speed data were then extracted 60 minutes before and after the crash. The probe data were only utilized for evaluating crashes due to the large variations in speed and speed patterns. The data presented opportunities for future efforts evaluating traffic conditions. Road weather information system (RWIS) and Cooperative Observer Program (COOP) stations were used by associating each site to a crash based on proximity or based on reference post. The daily and annual snowfall data were utilized in developing safety performance functions based on reference posts.

Summary

Opportunities exist to utilize weather and probe traffic data to understand the impacts on crashes. Data for both sources have utilized aggregated methods for analysis or made assumptions when extracting data or relating to other data sources. Most efforts to date have spent a significant portion of the research on developing integration methods with slight differences depending on the type of data sources and the availability of data.

This research project has developed a proof-of-concept data architecture that allows for easier extraction of both weather and probe data in Iowa. The architecture will support future research and analysis by providing a uniform method of associating crash data to other sources and providing methods of extracting additional data sources. As part of the integration outputs, attributes from both the weather and probe data are assigned to each crash that can be treated like all other data within the Iowa crash database. This allows for novice users or basic analysis to utilize weather and probe data with no additional effort.

Additional processes will be established that allow for easy extraction of additional data before and after the crash that can be utilized in more advanced analysis. This effort focuses on the integration process and creating the pipelines to extract the data but will show some potential use cases of the data. It is expected that future research will utilize the data output and process to improve weather, traffic, and crash related efforts moving forward.

DATA SOURCES

This chapter provides an overview of the data sources identified and used for integration. The data sources focus on the ability to provide actual conditions of the traffic and weather at the time of the crash. The data sets include the following:

- Iowa DOT crash data
- Weather data provided by the IEM
- INRIX probe data
- Iowa DOT Roadway Asset Management System (RAMS)

This project focused on all crashes statewide and provided any additional traffic or weather data that were available. Only crashes after 2015 were considered, due to the changes in reporting on the crash form in 2015. For the weather and crash integration, data were available for all crashes based on the availability of the data from the IEM. For the probe data and crash integration, the probe data from INRIX was only available on a subset of roadways—all primary roadways plus some additional roadways—so not all crashes had traffic information available.

Crash Data

The Iowa DOT crash database was provided by the Traffic and Safety Bureau and includes all crashes reported on public roadways resulting in an injury or minimum property damage of at least $1,500. The crash data includes multiple levels of information including crash-level information, vehicle-level information, and person-level information. For this effort, only crash- and vehicle-level information were used for integration. The crash data primarily uses data inputted in the crash report but also include derived data elements.

The way crash locations are geocoded can present challenges when integrating with other data sources. Crashes are geocoded in Iowa using an Incident Location Tool (ILT) within the Traffic and Criminal Software (TraCS) used by law enforcement agencies. The current ILT utilizes the Geographic Information Management System (GIMS) network, which represents all roadways in Iowa as a single centerline and not directional. Before 2017, GIMS was the primary asset management system in Iowa. Starting in 2017, the Iowa DOT moved to the RAMS, which allows for divided roadways but has not been fully implemented as part of the TraCS. Beginning in 2021, some law enforcement agencies have begun using the ILT that utilizes RAMS. This difference in geocoding presents challenges for users wanting to use RAMS as the integration methodology because only a small subset of the data is available.

Weather Data

The Iowa DOT and the Institute for Transportation (InTrans) worked with the IEM, a group that collects and archives weather from cooperating members with weather observing networks, to create an archive of weather data that can be used for transportation related research. Throughout the literature review, researchers have used weather station data but were limited in interpolating data between sensors or easily identifying the station representing a given location. As part of the coordination with the IEM, a grid across the entire state of Iowa was created and a process was developed to archive the weather data for each grid every five minutes. The grid across the state is represented as simple rectangles with a resolution of 0.01 decimal degrees in both directions. Figure 1 shows a map of the grid in the Ames area, where each black square represents a grid where weather data are reported.

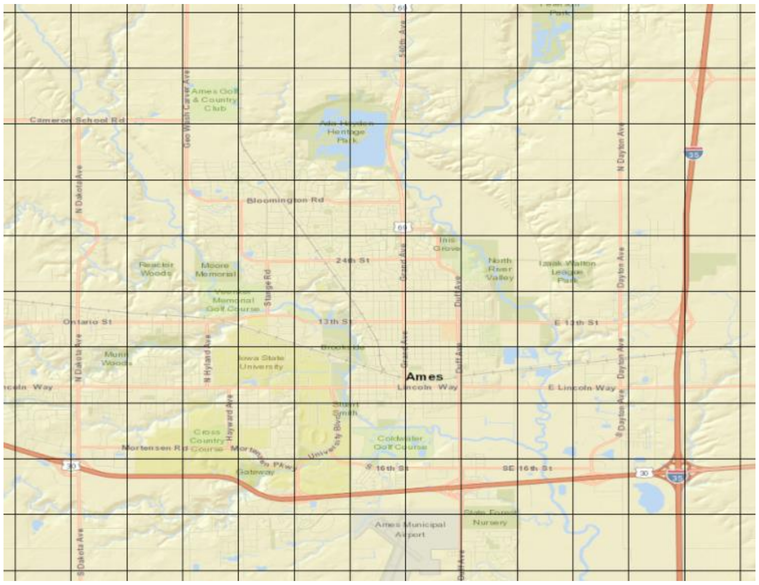


Figure 1. Grid resolution for an area around Ames

The weather data archived every five minutes comes from a variety of sources including the National Weather Service (NWS), the National Oceanic and Atmospheric Administration’s (NOAA’s) Multi-Radar/Multi-Sensor System (MRMS), the Federal Aviation Administration (FAA) weather stations, the Iowa DOT RWISs, the NWS COOP, and the Iowa State University Soil Moisture Network. The source of each data element is described in the actual weather output in the Data Integration Methodology chapter of this report.

The weather data are delivered as zipped JavaScript Object Notation (JSON) formatted files and uploaded to a file server. The extracted size of the data averages 17.9 GB per day and contains 61,395,552 records. Because of the size of the data, the weather data are difficult to work with and processes are needed to extract the relevant information.

Probe Data

The Iowa DOT currently procures probe data through INRIX. Probe data uses crowdsourced probe vehicles to estimate the vehicle speeds along a given section of roadway. This service provides traffic speed data every minute along a subset of the roadways in Iowa, including all primary roadways. The segmentation currently used by INRIX is XD Segmentation, which attempts to create roughly 1 mi long segments across the state. The segmentation is based on logical breaks in facilities where changes in traffic conditions may exist, including interchanges or major at-grade intersections. The XD segmentation is proprietary but provides greater resolution than TMC segments. For each minute, INRIX provides the current speed, the historical average speed, a free-flow speed, travel time, and data confidence scores for each segment across the state. These data are archived and available for integration with other data sources for analysis or performance reporting.

RAMS Data

Integrating data across the Iowa DOT and other agencies typically utilize an LRS. An LRS allows for data to be integrated based on a common network without any additional spatial analysis. The Iowa DOT LRS is part of the RAMS in Iowa and includes additional roadway features, such as the number of lanes, speed limit, and annual average daily traffic (AADT). In Iowa, the LRS is commonly referred to as RAMS. The RAMS network was utilized in this effort to integrate the crash and probe data but will also allow for additional integration in the future with minimal effort.

The LRS provides complete information for all roadways in Iowa and is managed through a Geographic Information System (GIS) interface. Coordinates can be passed to the LRS through a representational state transfer (REST) service that conflates the data to the network and returns a RouteID and Measure for all routes within a defined distance. The RouteID and Measure values are fundamental to locating the data spatially as well as integrating across data sources. RouteID represents the route the location is on, and Measure represents the distance along the route. The RouteID and Measure values obtained by conflating can be used through a database function to relate other spatial data without the computational expense for similar GIS related tasks.

One challenge when working with RAMS is that all routes are included in the network, but asset information is only associated with the most dominant route along the roadway. For example, if two interstates are signed along the same stretch of roadway, both routes will be present along the roadway but only one of the routes will be the dominant route that contains the asset information. When integrating data, route dominance must be factored into the assignment priority to ensure data can be integrated with other data sources.

DATA INTEGRATION METHODOLOGY

With the size of data available from both the probe and weather data, it is critical to develop systems that can automate the process of integrating and extracting the appropriate data. By implementing the processes described in this report, data can be made available to a larger user group that may not have the ability to extract the data themselves or regularly use the data to understand the nuances that must be considered when integrating the data. The outputs of the process ensure consistent integration across various research and other efforts within the Iowa DOT. This chapter describes the process used to integrate the data, which can serve as a proof-of-concept on data integration efforts within the Iowa DOT on a system wide basis and an example for future data integration with crash data.

This chapter is divided into two parts. The first part describes the outputs created as part of the data integration. Each of the outputs is described in detail including a description of all fields included in the outputs. The second part of this chapter describes in detail the process used to integrate the crash, weather, and probe data.

Date Integration Outputs

The data integration methodology for both the weather and probe data is a multistep process with intermediate outputs created along the way that are needed for later steps in the integration. Some intermediate outputs have value outside of the integration process described in this report and are archived to support other integration efforts in the future. Figure 2 provides a high-level overview of the seven outputs created and how each of those are related back to the crash data.

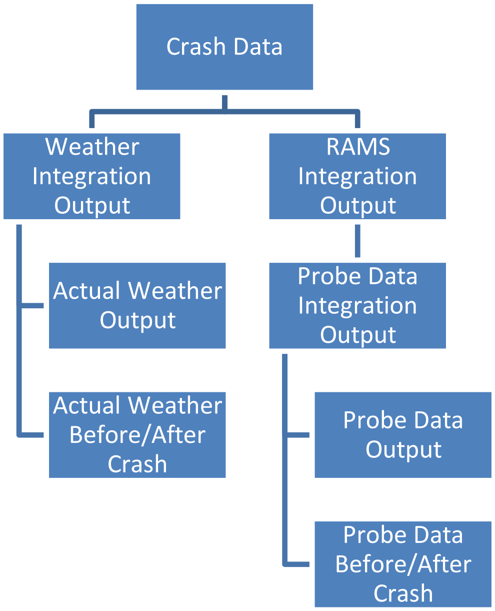

Crash Data
Weather Integration Output
RAMS Integration Output
Actual Weather Output
Probe Data Integration Output
Actual Weather Before/After Crash
Probe Data Output
Probe Data Before/After Crash

Figure 2. Overview of the outputs of the data integration process

The weather and crash data provide three outputs. The first output creates an integration layer between the unique identifiers for the crash data with the unique identifiers for the weather data. This integration layer is then used when extracting the weather data to create the actual weather output, which includes the weather at the time of the crash, and the actual weather before/after crash, which includes the weather for a configurable amount of time before and after the crash.

The RAMS integration output in Figure 2 is an example of an intermediate output that does not specifically relate to either the crash or probe data. The output provides the RouteID and Measure value for each crash along the LRS network and will be beneficial for any future efforts that utilize the LRS for integration without the need of re-conflating the crash data to the LRS. Any other intermediate outputs that could have use in the future were retained and described within this section.

Weather Integration Output

The weather integration output identifies the relationship between the crash data and the weather grid developed by the IEM. Each of the 0.01 decimal degree rectangles in the weather grid are assigned a unique identifier named gid. The gid is then associated to the unique CRASH_KEY identifier in the crash data. The output of this process represents a one-to-one relationship between the unique identifiers. The following fields are included in the output:

- **CRASH_KEY** – The unique identifier to relate back to the crash data.
- **gid** – The unique identifier for the weather data based on a simple rectangular grid of the state of Iowa. Each grid rectangle has a resolution of 0.01 degrees in both directions.
- **DateTime –** The timestamp reported for the crash.

Actual Weather Output

The actual weather output extracts the weather data at the time of the crash. This output uses the weather integration output to pull the weather data for the given gid at the time of the crash. The weather data are available every five minutes, so the crash time is rounded to the nearest five-minute time period for extraction. The following describes the fields provided in the weather data from the IEM and associated to each crash:

- **CRASH_KEY** – The unique identifier to relate back to the crash data.
- **gid** – The unique identifier for the weather data based on a simple rectangular grid of the state of Iowa. Each grid rectangle has a resolution of 0.01 degrees in both directions.
- **wawa** – These are watches, warnings, and advisories issued by the NWS. These alerts do not cover all alert types issued by the NWS, just those that contain a special coding called Valid Time Event Code (VTEC).
- **ptype** – This field is directly generated from the NOAA MRMS project. The integer codes in Table 2 present the state of precipitation being estimated by radar and model algorithms.

Table 2. Coded values for ptype field

Code	Value
-3	no coverage
0	no precipitation
1	warm stratiform rain
2	warm stratiform rain
3	snow
4	snow
5	reserved for future use
6	convective rain
7	rain mixed with hail
8	reserved for future use
9	flag no longer used
10	cold stratiform rain
91	tropical/stratiform rain mix
96	tropical/convective rain mix

- **tmpc** – Two meter above ground level air temperature. This value would be over a typical landscape for the location and not necessarily concrete, except in very urban areas. Units are Celsius.
- **dwpc** – Two meter above ground level dew point temperature. As with tmpc, the same landscape assumptions apply. Units are Celsius.
- **smps** – Ten meter above ground level wind speed. This speed does not include gusts but is some average over a couple of minute period. Units are meters per second.
- **drct** – Wind direction, where the wind is blowing from, at 10 m above ground level. Units are degrees from North.
- **vsby** – Horizontal visibility from automated sensors. Units are kilometers.
- **roadtmpc** – Pavement surface temperature derived from available RWIS reports. These reports include both bridge and approach deck temperatures. Units are Celsius.
- **srad -** Photoactive global solar radiation, sometimes called shortwave down. Units are watts per meter squared.
- **snwd** – Snowfall depth analyzed once per day at approximately 7 a.m. local time. If the reported snowfall depth was zero at 7 a.m., and it started snowing at noon, this field would still be zero until it updated the next day at 7 a.m. Units are millimeters.
- **pcpn** – Five minute precipitation accumulation ending at the time of analysis. This is liquid equivalent. Snow and sleet are melted to derive this value. Units are millimeters accumulation over those five minutes.
- **cst-time** – The timestamp of the weather data reported in local Central Time for easier integration with other data sets.

Actual Weather Before/After Crash Output

For some analysis, additional weather data before and after the crash event are needed. This can be used to understand the weather impacts leading up to the crash or for better refining the weather at the time of the crash, since the reported crash time is an estimate.

A separate process was developed for more advanced analysis that allows for users to enter the amount of time before or after the crash and return the weather data during that time period. The output fields from this process are the same as the actual weather output but result in a one-to-many relationship with the crash data. The number of records returned will depend on the amount of time before and after the crash requested by the user. All five-minute time periods within the defined time before and after the crash will be returned. The cst-time field can be compared with the crash timestamp to determine the amount of time before or after the crash the weather data represents.

RAMS Integration Output

The RAMS integration output identifies the relationship between the crash data and the Iowa DOT LRS, referred to as RAMS. By relating the crash data to the LRS, multiple other data sources can be integrated with the crash data in the future based on a simple linear overlay. The output of this process represents a one-to-one relationship with each crash given a RouteID and Measure for the dominant route it is comparable with. It is expected that future crashes will have the RouteID and Measure collected as part of the crash reports once the RAMS-based ILT is fully implemented. The following fields are included in this output:

- **CRASH_KEY** – The unique identifier to relate back to the crash data
- **RouteID** –The route identifier for the Iowa DOT's LRS
- **Measure** –The measure along the route for the given route in the Iowa DOT's LRS

Probe Data Integration Output

The probe data integration output identifies the relationship between the crash data and probe data. The probe data XD segments are related to the Iowa DOT's LRS, which can be used in coordination with the RAMS integration output to perform a linear overlay. The linear overlay compares RouteID and Measure values within both data sets to determine where overlaps occur. The overlay results in each crash key unique identifier being associated with unique identifiers for the INRIX XD segments. The output of this process represents a one-to-many relationship as both directions of travel in the probe data can be present along the roadway. The following fields are included in this output:

- **CRASH_KEY** – The unique identifier to relate back to the crash data
- **XDSegID** – The unique identifier for the INRIX probe data segment
- **DateTime –** The timestamp reported for the crash

Probe Data Output

This output uses the probe data integration output to pull the probe data for the given XDSegID at the time of the crash. The probe data are archived every minute with the speed, historical speed, average speed, etc. The output of this process is a one-to-many relationship because probe data contains traffic data for both directions of travel. Because of the nature of crashes, both directions of travel may be impacted and can be valuable for analysis. The following describes the fields provided by INRIX and associated to each crash:

- **CRASH_KEY** – The unique identifier to relate back to the crash data.
- **XDSegID** – The unique identifier for the INRIX probe data segment.
- **cvalue** – The confidence value of the data from 0–100 when the data reported is real-time (conf = 30).
- **segmentclosed** – Indicator if the road is reported as closed.
- **conf** – The score of the data to determine the source of the speed data. A score of 30 indicates real-time data, a score of 20 indicates the historical average speed, and a score of 10 indicates the reference speed.
- **speed** – The current speed along the roadway reported in miles per hour.
- **average** – The historical average speed for the given section of roadway based on the time of day reported in miles per hour.
- **ref_speed** – The traffic speed under free-flow conditions in miles per hour.
- **travelTime** – The travel time along the segment in minutes.
- **cst-time** – The timestamp of the weather data reported in local Central Time for easier integration with other data sets.

Probe Data Before/After Crash Output

Similar to the weather data before/after crash output, some advanced analysis may require additional probe data to understand the traffic conditions before and/or after the crash or to quantify the impacts the crash had on other motorists.

An additional process was developed that allows users to define the amount of time before and/or after the crash, which then returns the probe data during that specified time. The output fields from this process are the same as the probe data output. The probe data already contains a one-to-many relationship with the crash data due to the multiple directions available in the probe data, but additional outputs are created for each minute defined by the user when extracting the data. The cst-time field can be compared with the crash timestamp to determine the amount of time before or after the crash the probe data represents.

Data Integration Process

Integrating data can be a challenge due to the assumptions and limitations of each data source. The challenges can be related to how the data are geo-located, the spatial coverage of the data, or how the data are collected/derived. All of these must be considered when integrating data to ensure that the data are correctly related for analysis. This section describes the integration effort related to crash, weather, and probe data so that meaningful information is created that can support weather and traffic related safety analysis. Two separate processes were created for data integration including a process to integrate crash and weather data as well as a process to integrate crash and probe data.

Crash and Weather Data Integration Process

The weather data reported within the crash data are limited to only a handful of fields that describe in simple definitions the weather conditions, the road surface conditions, and any environmental contributing circumstances. Each of these are limited in what information can be provided, which in turn limits the amount of details differentiating a minor weather event from a major weather event. These details as well as various other weather impacts can be utilized to improve safety related models and analysis to capture potential contributing conditions to crashes. In addition, the reports are subjective based on the law enforcement officer submitting the form or what was relayed to the officer by the driver(s) involved in the crash.

The process of integrating crash and weather data focuses on reporting weather conditions based on radar, weather models, and weather networks that can better estimate the conditions at the time of the crash. The data also introduces quantitative variables that can be utilized as compared to the existing qualitative variables in the crash data. The crash and weather data integration are divided into four steps—which include the three weather related outputs described in the previous section—and are described in this section.

Step 1: Combine Crash Data with Weather Shapefile

The initial step of integrating crash and weather data is a simple spatial relationship between any crash point contained within the weather grid provided by the IEM. The output of the process assigns a gid, the unique identifier for each weather grid, to each CRASH_KEY, which is the unique identifier for each crash. Figure 3 shows an example of the crash data, represented as points on the map, and the weather grid, which is represented by the black squares across the map.

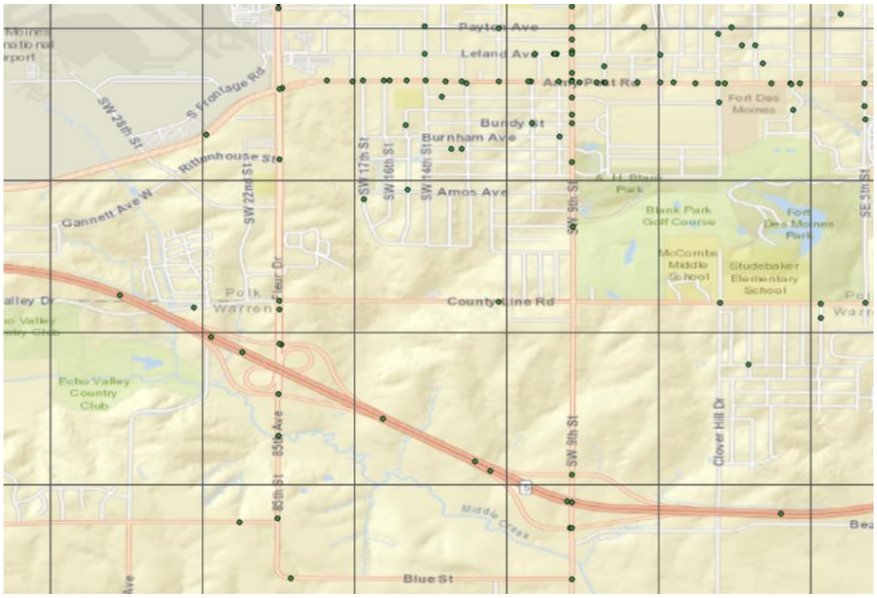


Figure 3. Weather grid and crash data points

Each of the crash points is assigned the gid that they fall within. The process creates a one-to-one relationship between crash data and weather grid, with the exception of any crashes that are not geo-located. The output of this process was described previously as the weather integration output. This output is used in later steps in the process to extract the weather data but may have other uses for future integration including extracting forecasted weather data or identifying weather surrounding the crash based on the relationships within the weather grid. This process was repeated for all crash data from 2015 through 2020.

Step 2: Extract Weather JSON Files

As described in the data description, the size of the weather data averages 17.9 GB per day and generates 61,395,552 records per day. The weather data would extrapolate to around 6.5 TB per year or 39 TB for the entire analysis period from 2015 through 2020. The data are initially stored as zipped JSON files that cannot be queried for data extraction. To support the data integration architecture, a process was established to extract these data on a daily basis back to 2015. As part of this extraction, multiple factors were considered to increase the speed of queries including reducing the size of the data, partitioning the data appropriately, and providing a query service to work with the data that minimizes cost.

Two methods were used to decrease the size of the data. The first involved decreasing the amount of records in the data sets by removing any grids that did not have an Iowa public roadway within the grid. This removed any grids that were located in the middle of farmland, lakes/rivers, or in surrounding states due to overlaps in Nebraska and Illinois. Multiple methods were evaluated to remove grids, but the research team chose to keep only the grids with public roadways so that the data could be used for any future efforts incorporating weather data related to transportation research. By eliminating these grids, the size of the data was reduced to 10.1 GB per day. The second method of reducing the size of the data involved converting the data to a

Parquet format. Parquet is an open-source file format used within the Hadoop ecosystem and designed to efficiently reduce storage size. After changing the file format, the size of data was further reduced to 0.35 GB per day.

Reducing the size of the data has the value of increasing query speed, but additional partitioning of the data can further reduce the time to query the data while also reducing cost. Partitioning involves dividing the data into smaller components but grouping similar data together based on common queries from users. This increases the query speed because all of the data does not need to be scanned with each query. Instead, only the relevant partitions are scanned and queried, reducing the time needed to return results. For the weather data, the data were partitioned by month, day, and hour.

Finally, a query service was utilized that allows for fast and interactive queries of big data sets, such as the weather data. To perform the queries, Amazon Athena was used, which is a serverless query service that allows for SQL queries to extract data stored on Amazon S3. This allowed the weather data to be stored similar to other traffic operations related data and allow for easier querying of the data to identify weather at the time of a crash.

When working with cloud-based services, such as Amazon Athena, cost must be considered throughout the process. The first cost that must be considered relates to the size of the data. By reducing the amount of data stored and converting the data to the Parquet format, the amount of data stored was reduced and allows for a longer duration of data to be retained. Most cloud services charge based on the amount of data scanned for a given query as well. If the entire database must be scanned for every query, then additional cost will be incurred. By partitioning the data, Athena can be used to query only the relevant partitions, reducing the amount of data scanned, which in turn reduces the total cost of each query.

When extracting the data from the JSON files, the original data from the IEM remains intact, but additional fields are added for the three partitions as well as an additional field that converts the coordinated universal time (UTC) timestamp to local Central Time to allow easier integration with other data sources. All partitions of the weather data are also based on local Central Time.

Step 3: Join Weather and Crash Data at Time of Crash Files

With a relationship between the crash and weather grid established in Step 1 and the weather data stored in a format that allows for querying of the database, a process was developed that extracts the weather reported through the IEM grid analysis for the five-minute time period in which the crash occurred. A simple Python script was used to query both the crash data and weather data in Athena and then join the weather data to the crash data. Initial testing to optimize the process was completed using PySpark and could be used in future efforts with larger data sets.

The crash data are reported for the specific minute the crash occurred, while the weather data are reported every five minutes. In most situations, the crash timestamp is an estimate of when the crash occurred, and it was rounded to the nearest five-minute time period to extract the corresponding weather data.

Once the join is complete, the actual weather output is created, which extracts all of the weather data reported by the IEM for the corresponding crash key. This output is similar to other z-tables as part of the crash data in Iowa and can be joined directly with the crash-level data for analysis. The join is a one-to-one relationship, meaning the data can be used similar to all other available fields in the crash data.

Step 4: Extract Additional Weather Data Before and After the Crash

Some users may require additional weather data before and/or after a crash. An additional process was established that allows users to dynamically enter the number of minutes before or after the crash to return additional weather data for analysis. For example, a user may want to request weather data 30 minutes before a crash and 15 minutes after a crash. The users can enter these values into the Python script and the corresponding 45 minutes of weather data will be returned for each crash. The process uses the actual time of the crash instead of the timestamp that was rounded to the nearest five-minute time period. The output corresponds to the actual weather before/after crash output described previously.

Crash and Probe Data Integration Process

Crash data are limited in the ability to report the traffic conditions at the time of the crash. Iowa only recently added a secondary crash field in 2018. Any additional traffic related information is only a subset of a larger category, such as roadway contributing conditions. This means that it is up to the law enforcement officers inputting the data to select the primary roadway contributing condition, which includes other options, such as work zones, debris, and disabled vehicles. Because of this, any actual impacts to traffic are not easily identifiable within the crash data.

Even with the given fields, the magnitude of the impact traffic had on the crash or the impact the crash had on traffic is not conveyed in the crash report. There is no ability to identify whether the traffic conditions at the time were recurring based on historical data or some other non-recurring slowdown. The process of integrating crash and probe data focuses on reporting traffic conditions based on readily available probe data in Iowa for all primary roadways in Iowa as well as some additional major roadways. Similar to the weather data, the probe data reported provides quantitative variables as compared to the limited qualitative variables in the crash data.

The crash and probe integration requires additional consideration as compared to the weather data due to the nature of how crashes occur on roadways and how probe data contains data for both directions of travel. In addition to these challenges, additional consideration was given to creating an integration method that can be utilized for other future integration. Instead of a simple spatial analysis identifying the nearest probe data segment to the crash, the crash and probe data segments were both related to the LRS for integration. This will simplify the process for integrating the crash data with other data related to RAMS in the future. The following steps describe the process used to integrate the crash and probe data, which include the four RAMS and probe data related outputs described in the previous section.

Step 1: Integrate Crash Data with the RAMS

Similar to most DOTs, the Iowa DOT utilizes an LRS, which allows the agency to manage assets but also easily integrate data sources based on a common referencing system. To relate data to the LRS, RAMS provides a REST service query using ESRI Roads and Highways where coordinates can be entered, which then returns route identifiers and measure values within a given distance. As described previously, the LRS was chosen for the integration method for crash and INRIX data primarily to ease the integration with other data sets that are also related to the LRS in the future. In addition to future integration, the LRS also provides some additional control when relating the crash data and INRIX segmentation that are not possible with a simple spatial join.

The Iowa DOT currently has a process established to relate the INRIX XD segments using RAMS, which provides a RouteID, FromMeasure, and ToMeasure for each XD segment. The details of the process are not discussed in this report but involve using multiple points along an XD segment to determine the correct route in the LRS with which the segment should be associated. The crash reporting system in Iowa is currently moving toward locating crashes based on RAMS, which would provide a RouteID and Measure value for each crash. Any historical crash data, though, are based on the previous GIMS road network, which contains a single centerline for divided roadways. This step in the integration takes the historical crash data and provides RouteID and Measure values for all crashes from 2015 through 2020. This same process can be used for any future crashes until RAMS is fully integrated in the crash reporting system for all crashes.

Conflating points to a network presents additional challenges compared to linear features. For linear features, the line can be broken up into multiple points, and the most common route the points are associated with can be selected. This is not possible for points, which can be related to a line in any direction. Because of this, multiple other factors must be considered. There are two primary challenges to overcome when relating the crashes to the LRS network. The first involves associating crashes to the LRS/RAMS network when the crash data are located on a single centerline. Figure 4 shows an example, where the blue pin represents a crash and the pink and purple lines represent the RAMS network with which the data are being associated.

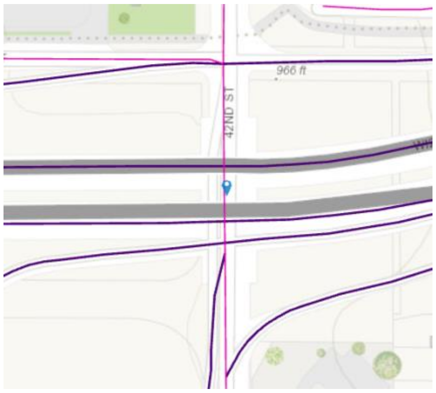


Figure 4. Issues with crashes located on single centerline

In this situation, the crash is actually on the main divided roadway, but if using only the nearest roadway, it would be incorrectly associated with the local cross street. With crashes representing only a single point, additional information is needed to ensure that the crash is associated to the correct route. A ranking process is described in this section that identifies all potential routes within a distance of the crash and then compares data within the crash data to roadway asset information to identify the most likely route on which the crash occurred.

The second challenge involves the nature of crashes not being related to a single direction of travel. This occurs on divided roadways but is also common at intersections. The LRS network is directional, so a crash could be related to multiple RouteIDs, but doing this can cause data management issues since users expect a single record for crashes. In the same example shown in Figure 4, the crash could involve a vehicle crossing the median and striking a vehicle from the opposing direction of travel. A case could be made to either represent the crash on the RouteID for both directions of travel or to relate it to only a single RouteID. The research team ultimately decided to identify the most likely RouteID and assign each crash to a single RouteID. A secondary process could be used to identify whether the opposite direction RouteID would need to be extracted or, when an intersection database is available, associate the crash to each approach for the intersection.

To begin the association of the crash data to the LRS, the first process involves querying all of the potential routes surrounding the crash. The ESRI Roads and Highways REST service query was used to provide the coordinates for each crash and then return all of the routes that are present within 70 m. An example of the returned points along a route are shown as the orange pins in Figure 5, where the crash location is represented by the blue pin.

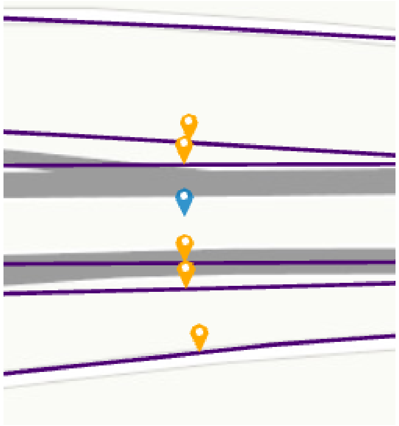


Figure 5. Identifying routes within 70 m of crash

The results returned also include any concurrent routes within the LRS. Concurrent routes occur when there are two signed routes along the same roadway.

Within the Iowa DOT’s system, route dominance is used when concurrent routes exist as well as when only a single centerline is used on undivided roadways. Route dominance is important because data in the RAMS are only related to the most dominant route at a given location. The crash data does not rely on the route dominance and could have been related to a non-dominant route. Because of this, each concurrent route in the initial query is retained in case the crash includes information about a less dominant route. The dominant route information is needed for all routes associated to the crash to identify the attributes, such as the speed limit. To do this, each of the coordinates for all routes associated with a crash are then processed again through the ESRI Roads and Highways REST service but using a tolerance of 0 m to find all concurrent routes at the given location. A route dominance function was then used to identify the most dominant route at the given location based on the RouteID structure depicted in Table 3.

Table 3. Iowa LRS network route identifier structure

Field name	Route-Description	Geo-Identifier	Sys-Code	Route-No	Direction	Ramp
Field size	1	4	1	4	1	4
Field description	S – State C – County M – Municipal P – Parks I – Institution	FIPS Code County No Municipal Code Parks No Institution No	1 – Interstate 2 – US 3 – Iowa 4 – Local	Actual No Sequential Sequential Sequential Sequential	N S E W	
Example route identifiers						
M058741265N	M	0587	4	1265	N	-
S001920018E5155	S	0019	2	0018	E	5155

With all of the associated routes and the corresponding dominant route for each, the data needed from both the crash and routes can be extracted for the ranking process. After exploring the relationships between the crash and routes, the research team determined that the primary fields that can assist in matching the crashes to a route include the following: direction, speed limit, route number, route system, and whether the roadway was a ramp. For the routes, the speed limit can be extracted by performing an overlay using the dominant route and measure value with the speed limit layer in RAMS. The resulting output returns the speed limit along the route. Additional attributes are also coded based on the structure of the RouteID in Table 3 and include the following:

- RouteRamp – Indicator given if the route is a ramp, based on whether characters 12–15 are used in the RouteID
- RouteDirection – The direction of the route based on the 11th character in the RouteID
- RouteSystem – The system type of the route based on the 6th character in the RouteID
- RouteNumber – The route number of the route based on characters 7–10 in the RouteID

The second challenge mentioned previously described issues with crashes involving vehicles traveling in multiple directions. The crash data contains multiple recorded directions including the Cardinal, LaneDir, and InitDir, which all represent different information. The Cardinal direction, for which the domains are shown in Table 4, is a derived field based on the direction of all of the vehicle(s) involved in the crash.

Table 4. Cardinal direction domains

Code	Value
1	Northbound (NB)
2	Eastbound (EB)
3	Southbound (SB)
4	Westbound (WB)
5	Both North and South
6	Both East and West
7	Ramp
8	No Travel Direction Consistent with Route
9	Unknown - Not Indicated - Unlocated

The field is intended to provide a high-level summary of the crashes but does have situations where no travel direction is reported. The Cardinal field also has the added benefit of providing the ability to identify if the roadway is a ramp. Because of the potential for the Cardinal direction not reporting a direction, the LaneDir is used, which is based on the road that the location tool associates the crash, with the domains for this field shown in Table 5.

Table 5. LaneDir domains

Code	Value
1	NB/EB
2	SB/WB
4	Contains both strings
77	Not reported

This field again can potentially cause issues if a direction is not reported, so the InitDir can be used, which is a vehicle-level attribute and provides the direction of travel for each vehicle in the crash. The available domains for the InitDir are shown in Table 6.

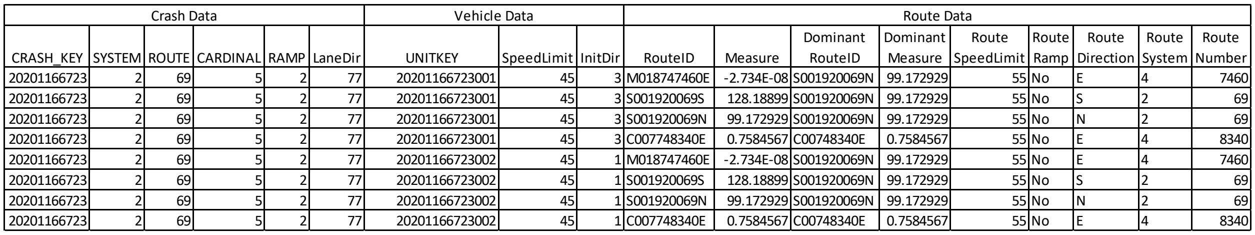
Table 6. InitDir domains

Code	Value
1	North
2	East
3	South
4	West
99	Unknown
77	Not reported

At this point in the process, each crash is associated to all routes within 70 m, and the attributes needed from the LRS routes have been obtained for ranking. Because the InitDir can provide information about the travel direction of vehicles involved in the crash, it is needed as part of the ranking process to identify the correct route. The InitDir is only available at the vehicle level, so the crash data must be joined to the vehicle-level data based on the CRASH_KEY, which is the unique identifier for each crash. In addition, the speed limit data for the crash is also only available in the vehicle-level information and can be extracted by joining the vehicle-level data to the crash data. Joining the vehicle-level data replicates all of the routes and crash data for each vehicle involved in the crash.

An example of this is shown in Table 7, where the first four records show the output after the crash data are related to the routes. Since the crash involved two vehicles, the total number of records increased to eight with each vehicle being related to each of the routes associated with the crash.

Table 7. Output of crash, vehicle, and route data for ranking



Crash Data						Vehicle Data			Route Data								
											Dominant	Dominant	Route	Route	Route	Route	Route
CRASH_KEY	SYSTEM	ROUTE	CARDINAL	RAMP	LaneDir	UNITKEY	SpeedLimit	InitDir	RouteID	Measure	RouteID	Measure	SpeedLimit	Ramp	Direction	System	Number
20201166723	2	69	5	2	77	20201166723001	45	3	M018747460E	-2.734E-08	S001920069N	99.172929	55	No	E	4	7460
20201166723	2	69	5	2	77	20201166723001	45	3	S001920069S	128.18899	S001920069N	99.172929	55	No	S	2	69
20201166723	2	69	5	2	77	20201166723001	45	3	S001920069N	99.172929	S001920069N	99.172929	55	No	N	2	69
20201166723	2	69	5	2	77	20201166723001	45	3	C007748340E	0.7584567	C00748340E	0.7584567	55	No	E	4	8340
20201166723	2	69	5	2	77	20201166723002	45	1	M018747460E	-2.734E-08	S001920069N	99.172929	55	No	E	4	7460
20201166723	2	69	5	2	77	20201166723002	45	1	S001920069S	128.18899	S001920069N	99.172929	55	No	S	2	69
20201166723	2	69	5	2	77	20201166723002	45	1	S001920069N	99.172929	S001920069N	99.172929	55	No	N	2	69
20201166723	2	69	5	2	77	20201166723002	45	1	C007748340E	0.7584567	C00748340E	0.7584567	55	No	E	4	8340

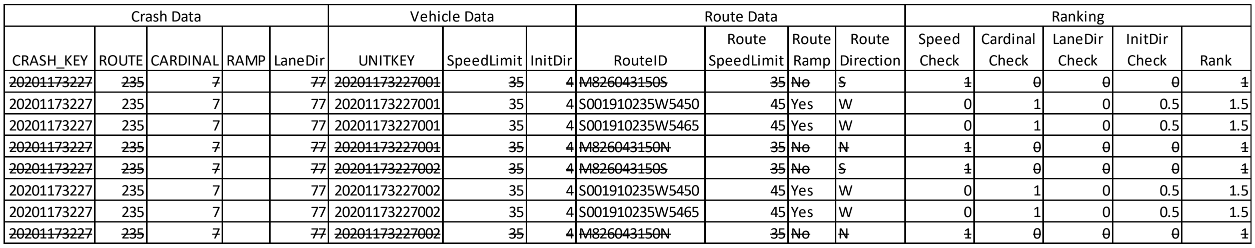
All eight of these records are ranked to determine the most appropriate route associated with the crash. Table 7 also displays all of the fields used for the ranking from the crash, vehicle, and route data.

With all of the attributes and records identified, the ranking process to identify the correct route to each crash can be completed. A two-stage ranking process was implemented, where all records are ranked based on an initial set of variables. The top-ranked records are retained and then ranked again based on additional variables. The initial ranking involved adding points to a records rank if attributes in the crash data are equal to attributes in the route data. The following logic was implemented for the initial ranking:

- Add 1 to the rank if the Route SpeedLimit is equal to the SpeedLimit in the crash data
- Add 0.5 to the rank if the Route Direction equals a value in the Cardinal direction from the crash data
- Add 0.5 to the rank if the Route Ramp is true and the Cardinal direction in the crash data are equal to 7 (ramp)
- Add 0.25 if the Route Direction equals the LaneDir in the crash data
- Add 0.25 if the Route Direction equals the InitDir in the vehicle data

Each route for a given crash has a rank score after the initial ranking process from 0 to 2.5. For each crash, the crash and route combination that have the highest scores are retained for the secondary ranking. An example of this is shown in Table 8, where eight records were ranked for a given crash.

Table 8. Example of removing records after initial ranking



Crash Data					Vehicle Data			Route Data				Ranking				
									Route	Route	Route	Speed	Cardinal	LaneDir	InitDir	
CRASH_KEY	ROUTE	CARDINAL	RAMP	LaneDir	UNITKEY	SpeedLimit	InitDir	RouteID	SpeedLimit	Ramp	Direction	Check	Check	Check	Check	Rank
~~20201173227~~	~~235~~	~~7~~		~~77~~	~~20201173227001~~	~~35~~	~~4~~	~~M826043150S~~	~~35~~	~~No~~	~~S~~	~~1~~	~~0~~	~~0~~	~~0~~	~~1~~
20201173227	235	7		77	20201173227001	35	4	S001910235W5450	45	Yes	W	0	1	0	0.5	1.5
20201173227	235	7		77	20201173227001	35	4	S001910235W5465	45	Yes	W	0	1	0	0.5	1.5
~~20201173227~~	~~235~~	~~7~~		~~77~~	~~20201173227001~~	~~35~~	~~4~~	~~M826043150N~~	~~35~~	~~No~~	~~N~~	~~1~~	~~0~~	~~0~~	~~0~~	~~1~~
~~20201173227~~	~~235~~	~~7~~		~~77~~	~~20201173227002~~	~~35~~	~~4~~	~~M826043150S~~	~~35~~	~~No~~	~~S~~	~~1~~	~~0~~	~~0~~	~~0~~	~~1~~
20201173227	235	7		77	20201173227002	35	4	S001910235W5450	45	Yes	W	0	1	0	0.5	1.5
20201173227	235	7		77	20201173227002	35	4	S001910235W5465	45	Yes	W	0	1	0	0.5	1.5
~~20201173227~~	~~235~~	~~7~~		~~77~~	~~20201173227002~~	~~35~~	~~4~~	~~M826043150N~~	~~35~~	~~No~~	~~N~~	~~1~~	~~0~~	~~0~~	~~0~~	~~1~~

Four of the records resulted in a rank of 1, while the four other records had a rank of 1.5. In this situation, only the four records with a rank of 1.5 were retained and analyzed for the secondary ranking process. The records without the highest ranking scores are struck through in the table to show which ones were removed.

The secondary ranking process introduces the system type and route number into the ranking. These were used in the secondary ranking because the direction and speed limit resulted in more refined results that better identified the potential routes. Introducing the system type in the initial ranking can result in some routes having significant matches but outranked solely based on the system defined in the crash data. Additionally, the route number and names are not consistent between the crash data and RAMS network. Using these fields still provides value in selecting the final routes, which used the ranking process as follows:

- Add 1 to the rank if the RouteSystem is equal to the System in the crash data
- Add 1 to the rank if the RouteNumber is equal to the Route in the crash data

Once the secondary ranking is completed, the top ranked crash and route combination is selected. If multiple crash and route combinations have equal ranking, then the route closest to the crash is selected. This final result represents the RAMS integration output, described in the previous section, which contains a one-to-one relationship between the crash data and RAMS. Each crash is assigned a RouteID and Measure value. This output allows for integration with the INRIX data, but the additional effort conducted in this step also allows for supporting other integration efforts in the future.

Figure 6 visually shows the final output of the ranking process. The blue pin on the left side of the figure represents the originally given crash location. Three potential routes were identified, shown as the orange and red pins, and included in the ranking process. The ranking process was able to accurately determine that the crash was not related to the cross street, which is closer to the original crash location, and correctly assigned it to the divided roadway in the correct direction of travel, shown as the left red pin.

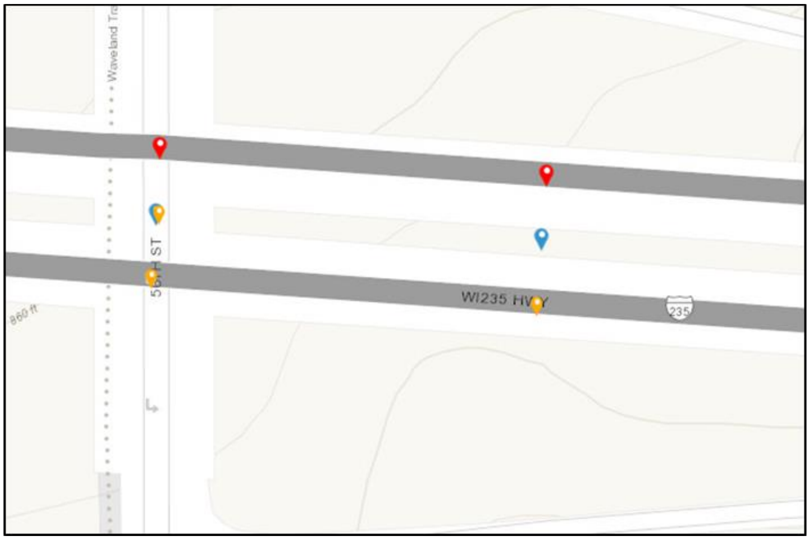


Figure 6. Final output of the RAMS route ranking process

Step 2: Integrate Crash Data and Probe Data

With the crash data and INRIX XD segments both related to RAMS, a simple linear overlay can be completed that associates each crash to any segment along the given section of roadway. This is completed by using the RouteID and Measure values associated to each data set.

The effort is complicated due to the fact that INRIX XD segments can change twice a year as the network is updated and modified. To accommodate this, a database was created that combines all of the various INRIX XD segmentation versions into a single database. The database can then be filtered based on the XD Segment version to see the corresponding XD segments and RAMS information for each segment. Table 9 provides the time frames for which each XD segmentation version is valid based on the data stored at InTrans. This is used in coordination with the date of the crash to determine the appropriate INRIX segment data available.

Table 9. XD segment version data ranges

XD segment version	Start date	End date
17.1	1/1/2016	12/31/2016
16.1	1/1/2017	3/31/2017
17.1	4/1/2017	4/24/2018
18.1	4/25/2018	12/2/2018
18.2	12/3/2018	4/15/2019
19.1	4/16/2019	10/7/2019
19.2	10/8/2019	4/1/2020
20.1	4/2/2020	9/28/2020
20.2	9/29/2020	3/29/2021

The RAMS integration output from Step 1 has a RouteID and Measure associated to each crash, while the conflated INRIX XD segment data from the Iowa DOT contains a RouteID, FromMeasure, and ToMeasure for each XD segment. Because the XD segments are linear features, the FromMeasure indicates the measure values at the start of the segment, and the ToMeasure identifies the measure values at the end of the segment. A linear overlay compares the RouteIDs for each data set and then joins the crash data and XD segments if the crash measure value falls between the from and to measures of the XD segment. In addition to the linear overlay, the crash data are joined to Table 9 based on the crash date falling between the start and end dates of the XD segmentation version. This version number will then be used as part of the linear overlay to select only the XD segment that was valid at the time of the crash. The resulting output is the probe data integration output.

Because the probe data provides data for both directions of travel along the roadway, the process creates a one-to-many relationship, where each crash can have multiple XD segments associated with it. This relationship only applies to a subset of the crashes, as INRIX data are only available on primary roadways as well as some additional major roadways. Any crash without a segmentation identified is excluded in the output. INRIX data were archived starting in 2016, so the process was conducted for only the crash data from 2016 through 2020.

Step 3: Join Probe and Crash Data at Time of Crash Files

With a relationship between the crash data and INRIX XD segments identified in Step 2, a process can be established that extracts the probe data stored in Athena similar to the weather data. The INRIX data extraction has been refined over the years at InTrans and has been well-implemented, including partitioning for other related projects in Iowa.

The process extracts the probe data speed and other related measures for the specific minute reported for the crash time. Inaccuracies may exist in the crash report time but latencies also exist with the probe data. The extracted probe data provides the best estimate of speed at the time of the crash based on these assumptions and further detailed analysis may be needed to evaluate speed before and after a crash.

Once the join is complete, the probe data output is created, which extracts all of the probe data for the segments associated with each crash key. This output is similar to other z-tables as part of the crash data in Iowa and can be joined directly with the crash-level data for analysis. These data should be treated similar to vehicle- or person-level data, because a one-to-many relationship may exist.

Step 4: Extract Additional Probe Data Before and After the Crash

Similar to the weather data, some users may require additional probe data before and/or after a crash. This can be used to analyze the traffic conditions leading up to the crash and/or estimate the overall impact the crash had on traffic conditions.

An additional process was established that allows users to dynamically enter the number of minutes before and/or after the crash to return additional probe data for analysis. For example, a user may want to request probe data 20 minutes before a crash and 10 minutes after a crash. The users can enter these values into the Python script, and the corresponding 30 minutes of probe data are returned for each crash. This is the probe data before/after crash output for which the corresponding fields were described previously.

FINDINGS

After developing the integration engine, a prototype online safety and operations evaluation tool was developed to explore the interactions between the crash, weather, and probe data. Methods of analyzing the data were explored to show the potential benefits of using the integration, but it is expected that future research will further explore and understand these relationships. This chapter highlights the online safety tool developed, including some initial comparisons of the data as well as lower levels of analyses conducted using the weather and probe data.

The online safety tool was developed similar to other safety data visualization at InTrans. The tool was created in Tableau, which allows users to explore data interactively by selecting charts and filtering the data to understand the relationships between the various attributes. In total, 16 pages were created as part of the tool that includes commonly utilized attributes from the crash, weather, and probe data.

The data utilized in the tool include the weather integration output and the probe data integration output described in the previous chapter. The before/after crash outputs were used in a separate tool described later in this chapter. Figure 7 provides an overview of the joins used within the safety tool.

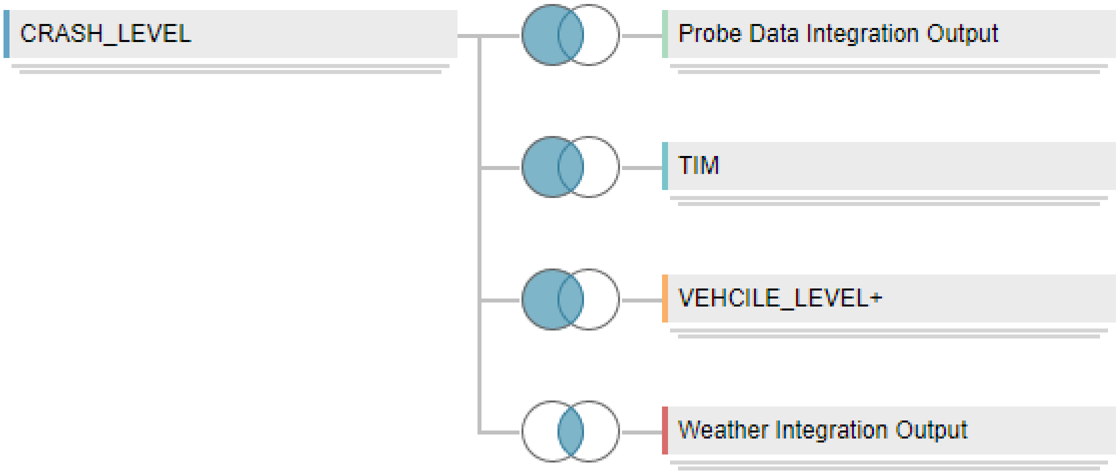


Figure 7. Data integration of safety tool

The crash level data provided by the Iowa DOT is the primary source, with all additional data sets relating back to this table based on the CRASH_KEY. The vehicle-level and TIM tables are also provided by the Iowa DOT and include vehicle-level information and traffic incident management (TIM) data, respectively. Both of these tables utilize a left join in case any vehicle and TIM data are missing for a given crash. The probe data integration output uses a left join as well as indicated by the left circle being completely shaded. This is due to the probe data only being available for a subset of the roadways, and the left join retains any crash without probe data. The weather data integration utilizes only an inner join due to the one-to-one relationship that exists between the weather and crash.

The first seven pages of the tool focus on the crash, vehicle, and TIM attributes provided by the Iowa DOT. These attributes are what would commonly be available to the Iowa DOT for any safety related analysis. The most commonly used attributes were included in the tool including, but not limited to, the crash severity, time, major cause, driver age, road type, and road classification. Figure 8 shows an example of the vehicle- and driver-level data available on one of the pages in the crash tool.

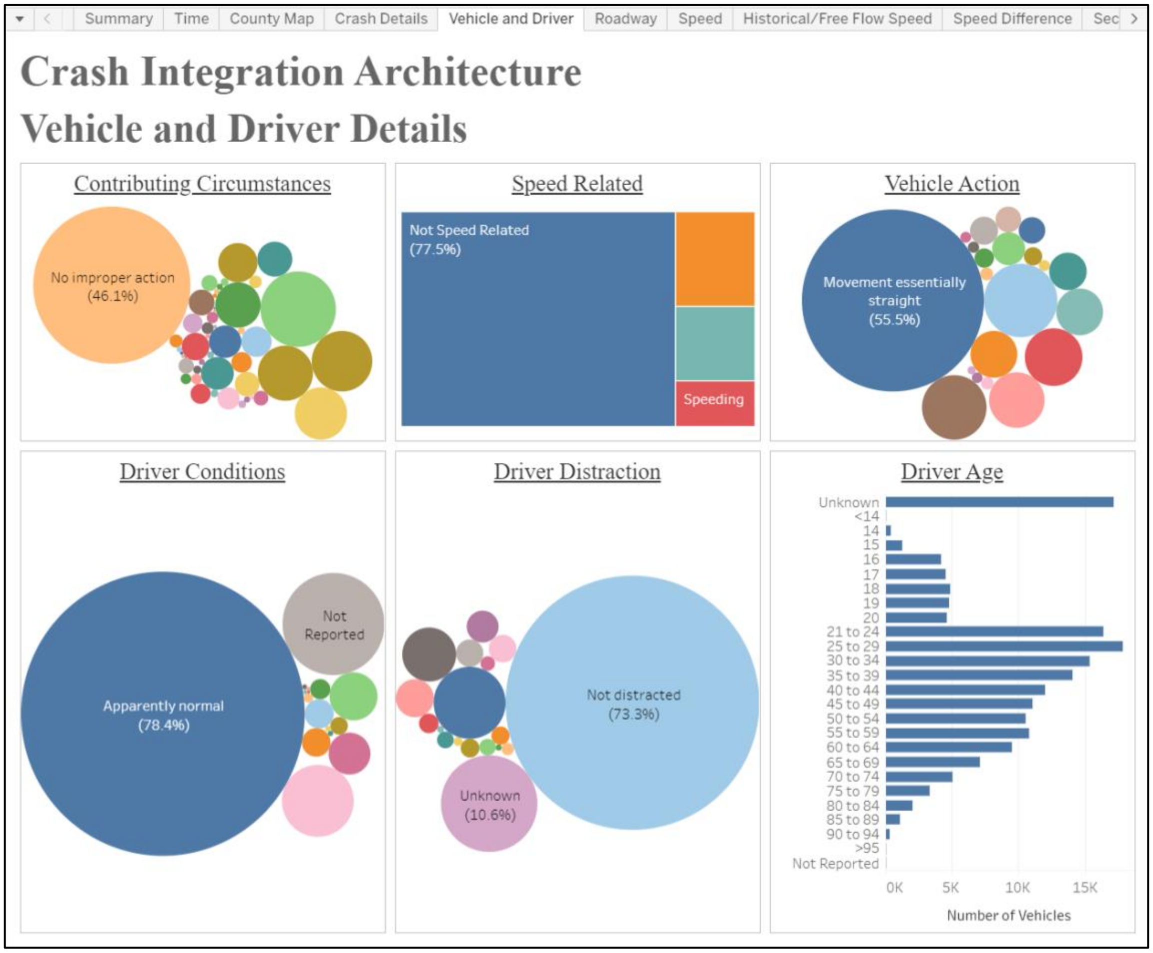
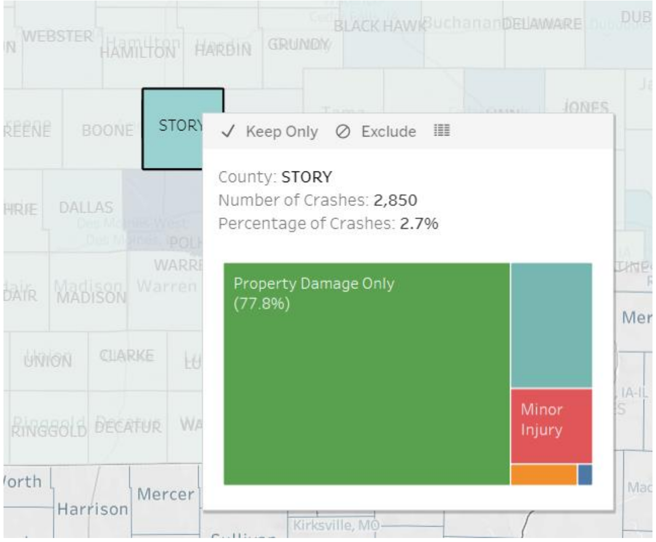


Figure 8. Example of crash data in safety tool

The next five pages in the safety tool focus on displaying the speed data based on the probe data integration output. The visualization focuses on summarizing the speeds at the time of the crash, the free-flow speed, historical speed, and the confidence score of the data. In addition to the data available from the output, calculated fields were developed utilizing both the probe and crash data. For example, with multiple potential speeds associated with the crash, the direction field was utilized to identify whether the speed was in the direction of the crash, the opposite direction of travel of the crash, or an unknown direction. This could provide value in determining if impacts to speed in the opposite direction may have contributed to the crash or if the impacts were limited to a single direction. The historical and free-flow speeds were also used to identify whether a slowdown existed at the time of the crash and whether the slowdown was recurring or non-recurring as a potential indicator of secondary crashes.

The final four pages in the safety tool display the weather data integration output for comparison with the crash data. The pages displayed attributes, such as the temperature, the amount of precipitation, wind speed, and weather advisories. Similar to the probe data, additional calculated fields were explored including comparing the wind direction to the road bearing and calculating the difference in road and air temperature.

As mentioned previously, the safety tool provides an interactive method for exploring and understanding relationships between attributes. When hovering over any chart, a tooltip is shown, which provides addition details as shown in Figure 9.



County: STORY
Number of Crashes: 2,850
Percentage of Crashes: 2.7%

Figure 9. Example of tooltip and selecting data in safety tool

The details can include charts, trends, or summary statistics that may be insightful for the user. Each chart can also be used as a filter to update all of the data throughout the tool. For example, users can go to the crash severity chart and select fatal crashes, which will in turn update every page in the crash tool to only include fatal crashes.

An initial step when exploring the weather data involved comparing the attributes given by the law enforcement officer to the weather station data. Figure 10 shows the precipitation types from the weather station sensors for the crashes that had snow listed as the weather condition at the time of the crash.

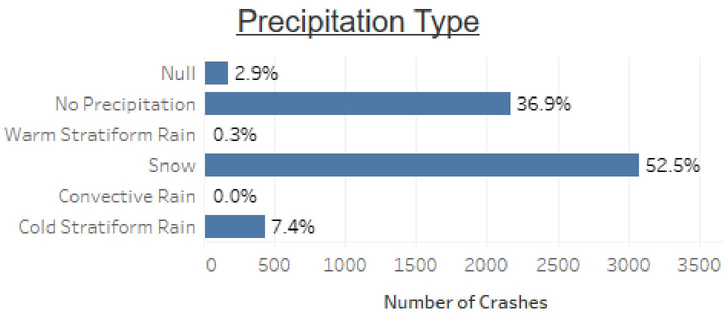


Figure 10. Precipitation types for crashes coded by officers as snow related

Of those crashes, 36.9% had no precipitation based on the station data. Severe winds were also selected as the crash weather type and showed a significant shift in the wind speeds. For all crashes, 6.6% of the crashes reported wind speeds over 20 mph compared to 66.8% when severe wind coded crashes were selected. Similar findings are available with fog, smoke, smog reported crashes, with 39.1% of the crashes having 0 mi of visibility, while all crashes only had 1% of crashes with zero visibility. In all of these situations, quantitative variables are available to further distinguish between these weather impacts outside of the qualitative variables the crash data provides.

As mentioned previously, the weather attributes also provide the ability to create calculated variables for analysis. With both road temperature and air temperature reported for each crash, comparisons can be made to determine if the road temperature is lower than the air temperature. Figure 11 shows this comparison, with each point representing a single crash.

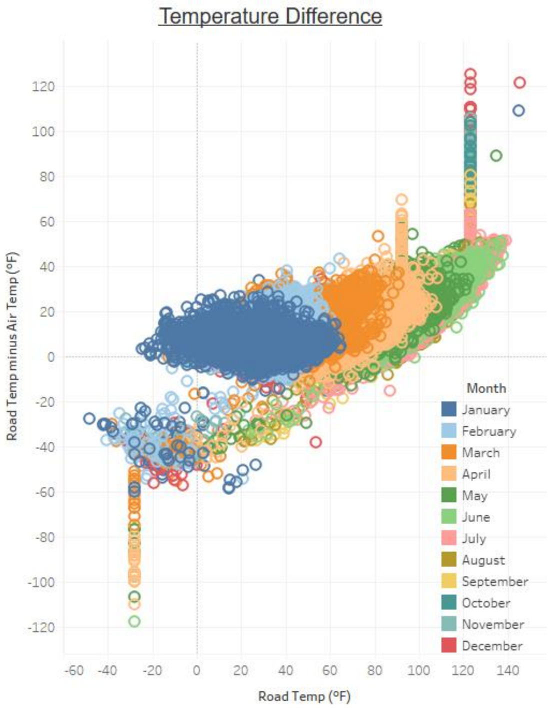


Figure 11. Comparison of road and air temperature reported for each crash

Most crashes follow a similar trend, but a subset of crashes appear to be outliers with significantly lower road temperatures as compared to the air temperature. Outliers such as these can be further explored to understand the causes and impacts on safety.

In addition to the severity of wind, the direction of the wind in comparison to the road bearing is also important, especially for freight. The wind direction reported in the weather data was compared to the bearing of the roadway to determine if the wind was perpendicular to the road, which has the potential to cause truck rollover crashes. Figure 12 shows the summary of this comparison with values closer to 0 indicating a head wind, values around 90 indicating a cross wind, and values close to 180 indicating a tail wind.

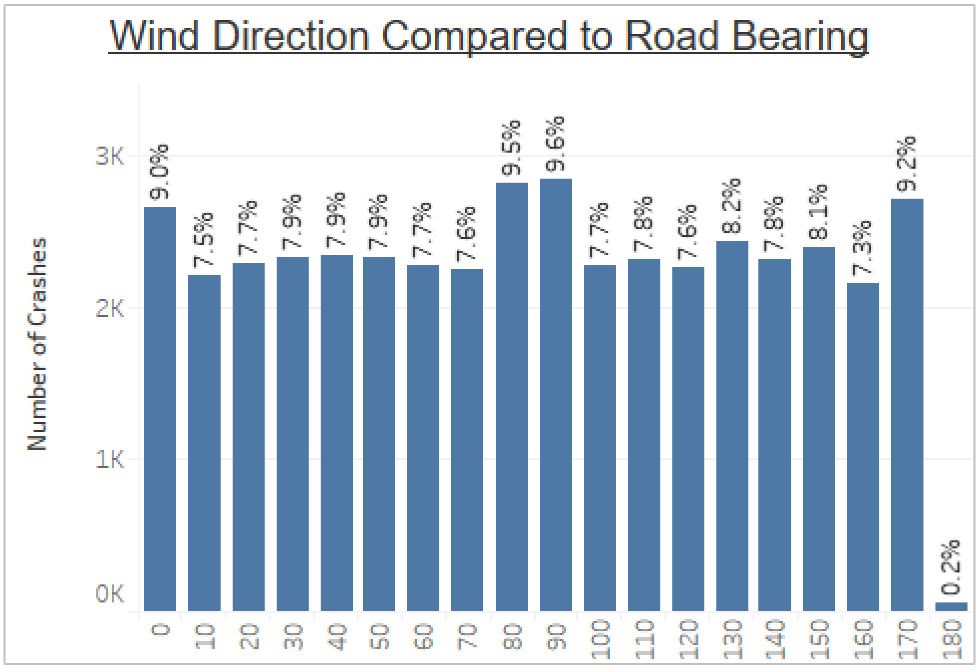


Figure 12. Wind direction compared to road bearing summary

From the summary, about 19% of crashes involve a cross wind between 80 and 100 degrees. This analysis can be further refined with additional exploration to determine the impacts for different vehicle types as well as the wind speed.

Due to the lack of traffic conditions in the crash data, comparisons between the crash and probe data were limited. Although not a direct comparison, a calculated value using the probe data to determine if a slowdown occurred at the time of the crash was used to compare to the field identifying secondary crashes in the crash database. To calculate this field, the speed, free-flow speed, and historical speed were used to identify a slowdown but also label the slowdown as either recurring or non-recurring. A common method used to identify slowdowns or bottlenecks is to use 60% of the free-flow speed. If the speed at the time of the crash was less than 60% of the free-flow speed, then the crash was labeled as having a slowdown at the time of the crash. To determine if the slowdown was recurring, the historical speed was used, which accounts for typical speeds along the segment at the given time of day. If the speed was less than the historical speed minus 5 mph, then the crash was labeled as non-recurring. Any speed greater than the historical speed minus 5 mph would indicate a recurring slowdown. Overall, 6.2% of the crashes with INRIX data occurred during non-recurring slowdowns, while 0.4% occurred during recurring slowdowns. Figure 13 shows the results when only secondary crashes are selected.

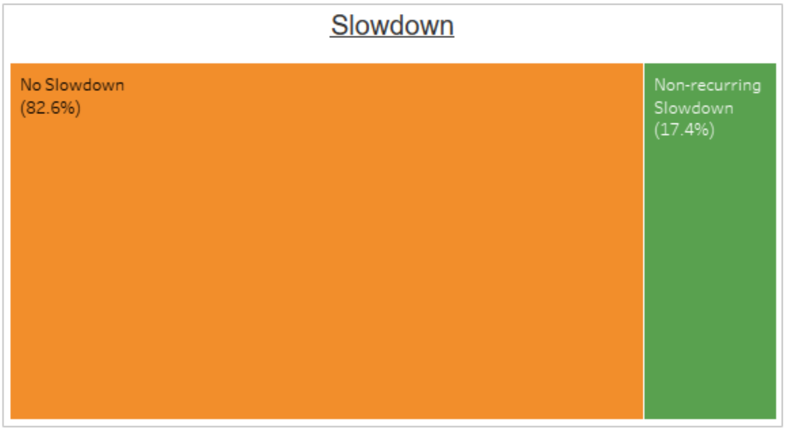


Figure 13. Summary of slowdown time for secondary crashes

The results show no crashes identified as a recurring slowdown, but only 17.4% of the crashes having a slowdown. On the other hand, when selecting only the crashes identified as non-recurring slowdowns, the number of secondary crashes increases from 1.6% to 4.8% as compared to all crashes.

The speed and crash data can also be used to compare the speeds at the time of the crash to the speed limit of the roadway. To do this, the probe data speed was subtracted from the speed limit. The result of this output will show values less than 0 if the speed was lower than the posted speed limit or values greater than 0 if the speed was greater than the posted speed limit. This does not indicate the speed of the actual vehicle but the approximate speed of vehicles along the roadway. Figure 14 shows this comparison broken down by the posted speed limit, with a box-and-whisker plot displaying the range in speed differences.

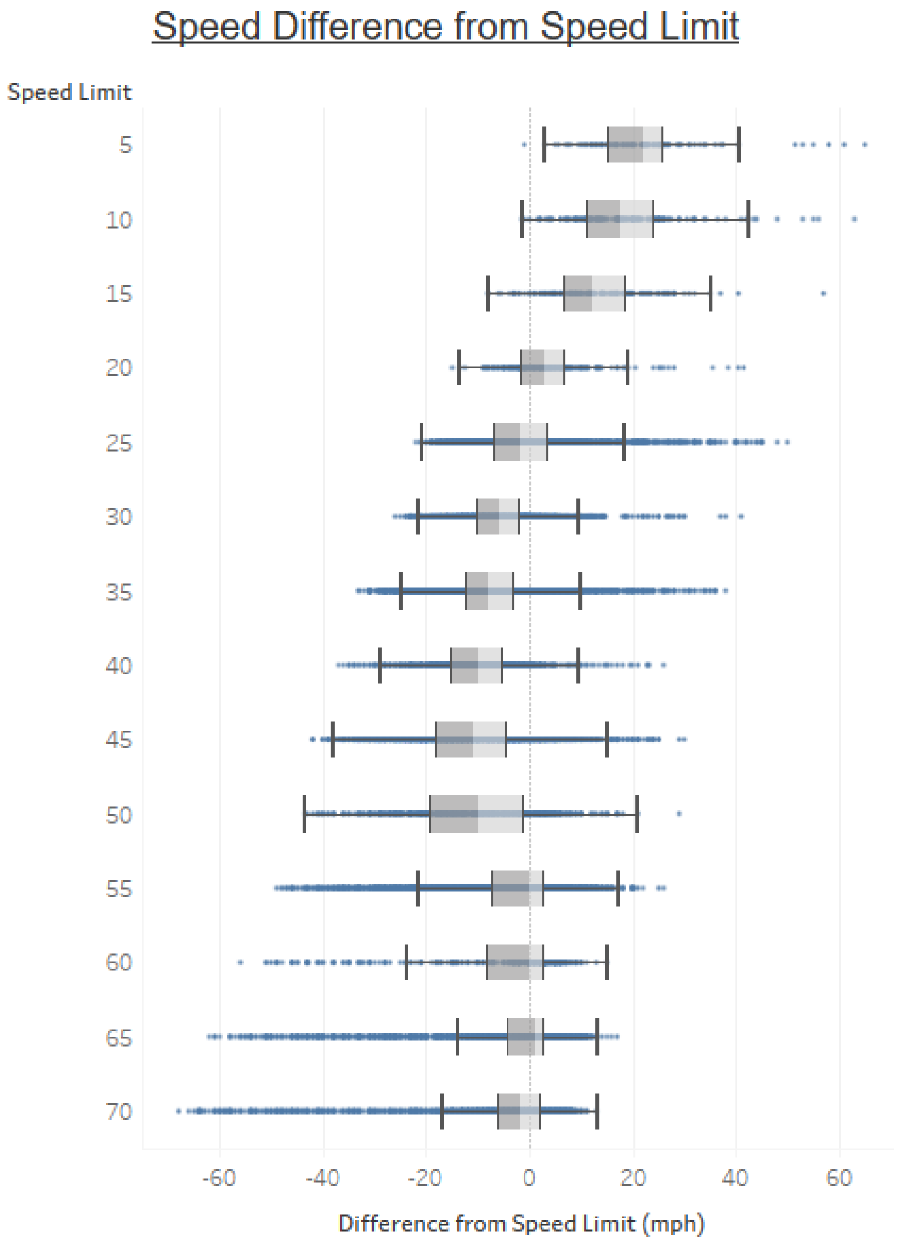


Figure 14. Crash speeds ranges as compared to the speed limit

The data show that roadways with a speed limit greater than 55 mph have median speeds comparable to the speed limit as indicated by the box plot median value near the zero speed difference from the speed limit value. For these speed limit values, a number of outliers are shown with speeds less than the speed limit. The speed limits from 30 to 50 mph show lower median speeds, as indicated by the shift in the box plot to the left of zero. These speed limits show additional outliers to the right, though, indicating higher probe data speed in comparison to the speed limit for those crashes. Providing quantitative measures of speed offers additional information that can be used when evaluating crashes or developing safety models.

The safety tool can be used to further explore the relationships between crash, weather, and probe data but is limited to the weather and probe data at the time of the crash. The final step in both the probe and weather data processes was to develop a script that allowed for a configurable amount of data before and after the crash to be extracted. A sample of the data was extracted to validate the process outputs but also shows potential uses of the data in more advanced analysis.

The weather data contains multiple quantitative variables that can be evaluated before and after the crash. Four of the fields reported in the weather data are shown for a single crash in Figure 15.

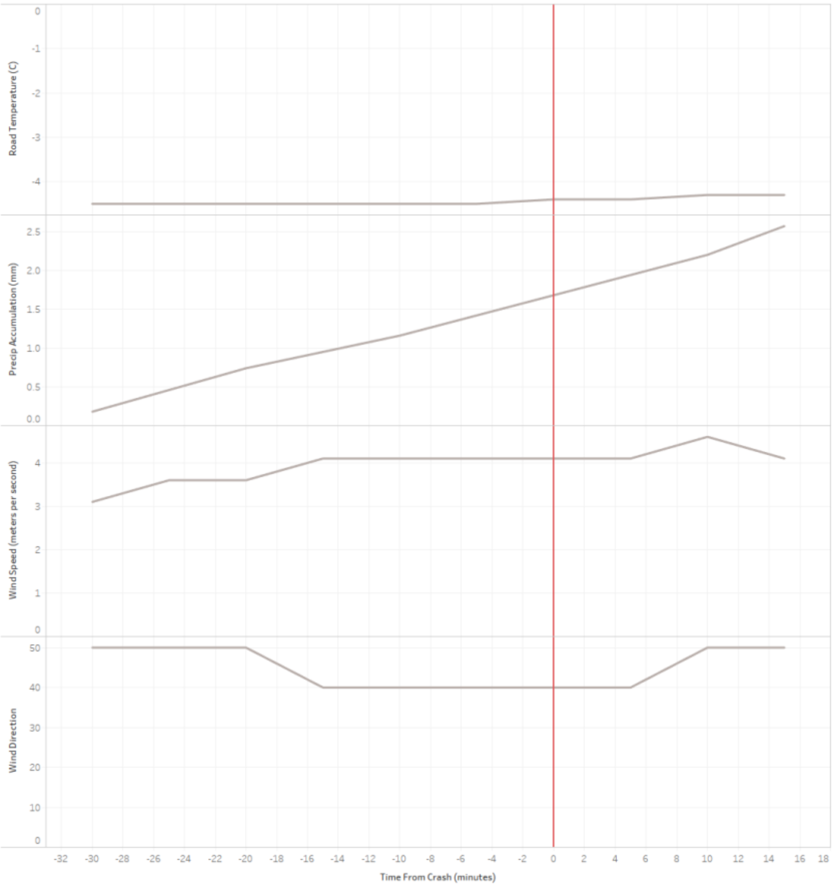


Figure 15. Weather data before and after a single crash

To allow for consistent visualizations when comparing the data, the timestamp of the crash was replaced with the time in minutes from the crash. In the example, weather data were extracted 30 minutes before the crash and 15 minutes after the crash. The red vertical line represents the reported time of the crash with a value of 0 minutes. The values to the left of the red line indicate measures before the crash and values to the right of the red line indicate measures after the crash.

With these data, there are very few changes in road temperature, wind speed, and wind direction leading up to or after the crash. The precipitation accumulation showed that 1.6 mm of precipitation was accumulated in the 30 minutes prior to the crash and an additional 0.9 mm in the 15 minutes after the crash. The precipitation is reported in liquid equivalents, but using the precipitation type field, it is known that the precipitation was snow. Using this additional information, the data can be further refined through analysis to include attributes, such as the amount of precipitation before the crash, whether the crash at the beginning or end of a watch/warning, or any other attribute that can be extracted using the time-series weather data.

Similar to the weather data, the probe data can provide additional insights using the speed before and after the crash. The speeds can be normalized similar to the weather data by calculating the minutes from the crash as shown in Figure 16.

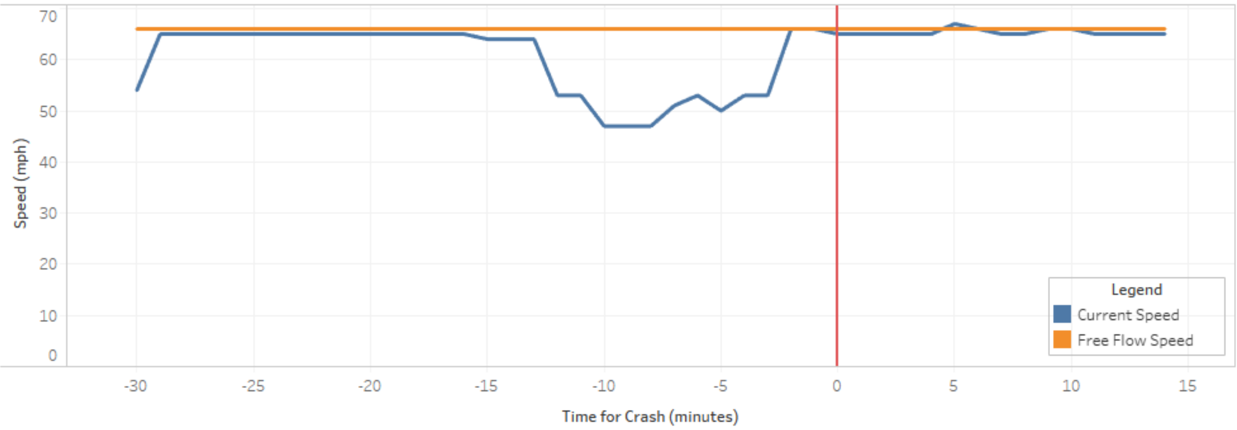


Figure 16. Probe data before and after the crash

The speeds to the left of 0 minutes, which is the time of the crash and shown by the red line, indicate the speed leading up to the crash, and the speed to the right of the line indicate the speed after the crash. The figure shows that a slowdown appears to have occurred directly before the crash time. The free-flow and historical speeds were consistent before and after the crash, indicating that the slowdown was not a recurring slowdown for the area.

The timeline can provide details including the impact to speed prior to the crash or, in some cases, the impact the crash had on traffic, where a dip in speed occurs after the crash. One limitation with the given method of extracting the data is the ability to quantify travel time impacts or hours of delay due to a crash. A travel time is reported for each segment that could be used to estimate travel time impacts but would ignore any impacts to travel time that occurred on segments upstream and downstream of the crash. The INRIX XD segments do provide the segments upstream and downstream of the given segment and can be used to extract these data to better estimate the impacts on traffic. This could be a future enhancement of the probe data extraction process. The vehicle hours of delay as well as delay cost have a similar limitation as the travel time but are also restricted by the missing traffic volumes. Other efforts within Iowa estimate the delay cost using the AADT as well as monthly, day of week, and time of day factors, which can also be extracted in future data integration work.

SUMMARY AND CONCLUSIONS

Decision-makers today have access to vast amounts of information but are often restricted in the ability to explore relationships between the data. Relationships between data sources are often nonexistent or involve complex processes limiting who can use the information. Simple integrations or questions often require a dedicated research project that ultimately does not support the ongoing use of the data moving forward. This project demonstrated a simple proof-of-concept architecture that addresses some of the constraints on decision-makers but also opens up additional data sets for the Iowa DOT or other researchers to explore without the additional time and effort it takes to integrate the data.

The current research literature shows that there is value in using weather and traffic data within safety analysis due to the impact these factors have on crashes. However, most literature showed that researchers often needed to aggregate data sets, used a variety of different integration processes, and likely spent a considerable amount of time integrating the data. The architecture in this report identified the various data sets needed to support crash, weather, and traffic analysis and then developed a process to extract the data. The considerable size of the data required developing a pipeline that allows the data to be stored cost-effectively while also reducing the time to query the data sets. The created outputs from these processes assign the attributes for the related weather and probe data to each crash, which can be treated like all other crash data within Iowa. This allows novice users with some experience with the crash data to complete analysis using both weather and probe data. The architecture was also designed to support future advanced analysis by developing simple scripts that can be used to dynamically extract the weather or probe data before and after a defined set of crashes. It is expected that future research will utilize these data outputs and processes to improve weather, traffic, and crash related efforts moving forward.

The Iowa DOT views this project as an initial effort to develop a system that enhances crash data reports by integrating additional data sources. The ultimate goal will be to have a system that has all available data sets readily available when evaluating crashes and that can be utilized within any safety and mobility decision-making. The work in this study has established a foundation to simplify the efforts to integrate additional data sources by associating the crash data to the Iowa DOT’s LRS. Additional data sets that can be used to enhance the crash data or used in future research, identified through coordination with the Iowa DOT and other relevant stakeholders, include the following:

- Advanced Traffic Management System data – These data include additional real-time attributes collected through the traffic management center that can supplement information within the crash report. The integration would also support the Iowa DOT’s claim management efforts by providing additional events captured in the ATMS.

- Snowplow automatic vehicle location (AVL) data – The Iowa DOT maintains a fleet of snowplows that are equipped with Global Positioning System (GPS) devices as well as additional sensors to report the location of the snowplow, the plowing status, and the type/amount of material applied to the roadway. The information is reported every about 10 seconds and can be integrated through the LRS.

- Winter road conditions – The Iowa DOT reports winter road conditions based on input from its maintenance supervisors and other DOT staff. The ability to also include winter road conditions could further support winter weather safety research by providing the estimated road conditions, which are not available within the weather data. Currently, the Iowa DOT winter road conditions are maintained independently of other databases but may ultimately be associated to the LRS.

- Traffic and road weather snapshot and videos – The Iowa DOT has a network of traffic cameras and road weather cameras that record videos for a defined period of time and download snapshots every five minutes. Associating camera imagery with crashes can allow the Iowa DOT to further understand the conditions before, during, and after the crash using the snapshots or video.

- Pavement condition data – There has been an interest in understanding the pavement conditions at crash locations in addition to the surface type inputted in the crash reports. The data are already associated with RAMS, which allows easy integration with data sets, such as rutting, friction, and other surface conditions that may impact safety.

- Intersections – The Iowa DOT is currently working on integrating an intersection database into RAMS, which will allow associating crashes to intersections in order to obtain additional attributes about the intersection. This will also allow for additional intersections to be identified, where the crashes may not be coded as intersection related but are in close proximity to an intersection.

- Work zones – The Iowa DOT has various efforts related to improving the collection and accuracy of work zone data in Iowa including the use of smart arrow boards, a work zone lane closure system, and the Work Zone Data Exchange. The goal of these systems is to have verified work zone data that can be made available to the public but also archived for use in safety and mobility related efforts. Throughout these discussions, most efforts will utilize RAMS at some level to integrate the data.

For a majority of the data set integration efforts, the RAMS integration developed as part of this project will allow for streamlined integration with other data sets. A simple linear overlay can be used to create the relationship between the data or to extract the relevant information. This will become more common as additional systems and data sets are integrated with the RAMS and have a common network to associate data. The Iowa DOT expects to continue to develop additional data integration processes to ensure that data from various data sources are easily assessable for any user for analysis.

Related to the architecture that has been developed, future enhancements can be made to allow for additional summary statistics to be created for each crash as well as the ability to extract additional data for nearby road segments or weather grids. The summary statistics can include information such as the amount of precipitation a defined amount of time before the crash, whether speeds were trending up or down before the crash, and whether speeds were impacted after the crash. The summary statistics can provide additional attributes but would require additional workflows to extract and summarize these data for other users.

As described in the Findings chapter, a limitation to determining the impact a crash had on the public is the lack of knowledge of the traffic impacts upstream and downstream of the crash. The ability to collect this information is available through the current INRIX XD segmentations, but additional enhancements would be needed to extract this information for each crash. A similar process could be developed to extract weather data surrounding a crash. The weather data provided by the IEM also includes weather forecasts every six hours based on the same grid and the same attributes. The forecast data have not been explored fully and may have benefits in some applications.

Overall, the proof-of-concept architecture developed provides an initial step in integrating crash, weather, and traffic data for more widespread use within Iowa. It is expected that the integration of data will continue to expand in Iowa, opening up the use of additional data for more users.

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