# Using Smart Work Zone Trailer Data to Evaluate and Predict Lane Closure Impacts with a Consideration of Work Intensity

**Final Report**
**June 2021**

SWZDI
Smart Work Zone Deployment Initiative

**Sponsored by**
Smart Work Zone Deployment Initiative
(Part of TPF-5(438))
Federal Highway Administration
(InTrans Project 20-733)

## About the Smart Work Zone Deployment Initiative

The Smart Work Zone Deployment Initiative (SWZDI) is a transportation pooled fund that supports research investigations into better ways to improve the safety and efficiency of traffic operations and highway work in work zones. The primary objective is to promote and support research and outreach activities that focus on innovative practice-ready policies, processes, tools, and products that enhance the implementation and constructability, safety, and mobility impacts of all types of work zones.

## Iowa State University Nondiscrimination Statement

Iowa State University does not discriminate on the basis of race, color, age, ethnicity, religion, national origin, pregnancy, sexual orientation, gender identity, genetic information, sex, marital status, disability, or status as a US Veteran. Inquiries regarding nondiscrimination policies may be directed to the Office of Equal Opportunity, 3410 Beardshear Hall, 515 Morrill Road, Ames, Iowa 50011, telephone: 515-294-7612, hotline: 515-294-1222, email: eooffice@iastate.edu.

## Disclaimer Notice

The contents of this report reflect the views of the authors, who are responsible for the facts and the accuracy of the information presented herein. The opinions, findings and conclusions expressed in this publication are those of the authors and not necessarily those of the sponsors.

This document is disseminated under the sponsorship of the U.S. DOT in the interest of information exchange. The sponsors assume no liability for the contents or use of the information contained in this document. This report does not constitute a standard, specification, or regulation.

The sponsors do not endorse products or manufacturers. Trademarks or manufacturers' names appear in this report only because they are considered essential to the objective of the document.

## Quality Assurance Statement

The Federal Highway Administration (FHWA) provides high-quality information to serve Government, industry, and the public in a manner that promotes public understanding. Standards and policies are used to ensure and maximize the quality, objectivity, utility, and integrity of its information. The FHWA periodically reviews quality issues and adjusts its programs and processes to ensure continuous quality improvement.

## Iowa DOT Statements

Federal and state laws prohibit employment and/or public accommodation discrimination on the basis of age, color, creed, disability, gender identity, national origin, pregnancy, race, religion, sex, sexual orientation or veteran's status. If you believe you have been discriminated against, please contact the Iowa Civil Rights Commission at 800-457-4416 or the Iowa Department of Transportation affirmative action officer. If you need accommodations because of a disability to access the Iowa Department of Transportation's services, contact the agency's affirmative action officer at 800-262-0003.

The preparation of this report was financed in part through funds provided by the Iowa Department of Transportation through its "Second Revised Agreement for the Management of Research Conducted by Iowa State University for the Iowa Department of Transportation" and its amendments.

The opinions, findings, and conclusions expressed in this publication are those of the authors and not necessarily those of the Iowa Department of Transportation or the U.S. Department of Transportation Federal Highway Administration.

**Technical Report Documentation Page**

| **1. Report No.** Part of SWZDI TPF-5(438) | **2. Government Accession No.** | **3. Recipient's Catalog No.** |
|---|---|---|
| **4. Title** Using Smart Work Zone Trailer Data to Evaluate and Predict Lane Closure Impacts with a Consideration of Work Intensity | | **5. Report Date** June 2021 <br> **6. Performing Organization Code** |
| **7. Author(s)** Hao Liu, Heidi Westerfield Ross, Gopindra Nair, and Natalia Ruiz-Juri | | **8. Performing Organization Report No.** Part of InTrans Project 20-733 |
| **9. Performing Organization Name and Address** Center for Transportation Research <br> The University of Texas at Austin <br> 3925 W. Braker Lane, Suite 4.11080 <br> Austin, TX 78759 | | **10. Work Unit No. (TRAIS)** <br> **11. Contract or Grant No.** |
| **12. Sponsoring Organization Name and Address** Smart Work Zone Deployment Initiative <br> Iowa Department of Transportation <br> 800 Lincoln Way <br> Ames, Iowa 50010 | Federal Highway Administration <br> U.S. Department of Transportation <br> 1200 New Jersey Avenue SE <br> Washington, DC 20590 | **13. Type of Report and Period Covered** Final Report <br> **14. Sponsoring Agency Code** Part of TPF-5(438) |

**15. Supplementary Notes**

Visit https://swzdi.intrans.iastate.edu/ for color pdfs of this and other Smart Work Zone Deployment Initiative research reports.

**16. Abstract**

This report describes the implementation of machine learning (ML) models to the prediction of work-zone traffic impacts including local speed and traffic volume changes and corridor-level travel time increases. It also summarizes efforts to refine an existing tool that estimates work-zone-related delays and costs by providing consistent estimates of typical travel times that consider variations across days of the week and months of the year.

All of the models described in this report were estimated/trained and tested using data collected on I-35 through Austin, Texas, on a 20.4-mile section on which smart work-zone trailers (SWZTs) were placed. Predictive models combined SWZT point speed and volume data with INRIX segment-level speed data. The researchers implemented artificial neural networks (ANNs) to forecast speed and volume changes for planned closures.

Speed forecasting models performed well on average (root mean square error [RMSE] of 10.19 mph) but tended to underestimate speed reductions when the closures were significant. The latter was likely a result of having a small fraction of time steps exhibiting significant speed reductions in the dataset, which consisted mostly of nighttime closures.

Models used to forecast changes in traffic volumes had an average error (RMSE) of 57 vehicles per hour per lane (vphpl), which was comparable to that of linear regression models. Further training with a more balanced dataset that includes daytime and nighttime closures is required to support a broader set of applications.

The researchers also analyzed the performance of three short-term travel-time prediction (STTTP) methods, trained as part of a separate effort during work zones. The trained models, which included a time series approach and two types of ANNs, were very successful on average, outperforming traditional approaches by up to 50 percent during the peak period. While model performance was not as impressive for predicting travel times when work zones were present, preliminary results were promising with ML models consistently outperforming the traditional approaches.

Further model refinements to explicitly consider the presence of work zones and their characteristics are expected to improve model predictions. The efforts described in this report illustrate the potential value of emerging data sources and modeling techniques to support work-zone planning and management.

| **17. Key Words** | | **18. Distribution Statement** | |
|---|---|---|---|
| artificial neural network—data driven method—machine learning—smart work-zone trailer—traffic impact forecasting | | No restrictions. | |
| **19. Security Classification (of this report)** Unclassified. | **20. Security Classification (of this page)** Unclassified. | **21. No. of Pages** 43 | **22. Price** NA |

**Form DOT F 1700.7 (8-72)** **Reproduction of completed page authorized**

# Using Smart Work Zone Trailer Data to Evaluate and Predict Lane Closure Impacts with a Consideration of Work Intensity

**Final Report**
**June 2021**


**Principal Investigator**
Natalia Ruiz-Juri, Director
Network Modeling Center, Center for Transportation Research
The University of Texas at Austin

**Research Assistants**
Hao Liu, Heidi Ross, and Gopindra Nair

**Authors**
Hao Liu, Heidi Westerfield Ross, Gopindra Nair, and Natalia Ruiz-Juri



Sponsored by the Midwest Smart Work Zone Deployment Initiative and
the Federal Highway Administration (FHWA) Pooled Fund Study TPF-5(438)

Preparation of this report was financed in part
through funds provided by the Iowa Department of Transportation
through its Research Management Agreement
with the Institute for Transportation
(InTrans Project 20-733)

A report from
**Smart Work Zone Deployment Initiative**
2711 South Loop Drive, Suite 4700
Ames, IA 50010-8664
Phone: 515-294-8103 / Fax: 515-294-0467
https://swzdi.intrans.iastate.edu/

## TABLE OF CONTENTS

## LIST OF FIGURES



## LIST OF TABLES

## ACKNOWLEDGMENTS

This research was conducted under the Smart Work Zone Deployment Initiative (SWZDI) and Federal Highway Administration (FHWA) Pooled Fund Study TPF-5(438), involving the following state departments of transportation:

- Iowa (lead state)
- Illinois
- Kansas
- Michigan
- Missouri
- Nebraska
- Texas
- Wisconsin

The authors would like to thank the FHWA, the Iowa Department of Transportation (DOT), and the other pooled fund state partners for their financial support and technical assistance. The authors would also like to thank the Austin District of the Texas DOT (TxDOT) for providing data access and complementary funding.

# EXECUTIVE SUMMARY


Lane closures are a necessity for the expansion, improvement and maintenance of transportation infrastructure. Unfortunately, most lane closures have an impact on the traveling public and, in some cases, may lead to significant delays and loss of reliability. Data-supported methods to evaluate the impact of past closures and predict the impact of planned closures are critical in designing and evaluating impact-mitigation strategies.

Transportation agencies use intelligent transportation system (ITS) devices, such as smart work-zone trailers (SWZTs) to monitor traffic and disseminate information during construction. SWZTs are equipped with multiple sensors and can collect data that have the potential to help agencies plan, evaluate, and optimize work-zone management. Common challenges faced when using data for the direct evaluation of work-zone impacts include data quality, coverage, spatial and temporal aggregation, and the lack of clearly defined metrics of performance that accurately represent the system conditions given the characteristics of available data.

This report summarizes research on two topics: the refinement of a data-based method to estimate work-zone-related delays and user cost for ongoing and past closures and the implementation of machine learning (ML) techniques to forecast the impacts of planned work zones on speeds and volumes and for short-term travel-time prediction. The data used in this effort were collected on a 20.4-mile section of I-35 in Austin, Texas, and includes SWZT point speed and volume data, along with INRIX segment speed data. Forecasting models were trained and tested using data from 133 work zones.

To enhance the estimation of work-zone-related delays and user costs, the researchers developed a systematic approach to calculate typical travel times at 15-minute intervals, which were used as the reference value against which work-zone travel times were compared. The method considers both the need to eliminate outliers that may bias the estimates and the importance of accounting for the variation of travel times across weekdays and months of the year. This work proposed clusters of days of the week and months of the year expected to have similar typical travel time values throughout the day and conducted statistical analyses to confirm that the differences among clusters are significant.

The final workflow involved computing typical travel times within each cluster at 15-minute intervals after removing data outliers using a three-sigma rule. Typical travel time estimates were provided by sensor and cluster and observed differences among clusters suggest that the proposed method is likely to provide more accurate delay estimates than approaches that consider a single reference value.

This effort also explored the use of artificial neural networks (ANNs) to forecast speed and volume reduction for planned closures. Speed forecasting models performed well on average (root mean square error [RMSE] of10.19 mph) but tended to underestimate speed reductions when they were significant. The latter is likely a result of having a small fraction of time steps exhibiting significant speed reductions in the training dataset, which consist mostly of nighttime closures.

Models used to forecast changes in traffic volumes have an average error of 57 vehicles per hour per lane (vphpl) RMSE, which is comparable to that of linear regression models that may be preferable given they are simpler to estimate. While these results were promising, the trained models can only be expected to perform well when analyzing nightly closures. Further training with a more balanced dataset that includes daily and nightly closures is required to support a broader set of applications.

The research team also analyzed the performance of three short-term travel-time prediction (STTTP) methods, trained as part of a separate effort, during work-zone activity. STTTPs are intended to provide a more precise estimate of expected travel times in real time.

The trained models, which included a time series approach and two types of ANNs, were very successful on average, outperforming traditional approaches by up to 50% during peak periods. While model performance was not as impressive during the presence of work zones, preliminary results were promising, with ML models consistently outperforming traditional approaches. Further model refinements to explicitly consider the presence of work zones and their characteristics are expected to improve model predictions during the presence of work zones. The efforts described in this report illustrate the potential value of emerging data sources and modeling techniques to support work-zone planning and management.

The original workplan for this project involved incorporating successful workflows into an existing web application. Unfortunately, the data pipeline that feeds such web application became inactive in late 2020 due to COVID-related budget costs. Instead of working on implementation, researchers emphasized the exploration of ML methods to support work-zone planning and operations. All findings were documented to facilitate their integration into the web application once the data pipeline is restored.

# INTRODUCTION

U.S. Department of Transportation (DOT) statistics show that work zones resulted in nearly 24 percent of non-recurring freeway and 10 percent of overall congestion in 2014, leading to an approximate delay time of 888 million hours (Schnell et al. 2002). Data-supported methods to evaluate the impact of past closures and predict the impact of planned closures are critical to designing and evaluating impact-mitigation strategies.

Evaluating the impact of past roadway closures allows practitioners to assess the benefits of and need for congestion mitigation strategies. Forecasting the impact of planned work zones based on specific work-zone characteristics and typical traffic conditions is important to support the identification of optimal time windows to schedule work zones to minimize negative impacts. This can also support the design of traffic management strategies.

This report describes research that enhances existing methods to evaluate the impact of work zone-related lane closures and work that explores the use of machine learning (ML) techniques for work-zone impact forecasting.

Work-zone impacts are often measured in terms of user delay and delay costs, although other metrics, such as queue length and traffic diversion, are often helpful when designing and evaluating traffic management strategies and public information dissemination. Given that delay is typically computed as the difference between travel times during the work zone and typical travel times, the estimation of typical travel times is important for impact evaluation and forecasting applications.

For this effort, the researchers proposed a replicable workflow to estimate typical travel times in order to provide consistent impact estimates for work zones occurring at different times of the day and days of the week. The research presented in this report also explores forecasting three different types of work-zone impacts using ML: speed and volume changes through the work zone and corridor-level travel-time increases. The latter was studied from the perspective of short-term forecasting and is intended to support the provision of real-time traveler information.

The data used to support this research was provided by the Texas DOT (TxDOT) and included point speed and volume data from smart work-zone trailers (SWZTs) as well as segment-level data provided by INRIX. The data used in this project were collected on a 20.4 -mile segment of I-35 in Austin, Texas, in 2019. The proposed models used work-zone characteristic parameters such as closure length, location, and duration, along with typical traffic conditions, as predictors to forecast traffic conditions on work-zone days. Work-zone characteristics were provided by TxDOT, and data from 133 closures were used for model training/estimation and testing.

The following chapters describe the data used in this project, the workflows proposed to enhance the estimation of typical traffic conditions, and the testing of ML models for work-zone impact forecasting.

## DATA DESCRIPTION

There were 33 SWZTs on I-35 through Austin, with 17 in the northbound (NB) direction and 16 in the southbound (SB) direction. The locations of these SWZT sensors are shown in Figure 1.

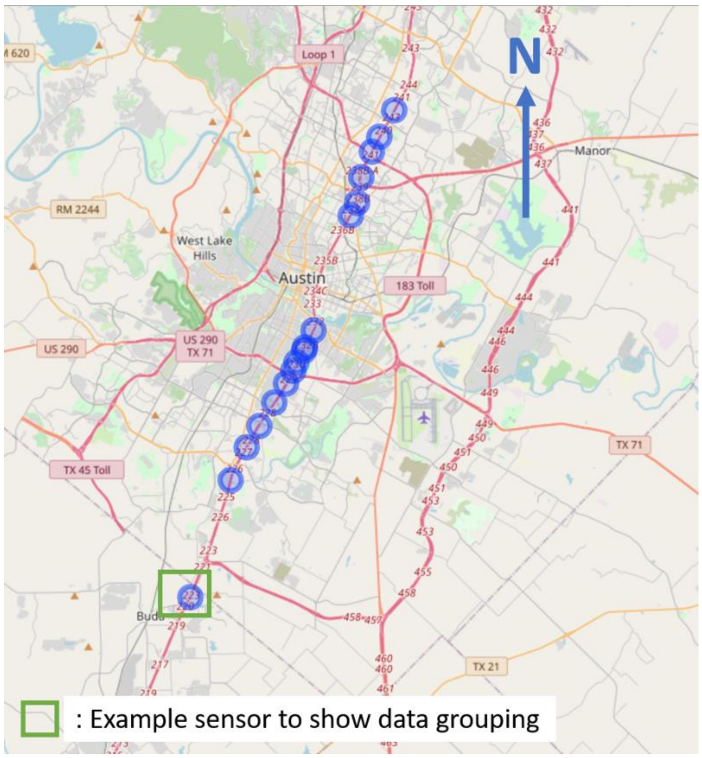


**Figure 1. SWZT locations**

SWZTs collected point speed and volume data every minute, which was streamed in real-time. The TxDOT Austin District was using SWZTs from two different vendors and, in a previous effort (Chen et al. 2019), the Center for Transportation Research (CTR) at Austin collaborated with the general engineering consultant (GEC) for TxDOT's Austin District to develop a pipeline to retrieve and archive data from both vendors in order to evaluate the impact of work zones. Data quality issues, such as missing data and erroneous data, were reported to TxDOT and documented in a technical memorandum titled 2020-6: Post-Event Estimation of Work Zone Traffic Impacts – Methodology White Paper, which is available from the authors of this report.

INRIX data consisted of spatial average speed in one-minute intervals for pre-defined segments, and the data provided were ready for use in this analysis without further processing. INRIX segment data were used for the stretch of segments shown in Figure 2.

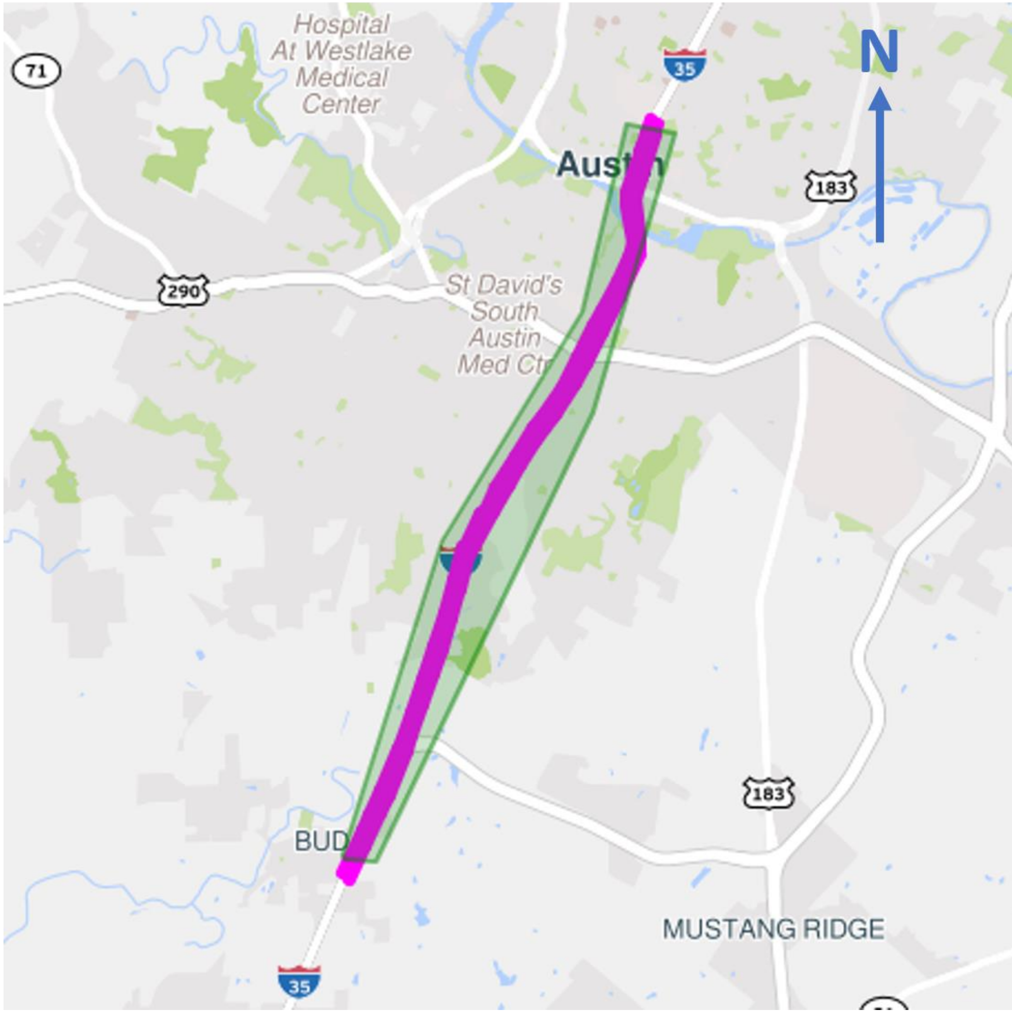


**Figure 2. INRIX segments**

There were 30 segments in the NB direction, with an average length of 0.545 miles each, and 32 segments in the SB direction, with an average length of 0.517 miles each.

A total of 1,919 work-zone records were provided by TxDOT. Of those, 133 occurred in 2019 and were located on the corridor segment shown in Figure 1. The locations of work zones were manually geocoded. Important attributes included start hour of closure, closure direction, coordinates of start and end points of closure, existing lanes, number of closed lanes, number of closure days, closure length, and closure durations. Examples of the work zone-related data are shown in Table 1.

**Table 1. Work-zone data samples**

| Start Date | Start Time | End Date | End Time | Direction | Existing Lanes | Lanes Closed | From Latitude | From Longitude | To Latitude | To Longitude |
|---|---|---|---|---|---|---|---|---|---|---|
| 7/22/2019 | 10 p.m. | 7/23/2019 | 5 a.m. | SB | 5 | Auxiliary Lane; Lane 3; Lane 4 | 30.3392 | -97.6999 | 30.3328 | -97.7043 |
| 7/21/2019 | 9 p.m. | 7/22/2019 | 5 a.m. | NB | 3 | Lane 1 | 30.2233 | -97.7472 | 30.2283 | -97.7443 |
| 7/22/2019 | 9 p.m. | 7/26/2019 | 5 a.m. | NB | 5 | Auxiliary Lane | 30.3222 | -97.7067 | 30.3328 | -97.7043 |
| 7/22/2019 | 10 p.m. | 7/24/2019 | 5 a.m. | NB and SB | 5 | Lane 1; Lane 2 | 30.3391 | -97.7001 | 30.3222 | -97.7067 |
| 8/5/2019 | 8 p.m. | 8/7/2019 | 5 a.m. | SB | 5 | Lane 1 | 30.3392 | -97.6999 | 30.3328 | -97.7043 |
| 7/24/2019 | 8 p.m. | 7/26/2019 | 5 a.m. | NB | 5 | Lane 1; Lane 2 | 30.3222 | -97.7067 | 30.3328 | -97.7043 |
| 7/22/2019 | 9 p.m. | 7/24/2019 | 5 a.m. | NB and SB | 5 | Lane 1; Lane 2 | 30.3582 | -97.6881 | 30.3222 | -97.7067 |

Figure 3 shows the distribution of selected work-zone characteristics from the dataset that was used.

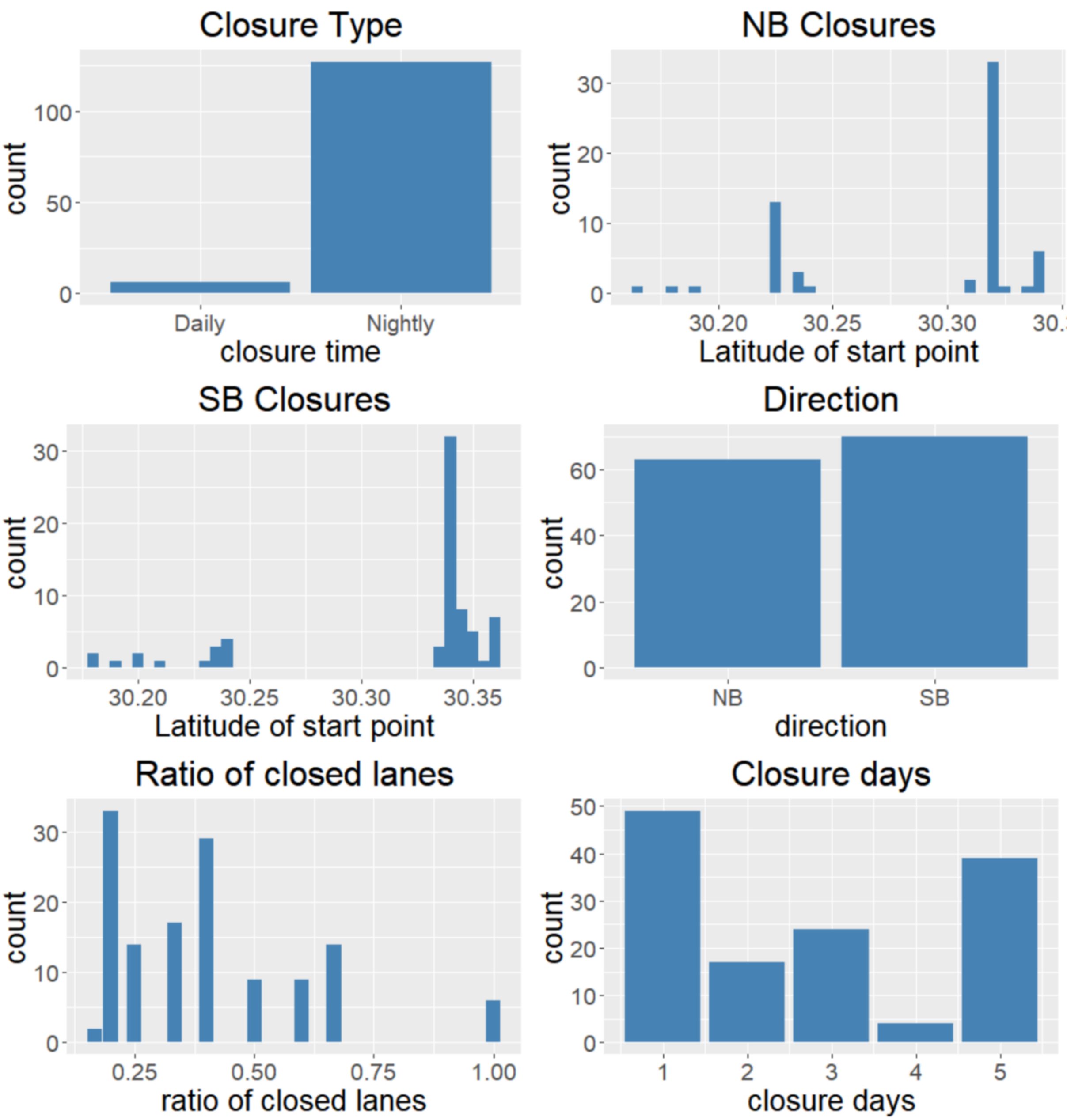


**Figure 3. Distributions of selected work-zone characteristics**

Most of the closures were nightly closures. In addition, in both directions, more than one third of the total closures were located at the intersection of I-35 and US 183. As a result of these limitations, the models trained in this effort were not expected to perform well during daytime hours, and their performance at different sites and during daytime hours may require further testing.

## ESTIMATION OF TYPICAL TRAFFIC CONDITIONS

In this effort, the researchers analyzed travel times and speeds on segments defined between two consecutive SWZTs in the same direction. Segment speeds, travel times, and traffic volumes were computed as functions of point speeds and volumes for each 15-minute interval, shown as Equations 1 through 3.

$$v_s^i(t) = \frac{v^i(t) + v^{i+1}(t)}{2},\ i \in [1, N_s - 1] \tag{1}$$

$$n_s^i(t) = \frac{n^i(t) + n^{i+1}(t)}{2},\ i \in [1, N_s - 1] \tag{2}$$

$$T_s^i(t) = \frac{l^i}{v_s^i(t)},\ i \in [1, N_s - 1], \tag{3}$$

where $v^i(t)$ and $n^i(t)$ indicate the speed and volume measured by the *i*th sensor during time *t*, $v_s^i(t)$ and $n_s^i(t)$ represent the segment speed and volume on the *i*th segment during time *t*, $l^i$ is the length of the *i*th segment, and $T_s^i(t)$ is its travel time during time *t*. Corridor travel time is defined as the sum of the corresponding segment travel time for the same time interval.

Typical travel times were used as a reference value to assess the delays imposed by work zones and as inputs in the proposed ML predictive models. To provide consistent delay estimates, it was important to estimate typical values in a systematic way. The approach that was used addressed the following practical considerations:

- Data may be missing or contain errors: Missing data points were identified, and duplicate data and records with zero speed or a zero volume count were removed

- Typical values may vary by day of the week and month of the year: Used a data grouping approach and assessed whether differences among the proposed clusters were significant

- Estimates may be biased by the presence of outliers: Used a simple data cleaning method to reduce the impact of outliers

In the analyses described in the following sections, we considered data for individual SWZTs aggregated into five-minute intervals, which is the aggregation level recommended by the *Highway Capacity Manual* (HCM) (TRB 2000). The aggregated speed was calculated as the average of the speed data in each five-minute interval, and the aggregated volume was the sum of the counts of one-minute intervals within each five-minute interval. In addition, if there were missing data within a five-minute interval, the aggregated volume was adjusted proportionally (available volume × 5 ÷ number of available data intervals). For example, if the data points at 08:01:00 and 08:03:00 were missing, the aggregated volume between 08:01:00 and08:05:00 were multiplied by 1.67 (5/3) to compensate for the two missing data intervals and, therefore, the underestimated volume.

## Data Grouping

There are various factors affecting traffic conditions, such as time (time-of-day, day-of-week, month), weather, and location. The goal of this section is to identify groups of days-of-week and months with statistically similar traffic patterns. The researchers estimated typical traffic conditions for each of these groups in order to provide consistent delay estimates across multiple work zones.

First, they considered day-of-week data groups. Figure 4 and Figure 5 show the volume and speed on different days of the week for an sample sensor (WZ I-35 NB near Brandt Road, as boxed in the previous Figure 1).

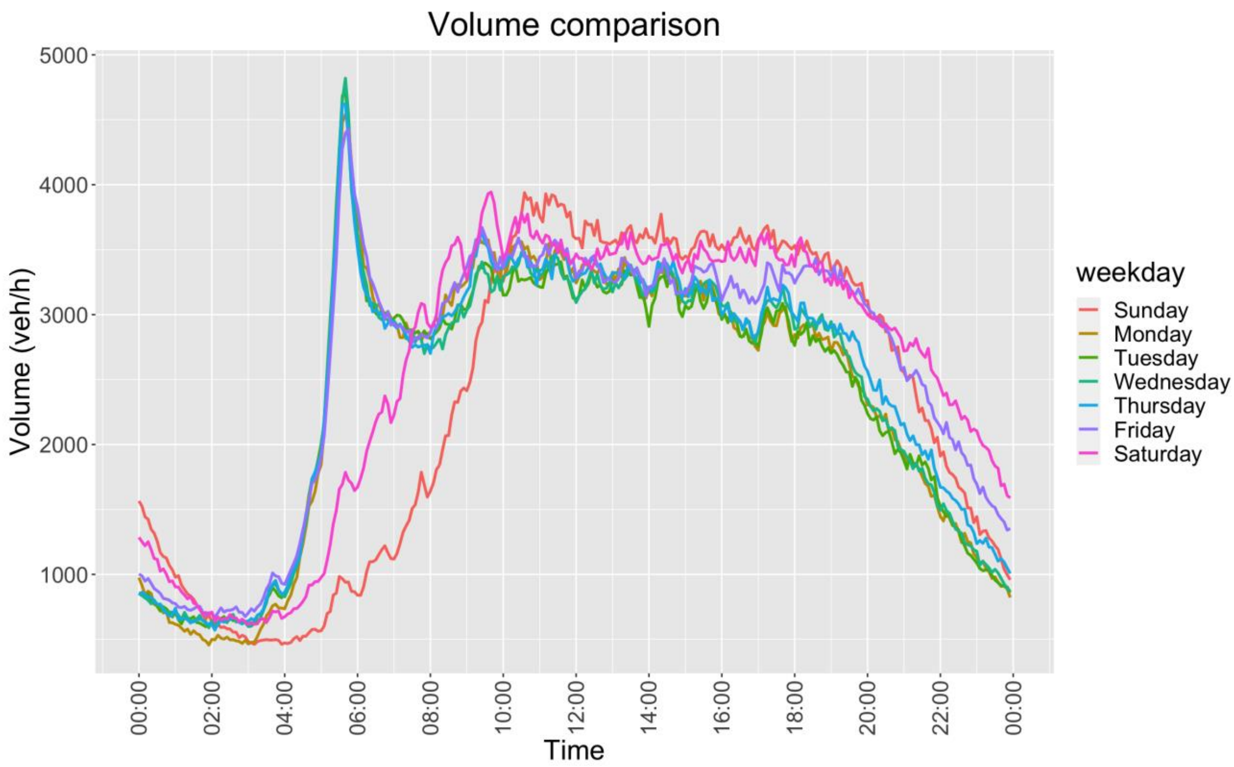


**Figure 4. Sensor volume data on different days of the week**

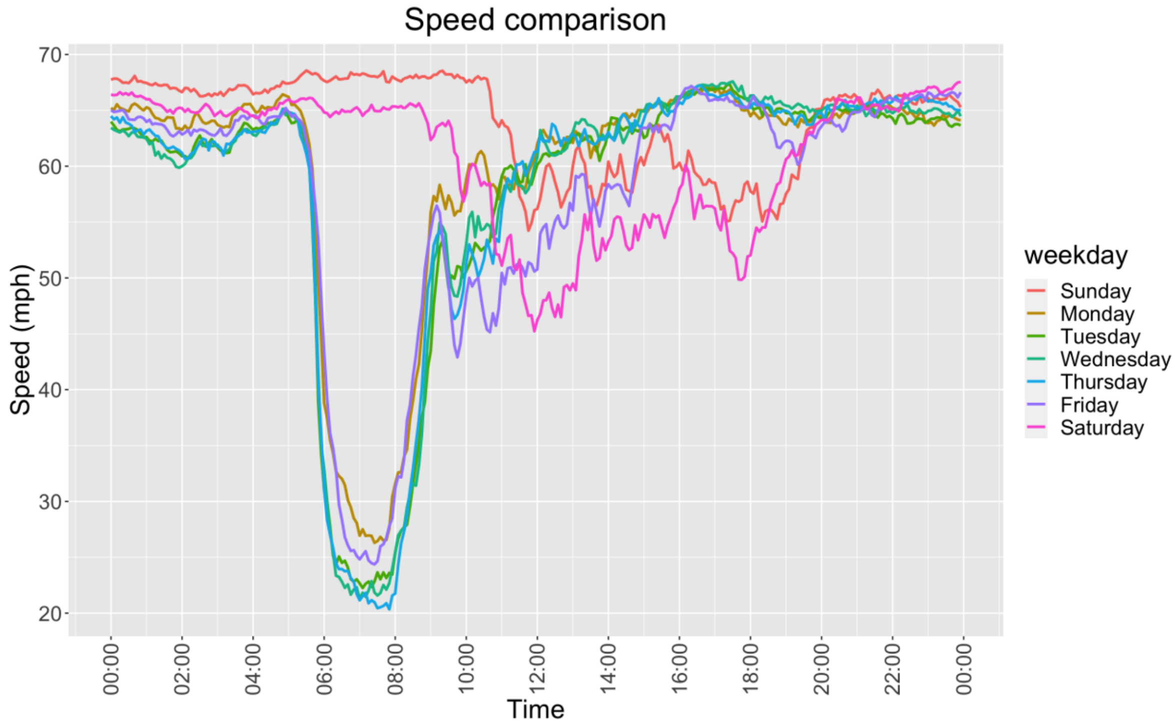


**Figure 5. Sensor speed data on different days of the week**

Both the speed and volume data were averaged over the year (2019). The figures show that the traffic conditions on weekends was distinct from that on weekdays. In addition, the data on Friday evenings presented a different trend from other weekdays.

Based on this analysis, the researchers classified the data in each month into five day groups: Monday, Tuesday/Wednesday/Thursday, Friday, Saturday, and Sunday. For simplicity, the Tuesday/Wednesday/Thursday grouping is referred to as Weekdays in this report.

Examination of the differences between Group Weekdays and each other group was significant, so two-sample t-tests were conducted. A t-test is a type of inferential statistic used to determine if there is a significant difference between the means of two groups, which may be related in certain features. The t-test is one of many tests used for the purpose of hypothesis testing in statistics.

In the t-tests for this study, time was aggregated into 15-minute intervals, and the traffic condition in each interval was assumed to be stable. Raw speed and count data were grouped into 15-minute intervals. Figure 6 shows the t-test results in January for a sample sensor (NB I-35 mile marker [MM] 2 after East 51st Street).

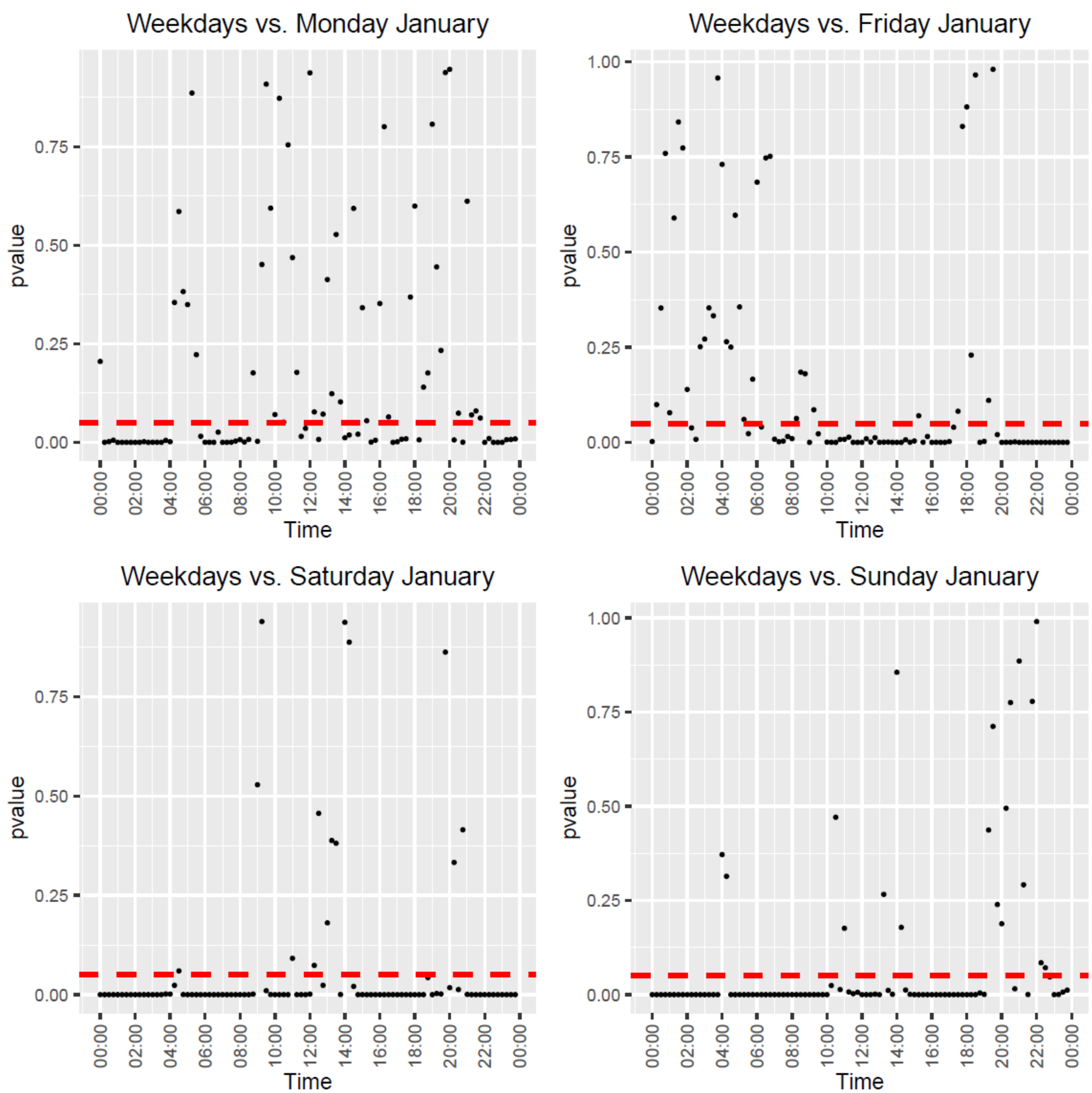


**Figure 6. T-tests results for volume comparison between group weekdays and other groups**

There were 96 points in each plot because there was one test for each 15-minute interval, and the plots showed one day, or 24 hours, of time (4 per hour × 24 hours = 96). In each t-test, the null hypothesis was that the mean value in a 15-minute interval from Group Weekdays was the same as the mean value in the same interval from other groups. The p-value was used to determine if the researchers should reject the null hypothesis.

In this example, the confidence level is 0.95, which means the null hypothesis should be rejected if the p-value is less than 0.05, as indicated by the red dashed line on each figure. In other words, if the p-value at a time point is less than 0.05, the mean value from Group Weekdays is different from the corresponding group. Figure 6 indicates the p-values for most 15-minute time increments in each of the other groups are less than 0.05, with the weekends showing more significant results than Monday and Friday. The t-test results for all sensors are available in a zip file of pdf charts as Appendix I.

In addition to the t-tests on individual sensors related to day-of-week data groups, the researchers used two metrics to validate the day-of-week data groupings across multiple sensors: the number of significant months for group $i$, $n_m^i$ and the number of significant sensors for group $i$, $n_s^i$. These were defined as follows: If the number of significant points of group $i$ in a month is larger than the threshold $N_d$, regard this month as a significant month for group $i$. If the number of significant months of group $i$ of a sensor is larger than the threshold $\lambda_m N_m{}^i$, where $N_m{}^i$ is the number of available months of group $i$ and $\lambda_m$, is a ratio less than 1, regard this sensor as a significant sensor for group $i$. If $N_d = 48$, which indicates more than half of the time points in the month are significant, and $\lambda_m = 0.75$, which indicates more than 3/4 of the total months for the sensor are significant, the number of significant sensors based on volume and speed is shown in Figure 7.

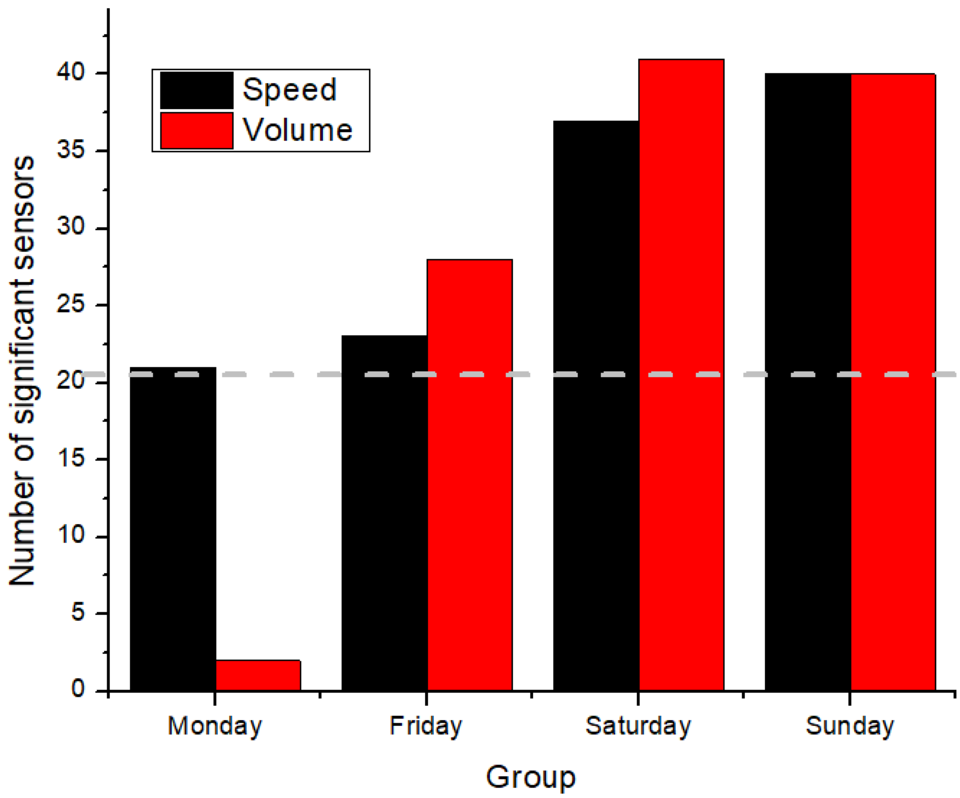


**Figure 7. Number of significant sensors**

The dashed line shows the half point for the total number of sensors. These results showed that most of the sensors were significant in Group Saturday and Group Sunday. More than half of the sensors were significant in Group Friday. There were only two sensors significant in Group Monday based on the volume data. However, there were more than half of the sensors that were significant in Group Monday based on the speed data. Therefore, combining Group Monday with Group Weekdays might lead to inaccurate speed estimation on Mondays. Overall, Figure 7 indicated the data day-of-week group classification is appropriate.

In addition, the data was further grouped into four groups by month as follows: January–May, June–August, September–November, and December.

### Outlier Removal

The three-sigma rule (Zhang et al. 2013) was used to remove data outliers. Normal distributions are required by this method. Therefore, the researchers first used the Box-Cox transformation to normalize the data in each group defined in the previous section (Box and Cox 1964). Then, the team removed the records if the transformed speed or volume was more than three standard deviations (or sigmas) outside the mean of the group (thus, the three-sigma rule). Figure 8 and Figure 9 show the outlier removal for Group Weekdays for a sample sensor (NB IH-35 MM 2 after East 51st Street) in August.

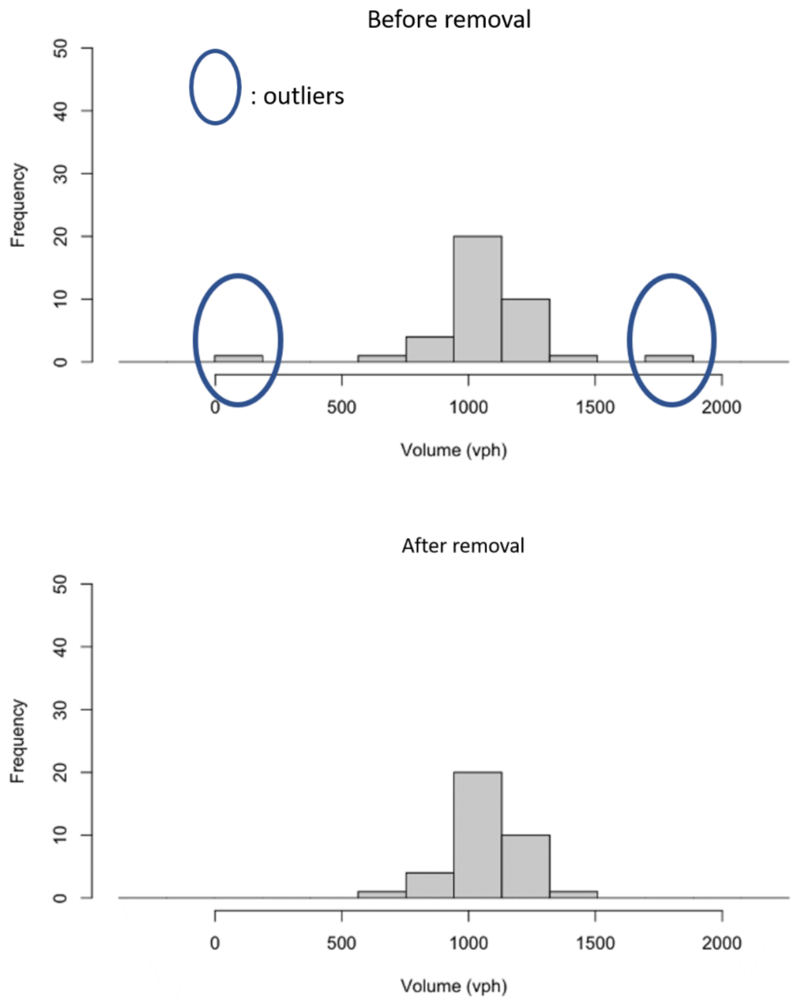


**Figure 8. Outlier removal for volume**

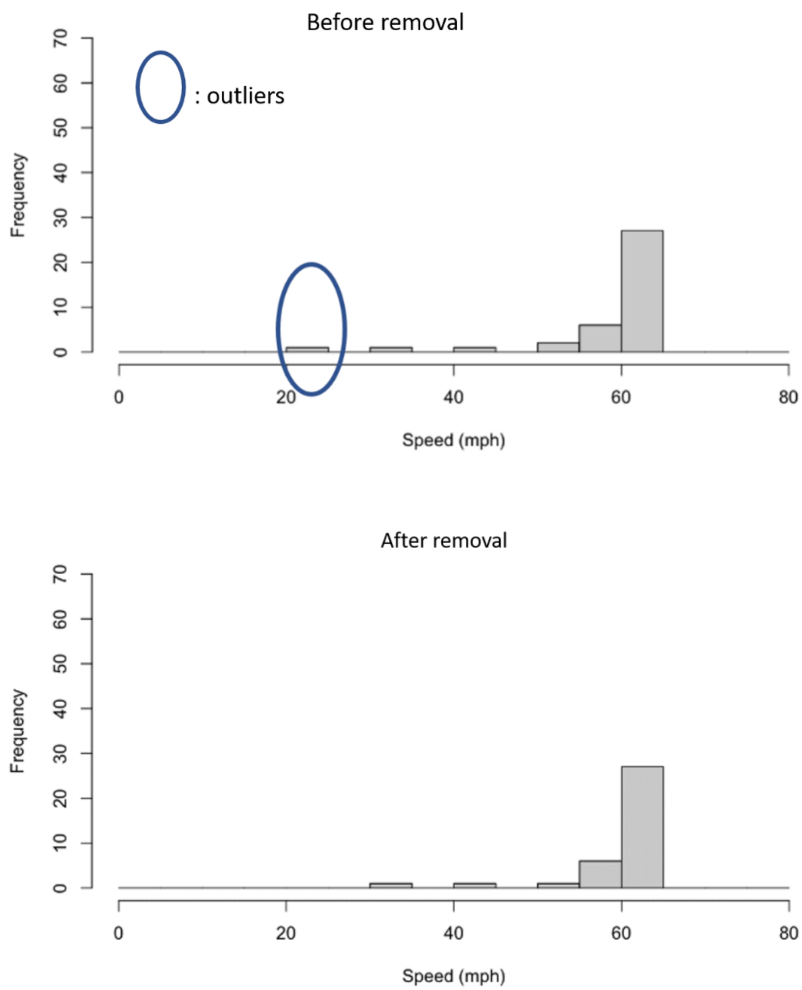


**Figure 9. Outlier removal for speed**

Five-minute aggregated data are used in this example. The data in the ovals were removed after using the three-sigma method.

In summary, 3.98% of the raw data were removed for all sensors. The percentage of data points removed for each sensor is available in the Appendix II spreadsheet file.

### Typical Traffic Condition Estimation

After removing the outliers, both one-minute speed and traffic count data were aggregated into 15-minute intervals. Typical traffic conditions were calculated as the average value in each interval in the same group across all considered days. A sample is shown in Table 2. Typical traffic condition data sample.

## Table 2. Typical traffic condition data sample

| Sensor | Time | weekday_group* | month_group** | Year | Mean Speed (mph) | speed.sd | Mean 15-minute Counts (vehicle/15-minutes) | count.sd |
|---|---|---|---|---|---|---|---|---|
| WZ-IH-35 SB near Woodward Street | 12:15:00 | 3 | 1 | 2019 | 59.78813559 | 3.289833973 | 999.0254 | 135.3667 |
| EB US 183 MM 1 after Burnet Road | 12:30:00 | 3 | 1 | 2019 | 57.10610932 | 10.7252338 | 972.8778 | 149.1259 |
| EB US 183 MM 2 after Lamar Boulevard | 12:30:00 | 3 | 1 | 2019 | 55.69874477 | 9.76236764 | 984.2887 | 135.0292 |
| EB US 183 MM 3 after Cameron Road | 12:30:00 | 3 | 1 | 2019 | 64.33755274 | 3.883360735 | 398.4177 | 99.87347 |

* weekday_group: 1=Tuesday–Thursday, 2=Monday, 3=Friday, 4=Saturday, 5=Sunday
** month_group: 1=January–May, 2=June–August, 3=September–November, 4=December

The volume.mean and volume.sd columns show the average vehicle count and its standard deviation during the corresponding 15-minute interval across days in the same group. The corresponding hourly quantities can be obtained by multiplying this value by 4. The integrated table is available in the Appendix III spreadsheet file. Figure 10. Typical speed in each day-of-the-week group for the four month-of-the-year groupings shows the typical speed evolution during the day-of-the-week groups for each month-of-the-year grouping.

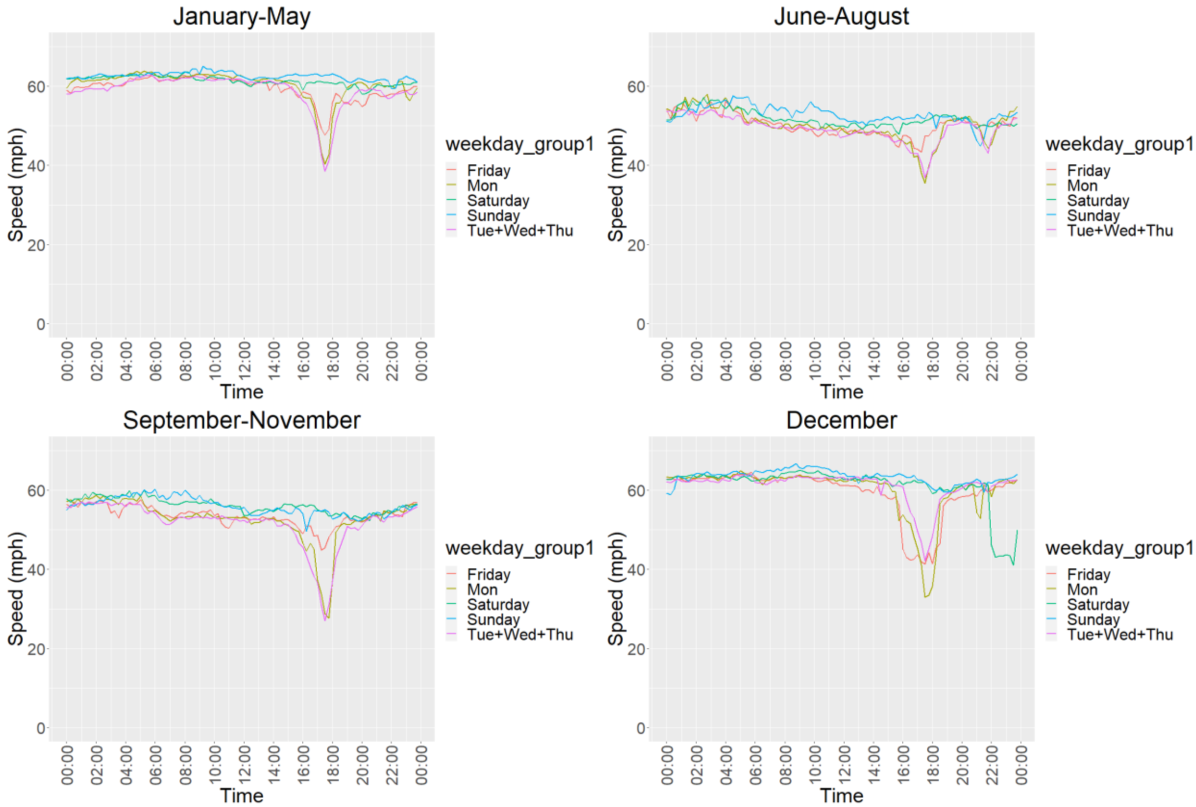


**Figure 10. Typical speed in each day-of-the-week group for the four month-of-the-year groupings**

In order to better understand the benefits of considering multiple reference speeds based on the day-of-the-week and month groups, the researchers compared the 2019 values to the 65th percentile speeds for each 15-minute interval at sensor WZ-IH-35 SB near Brandt Road. The use of a specific percentile to define typical speed values is a method that is often used by data providers, such as INRIX (Du et al. 2017). Figure 11. Speed comparison for day-of-the-week groups within the January–May month group shows the comparison between the 65th percentile of SWZT speeds in 2019 and the average speed for each day-of-the-week group during the January–May month group.

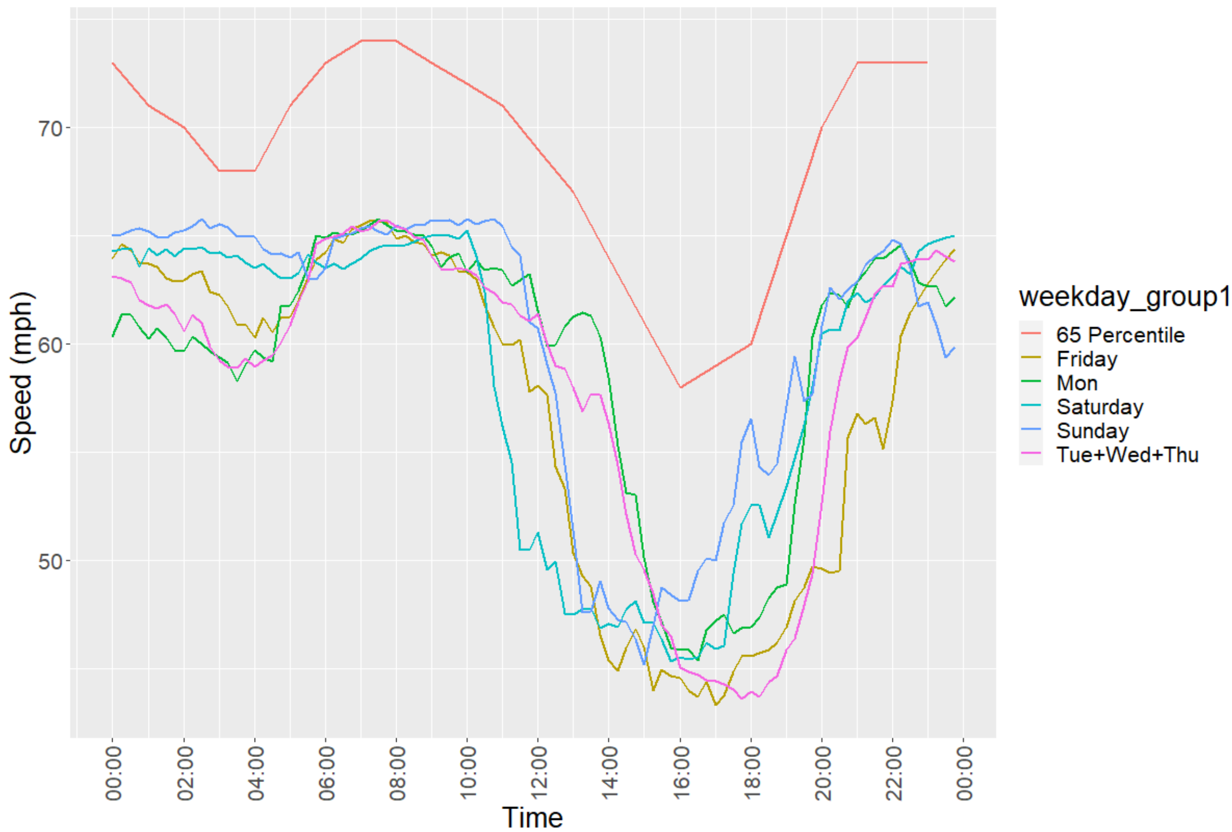


**Figure 11. Speed comparison for day-of-the-week groups within the January–May month group**

Figure 12. Speed comparison for month groups within the Weekdays group (Tuesday, Wednesday, and Thursday) shows the comparison between the 65th percentile of SWZT speeds in 2019 and the average speed in each month group for the Weekdays group (Tuesday, Wednesday, and Thursday).

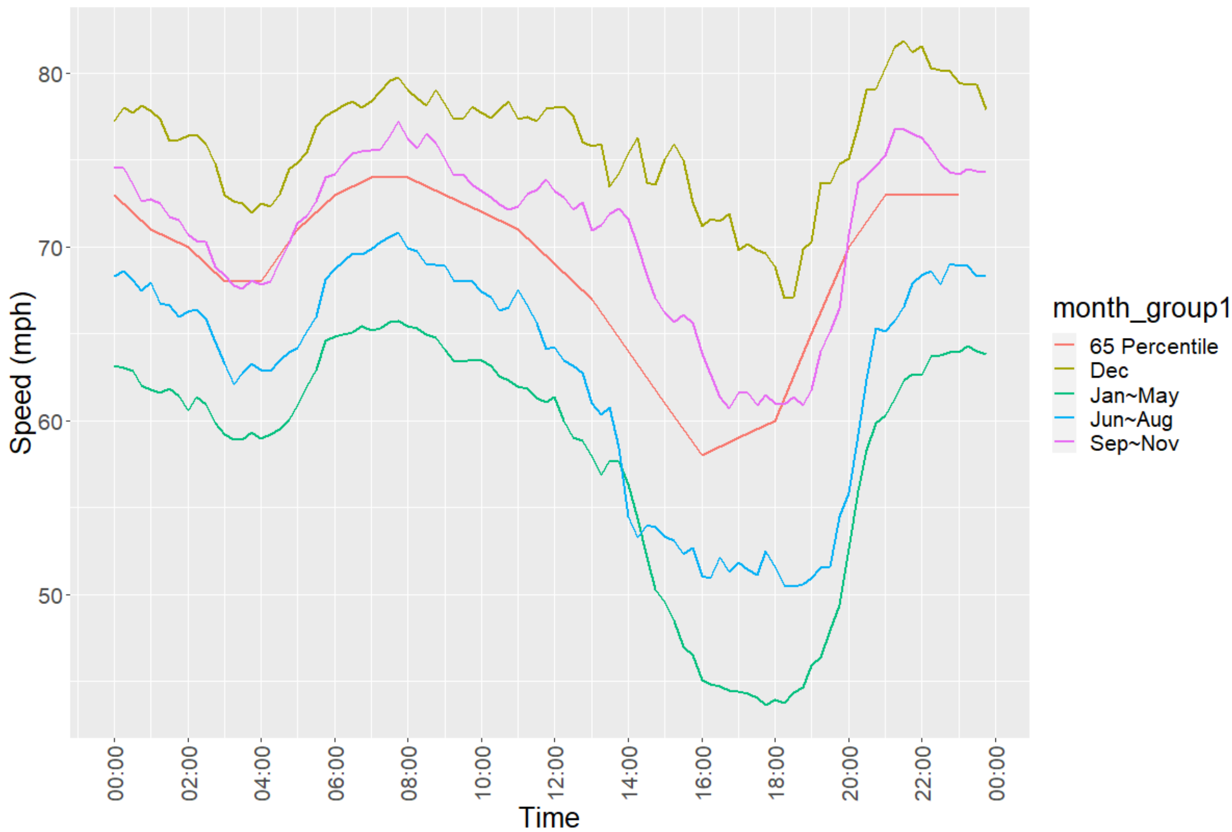


**Figure 12. Speed comparison for month groups within the Weekdays group (Tuesday, Wednesday, and Thursday)**

Both figures suggest that the 65th percentile method may not be able to capture the speed variation between defined groups. Thus, it would lead to biased estimations. For example, as shown in Figure 11. Speed comparison for day-of-the-week groups within the January–May month group, the 65th percentile value overestimates the typical speed for all day-of-the-week groups within the January–May group.

## MACHINE LEARNING MODELS

This chapter describes the ML models that were proposed to forecast the work-zone impact on traffic. First, an artificial neural network (ANN) was developed using INRIX speed data to predict the impact of work zones on speeds through the work zone. Second, an ANN with a similar structure was developed using the SWZT volume data to predict the impact on traffic volume. The researchers proposed two metrics to estimate volume: the volume on the segment upstream of the work zone (demand) and the volume on the work-zone segment (through-volume). Both values were averaged over the duration of the work zone.

The researchers also tested the performance of three short-term travel-time forecasting models to estimate corridor travel time in near real time. These models would support traffic operations and the provision of traveler information. The models were trained in the context of a separate project and without explicitly considering the presence of work zones, but their promising performance under typical conditions motivated the short-term travel-time model testing conducted in this effort.

### Overview of Artificial Neural Network Models

ANNs are a widely used ML model used to process the complex relationship between inputs and outputs that would prove impossible or difficult to process by human or statistical standards (Du et al. 2016 and 2017, Hou et al. 2015, Lana et al. 2018, Kamyab et al. 2020, Weng and Meng 2013). An ANN consists of nodes (artificial neurons) and connections of neurons between adjacent layers. Each neuron has an input and output; the output is equal to the input processed by an activation function. The number of neurons in the first layer is equal to the number of predictors, and the input for each neuron is the value of the corresponding predictor. Similarly, the number of neurons in the last layer is equal to the number of target variables, which are the variables predicted by the ANN. The input for a neuron in the middle layers is the weighted sum of the outputs of all neurons from its previous layer.

The mission of an ANN model is to find the optimal weights that can minimize selected metrics encoding the difference between the outputs of the last layer and the target values. The root mean square error (RMSE), mean squared error (MSE) and mean absolute error (MAE) are examples of the most commonly used metrics to evaluate the success of an ANN model. Figure 13 shows the structure of a typical ANN with four layers.

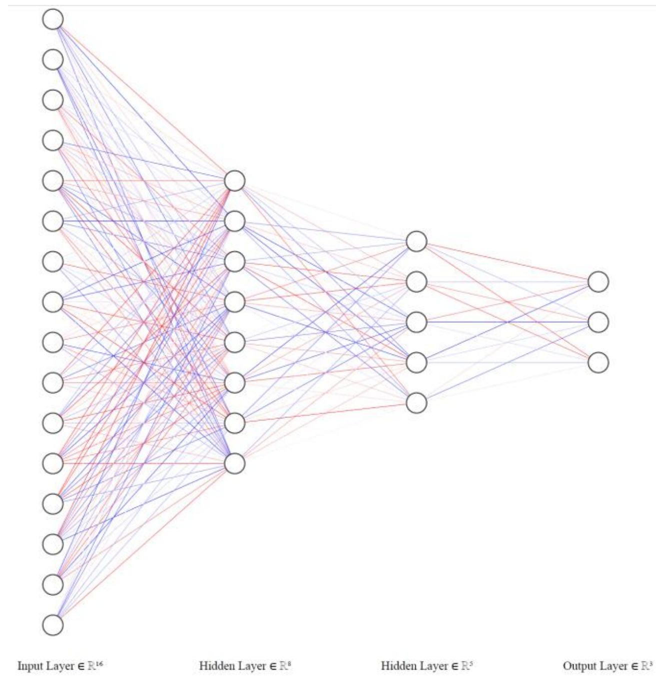


**Figure 13. Example of an ANN model structure**

The first layer and the last layer have 16 and 3 neurons, respectively, which indicates there are 16 predictors and 3 target variables. The lines between nodes in adjacent layers represent the weights that need to be optimized. The performance of ANNs depends on the selection of the parameters that define the structure of the network, which are called hyperparameters.

Common hyperparameters include the number of layers, the number of neurons in each layer, batch size (or number of samples considered in one iteration), and number of epochs, which are explained in the next section. These hyperparameters are usually tuned to find an optimal combination of hyperparameters that minimizes the predefined loss function to give better results.

### ANN Model for Speed Impacts

In this section, we describe the implementation of an ANN model to forecast the speed changes introduced by a planned closure, characterized by the variables defined in Table 3 and located on specific INRIX segments for which the researchers considered the attributes, as also listed in Table 3.

**Table 3. Predictor variables for ANN models of work-zone speed impacts**

| Predictor Variable | Description |
|---|---|
| Closure length | Length of work zone |
| Closure start time | Start hour of work zone |
| Closure duration | Number of hours of work zone |
| Percent of lanes closed | Number of closed lanes ÷ total existing lanes |
| Closure direction | – |
| Closure location | Distance between start point of work zone and start point of corridor |
| Day of week index | – |
| Time step index | – |
| Typical travel speed for relevant segments | Typical travel speeds every 15 minutes for duration of study period (normalized) |

For these models, the researchers aggregated segment speed data into 15-minute intervals and defined a study period that consisted of one hour prior to the beginning time of the work zone and one hour after the end time of the work zone. The selection of the study period was done empirically based on the characteristics of the work zones considered in this effort. The proposed models produce speed forecasts at 15-minute intervals for all relevant segments during the study period. For each closure there were three relevant INRIX segments (Figure 14):

- Upstream segment: the upstream segment from the start point of the work zone (shown in green)
- Start segment: the segment in which the start point of the work zone is located (shown in blue)
- End segment: the segment in which the end point of the work zone is located (shown in orange)

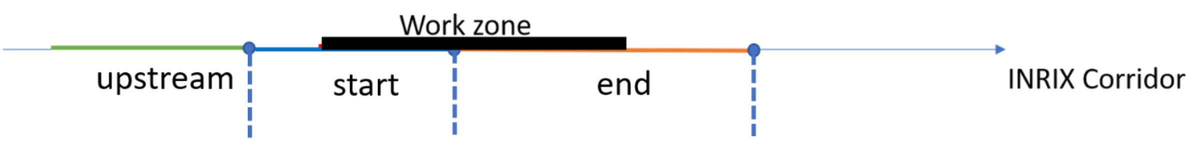


**Figure 14. Segment definition for speed prediction model**

Typical speeds were estimated using INRIX data using the same day-of-the-week and month grouping approach proposed for SWZT data and 2019 data. The speed was normalized using Equation (4) to stabilize the training process:

$$x_{\text{normalized}} = \frac{x - x_{\min}}{x_{\max} - x_{\min}} \quad \textbf{(4)}$$

where, $x$ is a raw speed data point for segment $s$ at interval $t$, and $x_{\min}$ and $x_{\max}$ are the minimum and maximum speed values, respectively, across all segments and time intervals. The researchers used the MSE (Equation 5) as the loss function that the training process aimed to minimize:

$$\text{MSE}=\frac{1}{n}\sum_{i=1}^{n}\left(Y_i-\hat{Y}_i\right)^2 \tag{5}$$

where, $n$ is the number of samples, $Y_i$ is the real value of a target variable, and $\hat{Y}$ is the predicted value. The sigmoid function, Equation (6), was used as the activation function:

$$S(x)=\frac{1}{1+e^{-x}}. \tag{6}$$

Available data were split into training data and testing data with a ratio of 0.75:0.25. Training data were used for the model to learn the relationship between predictors and target variables, and testing data were used to evaluate the performance of the trained model. Keras, which is a Python (programming language) deep learning application programming interface (API), was employed to train the model. Keras further splits the training data into trained data and validation data with a ratio of 0.67:0.33 to avoid overfitting. Only the trained data are used to train the model; validation data are used to evaluate the model performance at each iteration and adjust the model parameters correspondingly. The evolution of the loss value with the epoch is shown in Figure 15.

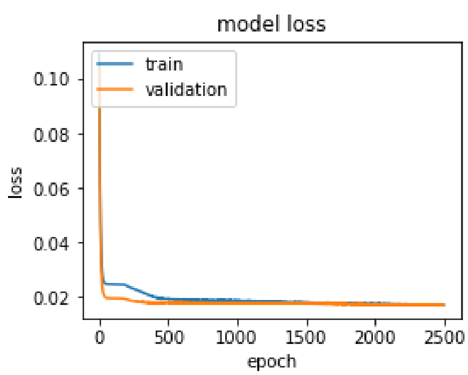


**Figure 15. Loss value for speed prediction model**

One epoch is one iteration in which all data in the trained set is trained once. As Figure 15 shows, the training process converges after 2,500 epochs.

In this case, Figure 15 compares observed and forecasted speeds on the three relevant segments for all work zones in the testing dataset. The green segment has a slope of 1 and represents a perfect prediction. The RMSE and MAE for the model performance were equal to 10.19 mph and 5.78 mph, respectively. The MAE value was within 10 percent of the mean value of the speeds for work zones in the testing data, which was equal to 59.5 mph, so the trained model was considered to perform well overall. However, Figure 16 suggests that the model performed well when the true speed was high but tended to overestimate the speed when the real speed was low.

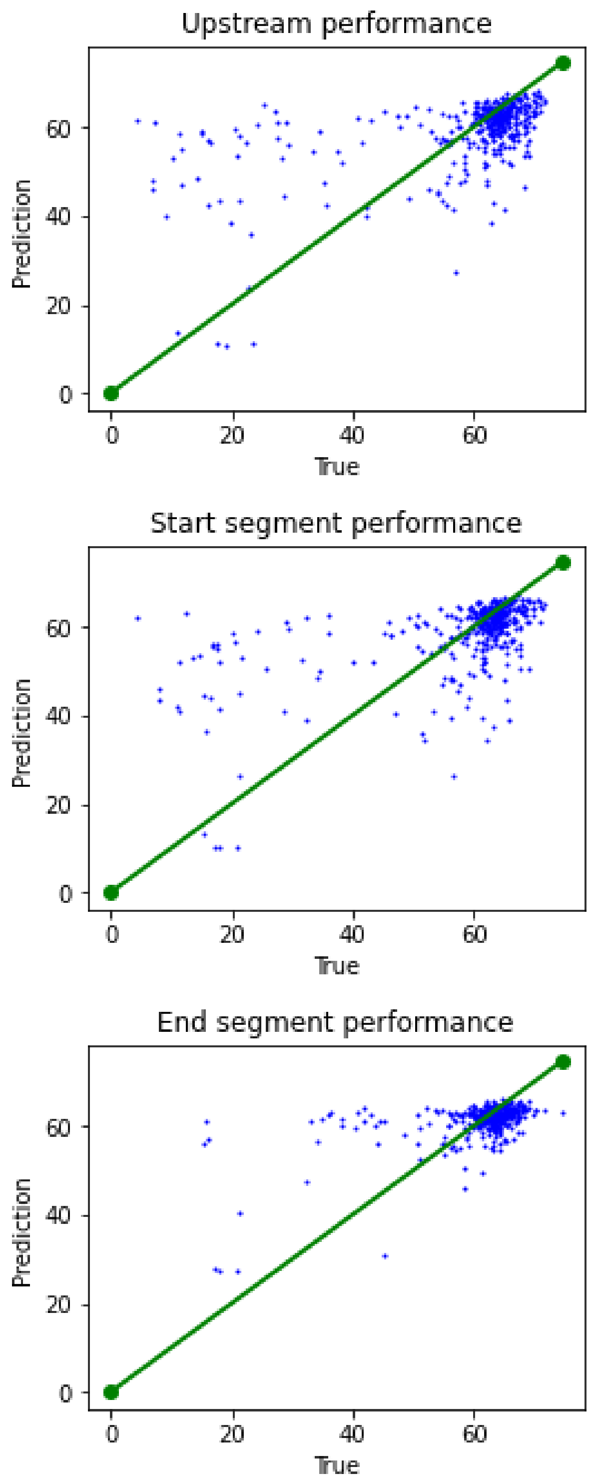


**Figure 16. Performance of ANN model for speed impact forecasting on testing data**

The poor performance for closures in which traffic speed was significantly reduced was likely a result of having few data points in the training dataset for which speeds through the work zone decreased by more than 5 mph. The former is not surprising given that most of the closures were scheduled during nighttime hours when the traffic volume was low and the travel speed was not significantly reduced. In other words, the model is not able to generate accurate predictions for cases that it is not trained to predict.

Figure 17 shows the comparison between typical speeds and speeds during work zones for all available work-zone data.

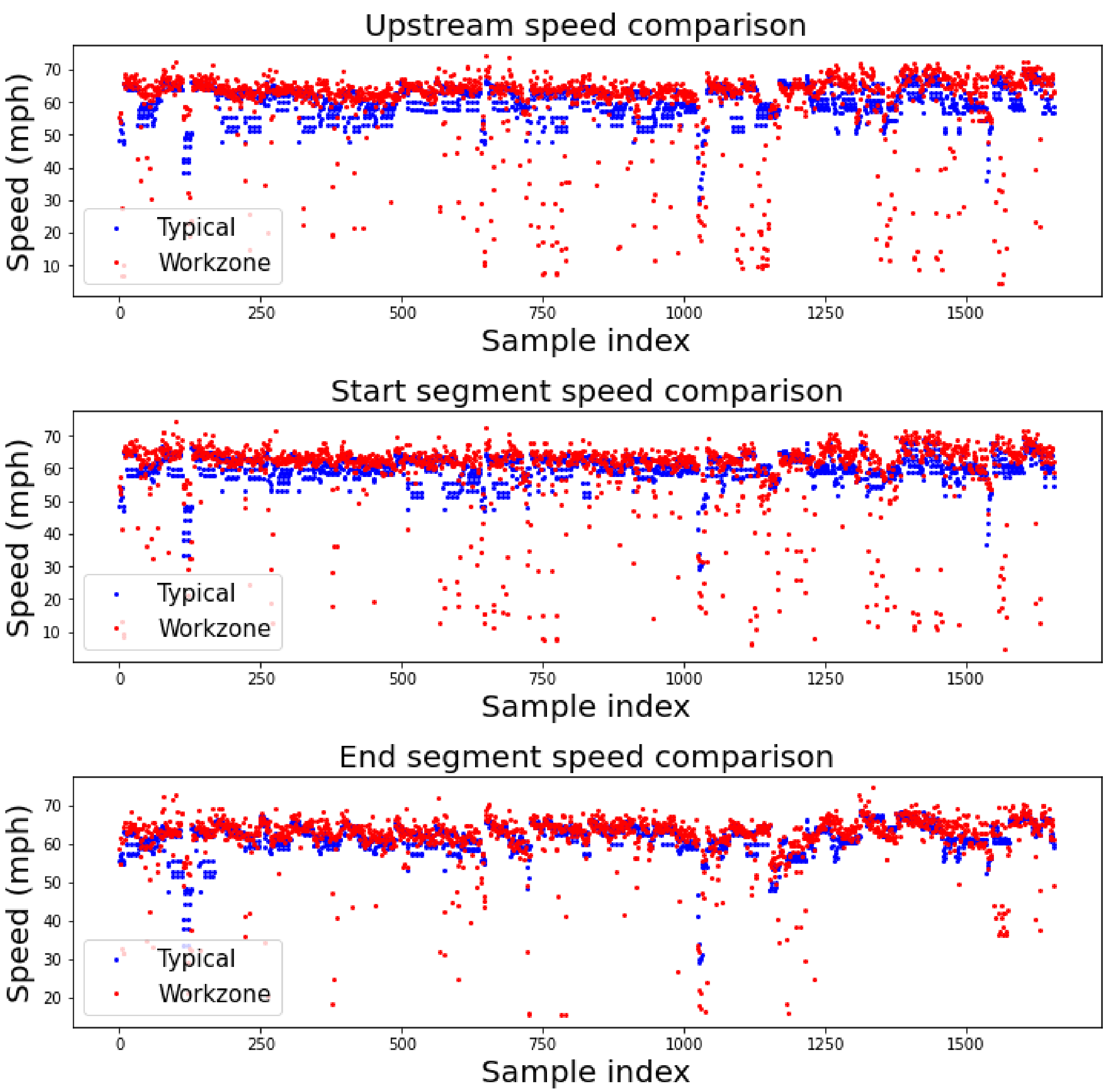


**Figure 17. Observed work-zone speed impacts for all work zones**

This figure shows a small portion of the work-zone data had reduced speeds, while most of the speeds were similar to typical speeds. Only 10.5 percent of SB and 23.5 percent of NB closures had more than 30 minutes out of two hours in which the speed reduction was more than 5 mph compared to the typical condition. As a result, the lack of enough samples with significantly reduced speed made the model unable to predict reduced speed accurately. It is expected that the model performance could be improved if a larger dataset is used for training.

### ANN for Work-Zone Volume Impacts

This section describes an ANN model to forecast the impact of work zones on traffic volume. In the context of this effort, volumes that were lower than typical values may be interpreted as a reduction of travel demand through the work zone, since the types of closures analyzed in this study did not lead to substantial queues. For this model, the researchers used SWZT volume data as predictors. The studied time period was the work-zone duration, and relevant sensors for the analysis are defined as shown in Figure 18.

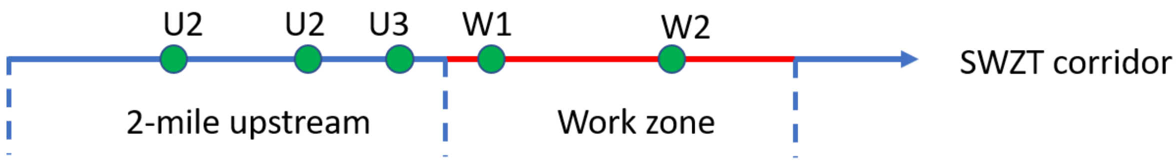


**Figure 18. Segment definition for volume prediction model**

The first set of sensors are upstream sensors within two miles of the start point of the work zone. The second set of sensors are on the work zone. The average volume measured by sensors located in the upstream segment was regarded as travel demand for the work-zone segment.

Table 4. Predictor variables for ANN models of work-zone volume impacts presents the predictor variables for this ANN model.

**Table 4. Predictor variables for ANN models of work-zone volume impacts**

| Predictor Variable | Description |
|---|---|
| Closure length | Length of work zone |
| Closure start time | Start hour of work zone |
| Closure duration | Number of hours of work zone |
| Percent of lanes closed | Number of closed lanes ÷ total existing lanes |
| Closure direction | – |
| Closure location | Distance between start point of work zone and start point of corridor |
| Day of week index | – |
| Time step index | – |
| Typical vehicle counts for relevant segments | Typical average vehicle counts every 15 minutes for duration of study period (normalized) |

The target variables were the average volumes (vehicles per hour per lane [vphpl]) for the duration of the closure on each segment.

A preliminary analysis of the training data suggested that sensor errors may have been present in the sample. Figure 19 shows a cluster of data points for which traffic volumes on the day of the closure were larger than typical volumes. These data points were removed from the data for final model training and validation.

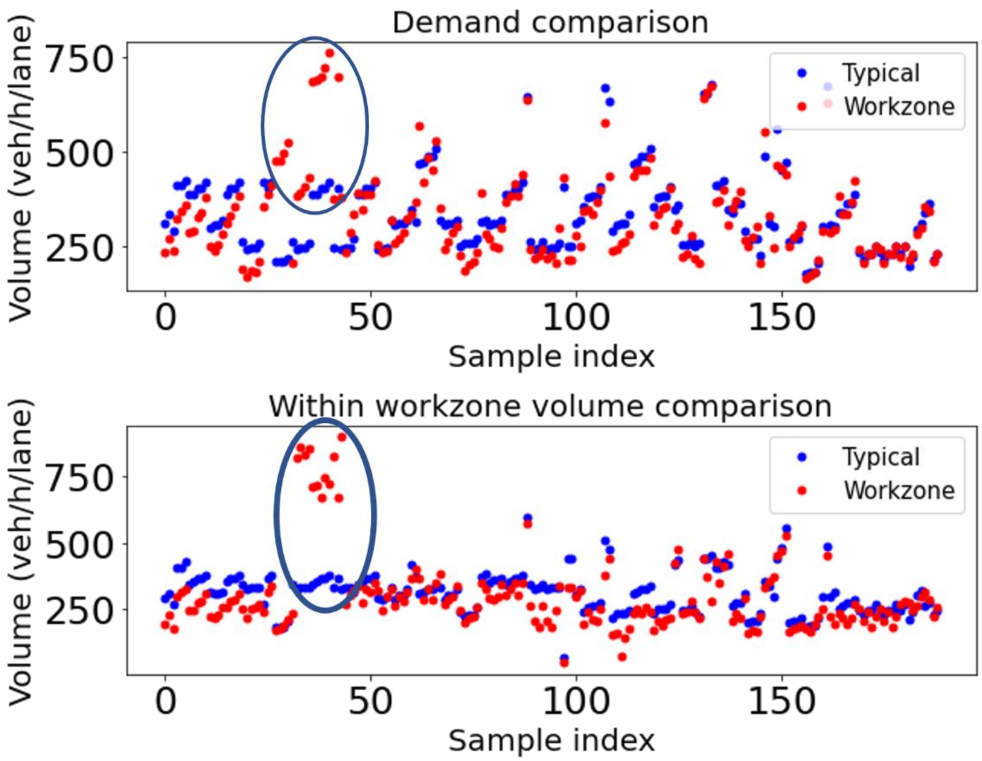


**Figure 19. Comparison between typical volume and volume during work zones**

The performance of the trained model on the testing data is shown in Figure 20, which suggested that model performance was consistently good for a range of actual volumes.

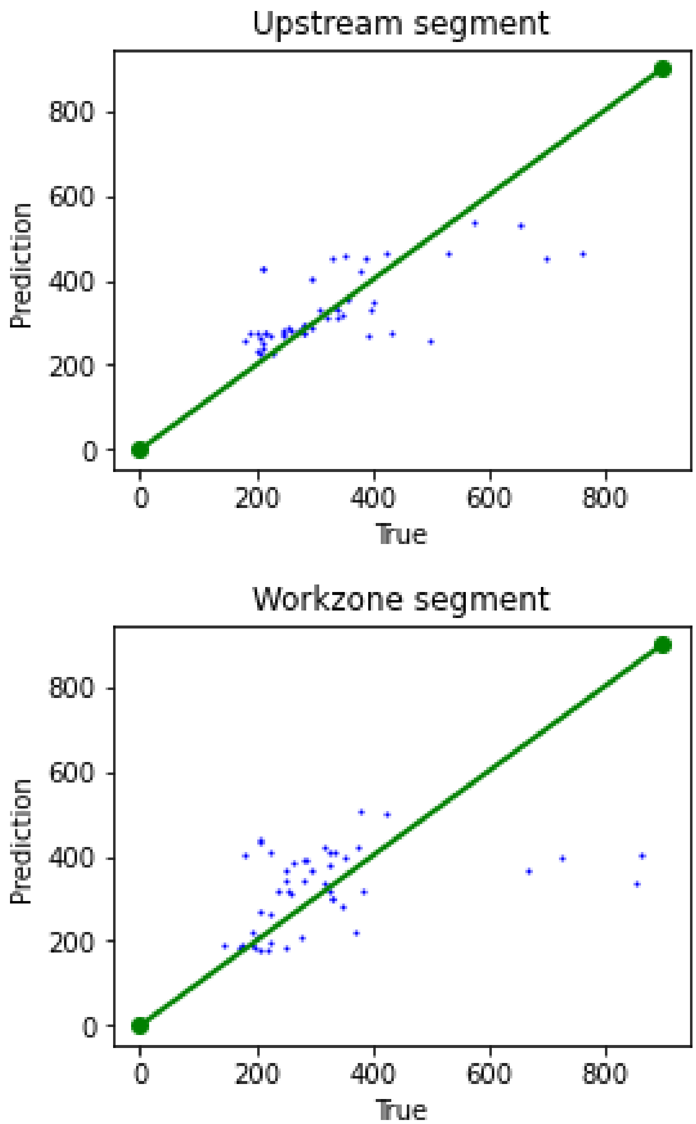


**Figure 20. Performance of the volume prediction model**

The RMSE and MAE were equal to 57 vphpl and 44 vphpl, respectively. The MAE approximated 14 percent of the average volume in the testing data, which was 309.4 vphpl.

The researchers compared the performance of the ANN model to the volume estimates obtained by using a fixed reduction ratio model based on historical data and a linear regression model. The two alternative approaches are appealing because they are simpler to estimate than an ANN. The fixed ratio reduction model assumes the volume reduction ratio for any work zone is equal to the average volume reduction ratio over all work zones, which equaled 3.7 percent and 12.6 percent for the upstream segment and work-zone segment, respectively. The linear regression model takes the same predictors as the ANN model. The RMSEs and MAEs are shown in Table 5.

**Table 5. Performance comparison after suspicious data removal**

| Model | RMSE (vphpl) | MAE (vphpl) |
|---|---|---|
| ANN | 57 | 44 |
| Fixed reduction ratio (3.7%, 12.6%) | 144 | 112 |
| Linear regression | 50 | 37 |

The linear regression model had higher accuracy than the ANN. The average volume in the testing data without outliers was 309.4 vphpl. Therefore, the MAEs of the ANN model and the linear regression model approximate 14 percent and 12 percent of the average volume, respectively, and both models are considered to perform well overall.

## Short-Term Travel-Time Prediction

This section describes the application of three short-term prediction models to the estimation of corridor travel times during work zones. Short-term travel-time prediction models are intended to provide real-time information to travelers or to support traffic operations. The models that were implemented were developed in the context of a separate project and will be documented in a final report to be submitted to TxDOT by August 31, 2021. The goal of the analysis presented in this document is to explore the potential value of short-term travel-time predictions models in the context of work-zone traffic management.

The models that were implemented were trained using 5-minute INRIX data and produce travel time forecasts at 5-minute time steps, one hour into the future. A separate model was trained for each segment on the corridor and for every 5-minute forecasting horizon. For each segment, model inputs consisted of the travel times on selected upstream and downstream segments during the previous time steps.

Corridor travel times were estimated using a dynamic approach that is expected to closely resemble the actual travel time experienced by a vehicle during a trip on multiple segments. Most practical methods to estimate travel times in real time use an instantaneous approach, in which the corridor travel time at time step t=0 is estimated as the sum of segment travel times at t=0. However, it is possible for vehicles to arrive to downstream segments at time $t = t_1$, during which the travel time may be different than what was observed at t=0. Therefore, the "instantaneous" prediction could be biased. A "dynamic" travel-time prediction framework uses the travel time for each segment corresponding to the arrival time at the segment, which requires forecasting future travel times for downstream segments.

The analysis that follows compares the performance of a naïve model, which uses the current travel times on each segment as the predicted travel time for future time steps (instantaneous travel time) to two dynamic travel-time prediction methods: 1) a linear time series (LTS) model that uses the INRIX speed from all INRIX segments and the SWZT speed and volume from all SWZT sensors in the past half hour to predict travel time for each INRIX segment in the next hour by applying linear regression and 2) a recurrent neural network (RNN) that uses the current

INRIX speed and SWZT speed and volume to predict the travel time on each INRIX segment in the next hour. RNN is a type of neural network that is able to predict temporal dynamic behavior. Note that these models do not consider the work-zone information as predictors, so the researchers expected a larger error for the prediction for a work-zone day than for a typical day.

Figure 21 exemplifies the prediction results for these models on two work-zone days.

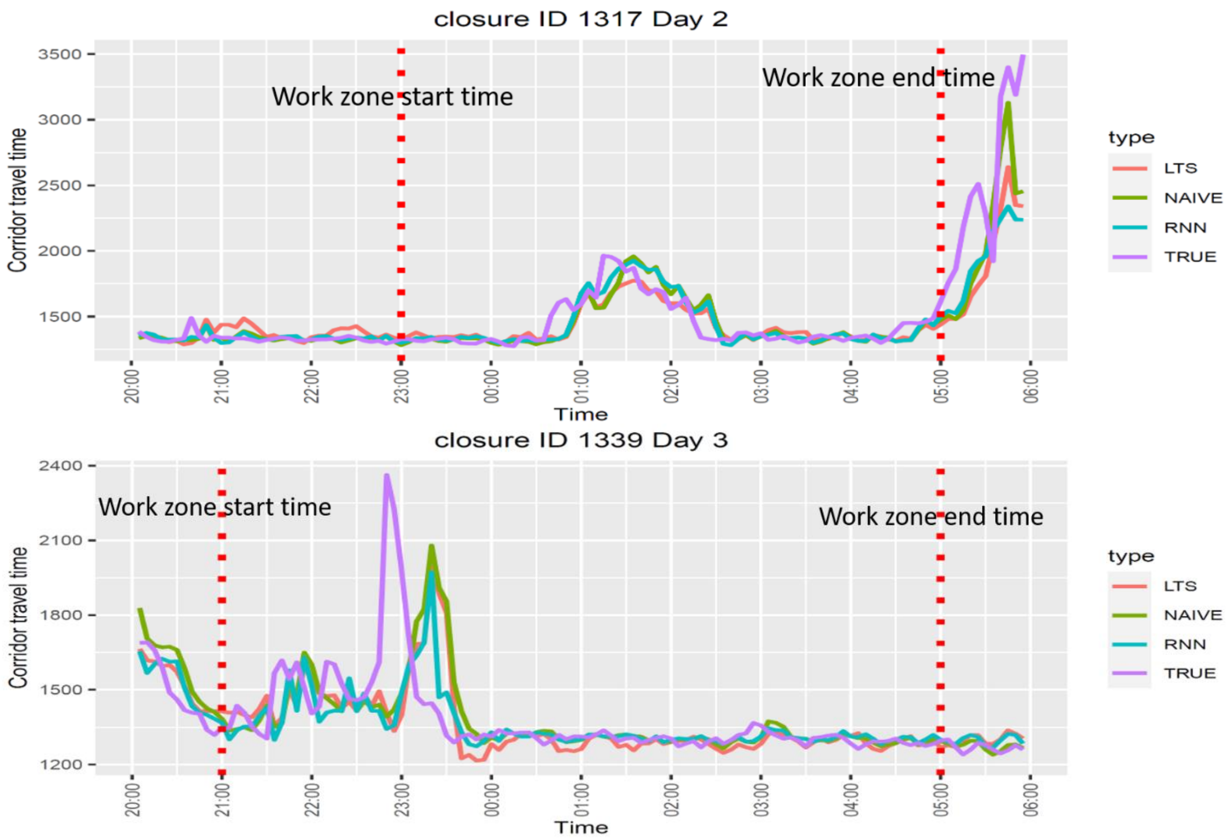


**Figure 21. Performance of short-term prediction models for a work-zone day**

The dashed lines indicate the start and end times of the work zone. For closure 1317, the model can accurately forecast the increased travel time, while, during closure 1339, all models underestimate the increase in travel times. This is likely due to the fact that the model is trained without considering work-zone characteristic parameters.

Figure 22 and Figure 23 show the RMSE and MAE of the travel time prediction during the work-zone hours (closure) and during the same hours of the day for all other days (typical) for the entire corridor (Figure 22) and for the work-zone segments (Figure 23).

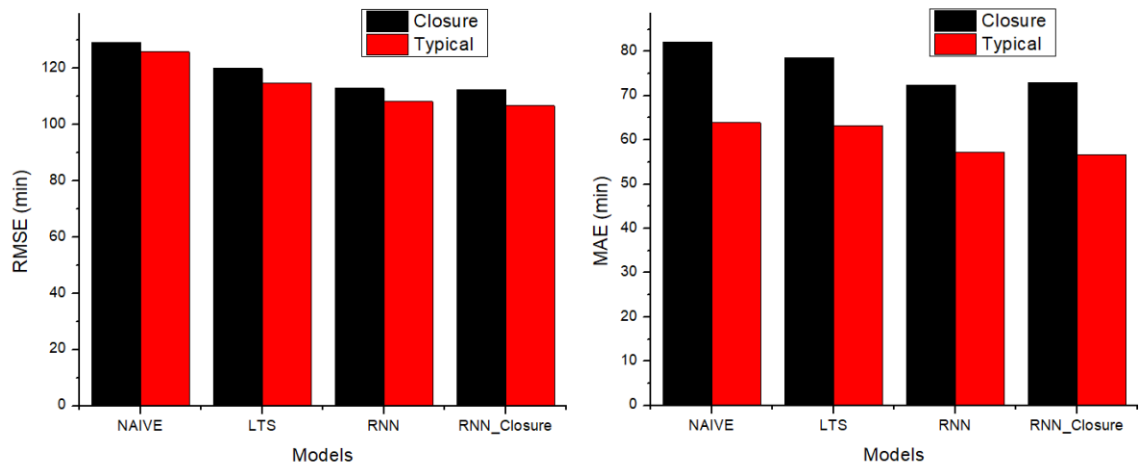


**Figure 22. Performance of short-term travel-time prediction models for total corridor travel time forecasting**

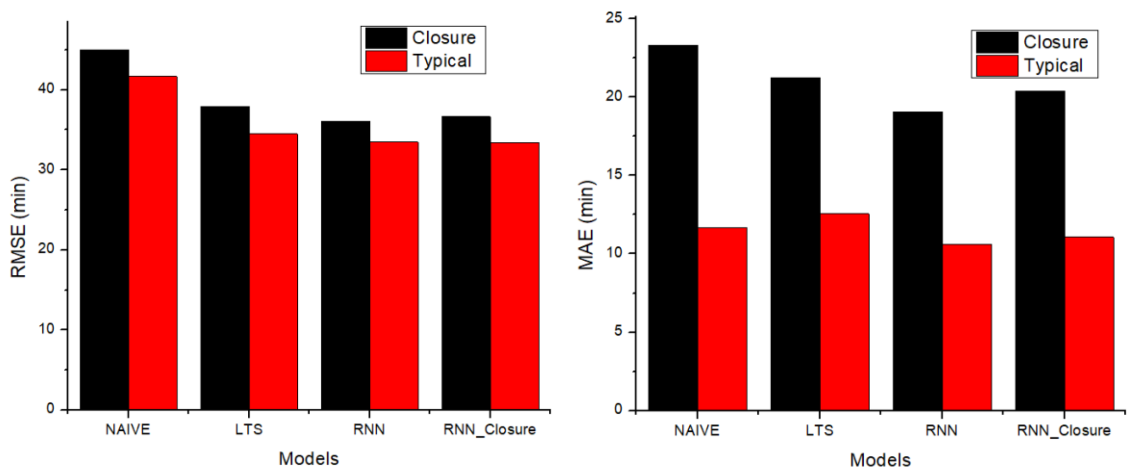


**Figure 23. Performance of short-term travel-time prediction models on segments affected by work zone**

It is important to consider that the average performance of the RNN and LST models was observed to be up to 50 percent better than that of the naïve model during a.m. and p.m. peak periods. The benefits of these models at nighttime (when most of the analyzed closures took place) is less pronounced, as reflected by the similar height of all red bars in Figures 22 and 23, particularly on typical days and when only the closure links are considered. However, the ML approaches were observed to perform consistently better than the naïve approach during work zones. All models performed worse during work zones, but it is expected that errors may be reduced by explicitly considering work-zone variables in the training process.

## SUMMARY AND FUTURE WORK

This report summarizes the implementation of ML techniques to forecast the impacts of planned work zones on vehicle speeds and traffic volumes and for short-term travel-time prediction. The data used in this effort were collected on a 20.4-mile section of I-35 in Austin, Texas, and includes SWZT point speed and volume data, along with INRIX segment speed data. Forecasting models were trained and tested using data from 133 work zones.

To enhance the estimation of work-zone related delays and user costs, the researchers developed a systematic approach to calculate typical travel times at 15-minute intervals, which were used as the reference values against which work-zone travel times were compared. The method considered both the need to eliminate outliers that may bias the estimates and the importance of accounting for the variations in travel times across days of the week and months of the year. This work proposed clusters of days of the week and months of the year expected to have similar typical travel time values throughout the day and conducted statistical analyses to confirm that the differences among the clusters were significant.

The final workflow involved computing typical travel times within each cluster at 15-minute intervals after removing data outliers using a three-sigma rule. Typical travel time estimates were provided by sensor and cluster and observed differences among clusters suggested that the proposed method is likely to provide more accurate delay estimates than approaches that consider a single reference value.

This effort explored the use of ANNs to forecast speed and volume reduction for planned closures. Speed forecasting models performed well on average (RMSE of 10.19 mph) but tended to underestimate speed reductions when they are significant. The latter is likely a result of having a small fraction of time steps exhibiting significant speed reductions in the training dataset, which consisted mostly of nighttime closures.

Models used to forecast changes in traffic volumes had an average error (RMSE) of 57 vphpl, which is comparable to that of linear regression models that may be preferable since they are simpler to estimate. Although the ANN model had slightly higher errors than a linear regression model, the researchers believe the ANN model would outperform the linear regression model if data for more daytime closures and more types of highway closure locations becomes available.

The research team also analyzed the performance of three STTTP methods, trained as part of a separate effort during work zones. STTTPs are intended to provide a more precise estimate of expected travel times in real time. The trained models, which included a time series approach and two types of ANNs, were very successful on average, outperforming traditional approaches by up to 50 percent during peak periods.

While model performance was not as impressive during the presence of work zones, preliminary results were promising, with ML models consistently outperforming the traditional approaches. Further model refinements to explicitly consider the presence of work zones and their characteristics are expected to improve model predictions during the presence of work zones. The efforts described in this report illustrate the potential value of emerging data sources and modeling techniques to support work-zone planning and management.

The original workplan for this project involved incorporating successful workflows into an existing web application. Unfortunately, the data pipeline that feeds such web application became inactive in late 2020 due to COVID-related budget costs. Instead of working on implementation, researchers emphasized the exploration of ML methods to support work-zone planning and operations. All findings were documented to facilitate their integration into the web application once the data pipeline is restored.

## REFERENCES


Box, G. E. P. and D. R. Cox. 1964. An Analysis of Transformations. *Journal of the Royal Statistical Society. Series B (Methodological)*, Vol. 26, No. 2, pp. 211–252.

Chen, A., N. Ruiz Juri, H. Westerfield Ross, Y. Li, and R. Juri. 2019. Understanding the Impacts of Freeway Lane Closures through Data: A Combined Analysis of NPMRDS and Fixed-Sensor Data. 98th Anuual Meeting of the Transportation Research Board, January 13–17, Washington, DC.

Du, B., S. Chien, and J. Lee. 2017. Predicting Freeway Work Zone Delays and Costs with a Hybrid Machine-Learning Model. *Journal of Advanced Transportation*, Vol. 2017.

Du, B., S. Chien, J. Lee, L. Spasovic, K. Mouskos, B. Du, S. Chien, J. Lee, and L. Spasovic. 2016. Artificial Neural Network Model for Estimating Temporal and Spatial Freeway Work Zone Delay Using Probe-Vehicle Data. *Transportation Research Record: Journal of the Transportation Research Board*, No. 2573, pp. 164–171.

Hou, Y., P. Edara, and C. Sun. 2015. Traffic Flow Forecasting for Urban Work Zones. *Transactions on Intelligent Transportation Systems*, Vol. 16, No. 4, pp. 1761–1770.

Kamyab, M., S. Remias, E. Najmi, S. Rabinia, and J. M. Waddell. 2020. Machine Learning Approach to Forecast Work Zone Mobility Using Probe Vehicle Data. *Transportation Research Record: Journal of the Transportation Research Board*, Vol. 2674, No. 9, pp. 157–167.

Lana, I., J. Del Ser, M. Velez, and E. I. Vlahogianni. 2018. Road Traffic Forecasting: Recent Advances and New Challenges. *Intelligent Transportation Systems Magazine,* Vol. 10, No. 2, pp. 93–109.

Schnell, T., J. S. Mohror, and F. Aktan. 2002. Evaluation of Traffic Flow Analysis Tools Applied to Work Zones Based on Flow Data Collected in the Field. *Transportation Research Record: Journal of the Transportation Research Board*, No. 1811, pp. 57–66.

TRB. 2000. *Highway Capacity Manual*. Transportation Research Board, Washington, DC.

Zhang, Z., D. Yang, T. Zhang, Q. He, and X. Lian. 2013. A Study on the Method for Cleaning and Repairing the Probe Vehicle Data. *Transactions on Intelligent Transportation Systems*, Vol. 14, No. 1, pp. 419–427.

Weng, J., and Q. Meng. 2013. Estimating Capacity and Traffic Delay in Work Zones: An Overview. *Transportation Research Part C: Emerging Technologies*, Vol. 35, pp. 34–45.

**THE INSTITUTE FOR TRANSPORTATION IS THE FOCAL POINT FOR TRANSPORTATION AT IOWA STATE UNIVERSITY.**

**InTrans** centers and programs perform transportation research and provide technology transfer services for government agencies and private companies;

**InTrans** contributes to Iowa State University and the College of Engineering's educational programs for transportation students and provides K–12 outreach; and

**InTrans** conducts local, regional, and national transportation services and continuing education programs.

INSTITUTE FOR TRANSPORTATION

IOWA STATE UNIVERSITY

Visit **InTrans.iastate.edu** for color pdfs of this and other research reports.