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

tech transfer summary

This effort illustrates the potential value in using emerging data sources and modeling techniques to support work-zone planning and management.

SWZDI
Smart Work Zone Deployment Initiative

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

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PRINCIPAL INVESTIGATOR
Natalia Ruiz-Juri, Director
Network Modeling Center
Center for Transportation Research
The University of Texas at Austin
nruizjuri@mail.utexas.edu / 512-232-3099

MORE INFORMATION
intrans.iastate.edu

SWZDI
Iowa State University
2711 S. Loop Drive, Suite 4700
Ames, IA 50010-8664
515-294-8103

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. The fund is administered by Iowa State University's Institute for Transportation, and the lead agency is the Iowa Department of Transportation.

IOWA STATE UNIVERSITY
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Goal

The goal of this project was to explore the use of artificial neural networks (ANNs) to forecast speed and volume changes for planned work-zone closures and analyze the performance of three short-term travel-time prediction methods. The researchers also proposed a workflow to estimate typical travel times using continuously collected data to support consistent delay estimates.

Objectives

- Refine methods to estimate work zone-related delays and user cost for ongoing and past closures
- Implement machine learning (ML) techniques to forecast the impact of planned work zones on I-35 on speed and volume
- Implement ML models for short-term travel-time prediction

Problem Statement

Work zone delays account for 20% of non-recurrent roadway congestion, so proactively managing the events that cause the congestion can lead to significant improvements in the performance of the transportation system.

Background

A number of sources of traffic and travel data have emerged in the last decade thanks to advances in the intelligent transportation system (ITS) and the increased availability of data from global positioning system (GPS) devices and location-based services. At the same time, current computational capabilities and software tools facilitate the use of ML methods that are being implemented in transportation research given their ability to capture the non-linear and complex relationships between predictors and target variables.

Developing data-supported methods to evaluate the impact of past work-zone closures and predict the effects of planned closures is critical in designing and evaluating effective mitigation strategies.

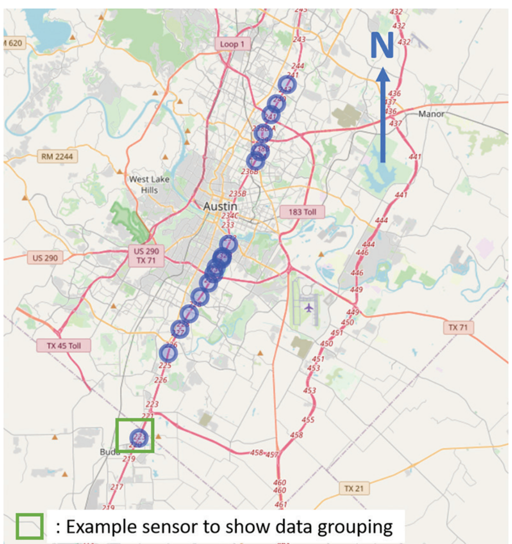
Project Description

This project explored the use of ANNs to forecast speed and traffic volume reductions for planned highway closures.

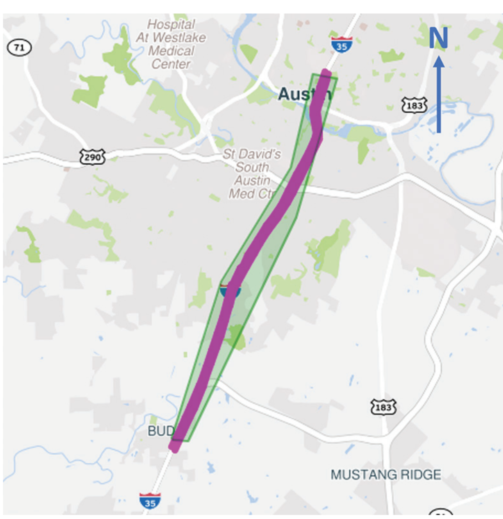
The data used for this project were collected on a 20.4-mile section of I-35 in Austin, Texas, and included smart work zone trailer (SWZT) point speed and volume data, as well as INRIX segment speed data.

To improve the estimation of work-zone related delays and decrease 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 researchers also analyzed the performance of three short-term travel-time prediction (STTTP) methods, which were 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.



SWZT locations on I-35 through Austin, Texas

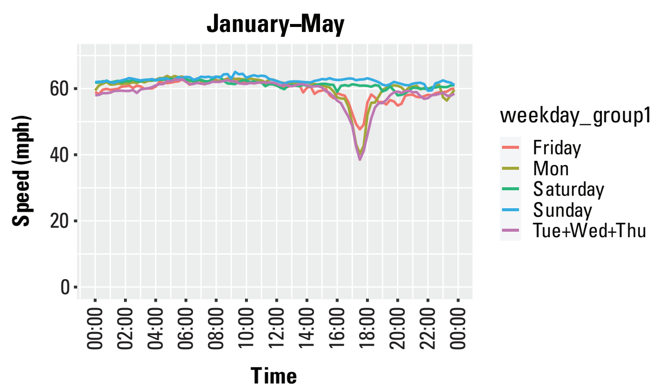


INRIX segments for the project

Key Findings

Estimation of Typical Traffic Conditions

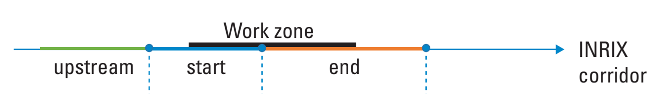
- Typical speed and volume values vary by the day of the week and the month of the year. Statistically significant differences were found among the following five groups for day of the week: Monday, Tuesday/Wednesday/Thursday, Friday, Saturday, and Sunday. Differences were also observed between the following four groups for month of the year: January–May, June–August, September–November, and December.
- The researchers proposed a simple data cleaning method to reduce the impact of outliers in the estimation of typical travel times, which removed 3.98% of the data points.
- The typical traffic conditions during each time interval were estimated using clean data as the average value over all days in the same group.



Typical speed for each day-of-the-week grouping for January–May

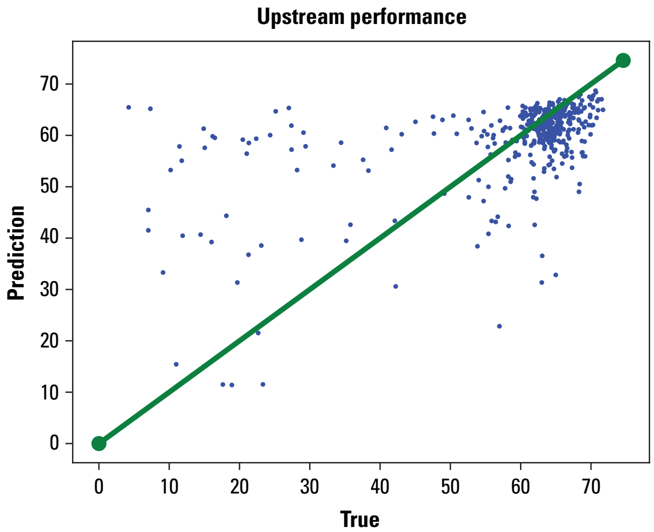
Machine Learning Models for Speed Change Prediction

- An ANN model was implemented for speed change prediction using INRIX speed data.
- Three segments were studied for a time period including one hour prior to and one hour after the work-zone duration.

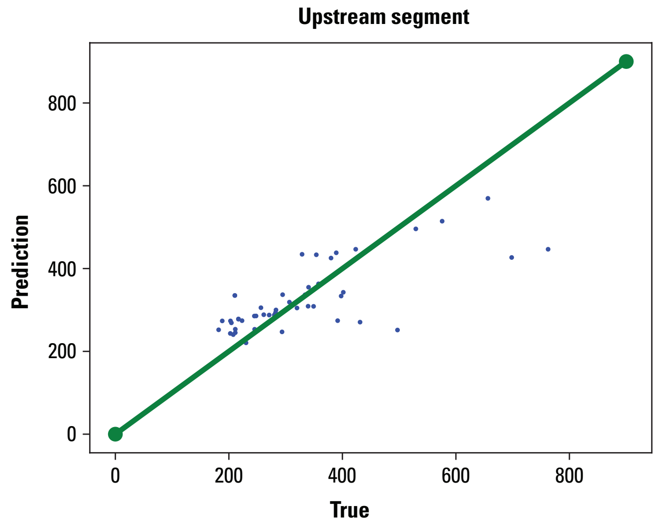


Segment definition for speed prediction model

- The predictors used were closure length, closure start time, closure duration, percentage of lanes closed, closure direction, closure location, day-of-week index, time-step index, and typical travel speed.



Performance of speed model

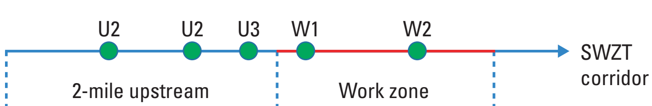


Performance of volume model on work-zone affected segments

- The target variable was travel speed within work zones.
- The root mean square error (RMSE) and mean absolute error (MAE) in the model results were 10.19 mph and 5.78 mph, respectively. The MAE value was within 10% of the mean value of the speeds for work zones in the testing data, which equaled 59.5 mph. This was considered acceptable performance for the use case.
- The model tended to overestimate the speed when the real speed was low, which suggests that further training is desirable.

Machine Learning Model for Volume Change Prediction

- An ANN model was also implemented for volume change prediction using SWZT volume data.
- Two segments were studied, and the studied time was the work-zone duration.

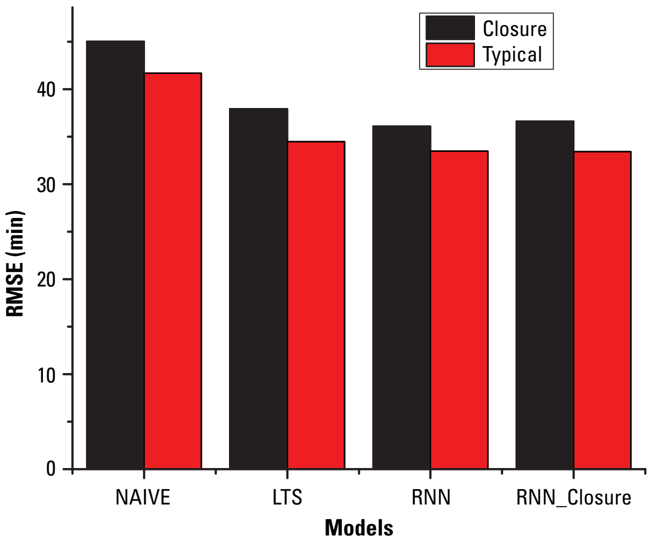


Segment definition for volume prediction model

- The predictors included the same work-zone characteristic parameters as those used for the speed model and typical volume.
- The target variable was the volume on the studied segments during work-zone hours.
- The RMSE and MAE were equal to 57 vehicles per hour per lane (vphpl) and 44 vphpl, respectively. The MAE approximated 14% of the average volume in the testing data, which was 309.4 vphpl.

Short-Term Travel-Time Prediction

- The research team implemented two models for short-term dynamic travel time prediction, one hour into the future.
- Model results were compared to a naïve model, which used the current travel time to predict the travel time in the next hour.
- A linear time series model used the INRIX speed from all INRIX segments 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.
- A recurrent neural network (RNN) model used the current INRIX speed and SWZT speed and volume to predict the travel time on each INRIX segment in the next hour.
- ML approaches were observed to perform consistently better than the naïve approach during work-zone activity. All models performed worse during work-zone activity than on typical days without work-zones, but it is expected that errors may be reduced by explicitly considering work-zone variables in the ML training process.



Performance of travel time prediction on work-zone affected segments

Conclusions and Recommendations

This project implemented ML techniques to forecast the impacts of planned work zones on traffic speeds and volumes and for STTTPs. The speed forecasting models performed well on average (RMSE of 10.19 mph) but tended to underestimate speed reductions when they are significant. Models used to forecast changes in traffic volumes had an average error of 57 vphpl. The performance of both models may be improved using data from daytime closures and a variety of closure locations.

The STTTP methods tested in this project consistently performed better than a naive approach during work-zone data. These models outperformed traditional STTTP methods by up to 50% for typical peak period conditions; their performance during work zone activity can be improved by explicitly considering the presence of work zones and their characteristics in the ML training process.

This project also proposed workflows to estimate typical travel conditions for pre-defined groups of day-of-the-week and month-of-the year. The computed values are expected to support consistent estimates of delay across locations and over time.

Implementation Readiness and Benefits

New data and techniques offer the possibility to quantify the impacts of work zones with more precision. In addition to user delay and costs, other metrics such as queue length and traffic diversion may now be computed on a continuous basis. These metrics can support the design and evaluation of traffic management strategies and public information dissemination for work zones.

The results of this research suggest that the ML models are capable of predicting work-zone impact on traffic in both the long-term and short-term. The proposed models use data that are widely available, and they may be trained and tested at different locations using the workflows described in the final report for this project. The performance of the models may vary depending on the characteristics of the training data, and it is important to carefully analyze model performance before implementing a model at a new site and/or under different conditions.