Exploring the Use of Artificial Intelligence to Leverage TxDOT Data for Enhanced Corridor Management and Operations — TxDOT Project 0-7034

Presenters: William Alexander, Stephen Boyles, Ken Perrine, Natalia Ruiz-Juri

CENTER FOR TRANSPORTATION RESEARCH

THE UNIVERSITY OF TEXAS AT AUSTIN

Abstract

This project investigates several methods for improving corridor management and operations via artificial intelligence techniques. By leveraging dynamic recurrent neural network (RNN) and time series (TS) models, we are able to improve corridor travel time predictions when compared to a naïve approach that predicts based solely on static observations. Our models, which incorporate probe-based speed data from INRIX and Smart Work Zone Trailers (SWZT), can be utilized to provide more accurate travel times on variable message signs to support traffic management.

Experiment Design

- Short-term segment-level forecasts made with RNN and TS models
- Model considers 23-mile span of IH-35 in Austin in 2019
- Five-minute aggregations used for both predictors and target variables
- 85 INRIX sensors, 33 SWZT sensors for input data
- 80% of records used for model training, 20% for model testing
- Compared models' segment-level mean squared error (MSE) and corridor-level MSE and mean absolute error (MAE)

Table 1: Example of static and dynamic travel time computation

Timestep	Segment Travel Time (in timesteps)				
	Segment 1	Segment 2	Segment 3	Segment 4	Segment 5
1	1.5	0.2	0.6	0.9	0.1
2	1.7	0.4	0.7	1	0.2
3	1.5	0.4	0.8	1.1	0.2
4	1.4	0.3	0.6	1	0.1
5	1.2	0.2	0.6	1	0.1
Cumulative Travel Time					
Static	1.5	1.9	2.6	3.7	3.8
Dynamic	1.5	1.7	2.3	3.2	3.3

Travel time for traversing segment based on static and dynamic approaches

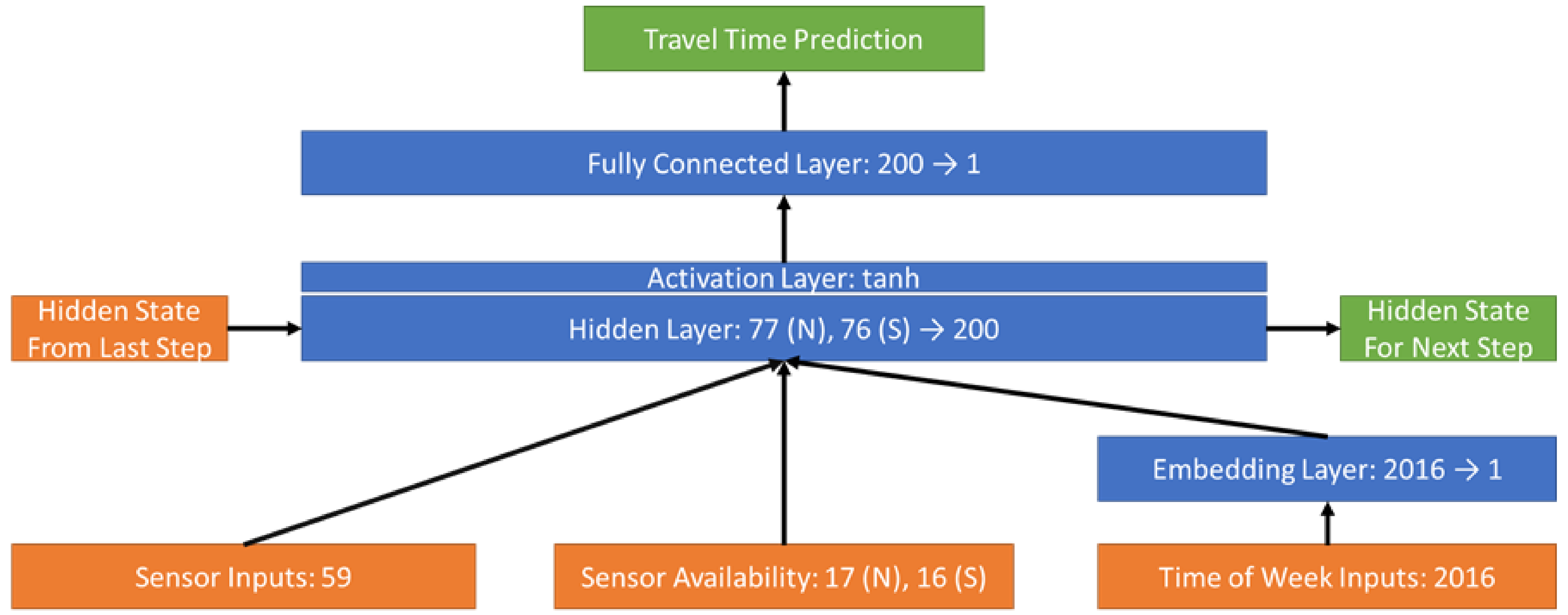
Travel time for traversing segment based on static approaches

Travel time for traversing segment based on dynamic approaches

Recurrent Neural Network Model

- Sequenced sensor data and sensor availability provided as input
- Activations of hidden nodes/states from previous pass through network used as inputs to next pass
- 27 hours of data input to maintain computational tractability
- 200 nodes in hidden layer, tanh activation function
- Time-of-week provided as categorical predictor

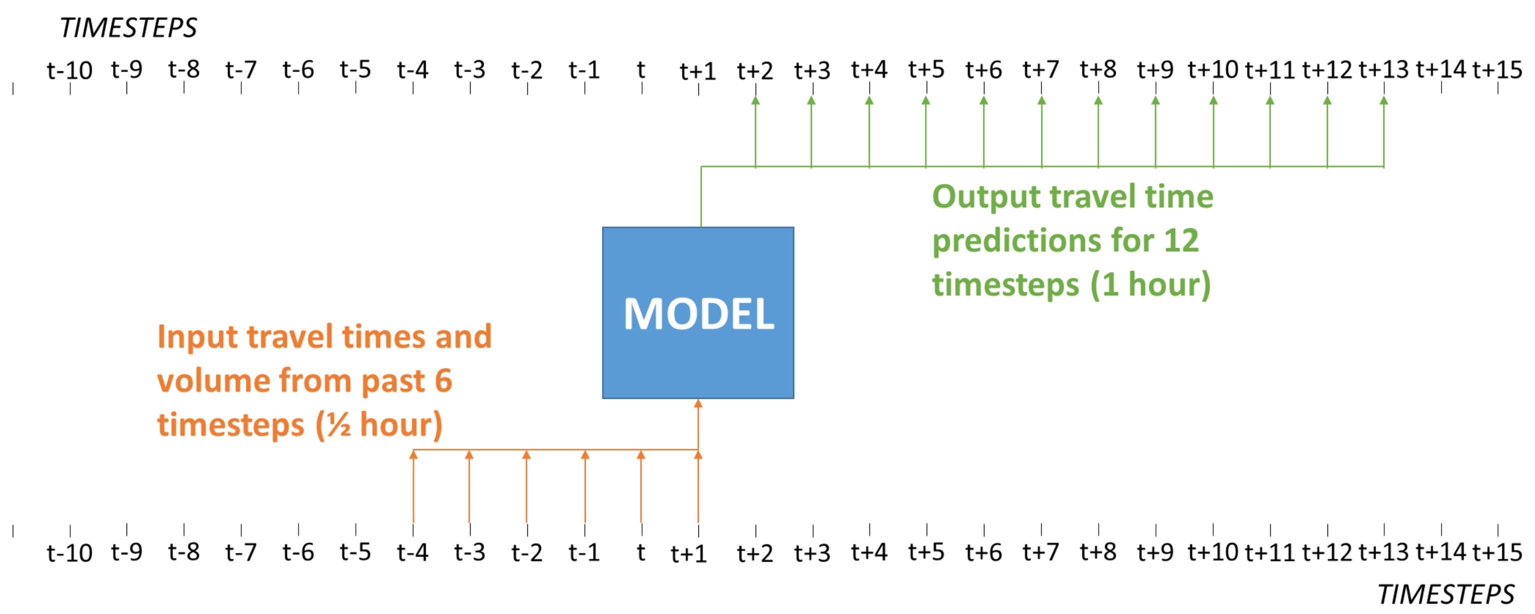
Figure 1: RNN model architecture



Auto-Regressive Time Series Model

- Express target variable as linear function of predictors
- Used INRIX travel times, SWZT volumes, & indicator variables for day of week

Figure 2: TS model architecture



Results

- RNN and TS models both have much lower segment-level MSE than static model, with mixed results when comparing RNN vs. TS models
- All model results degrade as segment predictions are made further into the future
- RNN and TS models account for time-based traffic pattern characteristics
- Static model fails to anticipate peak period traffic onset and dissipation
- RNN and static models perform well at atypically low volumes
- RNN and TS models may underperform during major traffic incidents

Figure 3: Short-term segment-level forecast MSE comparison

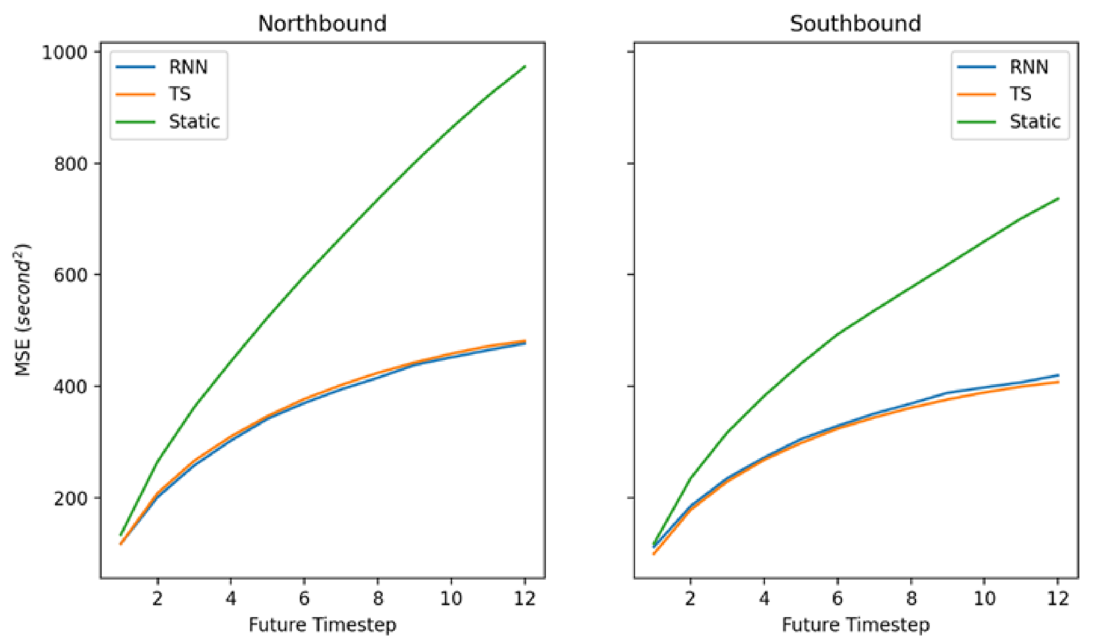
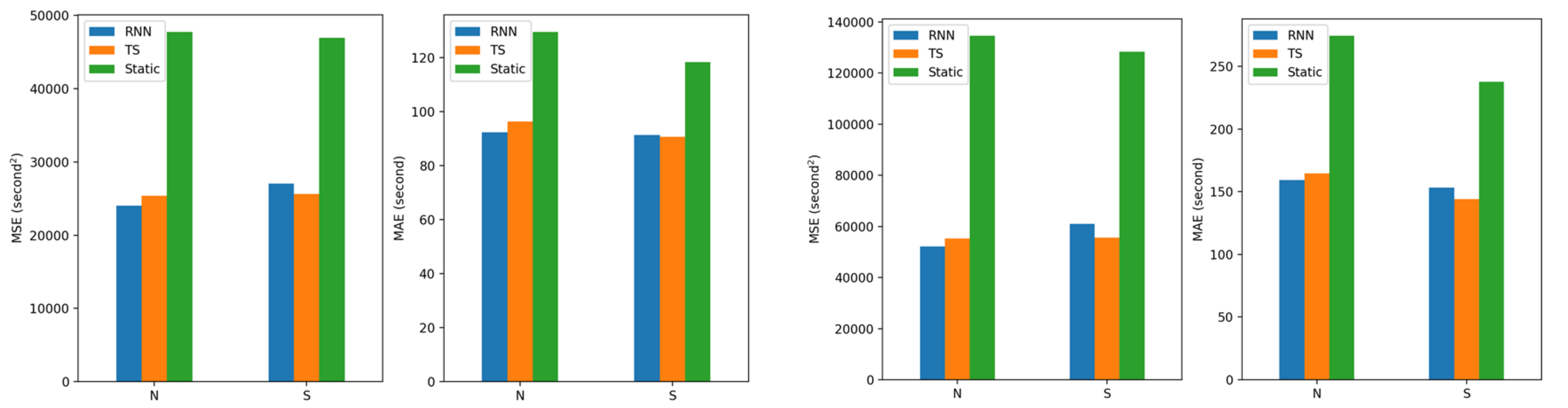


Figure 4: Dynamic travel time mean squared error and mean absolute error overall (left) and during peak periods only (right)



Conclusions & Future Work

- RNN and TS travel time prediction MSE were > 40% lower than static model, MAE saw a > 20% reduction
- No clear winner for TS vs. RNN model performance—situation-dependent benefits
- RNN training takes considerably more time/computation
- Future work will explore different corridors, advanced models, and performance under higher and lower levels of data availability