Advanced Traveler Information Systems (ATIS) 2.0 Precursor System

www.its.dot.gov/index.htm

March 2018
Publication Number FHWA-JPO-18-637

U.S. Department of Transportation

Produced by the U.S. Department of Transportation
Office of the Assistant Secretary for Research and Technology

Notice

Technical Report Documentation Page

1. Report No.	2. Government Accession No.	3. Recipient's Catalog No.
FHWA-JPO-18-637		

4. Title and Subtitle	5. Report Date
Advanced Traveler Information Systems (ATIS) 2.0 Precursor System: Final Report	March 2018
	6. Performing Organization Code
7. Author(s)	8. Performing Organization Report No.
Filmon Habtemichael, William A. Perez, Rama Boyapati	
9. Performing Organization Name and Address	10. Work Unit No. (TRAIS)
Battelle 505 King Avenue Columbus, OH 43201	
	11. Contract or Grant No. DTFH61-12-D-00040
12. Sponsoring Agency Name and Address	13. Type of Report and Period Covered
Federal Highway Administration 1200 New Jersey Avenue Washington, DC 20590	
	14. Sponsoring Agency Code

15. Supplementary Notes

FHWA Project Manager – Jimmy Chu

16. Abstract

Advanced Traveler Information Systems (ATIS) have experienced significant growth since their initial inception in the 1990s. Technologies have continued to evolve at a rapid pace, enabling the integration of advanced solutions for traveler information purposes.

As a result of the rapid evolution of technologies and tools available, the Federal Highway Administration (FHWA) has initiated new technical initiatives to investigate, plan, develop, design and implement 'Next Generation' or ATIS 2.0 solutions. This includes the investigation and design of new systems suitable for the collection and aggregation of traveler intent data from trip and route planning apps for use by system managers.

This report focuses on analysis of INRIX trip intent data for the test phase of the project. A modeling approach is illustrated, which helped to identify issues in the INRIX intent trip archive data. The available archived INRIX intent data was found to be insufficient (too low of a market penetration of INRIX app users) to support the development of a valid and reliable short-term traffic prediction model. Suggestions and recommendations for future analysis and development efforts are provided.

17. Keywords	18. Distribution Statement
Advanced Traveler Information Systems (ATIS), Traffic Prediction, Traffic Management Center, Driver Trip Intention	

19. Security Classif. (of this report)	20. Security Classif. (of this page)	21. No. of Pages	22. Price
Unclassified	Unclassified	45	

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

Table of Contents

List of Tables

List of Figures

Introduction

The U.S. DOT has conducted significant research over the years on the provision, use, and benefits of traveler information, including the more recent research in the Enabling Advanced Traveler Information Systems (EnableATIS) application area under the Dynamic Mobility Applications (DMA) Program (https://www.its.dot.gov/research_archives/dma/bundle/enableATIS_plan.htm).

Recognizing the opportunities of individual trip intent data from mobile applications such as INRIX, HERE, Google, and WAZE, the FHWA initiated this research project to investigate and potentially develop a system for traffic congestion prediction based on mobile trip intent data. The initial plan for this project was to execute a systematic set of research and analysis activities resulting in an Advanced Traveler Information System (ATIS) 2.0 Precursor System that would be sufficiently robust to be included as part of a field test. The plan assumed that once developed and tested, the system would be deployed in the Dallas region for a 6-month data collection period.

The premise for an ATIS 2.0 Precursor System is that it would need to deliver sufficient trip intent data in near real-time for use as an indicator of expected congestion on specific roadway segments. Traffic Management Center (TMC) managers can then incorporate this information into their traveler information systems as they see fit. A key focus of this project was to assess whether trip intent data improves the congestion prediction accuracy of traveler information systems. This was accomplished by comparing the traffic prediction accuracy of data from a traditional ATIS 1.0 system that uses system detectors (e.g., loop detectors) versus the same system enhanced with trip intent data from INRIX.

The project included the conduct of the following analytical steps that resulted in project reports or published technical reports:

- Stakeholder Registry and Engagement Plan
- Use Cases for Disaggregate Traveler Data Supporting System Management
- Disaggregate User Data Capture Approach and Testing Plan
- Disaggregate User Data Capture Approach
- Revised User Data Cleansing and Transformation Approach
- Field Test Concept Summary
- Concept of Operations
- System Requirements
- System Architecture and System Design.

The reports for the Use Cases, Concept of Operations, and System Requirements may be downloaded from the National Transportation Library at:

https://rosap.ntl.bts.gov/gsearch?collection=&terms=ATIS+2.0

Through the conduct of the above analytical steps it was determined that due to current limitations where the intent data cannot be obtained in real-time, the proposed demonstration would produce experiments on an intent data archive. Furthermore, due to this limitation, what was originally planned as a field test was later conducted as an analytical test using archived TMC and archived INRIX intent data from Houston, Texas.

This report focuses on documenting the results of the data processing and model development for the test phase of the project. INRIX trip intent data used during the pilot or prototype phase of the study were also reevaluated. Data on INRIX app user market penetration in Houston, Texas area are also presented. Appendix A of this report presents a listing of the original tasks and deliverables and their status at project completion.

Chapter 1. Short-Term Traffic Forecast Literature Review

Short-term traffic forecast refers to predicting the future traffic over a period ranging from a few minutes to few hours, using real-time or historic traffic data, or a combination. A number of models have been developed for this purpose. This section provides a brief review of literature on traffic forecast. Specifically, the review examines the general categories of traffic prediction models and data the models use. This review is conducted to provide a better understanding of the state of the art and practice in traffic forecast, and to provide technical support for the modeling approach followed in this project.

Models Used for Short-Term Traffic Forecast

According to Van Hinsbergen and Sanders (2007), as well as Van Lint and Van Hinsbergen (2012), the approaches used in short-term traffic forecast can be broadly classified into four categories: naïve, parametric, non-parametric, and hybrid.

1. **Naïve:** In this approach, models provide a simple estimate of traffic in the future based on simple historic averages based on day of the week and hour of the day, i.e., this approach does not take the current or real-time traffic conditions into consideration. Most regional transportation agencies employ this simple technique to predict the short-term traffic conditions.
2. **Parametric:** In this approach, the prediction models use a set of fixed parameters as a part of the mathematical or statistical equations. These models may use either real-time traffic and historic data or only historic data. The majority of these approaches face limitations from the assumptions they use for estimating model parameters. These approaches perform poorly during unstable traffic conditions and complex road settings as they are parameterized for a fix set of traffic conditions and road settings. Examples of these approaches include regression-based, time-series analysis-based, and other deterministic models (e.g., Wang et al., 2006).
    a) **Regression-based models:** These models include regression equations that are either linear or non-linear. Linear regression consists of a single basic equation with constant terms, while a non-linear regression equation can take many different forms because there can be more than one parameter per predictor variable. Regression-based traffic forecast was used by Sun et al. (2003).
    b) **Time series analysis-based models:** Autoregressive Integrated Moving Average (ARIMA) models and its variation Seasonal ARIMA (SARIMA) are the two key methods that use time series analysis (Cetin and Comert, 2006; Lin et al., 2013; and Szeto et al., 2009). A hybrid method, ARIMA-EGARCH-M-GED, was developed (Wang, et al., 2016) with the intent to address the limitations of nonlinear patterns and the challenges of diagnosing white noises in the data.
3. **Non-parametric:** In this approach, the prediction models apply empirical algorithms to forecast short-term traffic. Most of the non-parametric approaches are data driven. Since these models

are free from any assumptions on data distribution, they are advantageous in unstable traffic conditions. Examples of these approaches include pattern recognition and neural network techniques (Vlahogianni et al., 2014).

a) **Pattern Recognition Methods:** Cluster analysis (Xia et al., 2012), support vector machines (Castro-Neto et al., 2009; Wang and Shi, 2013), and K-nearest neighbor (Habtemichael and Cetin, 2016; Zheng and Su, 2014) methods use pattern recognition to forecast short-term traffic.

b) **Neural Networks:** Some of the works that focused on implementing neural network and its variations are Innamaa (2005), Vlahogianni (2007, 2008), Wang and Shi (2013), and Zheng et al. (2006).

4. **Hybrid:** In this approach, a combination and modification of above-mentioned approaches are used to improve forecast accuracy and reliability (e.g., Szeto et al., 2009; and Wang, et. al., 2016). Some of the hybrid approaches, such as ARIMA-EGARCH-M-GED, are proving to outperform non-parametric models in tracking the features of measured data and controlling the impact of abnormal data. For example, Wang and Zhirui (2016) performed short-term traffic forecasting for I-80 in California the using ARIMA-EGARCH-M-GED model. These model results were compared with ARIMA, artificial neural network, and a K-nearest neighbor model. The results showed that the hybrid model outperformed the other methods in terms of accuracy and reliability.

In general, various researchers observed that non-parametric models and hybrid models are forecasting techniques that are reliable and accurate when compared to the naïve and parametric models. Cui et. al. (2017) developed a long-short term memory model (LSTM) that predicts the expected travel speeds on a given location using the current traffic speeds on adjacent locations in the network. This model used a recurrent neural network to examine the recurring traffic conditions and their impacts on the adjacent traffic streams. Based on the experimental analysis performed on the loop detector data collected from a freeway on Seattle, Washington, this model forecasted at a better accuracy than neural network models and Support Vector Machine (SVM). Similarly, Haiyang et. al. (2017) developed a Spatiotemporal Recurrent Convolutional Network (SRCN) model for short-term traffic predictions by using a Convolutional Neural Network (CNN). This model captures temporal issues like traffic in the previous time periods, as well as spatial issues like impact of adjacent network traffic on the selected network. The SRCN model results indicated lesser absolute error and more accuracy when compared to SVM, CNNs, and LSTMs.

Non-parametric models are relatively popular as they provide more accurate predictions. This is because the non-parametric models are capable of adjusting to changing conditions and roadway settings. For example, Van Lint and Van Hinsbergen (2012) suggested that in the context of traffic forecast, the non-parametric approach is the first choice as the input and output traffic variables are noisy, and the relationship between them is nonlinear and poorly understood. Pattern recognition-based approaches, a subset of the non-parametric approaches, seem to be more appropriate as they are effective in identifying the similar traffic conditions needed to generate a prediction.

Naïve and parametric models are less complex to implement and are more suitable for regions with stable traffic conditions and simple roadway settings. However, most of the regions requiring a short-term prediction are busy urban areas that want to communicate the changing travel patterns with travelers and enhance corridor mobility. For these regions, using non-parametric and hybrid models is more suitable, as they are model-adaptable and reliable in complex and unstable traffic conditions.

Type of Data Used for Short-Term Traffic Forecasts

The type of data to be used in a traffic prediction plays an important role in the accuracy of the prediction. Considering the recentness of the data, data used for traffic can be grouped as real-time or historic data. Similarly, based on coverage, the data used can be grouped as temporal or spatial data. Temporal coverage refers to the time frame of historic data in the location of interest while spatial data refers to the traffic data on the network links that are adjacent to the location of interest. Disaggregated data samples or data aggregated in 5-minute to 15-minute intervals are used to capture the dynamic nature of the traffic forecast.

The following data types and sources are being used for testing models and forecasting short-term traffic:

- Traffic counts from loop detectors and Automatic Traffic Recorders are used as the data source in most of the short-term traffic forecasting studies.
- Imagery data from video detectors were also used by some studies to test the forecasting models.
- Probe vehicle data was captured and used for some short-term forecasts. But this data had limitations in capturing the network-level impact of congestion.
- Traffic conditions collected from web-based map services (e.g., Google Maps) was used as a data source by one study.

Aggregated data was collected for all the above-mentioned data sources, except for the probe vehicle data, in which disaggregate data was collected.

This updated literature review was conducted to put the current modeling effort in context of previous research and analysis in this area. It is apparent that travel intent data has not been used previously to enhance short-term traffic prediction. When embarking on a new and novel method it should be kept in mind that significant research and analysis may be required to determine if and how a potential real-world application may be developed.

Data Manipulation for Short-Term Traffic Forecast

Standard statistical techniques like simple smoothing, complex time series analysis, and filtering methods are used to conduct short-term traffic forecasts.

1. **Smoothing Techniques:** Given that real-time and historic data are noisy in nature, simple exponential smoothing, kernel smoothing (El Faouzi, 1996), and hybrid exponential smoothing (Chan et al., 2012) are some smoothing techniques applied for short-term traffic forecasts to suppress the noise in the data.
2. **Filtering Techniques:** Kalman filter (Guo et al., 2014) and particle filter-based algorithms (Chen and Rakha, 2014) are being applied for short-term traffic forecasts.

Use of Trip Intent Data for Traffic Forecast

In most of the above-mentioned studies, conventional data sets were used, i.e., historical data from loop detectors and real-time data from probe vehicles. However, a recent study by Chen et. al. (2016) proposed a stacked long short-term memory model that uses travel intent data from map-based services like Google Maps to learn and predict traffic patterns. The experimental testing results from this model proved more reliable over the multilayer perception model, decision tree model and support vector machine model.

Summary

The literature review provided valuable information on the types of models approaches and data used for short-term traffic forecasting. The following are the key conclusions from the reviewed literature on short-term forecasting:

- Model selection mainly depends on the type and size of data to be used.
- Non-parameteric models provide results with better accuracy compared to parametric models but require data of larger temporal coverage.
- To attenuate the noise in the data, most studies use some form of data manipulation.
- Incorporating traveler intent data in traffic prediction models remains unresearched.

Chapter 2. Field Test Demonstration Location and Datasets Used

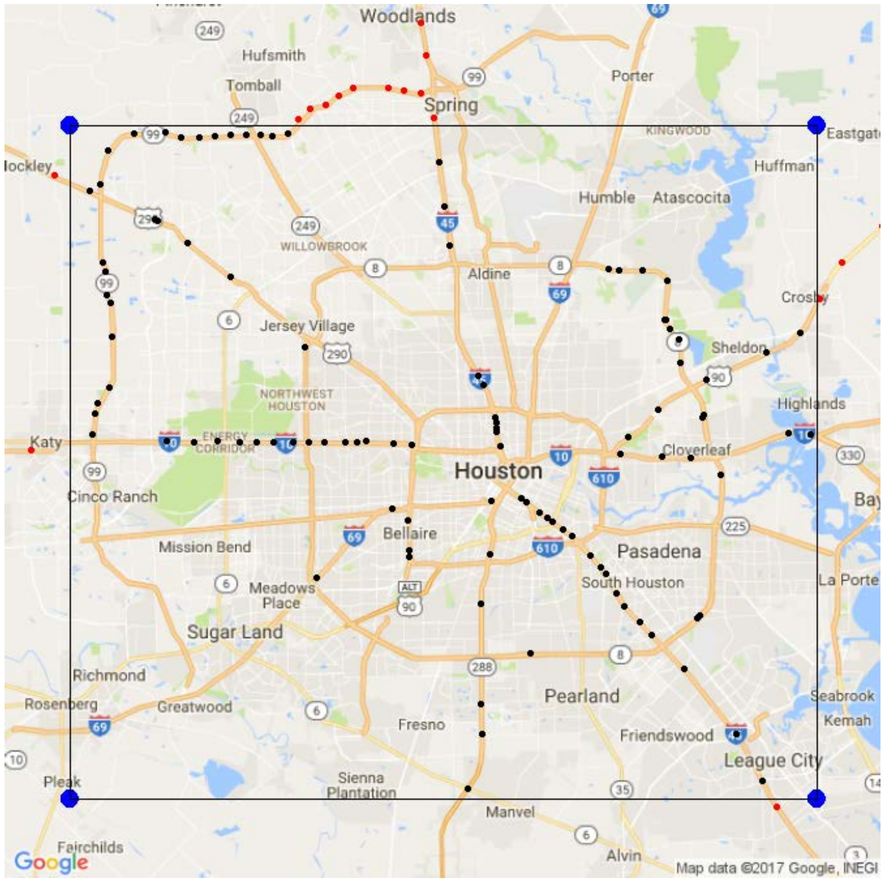
Demonstration Location

The Houston metro area was selected as the test site to demonstrate and evaluate the field test of the short-term forecast model for traffic and congestion alarm predictions. The team selected the Houston metro area because historical traffic data, travel intent data, and historical alarm data were readily available from TranStar and INRIX. The precursor system Pilot conducted under Task 4 of this project was developed for and tested using data from the Houston metro area.

The geographic area covered by the INRIX travel intent dataset is significantly larger than the targeted Houston metro area. Therefore, to limit the geographic area considered, a bounding box was used to filter out trips that do not include travel within the target area. Only trips that pass through the Houston bounding box were included in the geographically-filtered output dataset. This is also expected to increase the efficiency of data transformation and processing efforts. The bounding box encompassing the Houston metro area used in the precursor systems field test was defined by the following longitude and latitude coordinates:

- Northeast corner: -95.051W, 30.06N.
- Northwest corner: -95.799W, 30.06N.
- Southwest corner: -95.799W, 29.473N.
- Southeast corner: -95.051W, 29.473N.

Trips that were entirely outside the bounding box were completely ignored. Trips that were partially within the bounding box were generally included. However, trips originating hundreds of miles from the bounding box were not included because they have greater uncertainty in the screen line crossing times (that is, be less accurate) than trips originating a few miles from the box. The effects of trip lengths were examined, but given the limited data sample, there is no requirement to remove long trips at this time. Figure 1 shows the location of the radar detectors and the bounding box.



Source: Google Maps, 2017

Figure 1. ATIS 2.0 Precursor System Houston Evaluation Area Bounding Box and Radar Detectors

Description of Data Sets Used in the Study

Conventional Traffic Data

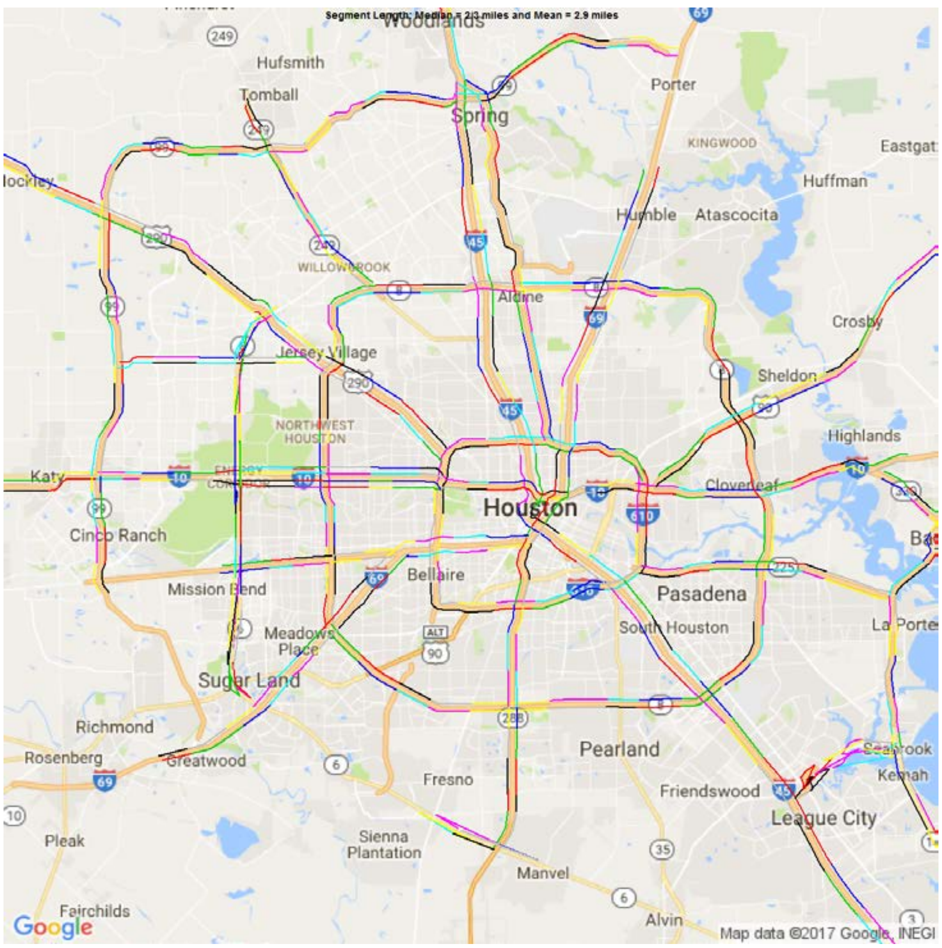
To understand the historical traffic pattern in the demonstration area, conventional traffic data, i.e., volume, speed, and occupancy, in the Houston metro area were provided by TranStar. The data were collected by radar detectors and were provided at a 5-minute aggregation interval separate for each direction of travel.

The black and red points in Figure 1 indicate the location of the radar detectors. Black points represent radar detectors inside the bounding box and the red points represent detectors outside the bounding box. Out of the 178 radar detectors, 123 are inside the bounding box. Along with INRIX traveler intent data, the conventional traffic data from these radar detectors was used to calibrate and validate the short-term traffic forecasting model.

This field test was limited to freeways because the ground truth radar data are limited to freeways in Houston and the greatest concentration of traveler intent data is on the freeways. Freeway locations in the Houston metro area that exhibited a relatively higher density of INRIX intent trips and a good quality of historical traffic data were identified and used for the testing described in this task.

TranStar Congestion Alarm Data

In addition to the conventional traffic data, TranStar provided historic congestion alarm data. The alarm data corresponds to segments with defined start and end points in both directions of the road. The alarm data contains timestamp, segment ID, segment start and end locations, the current (observed) speed, and the threshold speed for congestion alarm. Figure 2 shows the segments TranStar developed to generate the alarms.



Source: Google Maps, 2017

Figure 2. Alarm Segments as Provided by TranStar

Alarms were generated based on comparisons to the trailing six months of historical data and were issued when the observed speed was below a given threshold value. The threshold speed was calculated as:

- Either the observed speed falls below the 95th percentile speed for a specific time period (time of day/day of week)
- Or the speed falls below 40 mph.

The historical alarm data was used to validate the prediction of congestion alarms from the short-term forecasting model developed as part of this project.

INRIX Traveler Intent Data

INRIX provided traveler intent data used for the ATIS 2.0 field test. The data came in the form of many individual files containing records of every request and response from the INRIX trip planning application (software) users made across the entire world. Each file covers a time specified in the name of the file itself. The data inside each file is formatted as either JSON or XML. The INRIX traveler intent data format used for the project field test phase was different from the data format used during the project prototype (piloting of the approach) phase.

The INRIX data archive contained intent data from August 2015 until March 2016. This was used for the field test portion of the project. The traveler intent data's spatial coverage was the entire world.

The raw travel intent data contains trip records with origin, destination, timestamp, travel-time information, and alternative routes. The alternative routes were provided in a geographic data set in the form of an encoded polyline string. Additional decoding was required to finally obtain the route's actual coordinates in a sequence of latitude and longitude format. The number of alternative routes provided in each trip differs. Most trips contain three, others contain two, while some contain only one route. A sample of the decoded INRIX travel intent data is shown in Figure 3.

```
{
  "result": {
    "Trip": {
      "Routes": [
        {
          "CompressionPoints": "agwmE`nsmUlFdYrBnD~RaNdDe@\\hCgCNuAkHuAmV`@mU~TueAzDu`AyCqUm
          "BoundingBox": {
            "Corner1": {
              "Longitude": -117.747002,
              "Latitude": 33.86615
            },
            "Corner2": {
              "Longitude": -117.198329,
              "Latitude": 34.48529
            }
          },
          "Id": "1019636868",
          "HasClosures": false,
          "TravelTimeMinutes": 84,
          "AbnormalityMinutes": 2,
          "UncongestedTravelTimeMinutes": 82,
          "AverageSpeed": 51,
          "RouteQuality": 3,
          "TrafficConsidered": true,
          "TotalDistance": 72.9
        },
        {
          "CompressionPoints": "agwmE`nsmUlFdYrBnD~RaNdDe@\\hCgCNuAkHuAmV`@mU~TueAzDu`AyCqUm
          "BoundingBox": {
            "Corner1": {
              "Longitude": -117.747002,
              "Latitude": 33.86615
            },
            "Corner2": {
              "Longitude": -117.198329,
              "Latitude": 34.48175
            }
```


Source: Battelle, 2018

Figure 3. Sample of Decoded INRIX Travel Intent Data

Processing INRIX Traveler Intent Data

Cleaning INRIX Traveler Intent Data

Before the travel intent data was parsed for further use, it had to be cleaned. The vast majority of records did not contain trip-route data; therefore, they were discarded. At times, the data contained records that were superfluous or contained invalid characters and the invalid characters were then removed.

Checking for Duplicate INRIX Traveler Intent Records

Duplicated records can lead to inaccurate conclusions in data analysis. Since the INRIX traveler intent data comes from INRIX's trip planning application, the users can enter the same trip multiple times in the application leading to duplicate records of the same trip. Therefore, INRIX intent trips with common origin and destination and are timestamped within a small amount of time difference were identified as total duplicates.

Another cause of duplicate records is that the application may update the current route at any point along the trip in search of another route with lower travel time. In this case, the destination of the trip remains the same while the origin constantly moves closer to the destination. To capture such duplicate entries, trips which have the same destination and within time gap of three minutes are first identified as potential duplicates. This is followed by tracking the origin of the potentially duplicate trips. If the origin moves closer to the destination within the three-minute time gap, then the trips are deemed to be duplicated.

In the INRIX traveler intent data with the Houston bounding box (temporal coverage from 10/01/2015 - 03/31/2016), only four records were identified as duplicate. The duplicates were flagged and thus they were not used in the subsequent analysis. There were no duplicates found in the INRIX intent data used in the pilot[1].

Visualizing INRIX Traveler Intent Data

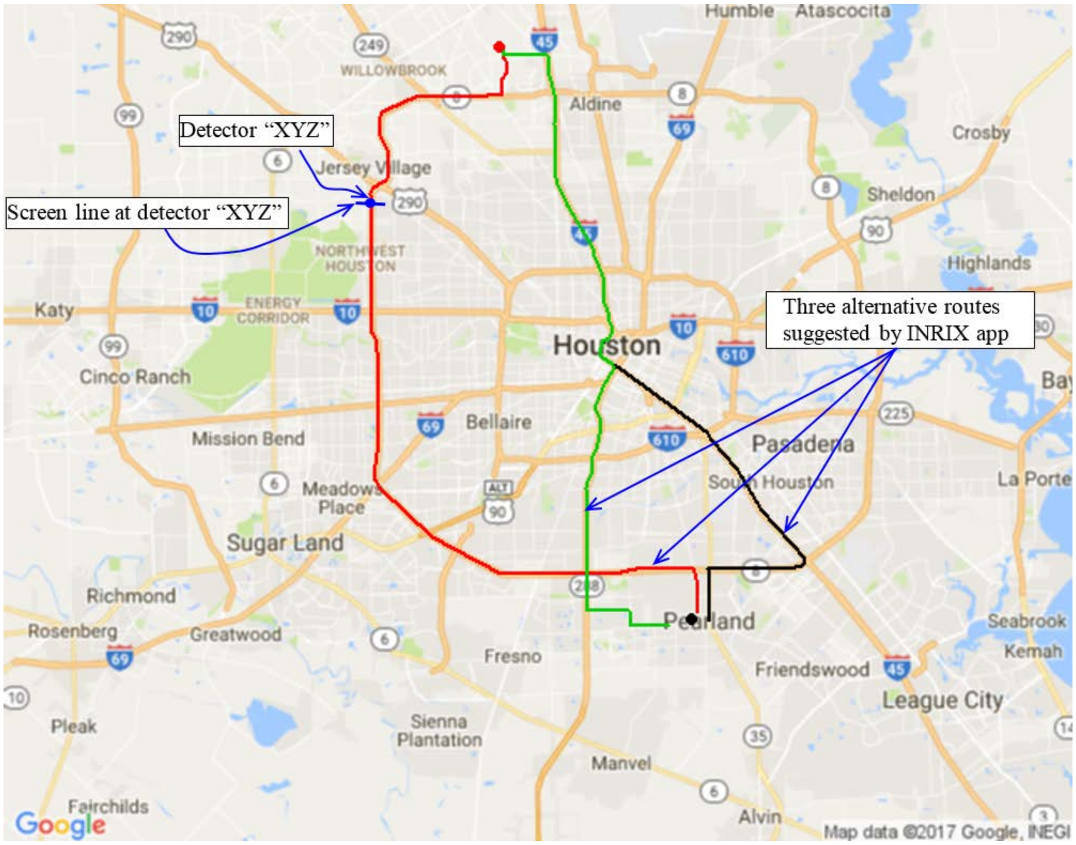
The spatial coverage of the intent data received from INRIX was the entire world, while the study area was the Houston metro area. A bounding box (see Figure 1) that encompasses the Houston metro area was used to parse the desired INRIX travel intent data.

The data loader performed a preliminary analysis of each route to determine whether it transited the bounds of the study's area. Routes that did intersect the bounding box were further analyzed to determine if they intersected any of the detector screen lines. The results of these analyses were added to the explicit route information as it was stored in the database.

The INRIX traveler intent data comes with up to three suggested routes for a given origin and destination. The first and last miles of the routes are truncated to preserve the personally identifiable information (PII) of the INRIX application users. Figure 4 shows the three alternative routes (represented by black, green, and red lines) suggested by the INRIX traveler application for a user-specified origin (black) and destination points (red).

The blue point indicates the location of an arbitrary radar station. To determine whether a route intersects with the detector location, a screen line was first created (this is a hypothetical line orthogonal to the direction of the road segment where the detector is located). For all the detectors in the study area, a screen line was drawn at the location of each detector and the number of intersections of travel intent routes with the screen line was counted. This provided an understanding of which radar detectors were traversed the most by INRIX-suggested routes so that the modeling work could be focused on corridors with a relatively higher count of INRIX traveler intent trips.

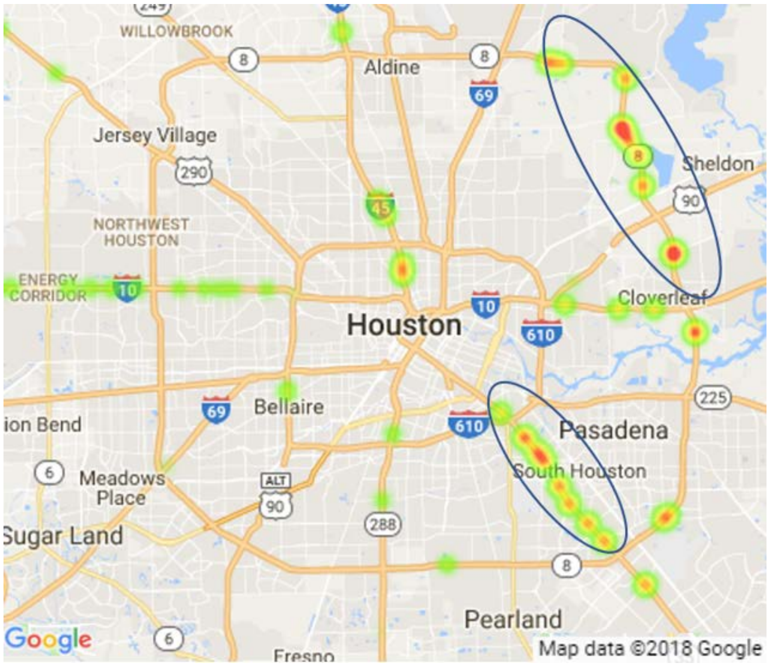
[1] The trip intent data is not a product priority for INRIX and does not fall under their normal QA/QC processes and hence contained duplicates for the same journey. However, in conducting the initial pilot these duplicates were not detected by the project team's data review/cleansing processes. Hence the opportunity of using trip intent data was over assumed in the pilot phase.



Source: Google Maps, 2017

Figure 4. INRIX Traveler Application Suggested Alternative Routes

A heat map was developed to aid the visualization of the number of intersection between INRIX-suggested routes and detector screen lines. A sample heat map is shown in Figure 5. The majority of the trips use the north-eastern part of Loop 8 and the southern part of I-45 near the interchange to I-610, as indicated by the ovals in Figure 5.



Source: Google Maps, 2018

Figure 5. Visualizing INRIX Travel Intent Data (02/01/2015 to 03/01/2015)

Exploration of the Count of INRIX Intent Routes and Detector Screen Line Intersection

To verify the quality of the INRIX travel intent data used in the field test phase of ATIS 2.0, the contents of the intent data in terms of total number of routes, number of routes intersecting the Houston metro area, and the number of routes intersecting Houston detectors (screen lines) were compared with a portion of intent data used during the prototype phase, which lasted over a duration of 2.8 hours (2014-12-16 03:10 PM to 2014-12-16 06:00 PM).

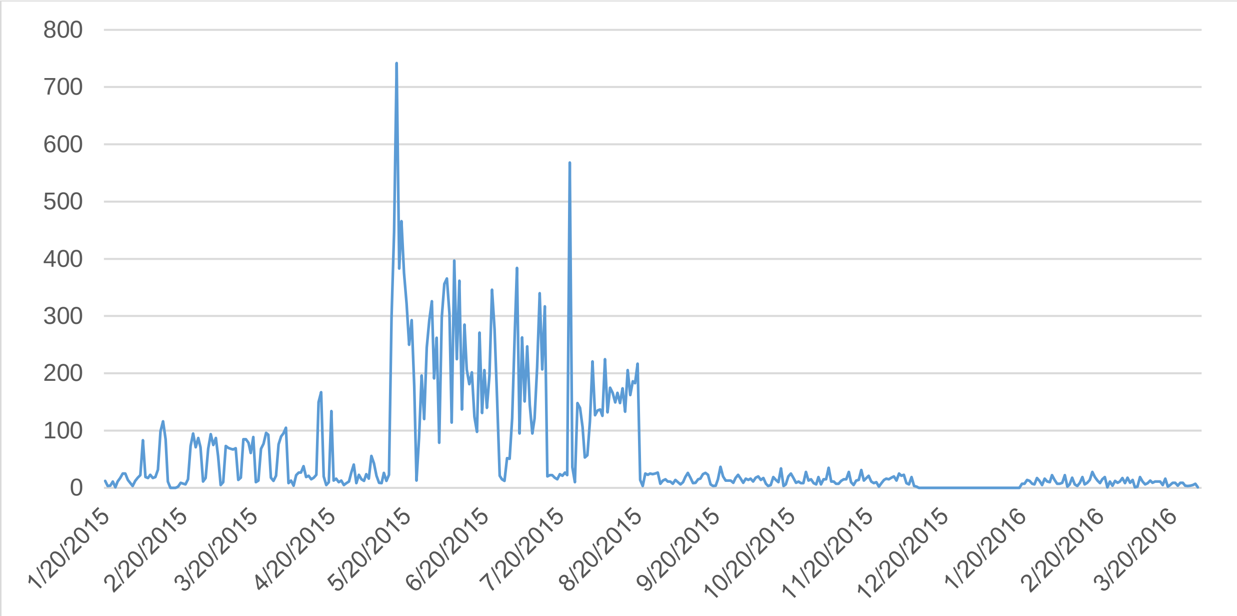
In the 2.8 hour travel intent data used in the prototype, there were 170,175 total routes, 4,009 routes intersecting the Houston bounding box, and 2,463 routes intersecting with detector screen lines. Similarly, the total number of routes, routes intersecting the Houston bounding box, and routes intersecting with detector screen lines data to be used in the field test was found to be 1,046,606, 3,701, and 2,009, respectively. After factoring the number of days the datasets cover, there was a significant reduction in the quantity of intent trip data between the prototype and field test project phases. This reduction amounted to data shrinkage of more than 99%. Table 1 summarizes the calculation of travel intent data shrinkage rate.

When this significant reduction in intent trip data was noted, analysis and reviews of procedures were conducted to determine what was the cause of this apparent reduction in the expected volume of data. The following sections provide information into the analyses and investigation conducted to determine what caused the difference in data volume from the pilot to the test phase.

Table 1. Comparison of Travel Intent Data Between Data Used During the Prototype and Field Test Phases of the Project

	INRIX intent data used in the prototype phase		INRIX intent data used in the field test phase		Intent data shrinkage rate
	Coverage: 2014-12-16 3:10 PM to 2014-12-16 6:00 PM (2.8 Hours)	Average # of trip intents per day	Coverage: 10/01/2015 - 03/31/2016 (183 days)	Average # of trip intents per day	
Total Routes	170,175	1,458,643	1,046,606	5,719	99.61%
Total Routes Intersecting Houston Bounding Box	4,009	34,363	3,701	20	99.94%
Total Routes Intersecting Houston Detectors (Screen Lines)	2,463	21,111	2,009	11	99.95%

Considering the traveler intent data to be used in the field test phase, the distribution of the number of total routes intersecting the detector screen lines was observed to significantly vary over time, as shown in Figure 6. Some extreme observations include the sudden spikes in the number of route-detector intersections on 5/16/2015 and 7/24/2015, which amount to counts of 742 and 568, respectively. Very low counts were observed in the time range from 8/20/2015 through 3/31/2016. In addition, there was a 40-day period (12/09/2015 - 01/20/2016) where route information was completely missing.



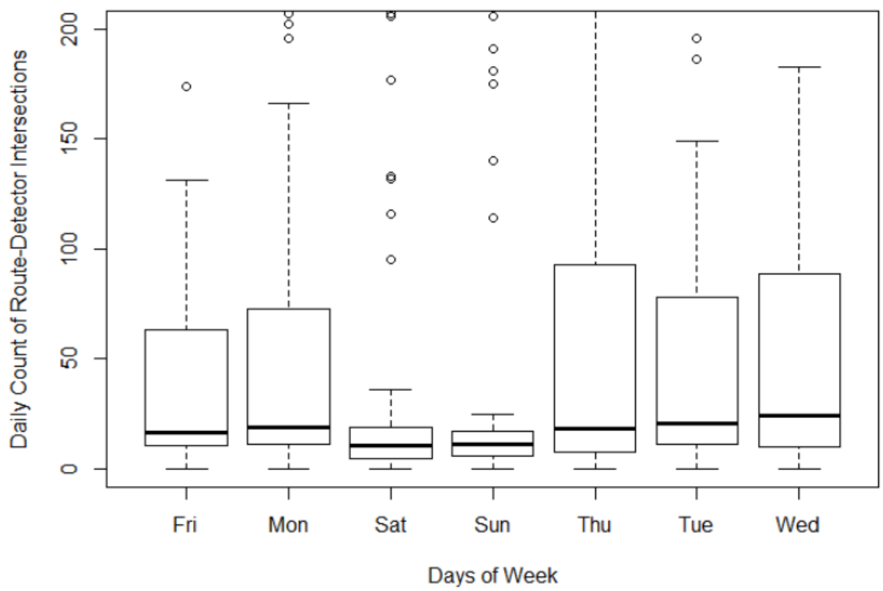
Source: Battelle, 2018

Figure 6. Variability of Daily Travel Intent Route Counts Intersecting Houston Detector Screen Lines

Further analysis of the travel intent data reveals that the mean daily count of total travel intent route and detector screen line intersections was about 58 while the median is only 16. This indicates a large variability in the daily counts.

As shown in Figure 1, there are 123 detectors in the Houston metro area. Therefore, the average count of traveler intent route and detector screen line intersections is 0.47 trips per day, i.e., 58 intersections per 123 detectors. This is less than one trip per day per detector. It is obvious that such data is not useful for any meaningful statistical modeling.

The distribution of travel intent data by days of the week is shown in Figure 7. The variability can be easily observed by the wide interquartile ranges, skewed median values, broader range of the whiskers, and the outlier data points in the plot. This is a box-plot where the box represents 50% of the data, the dark horizontal lines in the boxes are the arithmetic mean, the whiskers extend downward to the 25% percentile and upward to the 75% percentile.

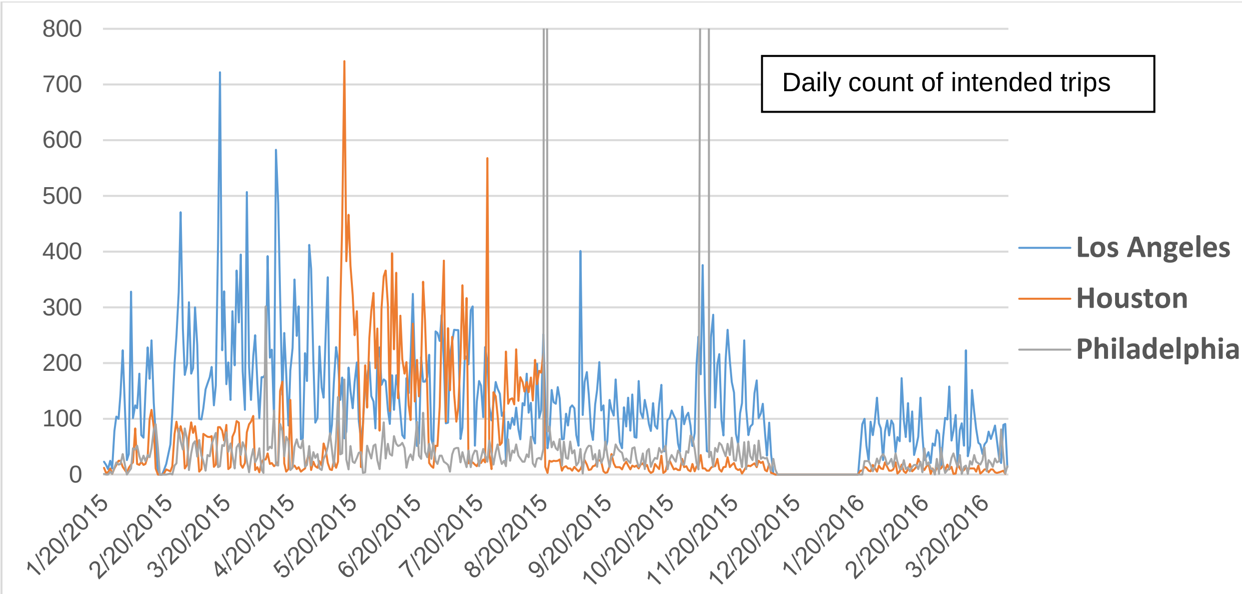


Source: Battelle, 2018

Figure 7. Distribution of Travel Intent Route-Detector Intersections by Days of the Week

To have a better understanding of the quality of the data, the Houston traveler intent data was compared with two other U.S. cities, Los Angeles and Philadelphia. As shown in Figure 8, the overall trend of the daily count of travel intent routes in these cities is fairly consistent with the variability trends observed in the Houston metro area data. This figure shows the number of intended trips requested over time in three different major cities. The number of intended trips and shape of these distributions suggests that there are few INRIX users (in spite of these large cities that have a high traffic volume), or that there are data quality issues with the archived INRIX data.

An important point to note is that the storage and archival of trip intent data is not a primary focus on INRIX as trip intent data is not one of their core data products. Therefore, the trip intent data archives are not subject to the rigorous quality assurance (QA) and quality control (QC) processes that INRIX's core data products are put through.



Source: Battelle, 2018

Figure 8. Comparison of Travel Intent Data Quality in Different US Cities

Revisiting INRIX Traveler Intent Data for Pilot Test

According to a communication from INRIX, "monthly counts of Consumer data (number of users) are averaging 15 per day. ConsumerDevice (device activation[2]) is about 20 per day. Again, both of these statistics trend downward as we move through 2015 and into 2016." Table 2 presents the number of device activation per month and averages per day for INRIX activations in Houston. The INRIX activation data does not show marked changes in market penetration that would explain differences in number of intended trips for the pilot versus the test phase of the project.

[2] A device activation refers to each time a user turned on or activated the INRIX App on their mobile device.

Table 2. Per Month INRIX App Activations for INRIX

	Per Month	Average Per Day
Month/2015		
Jan	632	20
Feb	633	23
Mar	605	20
Apr	497	17
May	652	21
Jun	443	15
Jul	376	12
Aug	483	16
Sep	520	17
Oct	481	16
Nov	318	11
Dec	401	13
Total	6041	199
Average	503	17

The number of intended trips for the Test Phase was significantly lower than that of the Pilot Phase because of the difference in the INRIX logging approach between the two phases. During the Pilot Phase, intended trips were being logged continuously throughout a journey, meaning, enroute recalculations of the best route for that same trip were being counted as new trip intents. This would result in an inflated number of trips during the pilot phase[3]. From an INRIX system standpoint, the Pilot Phase data was stored on one server with logging data being captured on a short-term basis. For a longer-term dataset for the Test Phase, the INRIX mobile team moved to a different storage server, and in the process of moving the code, realized they were storing every updated route request for the same trip. As this was a special non-standard dataset, there was no formal quality assurance (QA) process and the difference could not be determined until after the data was collected and transmitted. For the Test Phase, only one set of planned trips was saved per driver-trip. If they had planned multiple trips to different destinations those would have been saved.

These additional data and communications from INRIX indicate that Houston did not have sufficient market penetration of INRIX users to support this research effort. The analysis during the pilot phase of the project failed to determine the low market penetration in Houston. Furthermore, errors or differences in data logging during the pilot phase resulted in over estimating the quantity of available of INRIX intent

[3] Note that the project team deleted origin/destination information from these saved trips before further processing. This was done to ensure confidentiality of people driving with the INRIX devices. This made it somewhat difficult to spot repeated or duplicate trips.

trips for analysis. Query and analysis of a data base of INRIX device activations on a monthly basis in the Houston area support the current interpretation of the significant differences in the amount intent trips available during the project's pilot versus test phases.

Summary

Overall, the quantity of travel intent data from the Houston metro area was found to be below the level needed for developing a statistically significant short-term forecast model. As evidenced in the data analysis, it is highly likely that the number of trip intent data points was significantly over estimated during the pilot phase. In addition, the high variability in the daily count of routes and detector screen line intersections makes the travel intent data trend unpredictable and very difficult to use in combination with other datasets, such as the conventional traffic pattern data and the congestion alarm data. This difference in number of intended trips between the pilot and test phase of the project were explained by INRIX as an error or difference in logging of data between the two phases. The data verification and testing procedures employed in the project did not detect the fact that multiple intended trips were all coming from the same journey by the same traveler during the pilot phase.

The upcoming section of the report will address how these data (i.e., the conventional traffic data, congestion alarm data, and INRIX traveler intent data) were used to develop the precursor system for short-term traffic prediction. The purpose of the section is to illustrate the process that may be used if sufficient travel intent data were available to support valid and reliable analysis.

Chapter 3. Field Test Demonstration Modeling

The traffic precursor system developed for this field test demonstration has three components: traffic volume prediction, traffic speed prediction, and congestion alarm prediction. Various modeling approaches were investigated for each traffic prediction component. The short-term traffic volume prediction used a multi-variable linear regression model. Short term traffic speed prediction used the relationship between traffic volume and speed. For predicting congestion alarms, the threshold speed-based approach was used.

The test was designed to evaluate the benefits of using the INRIX traveler intent data as additional information to predict traffic over a forecast horizon of 15 minutes. Therefore, two traffic prediction systems were developed. The first system does not use the INRIX traveler intent data (ATIS 1.0) while the second system does use the INRIX traveler intent data (ATIS 2.0). Both models had the same model formulation, parameters, and input data, except that the ATIS 2.0 model uses additional information, INRIX travel intent data.

Modeling Approach Used in this Project

As discussed in Chapter 1, there are a wide variety of models developed for short-term traffic forecasts and identifying a traffic forecasting model is critical for the success of the project. Model selection heavily depends on the model's intended use, local traffic characteristics, road geometry conditions, and data availability (in terms of type, level of detail, and temporal coverage). Striking a balance between prediction error tolerance and model simplicity is also another crucial factor to consider in model selection.

Non-parametric and hybrid traffic forecasting models have high complexity, making the forecasting process slow and costly. In addition, such models require highly detailed input data with considerably large temporal coverage. On the other hand, naïve and parametric models are not complex and function better when available data is of a relatively short temporal coverage.

Given that the traffic forecast in this project is experimental, and because the INRIX intent trip data to be used in this project is of short duration and of potential low reliability, a less complex model is preferred. Therefore, a parametric modeling approach, specifically a multi-parameter linear regression modeling, will be used as the experimental traffic forecast model. The details of the approach and model used are discussed in detail in Chapter 3. This type of model was previously developed and used in this project in the pilot testing of the approach (see the Revised User Data Cleansing and Transformation Approach report). ATIS 1.0 and ATIS 2.0 Traffic Volume Prediction.

As discussed in the literature review, the intended purpose and data availability dictates the type of prediction model to be used. In the context of this project, a parametric modeling approach was chosen as a traffic volume prediction method. Specifically, the ATIS 1.0 and ATIS 2.0 models for traffic volume prediction were multivariable-based linear regression models. The regression models used continuous and categorical variables as input data. The following are some of the predictor variables that were included in the model:

- **Current volume – CV (continuous):** The volume of traffic in the current time interval, as observed in real-time. There could be slight latency in the real-time traffic volume, but this was not accounted for in developing the precursor system.
- **Historical average volume – HV (continuous):** The average traffic volume on the same day of the week and hour of the day over the last six-months.
- **Day of the week – DW (categorical):** The day of the week indicator accounts for the daily traffic variability.
- **Time of day – TD (categorical):** The time of day indicator accounts for hourly traffic variability within a given day.
- **INRIX intent route-detector screen line intersection count – IV (continuous):** This is derived from the INRIX traveler intent and represents the number of intent route and detector screen line intersections.

The general forms of the regression-based ATIS 1.0 and ATIS 2.0 traffic volume prediction models were:

$$\boldsymbol{ATIS\ 1.0\ Volume = \beta_0 + \beta_1 CV + \beta_2 HV + \beta_3 DW + \beta_4 TD + \varepsilon}$$

$$\boldsymbol{ATIS\ 2.0\ Volume = \beta_0 + \beta_1 CV + \beta_2 HV + \beta_3 DW + \beta_4 TD + \beta_5 IV + \varepsilon}$$

Where:

ATIS 1.0 Volume = the predicted traffic volume in the next time step where INRIX travel intent data is not included as an additional predictor.

ATIS 2.0 Volume = the predicted traffic volume in the next time step where INRIX travel intent data is included as an additional predictor.

CV = the current volume observed in (near) real-time.

HV = the average historical volume aggregated by same day of the week and hour of the day, observed in the last six months.

DW = a categorical variable that indicates the day of the week.

TD = a categorical variable that indicates the time of the day (hourly).

IV = the INRIX intent route-detector intersection count.

$\boldsymbol{\beta_0}$ = the intercept term.

$\boldsymbol{\beta_1}$**,** $\boldsymbol{\beta_2}$**,** $\boldsymbol{\beta_3}$**,** $\boldsymbol{\beta_4}$**, and** $\boldsymbol{\beta_5}$ = are the coefficients for CV, HV, DW, TD, and IV, respectively.

$\boldsymbol{\varepsilon}$ = is the error term.

The input variables can be transformed and manipulated to reduce the noise in the raw datasets. For example, the weighted average of INRIX travel intent route and detector intersection counts can be used to smooth the irregularity of the counts and reduce the noise. In addition, logarithmic transformation of the predictor variables can also be used if deemed to provide additional predictive benefit. Another manipulation can be to adjust the aggregation interval of the input data.

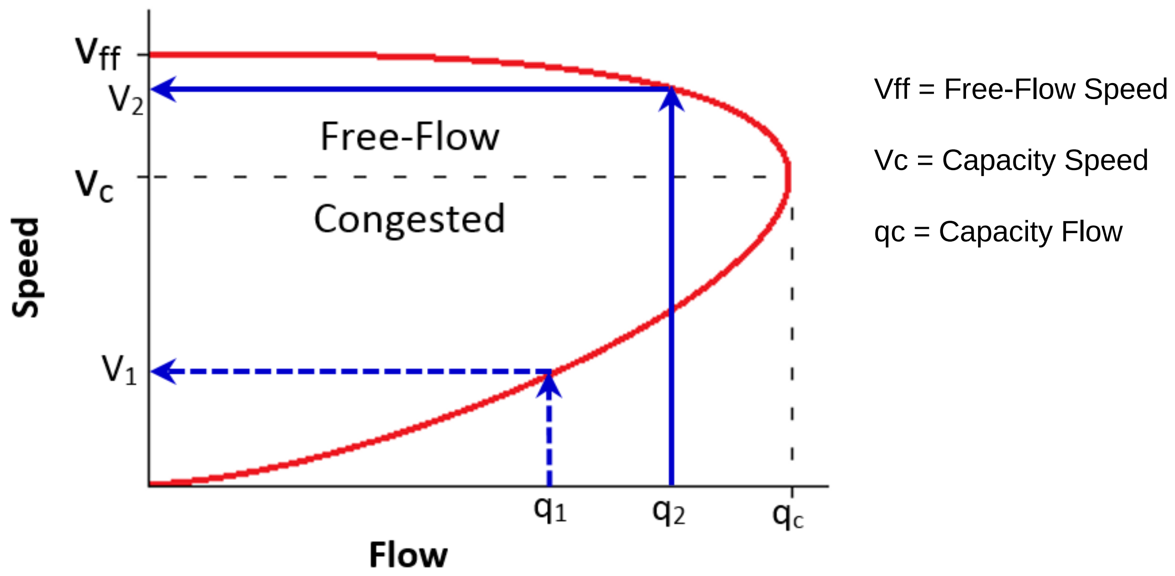
The regression-based ATIS 1.0 and ATIS 2.0 traffic volume prediction models were calibrated using a training dataset for fine tuning the model parameters and identifying the variables to be included in the model. Later, the models were validated using a testing dataset so that the stability of the outputs and their prediction accuracy were verified. The prediction accuracy was assessed by comparing the model output against ground truth data. The benefit derived from including the traveler intent data can be evaluated by examining the significance of the coefficient for variable “IV” in the regression model of the ATIS 2.0 traffic volume prediction model. The prediction benefit gained from including INRIX traveler intent data can be verified using by using suitable statistical tests, e.g., an f-test or t-test.

ATIS 1.0 and ATIS 2.0 Traffic Speed Prediction

The traffic volumes predicted using the regression-based ATIS 1.0 and ATIS 2.0 models presented above will need to be translated into speeds. The conversion from volume to speed was accomplished through a fundamental diagram that describes the relationship between volume and speed at a specific road section. The relationship between speed and flow depends on various factors: lane width, number of lanes, presence or absence of shoulders, proportion of trucks in the traffic, road grade, and curvature to mention a few. Therefore, a separate fundamental diagram must be calibrated for each detector site using historical traffic volume, speed, and occupancy data.

There are various types of fundamental diagram models that depend on the assumptions considered and complexity of the curve fitting technique used. Some specific models include: Greenshields, Greenberg, Gurein, triangular, and Van Aerde models. The Van Aerde model is considered a good model in this case as it better fits the field-observed traffic data (Rakha & Crowther, 2002). See Kühne and Gartner (2011) for a complete discussion of the various types of fundamental diagrams.

The general form of a fundamental diagram is shown in Figure 9. A fundamental diagram has two regimes, the congested and free-flow regimes. If the traffic speed is less than the speed at capacity (critical speed), then traffic is congested, and the lower part of the fundamental diagram is used to convert a volume (q_1) into a speed (V_1), as shown by the broken blue lines. Conversely, if traffic is free-flowing, the upper part of the fundamental diagram is used to convert a volume (q_2) into a speed (V_2), as shown by the solid blue lines. The (near) real time speed observed can be used to distinguish whether traffic is congested or free flowing.



Source: Battelle, 2018

Figure 9. A Fundamental Diagram for One Radar Detector in the Houston Metro Area

The ATIS 1.0 and ATIS 2.0 traffic speed predictions used ATIS 1.0 and ATIS 2.0 traffic volumes predicted from the regression-based model as fundamental diagram inputs, respectively. The accuracy of these predictions was compared by examining the predictions against ground truth data, which is the speed data collected by the radar detectors (the radar detectors collect both volume and speed). The significance of including traveler intent data in accurately predicting future traffic speed was assessed using suitable statistical tests.

ATIS 1.0 and ATIS 2.0 Congestion Alarm Predictions

In the Houston metro area, TransStar generated automated congestion alarms based on a threshold speed value that depends on site, day of week, time of day, and traffic direction. The threshold speed is the minimum of either 40 mph or the 95th percentile of speed values captured over the last 90 days for the same day and time. If the predicted speed is less than the threshold value, then a congestion alarm was issued.

The alarm prediction process compares the ATIS 1.0 and ATIS 2.0 predicted congestion alarms. Alarm prediction accuracy was estimated by the number of false positives (type I error or false alarm) and false negatives (type II error or alarm not issued when it was supposed to be issued).

Appendix B presents example calculations for model development. Please note that this model development and analysis was done to illustrate the process for potential model development using trip intent data. The project team understands that given the very low volume of available INRIX data for this test, no statistically significant effects will be found. Therefore, it is not possible at this time to determine whether the use of trip intent data for real-time traffic prediction is a viable option.

Summary

This chapter presented the modeling approach that would have been adopted to demonstrate the use of travel intent data for short-term traffic volume and speed predictions. However, due to lack of sufficient INRIX traveler intent data, the expected results of the project were not realized. Specific features of the travel intent data that hampered the demonstration include: inadequate data quality, low penetration rate, unpredictable pattern, and small temporal coverage. The result of the analysis conducted with the available travel intent data revealed that there was no significant difference between ATIS 1.0 and ATIS 2.0 predictions for traffic volume, speed, and congestion alarms. Though there wasn’t enough data available from INRIX for this project, the concept and modeling technique used in the project can potentially be of value towards investigating other travel intent data sources that may have higher penetration.

Chapter 4. Conclusions

There were two major technical issues in this project that led to significant mitigating responses:

- This project originally expected to implement the ATIS 2.0 Precursor System in a live environment where its ability to affect the system manager's decision making could be assessed. However, intent data was not available in real-time (or near real-time). Therefore, the project employed archived INRIX trip intent data and related historical TMC data to conduct analysis.
- The archived INRIX travel intent data were not of sufficient quantity to support the test (with the recognition that the archival of trip intent data is not a core product focus for INRIX). The response to this issue was to document the known issues with the archived data; and develop a conceptual modeling approach that may be used, if and when sufficient data became available. This information may be useful to researchers who may work with travel intent data in the future.

The following presents a brief discussion of the analysis along with recommendations for future work in this area. While conducting the test portion of the study (what was to be a field test) it appeared that there was significant decrease in intent data relative to the pilot testing phase. Additional investigation, analysis and discussions with INRIX personnel led to the following conclusions:

- The volume of INRIX trip intent data during the pilot phase was over estimated. This was due to differences in logging software and servers used during the pilot and test phases.
- Examination of separate data sources from INRIX (INRIX provided summary statistics of device activations from a database that tracked usage by subscribers) on device users during the pilot and test showed that there was very little difference in the number of users between the pilot and test phases. This further indicates that INRIX market penetration was generally low both during the pilot and test phases, and that the pilot phase data volume was over estimated.
- Discussions with INRIX managers and analysts confirmed the above observations.
- Houston did not have sufficient market penetration of users with the INRIX app to support the objectives of this study.
- The study employed archived INRIX and TMC data. This was an alternative to the original plan of a real-time system in a TMC, which could not be successfully conducted due to the lack of real-time INRIX intended trips.

Based on the analyses conducted, the following recommendations and observations are provided:

- This project involved research using data and analysis not previously employed and thus presented more technical risk than a system development project based on a strong and extensive research and test base.
- If there is ongoing interest in the use of trip intent data, analyses should focus on identifying cities or metropolitan areas with sufficient market penetration of a trip planning app and service. Additional research should be conducted before selecting one or more providers of trip intent data.

- Initial research to determine the correlation between intended trips and actual trips should be conducted. In other words, do intents translate to actual trips? Also, determine a reasonable intent to actual trip ratio or relationship.
- Unfortunately, at this stage we do not know how much intent trip data are needed to make accurate short-term traffic predictions.
    - Future research would need accurate historical data (e.g., from TMCs) of what happened in the network. These types of data were available for this project from the TMC in Houston.
    - Locations with high market penetration and large volumes of intended trips would be needed to conduct modeling and trade-off analysis. Determination of what might be a minimum or necessary level of market penetration and daily volume of intended trips should be made.
- Consider different modeling techniques – non-linear, machine learning type models. Again, all these methods would need a significant volume of data. Multiple approaches to the models will also be useful. Trade-off analysis of more complexity vs. model effectiveness should be conducted. In other words, what is good enough?
- Assuming the above steps or a similar set of analytical steps are conducted where viable trip intent data are available and used in prediction models; only then will the systems engineering steps previously conducted in this project be usable. This means that a comprehensive evaluation and validation of trip intent data availability, volume, and quality is required prior to the developing use cases, performing systems engineering, and other related design and implementation activities.

References

Castro-Neto, M., Jeong, Y.S., Jeong, M.K., and Han, L.D. (2009). Online-SVR for short-term traffic flow prediction under typical and atypical traffic conditions. *Expert Syst. Appl*. 36, 6164–6173.

Cetin, M., and Comert, G. (2006). Short-term traffic flow prediction with regime switching models. *Transp. Res. Rec. J. Transp. Res. Board*. 1965, 23–31.

Chan, K.Y., Dillon, T.S., Singh, J., and Chang, E. (2012). Neural-network-based models for short-term traffic flow forecasting using a hybrid exponential smoothing and Levenberg–Marquardt algorithm. *Intell. Transp. Syst. IEEE Trans*. On 13, 644–654.

Chen, Y.Y., Lv, Y., Li, Z., and Wang, F.Y. (2016). Long short-Term memory model for traffic congestion prediction with online open data. *IEEE Conference on Intelligent Transportation Systems, Proceedings*, ITSC p 132-137.

El Faouzi, N.E. (1996). Nonparametric traffic flow prediction using kernel estimator. In *International Symposium on Transportation and Traffic Theory*, pp. 41–54.

Guo, J., Huang, W., and Williams, B.M. (2014). Adaptive Kalman filter approach for stochastic short-term traffic flow rate prediction and uncertainty quantification. *Transportation Research Part C: Emerging Technologies*, 43, 50-64.

Habtemichael, F.G., and Cetin, M. (2016). Short-term traffic flow rate forecasting based on identifying similar traffic patterns. *Transportation Research Part C: Emerging Technologies*, 66, 61-78.

Innamaa, S. (2005). Short-term prediction of travel time using neural networks on an interurban highway. *Transportation*. 32, 649–669.

Kühne, R., and Gartner, N., eds. (2011). 75 Years of the Fundamental Diagram for Traffic Flow Theory: Greenshields Symposium, vol. E-C149 of *Transportation Research Circular, Traffic Flow Theory and Characteristics Committee*, Transportation Research Board of the National Academies. http://onlinepubs.trb.org/onlinepubs/circulars/ec149.pdf

Lin, L., Li, Y., and Sadek, A. (2013). A K-Nearest Neighbor based Local Linear Wavelet Neural Network Model for On-line Short-term Traffic Volume Prediction. *Procedia-Soc. Behav. Sci*. 96, 2066–2077.

Lin, L., Wang, Q., and Sadek, A. (2013). Short-term forecasting of traffic volume: evaluating models based on multiple data sets and data diagnosis measures. *Transportation Research Record: Journal of the Transportation Research Board*, (2392), 40-47.

Rakha, H., and Crowther, B. (2002). Comparison of Greenshields, Pipes, and Van Aerde car-following and traffic stream models. *Transportation Research Record: Journal of the Transportation Research Board*, (1802), 248-262.

Szeto, W.Y., Ghosh, B., Basu, B., and O'Mahony, M. (2009). Multivariate traffic forecasting technique using cell transmission model and SARIMA model. *J. Transp. Eng*. 135, 658–667.

Van Hinsbergen, J.W.C., and Sanders, F.M. (2007). Short Term Traffic Prediction Models. In *14th World Congress on Intelligent Transport System*, (Beijing, China).

Van Lint, J., and Van Hinsbergen, C. (2012). Short term traffic and travel time prediction models, in artificial intelligence applications to critical transportation issues. In *Transportation Research Circular*, (Washington D.C.: National Academies Press).

Vlahogianni, E.I. (2007). Prediction of non-recurrent short-term traffic patterns using genetically optimized probabilistic neural networks. *Oper. Res*. 7, 171–184.

Vlahogianni, E.I. (2008). Short-term predictability of traffic flow regimes in signalized arterials. *Road Transp. Res. J. Aust. N. Z. Res. Pract*. 17, 19.

Vlahogianni, E.I., Karlaftis, M.G., and Golias, J.C. (2014). Short-term traffic forecasting: Where we are and where we're going. *Transp. Res. Part C Emerg. Technol*.

Waisley, M., Boyapati, R., Toth, C., Brydia, R., & Miller, B. (2016). A Next Generation Advanced Traveler Information Precursor System (ATIS 2.0 Precursor System) System Requirements. Technical Report No. FHWA-JPO-17-590. U.S. Department of Transportation, Federal Highway Administration. Washington, DC.

Wang, C., and Ye, Z. (2016). Traffic flow forecasting based on a hybrid model. *Journal of Intelligent Transportation Systems – Technology, Planning, and Operations*. p 428–437.

Wang, J., and Shi, Q. (2013). Short-term traffic speed forecasting hybrid model based on Chaos–Wavelet Analysis-Support Vector Machine theory. *Transp. Res. Part C Emerg. Technol.* 27, 219–232.

Wang, Y., Papageorgiou, M., and Messmer, A. (2006). RENAISSANCE–A unified macroscopic model-based approach to real-time freeway network traffic surveillance. *Transp. Res. Part C Emerg. Technol*. 14, 190–212.

Xia, J., Huang, W., and Guo, J. (2012). A clustering approach to online freeway traffic state identification using ITS data. *KSCE J. Civ. Eng*. 16, 426–432.

Zheng, W., Lee, D.H., and Shi, Q. (2006). Short-term freeway traffic flow prediction: Bayesian combined neural network approach. *J. Transp. Eng*. 132, 114–121.

Zheng, Z., and Su, D. (2014). Short-term traffic volume forecasting: A K-nearest neighbor approach enhanced by constrained linearly sewing principle component algorithm. *Transp. Res. Part C Emerg. Technol*. 43, 143–157.

Cui, Z., Ke, R., & Wang, Y. Deep Stacked Bidirectional and Unidirectional LSTM Recurrent Neural Network for Network-wide Traffic Speed Prediction. https://pdfs.semanticscholar.org/f7bd/b849dafe17c952bfd88b879e01f74cf59d78.pdf

Appendix A: List of Original Task and Status at Project Completion

Table 3 summarizes the original projects tasks and their status. Note that some activities of Task 6, Task 7, Task 8, and Task 9 are not completed due to lack of travel intent data with acceptable levels of quality and quantity that resulted in subsequent modification of the scope of the project.

Table 3. List of Project Tasks and Status

WBS	Task Name / Deliverable	Status
1	**Task 1 - Project Management**	**-**
1.1	Kickoff Meeting	Completed
1.2	Draft Project Management Plan	Completed
1.3	Revised Final Project Management Plan	Completed
1.4	Monthly Status Reports	To 4/30/2018
1.5	Closeout Meeting	At end of POP 4/30/2018
1.6	Team Meetings	Completed
1.7	Team Meeting Summaries	Completed
1.8	Presentation Material	Completed
2	**Task 2 - Develop Potential Use Cases for System Managers**	**-**
2.1	Draft Stakeholder Registry & Engagement Plan	Completed
2.2	Final Stakeholder Registry & Engagement Plan	Completed
2.3	Draft Use Cases Report	Completed
2.4	Final Use Cases Report	Completed
3	**Task 3 - Develop and Test Enhanced Traveler Information Services**	**-**
3.1	Draft Data Capture Approach and Testing Plan	Completed
3.2	Final Data Capture Approach and Testing Plan	Completed
3.3	User Data Capture Approach Acceptance Tests	Completed
3.4	Data Capture Testing Summary Briefing	Completed
3.5	Draft User Data Capture Approach	Completed
3.6	Final User Data Capture Approach	Completed
4	**Task 4 - Develop and Test Data Processing Methods**	**-**
4.1	Draft User Data Cleansing and Transformation Approach	Completed
4.2	Final User Data Cleansing and Transformation Approach	Completed
4.3	Data Cleansing and Transformation Acceptance Testing	Completed

WBS	Task Name / Deliverable	Status
4.4	Data Cleansing and Transformation Testing Summary Briefing	Completed
4.5	Draft Revised User Data Cleansing and Transformation Approach	Completed
4.6	Final Revised User Data Cleansing and Transformation Approach	Completed
5	**Task 5 - ATIS 2.0 Precursor System ConOps and System Requirements**	**-**
5.1	Draft Field Test Concept Summary	Completed
5.2	Final Field Test Concept Summary	Completed
5.3	Draft ATIS 2.0 Precursor System Concept of Operations	Completed
5.4	ConOps Review Meeting	Completed
5.5	Final ATIS 2.0 Precursor System Concept of Operations	Completed
5.6	Draft ATIS 2.0 Precursor System Requirements	Completed Note: the system requirements specified that the Field Test would be a test using archived data from INRIX and the Houston TMC. It was determined that the data could not be obtained in real time to perform a field test in a TMC.
5.7	ATIS 2.0 Precursor System Requirements Walkthrough	Completed
5.8	Final ATIS 2.0 Precursor System Requirements	Completed
5.9	Walkthrough Comment Resolution Report	Completed
6	**Task 6 - ATIS 2.0 Precursor System Development and Testing**	**-**
6.1	Draft System Architecture Document	Completed
6.2	Final System Architecture Document	Completed
6.3	Draft System Design Document	Completed
6.4	Draft System Acceptance Plan	Completed
6.5	Final System Design Document	Completed
6.6	Final System Acceptance Plan	Completed
6.7	System Acceptance Tests	Removed from the project via Modification 3.
6.8	Draft Acceptance Test Summary Report	Removed from the project via Modification 3
6.9	Final Acceptance Test Summary Report	Removed from the project via Modification 3
7	**Task 7 - Develop Field Test Plan**	**-**
7.1	Draft Field Test Experimental Plan	Completed Note: Field Test was now designed to be a test using archived INRIX and Houston TMC data.
7.2	Final Field Test Experimental Plan	Completed
7.3	Updated Field Test Experimental Plan	Completed

WBS	Task Name / Deliverable	Status
8	**Task 8 - Conduct Field Test**	-
8.1	Field Test Briefing Materials	Removed from the project via Modification 3. Note: during the conduct of the Task 7 plan it was determined that there was not sufficient INRIX data to perform the test.
8.2	Field Test and Post-Mortem Briefing	Removed from the project via Modification 3
9	**Task 9 - Prepare Field Test Report and Briefings**	-
9.1	Precursor System Source Code/Documentation for OSADP	Removed from the project via Modification 3
9.2	Field Test Data/Supporting Documentation for Posting to RDE	Removed from the project via Modification 3
9.3	Draft Field Test Report	Completed
9.4	Field Test Summary Briefing	Removed from the project via Modification 3
9.5	Final Field Test Report	The current report
10	**Task 10 – Coordinate with Related DMA and Standards Activities**	-
10.1	Support for related DMA efforts underway that are related to evaluation and standards development, including meeting summaries and trip reports. (Includes extra 2 months for final ITS-JPO document approvals)	Completed as required

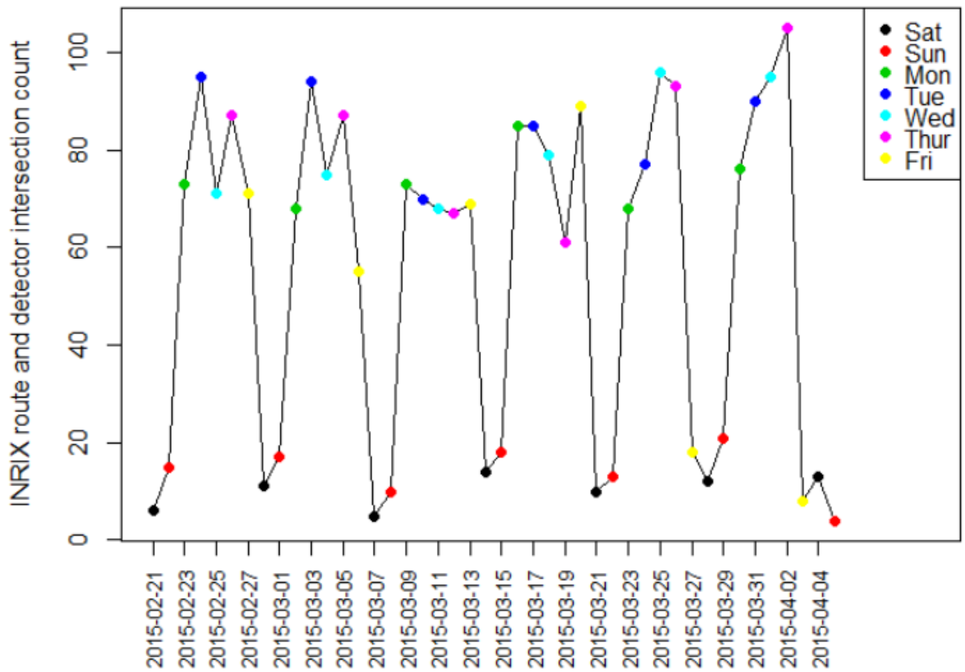
Modification 3 removed tasks and deliverables associated with the conduct of the planned test using archived INRIX and Houston TMC data. As the plan under Task 7 was being executed it was determined that there was insufficient data to conduct the field test type of study using archived INRIX data. Appendix B presents sample calculations using the available data.

Appendix B: Example Case for ATIS 1.0 and ATIS 2.0 Precursor System Results

As discussed in the data processing section, the quality of the INRIX traveler intent data was very poor due to this data not being a focus product for INRIX. The average count of traveler intent route and detector screen line intersections per day was 0.47. This would equate to an average of 0.001 traveler intent route and detector screen line intersection per 15-minute time interval, i.e., only one instance of traveler intent count over 1,000 timesteps of 15 minutes. This is an extremely low count to be useful for any meaningful statistical modeling. As a result, given such poor data quality, no significant benefit was expected to be drawn from using the INRIX travel intent data. The predictions between the ATIS 1.0 and ATIS 2.0 precursor systems were expected to have no significant difference (for all of the precursor system components: traffic volume, speed, and congestion alarms).

As demonstrated previously, there was a considerable amount of variability in the count of INRIX traveler intent route and detector screen line intersections. Such random, unpredictable variability makes it difficult for use in any statistical modeling. Therefore, a small portion of the INRIX traveler intent data with relatively stable variability over six-weeks (from February 21, 2015 to April 5, 2015) was selected to develop and test the ATIS 1.0 and ATIS 2.0 precursor system, i.e., traffic volume, speed, and congestion alarm predictions. The data from February 21, 2015 to March 28, 2015 were used as training data to calibrate the ATIS 1.0 and ATIS 2.0 precursor systems. The remaining data from March 29, 2015 to April 5, 2015 were used as test data to validate the prediction.

Figure 10 shows the pattern of the traveler intent route and detector intersection counts during the six-weeks. The pattern is consistent with common traffic patterns, i.e., higher travel intent counts were observed during weekdays and low counts during weekends. However, the count of INRIX travel intent data during the six weeks is still very small, only about 1% of the 15-minute intervals had INRIX traveler intent route and detector screen line intersections. As stated above, the low count was not expected to be suitable for any modeling use.



Source: Battelle, 2018

Figure 10. INRIX Travel Intent Route and Detector Intersection from 2/21/2015 to 4/5/2015

To show the ATIS 1.0 and ATIS 2.0 prediction results, the site with the highest number of INRIX traveler intent routes and detector screen lines was selected. The selected detector was ID 7075 East, along the Houston metro area Loop 8. Using the training data set, the parameters for ATIS 1.0 and ATIS 2.0 regression-based traffic volume prediction models were estimated as shown in Table 4. The table displays the t-value and P-value, and the significance of each model parameter. Note that for the ATIS 2.0 traffic volume prediction model, the model parameter INRIX traveler intent route and the detector screen line intersection was found to be not significant, i.e., it had no benefit prediction benefit. Since day of the week and hour of the day are categorical variables, Friday and the first hour of the day were taken as references levels, thus their coefficients are always zero.

Table 4. ATIS 1.0 and ATIS 2.0 Traffic Volume Prediction Model Parameters for Detector ID 7075 East

Model Parameters		ATIS 1.0 Traffic Volume Prediction				ATIS 2.0 Traffic Volume Prediction			
		Coefficient	t-value	P-value	Significant	Coefficient	t-value	P-value	Significant
Intercept		3.240	1.34	0.18	No	3.209	1.32	0.19	No
Current Volume		0.588	30.46	0.00	Yes	0.588	30.45	0.00	Yes
Historic Volume		0.332	16.79	0.00	Yes	0.333	16.80	0.00	Yes
Day of the week	Monday	-2.17	0.03	0.03	Yes	-3.623	-2.16	0.03	Yes
	Tuesday	-2.74	0.01	0.06	Yes	-4.449	-2.73	0.01	Yes
	Wednesday	-1.99	0.05	0.05	Yes	-3.117	-1.97	0.05	Yes
	Thursday	-2.23	0.03	0.03	Yes	-3.729	-2.23	0.03	Yes
	Saturday	-4.11	0.00	0.00	Yes	-6.622	-4.11	0.00	Yes
	Sunday	-6.81	0.00	0.00	Yes	-12.586	-6.80	0.00	Yes
Hour of the day	01:00-01:59	-2.00	0.05	0.05	Yes	-6.100	-2.00	0.05	Yes
	02:00-02:59	0.27	0.78	0.78	No	0.851	0.28	0.78	No
	03:00-03:59	1.86	0.06	0.06	No	5.572	1.87	0.06	No
	04:00-04:59	5.00	0.00	0.00	Yes	14.656	5.00	0.00	Yes
	05:00-05:59	15.04	0.00	0.00	Yes	45.832	15.02	0.00	Yes
	06:00-06:59	10.14	0.00	0.00	Yes	34.952	10.10	0.00	Yes
	07:00-07:59	6.60	0.00	0.00	Yes	23.287	6.56	0.00	Yes
	08:00-08:59	3.62	0.00	0.00	Yes	12.394	3.59	0.00	Yes
	09:00-09:59	4.82	0.00	0.00	Yes	16.004	4.80	0.00	Yes
	10:00-10:59	5.68	0.00	0.00	Yes	18.467	5.64	0.00	Yes
	11:00-11:59	5.21	0.00	0.00	Yes	17.148	5.18	0.00	Yes
	12:00-12:59	6.49	0.00	0.00	Yes	21.673	6.47	0.00	Yes
	13:00-13:59	9.16	0.00	0.00	Yes	30.376	9.12	0.00	Yes
	14:00-14:59	8.22	0.00	0.00	Yes	28.528	8.19	0.00	Yes
	15:00-15:59	10.44	0.00	0.00	Yes	38.784	10.39	0.00	Yes

Model Parameters		ATIS 1.0 Traffic Volume Prediction				ATIS 2.0 Traffic Volume Prediction			
		Coefficient	t-value	P-value	Significant	Coefficient	t-value	P-value	Significant
	16:00-16:59	10.75	0.00	0.00	Yes	43.722	10.71	0.00	Yes
	17:00-17:59	5.80	0.00	0.00	Yes	24.753	5.83	0.00	Yes
	18:00-18:59	-0.43	0.67	0.67	No	-1.596	-0.43	0.67	No
	19:00-19:59	-0.44	0.66	0.66	No	-1.523	-0.47	0.64	No
	20:00-20:59	2.35	0.02	0.02	Yes	7.219	2.34	0.02	Yes
	21:00-21:59	1.32	0.19	0.19	No	4.005	1.31	0.19	No
	22:00-22:59	0.14	0.89	0.89	No	0.379	0.13	0.90	No
	23:00-23:59	0.97	0.33	0.33	No	2.846	0.97	0.33	No
INRIX travel intent route and detector screen line intersection count		-	-	-	-	-0.681	-0.65	0.51	No

Using the validation data set, the accuracy of ATIS 1.0 and ATIS 2.0 traffic volume prediction models was tested. Since the difference between the two models is the presence or absence of the INRIX travel intern route and detector screen line intersection, and that variable was deemed to be insignificant, no significant difference between the two prediction models was expected. The mean absolute percent error (MAPE) for both ATIS 1.0 and ATIS 2.0 traffic volume prediction models was found to be 18%. Given the traffic volume prediction models used are simplistic linear regression-based and the project objective is not to develop a new or advanced traffic prediction algorithm, but rather to see if travel intent data provides predictive benefit, a MAPE of 18% is still acceptable.

As discussed earlier, the traffic speed prediction model used the traffic volume prediction as an input, and a well-calibrated fundamental diagram for detector ID 7075 East. Since there was no difference between the ATIS 1.0 and ATIS 2.0 traffic volume prediction, it can be concluded that no significant benefit was derived from using the INRIX traveler intent information in predicting future traffic speed.

Similar to the ATIS 1.0 and ATIS 2.0 traffic volume and speed predictions, no benefit was derived from INRIX traveler intent information in predicting future congestion alarms. The lack of significant benefit from INRIX traveler intent information can be attributed to several reasons, including:

- The penetration rate of the travel intent information was very small.
- The travel intent information had an unpredictable pattern, which cannot be explained by other variables.
- Since the travel intent data had little penetration rate and an unpredictable pattern, a slight random variation translates into a large percentage change.

U.S. Department of Transportation
ITS Joint Program Office – HOIT
1200 New Jersey Avenue, SE
Washington, DC 20590

Toll-Free “Help Line” 866-367-7487

www.its.dot.gov

FHWA-JPO-18-637

U.S. Department of Transportation