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Northern Virginia Case Study Validation:
Travel Time Reliability Monitoring

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1. MONITORING SYSTEM

STUDY DESCRIPTION

This case study is the second of five, performed by the project team in order to validate the approaches to travel time reliability monitoring described in the Travel Time Reliability Monitoring Guidebook. The goal of each case study is to illustrate how agencies apply best practices for: monitoring system deployment; travel time reliability calculations; and agency use and analysis of the system. To accomplish this goal, the team is implementing prototype travel time reliability monitoring systems at each of the five sites. These systems take in sensor data from a variety of transportation networks, process this data inside a large data warehouse, and generate reports on travel time reliability for agencies to help them better operate and plan their transportation systems. This case study consists of the following sections:

- Monitoring System
- Methodological Advancement
- Use Case Analysis
- Lessons Learned

These sections map to the master system components, as shown below in Figure 1-1.

![Travel Time Reliability System Description](image)

Figure 1-1: Travel Time Reliability System Description

This monitoring system description section details the reasons for selecting Northern Virginia as a case study and gives an overview of the region. It briefly summarizes agency monitoring practices, discusses the existing sensor network, and describes the software system that the team used to analyze use cases. The section also details the development of travel time reliability software systems, and their relationships with other systems. Specifically, it describes the steps and tasks that the research team completed in order to transfer data from a pre-existing collection system into a travel time reliability monitoring system.

The section on methodology describes the implementation of a multi-state travel time reliability model, developed by the SHRP 2 L10 research team, using the Northern Virginia freeway data. It is intended to showcase a tractable method for assembling travel time
probability density functions from historical travel time data, as well as highlight the tie-ins of this project with others under the SHRP 2 umbrella. It was selected for emphasis in this case study because the original work was performed using model-generated travel times from the same I-66 corridor being monitored as part of this case study. Work on refining the Bayesian travel time reliability calculation methodology outlined in this project’s Task 7 document and introduced in the San Diego case study will resume as part of the final three case study sites.

Use cases are less theoretical, and more site specific. Their basic structure is derived from the user scenarios described in the Task 2/3 document, which are the results of a series of interviews with transportation agency staff regarding agency practice with travel time reliability. Since the focus of this case study is to describe the required steps and considerations for integrating a travel time reliability monitoring system into existing data collection systems, only one use case is described in this case study.

Lessons Learned summarizes the lessons learned during this case study, with regard to all aspects of travel time reliability monitoring: sensor systems, software systems, calculation methodology, and use. These lessons learned will be integrated into the final guidebook for practitioners.

Figure 1-2: Map of the NOVA District
SITE OVERVIEW

The team selected Northern Virginia to provide an example of a more traditional transportation data collection network operating in a mixture of urban and suburban environments. The Northern Virginia (NOVA) District of the Virginia Department of Transportation (VDOT) includes over 4,000 miles of urban, suburban, and rural roadway in Fairfax, Arlington, Loudoun, and Prince William counties. Traffic operations in the District are overseen from the NOVA Traffic Operations Center (TOC), which manages more than 100 miles of instrumented roadways, including HOV facilities on Interstates 95/395, 295, 66, and the Dulles Toll Road. To support these activities, the TOC has deployed a wide range of intelligent transportation system (ITS) technologies, including:

- 109 cameras
- 222 dynamic message signs
- 24 gates on I-66 HOV lanes for use during peak travel hours
- 21 gates on I-95/I-395 for reversible HOV lanes
- 25 ramp meters on I-66 and I-395
- 30 lane control signals
- 23 vehicle classification stations
- ~250 traffic sensors (see Figure 1-3 for deployment locations)

Overall, the NOVA TOC is a high-tech communications hub that manages some of the nation's busiest roadways. Its systems collect, archive, manage, and distribute data and video generated by these resources for use in transportation administration, policy evaluation, safety, planning, performance monitoring, program assessment, operations, and research applications. Moreover, an Archived Data Management Systems (ADMS) has been developed by the University of Virginia (UVA) Smart Travel Lab (STL) to support VDOT in conducting these activities. TOC staff use dynamic message signs (DMS) and Highway Advisory Radio (HAR) sites to alert commuters about changing traffic conditions. Commuters and other travelers can also tune to AM 1620, call the Highway Helpline at 1-800-367-ROAD (7623) for real-time traffic information, or view the road conditions map on 511 Virginia.

Figure 1-3: Locations of Nova District Freeway-based Traffic Sensors

VDOT's management strategy has undergone a dramatic change in the last few years, transitioning from a two-pronged “build-maintain” regime, to a three-pronged “build-operate-maintain” scheme. As such, VDOT is evolving into a customer-driven organization with a focus
on outcomes and a “24/7” performance orientation. As part of these efforts, VDOT has developed four “Smart Travel” goals:

1. Enhance public safety
2. Enhance mobility
3. Make the transportation system user-friendly
4. Enable cross-cutting activities to support goals 1-3

These goals are geared toward providing better services to NOVA District customers by improving the quality of their travel and responding promptly to their issues. The focus is on attaining greater operating efficiencies from existing roadway infrastructure as an alternative to building additional capacity. The NOVA Smart Travel Vision is as follows:

“Integrated deployment of Intelligent Transportation Systems will help NOVA optimize its services, supporting a secure multimodal transportation system that improves quality of life and customer satisfaction by ensuring a safer and less congested transportation network.”

As part of its activities, the NOVA District has significant interaction with agencies in the District of Columbia and Maryland (in particular in Montgomery and Prince Georges Counties). A number of Federal, state, and local transportation stakeholders, including transit, police, emergency, medical, and other agencies, also play important roles in operating and managing area roadways and other regional transportation systems. Recently, there has been a push within the region to strive towards increased regional coordination and interoperability. To that end, a regional coordinating entity called CapCOM (Capitol Region Communications and Coordination) has been created to focus on collecting data from a variety of sources to facilitate the creation of a “big picture” of regional traffic.

Due to the major transportation-related construction that began in the region during 2008 and which is anticipated to continue through 2011, mitigation of construction-related congestion is a major focus for the district. Major projects are concurrently occurring, including:

- Construction of 14 miles of HOT lanes on I-495;
- Construction of 56 miles of HOT lanes on I-395/95;
- Widening of I-95 between Newington and Dumfries;
- Widening of I-495, and;
- Roadway improvements at the I-495/Telegraph Road interchange

SENSORS

Northern Virginia suffers from severe road congestion, and is generally considered one of the most congested regions in the nation. To help alleviate gridlock, VDOT encourages use of Metrorail, carpooling, slugging, and other forms of mass transportation. Major limited-access highways include Interstates 495 (the Capital Beltway), 95, 395, and 66, the Fairfax County Parkway and Franconia-Springfield Parkway, the George Washington Memorial Parkway, and the Dulles Toll Road. High-occupancy vehicle (HOV) lanes are available for use by commuters and buses on I-66, I-95/395, and the Dulles Toll Road. A portion of the region’s HOV lanes have been designed to be reversible, accommodating traffic flow heading north and east in the morning and south and west in the afternoon.

VDOT operates five (5) regional TOCs located in NOVA, Hampton Roads, Richmond, Staunton, and Salem. At the core of each VDOT TOC is an Advanced Transportation Management System (ATMS), which controls each region’s field devices and manages
Information associated with the operation of the roadway network. Operators at each TOC monitor traffic and road conditions on a continuous basis via closed circuit television (CCTV) cameras, vehicle detection infrastructure, and road weather information sensors. In Northern Virginia, VDOT has deployed an extensive network of point-based detectors (primarily inductive loops and radar-based detectors) to facilitate real-time data collection on freeways. Volume, occupancy, and (some) speed data are collected from these detectors and used by NOVA TOC staff to manage traffic and incidents and provide information to motorists regarding current conditions. The breakdown of NOVA data sources is as follows:

- Multiple types of traffic sensors along I-95, I-495, I-395, and I-66. The mix of sensors deployed along these roadways includes: inductive loop detectors, RTMS radar, magnetometers, SmartSensor digital radar, and SAS-1 sensors.
- Trichord – has deployed acoustic sensors on I-95, I-395, I-495, and I-66.

TOC operators also enter incident data, planned events/work zones, and weather events into a web-based application called the Virginia Traffic Information Management System (VaTraffic). VaTraffic information is shared with the public, VDOT management and other key state and local emergency response agencies.

Although a number of major Interstate roadways pass through the NOVA region, including I-95, I-495, I-395, and I-66, for the purposes of this study we conducted analyses exclusively on I-395 and I-66, the two primary entry/egress interstates southwest of Washington, D.C.

On I-66 and I-395, point detectors are placed at approximately ½ mile intervals. Due to accuracy and maintainability issues with inductive loop detectors and other older sensors, there are no plans to replace failed units which have been deployed on the mainline lanes. Instead, plans are in motion to transition to the use of non-intrusive radar-based detection technologies. These sensors are being deployed both as replacements for older failed units, as well as at all locations where detection infrastructure is being deployed for the first time. As a result of a combination of older loop detector station failures, ongoing roadway construction, and the need to configure many of the newer radar-based units, data is currently available for only about 75 of the detectors. Figure 1-4 provides a visual indication of the availability of data on I-66 and I-395; lighter colored icons indicate working stations, darker icons indicate non-working stations.

Figure 1-4: Map of Working vs. Non-Working Sensor Stations
DATA MANAGEMENT

NOVA TOC staff use a regional Freeway Management System (FMS) to monitor and manage traffic data from the ATMS, respond to incidents, and disseminate traveler information. The FMS is linked to the Virginia Traffic Information Management System (VaTraffic), a statewide traffic information management and conditions reporting system developed by VDOT to provide an efficient, integrated platform for managing activities that affect the quality of travel experienced by motorists. It comprises a suite of applications that VDOT staff use to manage planned events such as roadway maintenance, unplanned events such as traffic accidents and heavy congestion, and to provide information for use by other VDOT systems. These data are made available via a Data Gateway.

The Data Gateway was first deployed in VDOT in 2004 as an interconnection between the Virginia State Police (VSP) and the Richmond Traffic TOC. Since that time, it has grown into a statewide network that is used to exchange critical information. The Data Gateway is an XML Publish and Subscribe network fully compliant with the Emergency Data Exchange Language (EDXL) standard, providing the maximum degree of interoperability between systems. The Data Gateway presently allows a number of diverse systems to share data, including:

- **VaTraffic** - uses the Data Gateway to exchange information with nearly 1500 statewide users, the 511 Interactive Voice Response (IVR) and Web applications, and other VDOT systems. VaTraffic publishes information for incidents, planned events, road conditions, snow conditions, and bridge schedules.
- **OpenTMS** - is deployed in the Northern, Central, Northwest, and Southwest TOCs, and publishes information concerning incidents and DMS messages. In the future, OpenTMS is planned to provide information on weather sensors, work zones, HOV gate control, and other lane control data.
- **Virginia State Police** - the Data Gateway has been used to share VSP data since 2004. Data entered in to the VSP CAD system is shared in real-time with all participating TOCs.

VDOT currently reports on roadway conditions via a number of performance-related products, including its Quarterly Report, Web-based Performance Dashboard, and bi-monthly performance reports to the VDOT Commissioner (internal).

The VDOT Performance Dashboard ([http://dashboard.virginiadot.org/](http://dashboard.virginiadot.org/)) provides a wide range of transportation performance-related data, including:

- Travel Times on Key Commuter Routes
- Congestion along Interstates
- HOV Travel Speeds
- Incident Duration
- Annual Hours of Delay

Performance measurement has become an important function within VDOT and serves to enable TOC engineers and operators to identify, measure, and report the status of the both the freeway system and individual facilities at different geographic (spatial) and temporal scales.
SYSTEM INTEGRATION

Overview

For purposes of this case study, data from NOVA’s data collection network and system were integrated into a developed archived data user service and travel time reliability monitoring system. The steps and challenges encountered in enabling the information and data exchange between these two large and complex systems are described in detail in this section. The goal of this section is to provide agencies with a real-world example of the resources needed to accomplish data collection to monitoring system integration, and the likely challenges that will be encountered when procuring a monitoring system.

This section first describes the source system (VDOT’s data collection system) and the reliability monitoring system (PeMS). It then describes the data acquisition and processing steps need to transfer information between the two systems. Finally, it summarizes findings and lessons learned.

Source System

VDOT’s Northern Region Operations site receives detector data from two different systems; one that collects data along part of I-66, and one that collects data for the rest of I-66 and I-395. These two data streams are integrated into a standardized format in a single text file that is generated every minute. This text file is passed in real-time to the Regional Integrated Transportation Information System (RITIS), developed and maintained by the CATT Laboratory at the University of Maryland (UMD). RITIS, without doing any further processing of the data, parses the text file and puts it into an XML document that is updated every minute on a page of the RITIS web site. Access to this webpage is limited to pre-approved IP addresses. These real-time detector data XML documents were the primary traffic data source for NOVA PeMS. When data quality, largely due to recent construction on monitored roadways, proved to be a major issue impeding the study of reliability on the 2011 data, the research team also acquired a database dump of detector data along I-66 and I-395 for the entire year of 2009 from the UMD CATT lab.

Reliability Monitoring System

PeMS is a traffic data collection, processing, and analysis tool that extracts information from real-time intelligent transportation systems (ITS) data, saves it permanently in a data warehouse, and presents it in various forms to users via the web. PeMS can calculate many different performance measures; and as such, the requirements for linking PeMS with an existing system depend on the features being used. Since the function of PeMS in this case study is to collect traffic data from point detectors, quality control it, generate and store travel times, and report reliability statistics, the following describes what PeMS uses from the source system to support these functions:

- Metadata on the roadway linework of facilities being monitored
- Metadata on the detection infrastructure, including the types of data collected and the locations of equipment
- Real-time traffic data in a constant format at a constant frequency (such as every 30-seconds or every minute)

The foundation of PeMS is the traffic detector, which reports at least two of the three fundamental parameters that describe traffic on a roadway: flow, occupancy, and speed.
Detectors report or are polled for data in real-time at a pre-defined time interval. In PeMS, detectors have a location denoted by a freeway number, direction of travel, latitude and longitude, and a milepost that marks the distance of a detector down a freeway. Each detector is assigned a unique ID which remains with it throughout time, and can never be assigned to another detector, even if the original detector is removed. Every detector belongs to a station, which is a logical grouping of detectors that monitor the same type of lane (for example, mainline versus HOV) along the same direction of freeway at the same location. Each station has a unique ID, a type (such as mainline, HOV, ramp, etc), a number of lanes, and a corresponding set of detectors. The final pieces of equipment in the PeMS framework are controllers, which are located along the roadside and collect data from one or more stations. They have a latitude/longitude and mile marker location, as well as a set of corresponding stations. This hierarchy- a controller collecting data from stations composed of detectors- gives structure to the roadway instrumentation configuration, making it easy to spatially aggregate data and diagnose problems in the data collection chain, such as a broken detector or controller, or a failed communication line.

PeMS collects detector data- either by directly polling each detector or obtaining it from an existing data collection system- in real-time and stores it in an Oracle database. The raw data is permanently stored in a raw database table, and is also aggregated up to the five-minute level, at which point PeMS computes the average five-minute speed for detectors that transmit flow and occupancy, and the average five-minute occupancy for detectors that transmit flow and speed. This data is stored in a five-minute detector database table. At the five-minute level, PeMS also aggregates the lane-by-lane detector data up to the station level, which represents the total flow, average occupancy, and average speed across all the lanes at that location during that five-minute period. This data is stored in a five-minute station database table. The station data is further aggregated up to the hourly and daily levels, and stored in corresponding database tables.

PeMS computes travel times on routes, which can traverse more than one freeway, and which are defined by a starting on-ramp, freeway-to-freeway connectors (if any), and an ending off-ramp. It computes travel times for routes at the five-minute and hourly levels from the data in the detector and station database tables, using the infrastructure-based sensor calculation method described in Chapter 11 of the Guidebook. It stores these travel times permanently in five-minute and hourly travel time database tables. These travel times can then be queried to assemble the historical distribution of travel times along a route for different times of the day and days of the week, as well as compute reliability metrics such as the buffer time index and percentile travel times.

Data Acquisition

This section describes, in general, the transfer of data between the source system and the monitoring system in order to monitor travel time reliability. It also details the specific data exchanges occurring between the source system and PeMS in this case study.

General. Typically, reliability monitoring systems must acquire two categories of information from the source system in order to produce accurate performance metrics: (1) metadata on the roadway network and detection infrastructure; and (2) traffic data. The traffic data are unusable for travel time calculation purposes if not accompanied by a detailed description of the configuration of the system. Configuration information provides the contextual and spatial information on the sensor network needed to make sense of the real-time data. Ideally, these two types of information should be transmitted separately (i.e., not in the same file or data feed). Roadway and equipment configuration information is more static than traffic data,
as it only needs to be updated with changes to the roadway or the detection infrastructure. Keeping the reporting structure for these two types of information separate reduces the size of the traffic data files, allowing for faster data processing, better readability, and lower bandwidth cost for external parties who may be accessing the data through a feed.

Additionally, the data acquisition step often involves reconciliation between the framework of the source system and the monitoring system. For example, different terminology can lead to incorrect interpretations of the data. As such, this step often requires significant communication between the system contractor and the agency staff who have familiarity with the data collection system, in order to resolve open questions and make sure that accurate assumptions are being made.

**Metadata.** PeMS needs to acquire two types of metadata before traffic data can be stored in the database: roadway network information and equipment configuration data. To represent the monitored roadway network and draw it on maps, PeMS needs to have GIS-type roadway polylines defined by latitudes and longitudes. To help the agency link PeMS data and performance metrics with their own linear referencing system, PeMS also associates these polylines with state roadway mileposts. In most state agencies, mileposts are a reference system used to track highway mileage and denote the locations of landmarks. Typically, these mileposts reset at county boundaries. In cases where freeway alignments have changed over time, it is likely that the difference between two milepost markers no longer represents the true physical distance down the roadway. For this reason, PeMS adds in a third representation of the roadway network, called an absolute postmile. These are akin to mileposts, but they represent the true linear distance down a roadway, as computed from the polylines. They do not reset at county boundaries, in order to facilitate the computation of performance metrics across long sections of freeway. In PeMS, this information is ultimately stored in a freeway configuration database table that contains a record for every 10\( ^{th} \) of a mile on every freeway. Each record contains the freeway number, direction of travel, latitude and longitude, state milepost, and absolute postmile.

The research team was not able to obtain any GIS data for the NOVA network within the project time frame. Since the monitored network consisted of only two corridors, roadway linework was obtained by entering the starting and ending points of each corridor into Google Maps and exporting the results into a KML file. From these data, polylines and their latitudes and longitudes were parsed and placed in a PeMS database. The next step was to add state milepost markers to these latitude/longitude freeway locations. Since both of the monitored freeway segments fell into only one county, this was done by researching the mileposts at the county boundary, and then interpolating the mileposts in at least 0.10 mile increments along the rest of the freeway segment. In the NOVA case, state mileposts and PeMS absolute postmiles are the same.

The second type of metadata required is information about the detection equipment from which the source system is collecting data. PeMS has a very strict equipment configuration framework which is described in the Reliability Monitoring System subsection. All source information must conform. The rigidity of this framework is due to the need to standardize data collection and processing across all agencies, regardless of their source system structures. Configuration information ultimately populates detector, station, and controller configuration database tables in PeMS, and is used to correctly aggregate data and run equipment diagnostic algorithms.

NOVA equipment configuration information was obtained from an XML file posted on the RITIS website that is updated periodically (typically, not more than every few days). A
representative section of this file is shown in Figure 1-5. The file is composed of <detector> elements, which each have a unique ID, a textual name that includes a mile marker, a latitude and longitude, a type (such as inductive loop), and one or more <detection-zone> elements. Each <detection-zone> element has a unique ID, a number of lanes, a latitude and longitude, a direction, and, sometimes, a type (such as shoulder or lane).

```xml
<detector>
  <detector-id>578</detector-id>
  <detector-name>I-66 NEAR Fairfax Co. Pkwy @ MM 56.21</detector-name>
  <detector-location>
    <latitude>38.855830</latitude>
    <longitude>-77.381708</longitude>
  </detector-location>
  <detector-type>inductive loop</detector-type>
  <detection-zone>
    <detection-zone-item>
      <zone-number>1339</zone-number>
      <num-lanes>1</num-lanes>
      <zone-location>
        <latitude>38.855620</latitude>
        <longitude>-77.381693</longitude>
      </zone-location>
      <zone-direction>east</zone-direction>
    </detection-zone-item>
  </detection-zone>
  <detection-zone>
    <detection-zone-item>
      <zone-number>1142</zone-number>
      <num-lanes>2</num-lanes>
      <zone-location>
        <latitude>38.855553</latitude>
        <longitude>-77.381669</longitude>
      </zone-location>
      <zone-direction>east</zone-direction>
    </detection-zone-item>
    <detection-zone-item>
      <zone-number>1143</zone-number>
      <num-lanes>2</num-lanes>
      <zone-location>
        <latitude>38.855854</latitude>
        <longitude>-77.381725</longitude>
      </zone-location>
      <zone-direction>west</zone-direction>
    </detection-zone-item>
  </detection-zone>
</detector>
```

Figure 1-5: NOVA RITIS Detector Configuration XML Format

Once the file was obtained, the next step was to fit the data into the PeMS configuration framework. The third step was to parse the XML file, insert relevant fields into the PeMS database, and write a program to automatically download the configuration file from the RITIS
website and populate relevant information into the database whenever the file is updates. Since the XML file was not accompanied by an explanatory text file, the second step took considerable time and effort, as a number of issues were uncovered that made it challenging to map the NOVA information into the PeMS database. The issues, described below, related to conflicting terminologies, information required by PeMS that was missing from the configuration file, and equipment types not supported by PeMS.

The first challenge was to determine how the NOVA <detector> and <detection-zone> elements should map to the PeMS equipment framework of detectors, stations, and controllers. From the properties of the NOVA <detectors>, it was clear that they did not refer to the same entity as a PeMS detector. NOVA detectors contain multiple zones, and each zone has a lane count, a location, a direction, and a type. From these attributes, it was concluded that the NOVA detection zone was conceptual equivalent to the PeMS station, and that the NOVA detector was the conceptual equivalent of the PeMS controller. This was confirmed by looking at samples of the RITIS traffic data XML files, which report flow, occupancy, and speed data for each <detection-zone>. After performing this matching and reviewing the traffic data, the team concluded that, despite the terminology used, the NOVA configuration information had no notion of a detector in the PeMS or the conventional sense, i.e., a sensor that monitors traffic in a single lane at a single location. Since PeMS is built around the collection of lane-specific data from detectors, which enables the capability to report lane-by-lane flows, volumes, and occupancies at point locations and lane-by-lane travel times along routes, this presented a challenge. The problem was ultimately solved by using the number of lanes reported for each NOVA detection zone to assign artificially constructed PeMS detectors to monitor each lane. Each detector was given an ID, assigned by appending to the detection zone ID an integer representing the lane number. Then, during the real-time data integration, the flows, volumes, and occupancies reported by each detection zone were divided by the number of lanes and assigned to each detector.

Another challenge was matching the NOVA detection zone types with the station types supported by PeMS. Every station in PeMS is assigned a type to denote the lane type that it monitors. Station types must be one of the following: mainline, HOV, collector/distributor, freeway-freeway connector, off-ramp, or on-ramp. In the NOVA configuration XML file, not every detection zone is assigned a type, and the types that are assigned (shoulder, lane, exit ramp, rhov, and hov) do not align with those defined in PeMS. The NOVA “shoulder” zone type is a reflection of the fact that, during peak hours, the shoulder lanes on I-66 are open to traffic. The “rhov” zone type is assigned to HOV lanes that are reversible based on the time of day. These two operational characteristics added significant complexity into the monitoring process. The operation of shoulder lanes meant that the number of lanes at a given location changed by time of day, a characteristic that PeMS could not accurately represent. Similarly, the reversible HOV lane operation meant that sensors monitored different directions of travel based on the time of day, which PeMS also could not accurately configure. For this reason, “shoulder” and “rhov” stations were not stored in the PeMS database. A related problem was that many detection zones were not assigned types in the configuration file. To solve this, the latitude and longitude of each NOVA detection zone was mapped in Google Earth and manually inspected to determine which PeMS station category it belonged to. The end product of this step was a csv file that listed each detection zone ID and its corresponding PeMS station type.

A third issue was that, through the metadata, PeMS needed to learn what types of data it would be receiving from each station. Typically, detectors can report up to three values: flow, occupancy, and speed. Some detectors, such as on- and off-ramp loop detectors, only report flows. Single inductive loop detectors report flow and occupancy. Radar detectors report flow
and speed. Double loop detectors report flow, occupancy, and speed. PeMS needs to know which detectors report which values, so that, for detectors reporting two of the three values, the third is calculated via an algorithm. This information is not directly present in the NOVA configuration XML file. NOVA detectors (PeMS controllers) are assigned types (either inductive loop or microwave radar) in the configuration file. Since VDOT staff confirmed that the inductive loops are single loop detectors, we expected that zones made up of inductive loops would report flow and occupancy, and zones made up of microwave radar sensors would report flow and speed. However, in the traffic data XML file, all zones, regardless of their detector type in the configuration file, reported all three values or only flow. The implications of this finding are further described in the Traffic Data section that follows. From a metadata perspective, there was no sure way of tagging NOVA zones with the types of data expected to be received. For this reason, PeMS ultimately stored whatever values each zone transmitted via the XML file. This meant that, for detectors reporting only flow, their speeds and occupancies were entered as zero, even though this clearly did not reflect the actual field conditions.

The metadata quality control steps described above were the bulk of the work to insert NOVA configuration information into PeMS. Following this, a custom program was written to parse the PeMS-required fields from the XML configuration file, supplement them with the zone type information in the csv file, throw away metadata for elements that PeMS could not support, and insert information into the required database tables in PeMS. Ultimately, PeMS consumed configuration information for a total of 260 mainline zones and 69 HOV zones, which became the equivalent of PeMS mainline and HOV stations, respectively.

Traffic Data. Following the metadata acquisition, the next step was to acquire traffic data and archiving it. Real-time traffic data was acquired via an XML file posted every minute onto the RITIS web page, in the same location as the configuration XML file. The end goal of the traffic data acquisition process was to take one-minute traffic data from the XML file and insert it into the appropriate tables in the PeMS database. Before this could be done, the research team had to develop a full and accurate understanding of the NOVA real-time data. Because the generation of accurate reliability information requires a large set of historical travel times, the team wanted to minimize the delay in acquiring traffic data. For this reason, as soon as the metadata were inserted into PeMS, the team implemented a program to download the traffic data XML file from the RITIS website every minute and save it, so that data could be parsed from the files and placed into the PeMS database as soon as the file format was thoroughly understood.

A sample of the real-time traffic data XML file is shown in Figure 1-6. It is composed of <collection-period-item> elements each defined by a timestamp and a 60 second measurement duration. This element contains the most recent measurements for each NOVA <detector> that most recently sent data during that timestamp. Working controllers are reported in the <collection-period-item> element marked by the most recent timestamp. If a controller is not currently transmitting data, its most recent data transmission is included in a <collection-period-item> marked by the timestamp for which the system last received data from it. Each <collection-period-item> element contains a <zone-report> element for each controller that last reported data during that timestamp. Each <zone-report> element then contains a <zone-data-item> with each zone's most recent flow, occupancy, and speed values. For many zones, the flows are non-zero while the occupancies and speeds are zero. For others, all three values are non-zero.
Review of the data led to a number of questions. We first wanted to know what processing was done on the data to generate the values in the XML files. This relates to a fundamental issue that agencies collecting data should consider. Many agencies encounter external parties that have an interest in obtaining a traffic data feed generated from public-sector detection infrastructure. The level of interest in raw versus processed data differs depending on the intended use. Maintaining even one data feed can be a challenge; maintaining multiple data feeds is likely to be infeasible for many agencies. As such, if agencies want to provide a feed of processed data, all steps should be documented in as much detail as possible to inform data users on what is being reported and how values are being generated. Optimally, a mature reliability monitoring system would collect raw data, then apply quality controls, and aggregate and report it using robust methods. This would ensure uniformity in the
We concluded that the NOVA data was heavily pre-processed before being placed in the data feed. Firstly, the XML file contains no lane-by-lane data, despite the fact that a number of the NOVA “detector types” are single inductive loop detectors, which monitor individual lanes. This means that, at some point, the source system aggregates values from individual lanes into total flow and average occupancy and speed across all lanes at a given location. Since the foundation of PeMS is lane-by-lane data, this issue was addressed by dividing the flows by the number of lanes and assuming that the reported average speeds and occupancies applied to all lanes. While this allowed the data to be transformed into the PeMS framework, it showed that a loss of information can occur when an agency pre-processes the data. In this case, the reliability monitoring system no longer has the ability to report on the differences in travel times along different lanes on the same route. Another sign that the NOVA data was preprocessed lay in the fact that many zones reported flow, occupancy, and speed. Since the corridor detectors were all single loop detectors or microwave radar detectors, they only directly transmitted two of the three values. In these cases, PeMS would normally calculate the third value from the known two using a lane, location, and time-specific assumption about the average vehicle length, called a g-factor (1). When receiving all three values, PeMS does not have to perform this calculation step, but this comes at the expense of not knowing how the third value was computed. The team contacted UMD and VDOT staff to determine what is being done, but both organizations stated that they do no processing on the data ultimately posted in the RITIS XML file. From this, it was concluded that the data collection system in the field is doing the pre-processing, but we were not able to ascertain exactly what was being done. Without being able to evaluate the methods, we decided to have PeMS store whatever data it received via the XML files. In all cases, whether PeMS received all three values, or whether it received a non-zero flow and zero occupancy and speed, it stored these values in the database.

The second issue that had to be addressed was determining the units of the occupancy values being reported. Typically, occupancy is reported as the percentage of the reporting period that a vehicle was directly above the detector. Reasonable values range from 0 to 15. When reviewing the traffic data XML file, we noted that many of the occupancy values were high, with some even consistently exceeding 100. We surmised that perhaps occupancy was being reported in tenths of a percent. The issue was ultimately discussed with VDOT staff, who confirmed that the units of occupancy are whole percentage points, and that zones reporting high occupancies are broken, largely due to construction projects in the vicinity.

The third issue related to the discrepancy between the NOVA data being reported at the “zone”, or “station” level, and the PeMS requirement for lane-by-lane data. From a metadata perspective, as previously described, this was resolved by assigning detectors to each zone within PeMS. For the real-time data, the team decided to simply divide the zone flows by the number of lanes at the zone and assign them to each lane. To keep flows as whole numbers, any remainders following the division were assigned starting at lane 1 (the left-most lane), resulting in an overall upward bias of vehicle counts in the left-hand lanes. For occupancy and speed, the team assigned the values reported by the zone to each of its detectors.

By the time the above-described issues had been resolved, we had been downloading and saving the one-minute traffic data XML files from the RITIS website for three weeks. The next step was to write a program to parse out the zone values, assign them to the PeMS detectors, and store them in the PeMS database according to the <detection-time-stamp> element. The team did this for the three weeks of archived traffic data XML files, and also
developed a program to download the XML files every minute from the RITIS website and perform the same steps to place data in the database in real-time.

Data Processing

The data acquisition phase resolved all discrepancies between the NOVA framework and PeMS framework, and successfully mapped over all of the relevant fields in the XML files to the PeMS database. It also resulted in an automated, real-time acquisition chain between the RITIS web page and PeMS, with PeMS obtaining data from the web page every minute and inserting it into the PeMS database. From this point forward, PeMS could perform its standard data processing to assess the health of NOVA detection infrastructure, throw out bad data and impute values, aggregate data across lanes and over time, and calculate performance metrics such as travel times.

In its detector health assessment step, PeMS looks at the data transmitted by each detector over a single day and makes a determination as to whether the data is good or problematic. PeMS makes this assessment based on the flow and occupancy values for each detector. There are a few common problems with detection infrastructure, and they manifest themselves in distinct ways in transmitted data, allowing for an automated quality control process. One example is the situation where PeMS receives no data or few data samples from a detector, a station, or a controller over a day. This is most likely evidence that a communication line is down or that there is a hardware malfunction in the device. Another example is a detector repeating the same flow and/or occupancy values across multiple time periods. Other examples include detectors reporting high occupancy values, indicating that the detector is stuck on, or reporting mismatched flow and occupancy values (for example zero flow and non-zero occupancy, or vice versa), indicating that the detector is hanging on. If PeMS detects any of these scenarios over a day, it discards the detector’s data and imputes replacement values. In this imputation process, PeMS makes estimates of what the detector’s data might have been based on developed statistical relationships with nearby detectors, or based on historical averages observed at the broken detector. PeMS then aggregates the full set of observed and imputed detector data across all lanes to the station level and computes spatial performance metrics. To inform the user about the quality of the data or performance measure that they are viewing, PeMS reports the “percent observed” of every metric, which represents the percentage of data points used to compute the metric that were directly observed from a detector, as opposed to imputed. For example, if the percent observed for a 5-minute travel time along a route is 75%, then 75% of the detectors on the route were reporting good data, and 25% were reporting bad data.

When the detector health algorithms were run on the NOVA data, we realized that the majority of the detectors on the selected corridors were reporting no data or bad data. Figure 1-7 plots the daily percentage of good detectors between March 1, 2011 and May 9, 2011, as well as the percentage of bad detectors attributable to the two leading causes: no data and stuck. The number of good detectors never exceeds 30%, and generally hovers around 25%. The highest percentage of detectors are in the “stuck” category, meaning that they are reporting constant flow and/or occupancy values. VDOT staff attributed this high percentage to the need to calibrate new detectors following large-scale construction projects. Additionally, a significant percentage of the detectors (around 30%) never sent PeMS any data. The days where there were drops in every category represented times when internet outages prevented the research team from acquiring the XML files from the RITIS website.
The low percentage of usable data available over the 2011 study time frame greatly concerned the research team, as the quality of computed travel times would be poorer given the missing data. Additionally, because the majority of detectors in the network never sent PeMS any good data, it was not possible to develop historical statistical relationships with the data at nearby working detectors needed to drive the most accurate imputation algorithms. Without these statistical relationships, PeMS had to use less robust imputation algorithms, which further decreased the accuracy of computed travel times.

To show the effect this has on the detector data recorded, consider a detector on WB I-66 that fell into the “stuck” category for two weeks (Monday-Sunday). This resulted in imputed flows across that entire time period as shown in Figure 1-8. Because this detector never sent PeMS any good data, PeMS could only crude estimates of its flow values based on flows observed at nearby detectors. This meant that PeMS repeated the same flow, occupancy, and speed data for a given hour from week to week. In the sample plot, the hourly flows imputed for the first week are identical to those imputed for the second week. This constancy in imputed data is not ideal for computing reliability, which relies on the ability of the traffic network to capture the real variability in conditions over time. Since data had to be imputed for such a large percentage of the detectors in 2011, the research team decided to seek additional data for 2009 hoping that the data quality would be sufficient to support methodological advancement and use case analysis. This effort is described in the following section.
Historical Data

The research team worked with the University of Maryland CATT lab to obtain traffic data for 2009. The historical data was delivered in 12 zipped csv files, each about 45 MB in size. The csv files contained the same information as the traffic data XML files, so it was straightforward to write a program to parse information from the csv files and put it in the correct database tables in PeMS, with an associated timestamp corresponding to when the data was collected. The one issue that was encountered was that no historical configuration data was available. We manually compared the IDs of detectors and zones reported in the archived data with those present in the 2011 configuration XML file, and determined that the 2011 configuration data would suffice to represent the 2009 detector locations.

After the historical data was entered into the PeMS database, and processed, its helath was then investigated to see if the 2009 data was better than the 2011 data. Figure 1-9 plots the weekly percentage of good detectors over 2009, as well as the percentage of detectors falling into the leading two error categories- No Data and Stuck. During 2009, the number of working detectors was significantly higher than in 2011, generally hovering above 70% for most of the year. The percentage of detectors that were stuck and transmitting constant data was much lower, being less than 5% across the whole year. The biggest error category remained the No
Data condition, which likely represented detectors that were listed in the configuration file but were not yet calibrated to send data.

Figure 1-9: Weekly Detector Health Status, NOVA PeMS Deployment, 2009

**Travel Time Results**

Following acquisition of the real-time and 2009 data, eight different routes were constructed in PeMS to monitor reliability across different segments of the four study freeway-directions. Five-minute and hourly travel times were created for these eight routes for the entire year of 2009 and March through May in 2011. To evaluate the impact of individual detector data quality on route-level travel times, the team compared the route travel times for 2009 with those for 2011. Figure 1-10 plots the hourly travel times calculated on a 26 mile stretch of westbound I-66 for March through April of 2009. Overall, the PeMS percent observed for this travel time data was 79%. Figure 1-11 plots the same data for the same months of 2011; in this case, only 22% of the data were observed. Overall, the 2009 data follows the pattern expected of a highly congested facility with a peak hour commute; travel times are high on every weekday, but the peak value varies from day to day. Due to the high percentage of imputed detector data, the travel time patterns for the month of April 2011 the weekly travel time patterns look almost identical. It is doubtful that such consistency exists. These patterns are more likely to be caused by the high percentage of imputed data. For this reason, we chose to base the methodological advancements of this case study on the 2009 data, and use the 2011 data only to compare with probe travel time runs, to further evaluate the data quality.
Summary

Data collection is an essential part of any transportation planning or operations activity. Today, transportation agencies are increasingly turning to sophisticated sensor arrays to monitor the performance of their infrastructure, which allow for the use of advanced traffic management techniques and traveler information services. External systems, such as a reliability monitoring system, can leverage this data to further maximize the value of installing and maintaining detection. As evidenced by this case study, data collection for a travel time reliability monitoring system communication can be automated, but it requires significant time and resources to get it started.

REFERENCES

[1] Zhanfeng Jia, Chao Chen, Ben Coifman and Pravin Varaiy. The PeMS algorithms for accurate, real-time estimates of g-factors and speeds from single-loop detectors.
2. METHODOLOGY EXPERIMENTS

OVERVIEW

Because of the type of data available in this case study, and investigations done previously in the I-66 corridor, the research team elected to experiment with travel time reliability monitoring ideas that are being developed in SHRP2 project L10. In L10, researchers are experimenting with a multi-state travel time reliability modeling framework using mixed mode normal distributions to represent the PDFs of travel time data from a simulation model of eastbound I-66 in Northern Virginia. (They are also using this same technique to analyze travel times from toll tag data collected on I-35 in San Antonio (1)). This case study adopted that technique and applied it to the travel times calculated from the freeway loop detectors on eastbound I-66.

According to the SHRP2 L10 research, multi-state models are appropriate for modeling travel time distributions because most freeways operate in multiple states across the year (or some other timeframe): for example, an uncongested state, a congested state, and a state caused by non-recurring events, such as incidents, construction, weather, or fluctuations in demand. This concept is illustrated in Figure 2-1, which shows the distribution of weekday travel times on a corridor in Northern Virginia. Three travel time “modes” are evident, which may be interpreted as the most frequently occurring travel times for the uncongested state, the congested state, and the non-recurring congestion state. Multi-state models also provide a helpful framework for delivering understandable information to the end consumer of travel time reliability information: the driver. They provide two pieces of information: (1) the probability that a particular state will be extant during a given time period; and (2) the travel time distribution for that state during that time period. This provides a way of creating reliability information that is similar to how people are accustomed to receiving weather forecasts, for example: “there is a 60% chance that it will rain tomorrow, and if it does rain, the expected precipitation will be 1 inch”. The reliability analog to this is, for example: “The percent chance of encountering an incident-based congestion state during the AM peak period is 20%. If one does occur, the expected average travel time is 45 minutes and the 95th percentile travel time is one hour”.

Beyond its suitability for modeling travel time distributions and providing useful metrics, this methodology was also fits well with the work that the SHRP2 L02 team is doing to develop travel time distributions for different operating regimes. The different states of the normal mixture models are the conceptual equivalent of the regimes that L02 is working on to classify the operating conditions of routes and facilities. It also provides an opportunity to test a methodology that was developed for modeling the distribution of individual vehicle travel times on aggregated travel times calculated from loop detectors.
SITE DESCRIPTION

A multi-state model was developed for a 26 mile stretch of eastbound I-66 from Manassas to Arlington, Virginia. A map of the corridor is shown in Figure 2-2. This segment of freeway is monitored by 96 sensors, which are a mix of radar detectors and loop detectors. The selected dataset consists of 17,568 travel times at the five-minute level aggregation, which represent the average travel time experienced by vehicles departing the route origin during that five-minute time period. This dataset covers the travel times for departures every five minutes during the weekdays between January 1, 2009 and March 30, 2009.

The route is a major commute path from the suburbs of Northern Virginia into Washington D.C. As such, it sees the highest demand levels during the AM peak period, as well as a smaller increase in demand during the PM peak. A PeMS-generated plot of the minimum, average, and maximum travel times by hour of the day measured over the study time frame is shown in Figure 2-3.
METHOD

The goal of this study was to generate, for each hour of the day, two outputs: (1) the percent chance that the traveler would encounter a certain condition; and (2) for each condition, the average and 95th percentile travel time. The mathematical details of these steps are explained in the referenced paper by Rakha et al (1). Under this framework, three questions are answered for each time period:
1. How many states are needed to model the travel time distribution?
2. What is the probability of each state occurring?
3. What parameters describe the normal distribution for each state?

Analysis was performed using the Mclust package in R, which provides functions to support normal mixture modeling and model-based clustering (2). Normal mixture models were developed to represent travel times for each hour of the day between 4:30 AM and 12:30 AM. The early morning hours were not considered due to the lack of any congestion. The first question above was answered by putting the data set for each hour into a function that initially clusters the data into the number of states that provide a best fit (in this paper, the “optimal” number of states). The best-fit was determined using the Bayesian Information Criterion (BIC), defined as $-2\log(L) + k\log(n)$, where $L$ is the likelihood function of the model parameters, $k$ is the number of parameters, and $n$ is the sample size of the data. This function considers the fit of the model while also penalizing for an increased number of parameters, to prevent against overfitting. The model with the number of states that produces the lowest BIC is selected as the optimal model, and each data point is given an initial probability of belonging to each state. The outputs of this step (the model type, number of states, and initial probabilities of a data point belonging to each state) are then put into an Expectation-Maximization (EM) algorithm, which is an iterative method, appropriate for mixture models, that is used to find maximum likelihood estimates of parameters. The EM algorithm outputs the mixture component for each state (its probability of occurrence), the mean and standard deviation of each state, and the final estimates of the probability that a data point belongs to each state. These estimates are used to form the user-centric output of, for example, “If you depart on a trip at noon, you will have a 20% chance of experiencing congestion. During congestion, the average travel time is 30 minutes and the 95th percentile travel time is 45 minutes.”

During the analysis process, complications arose that required the research team to balance the desire for a best-fitting model with the need to provide useful and clear information to the end user. The initial clustering step suggested that either three or four states were needed to optimally model the travel times for each hour. The “optimal” number of states for each hour’s model is summarized in Table 2-1 along with the associated BICs. However, in the practical realm, a historical set of travel times from a given hour can be conceptualized as consisting of only up to three states. Early morning time periods may only have one state, non-congested, and can thus be described by a single distribution. Time periods where demand fluctuates may have two states: non-congested and congested, with congestion being triggered either by high demand or a non-recurrent condition. Finally, the peak periods may have three states: a non-congested state, likely rare, when demand is low, a congested state, which is common, and a very congested state, which may be triggered by an incident or special event. The fourth state has no clear physical explanation that can be effectively conveyed to the end user. As such, each hour’s data set was run through the clustering algorithm again, this time with a constraint of three maximum states. The “constrained” best-fit state for each hour and its associated BIC is shown in Table 2-1. Three states provided the best-fit for all but two hours (12:30 PM and 2:30 PM), when two states provided the best-fit.

Following the EM step using the “constrained” number of states, the mean travel time estimates for each state were evaluated. These mean travel times are summarized in Table 2-2. For the majority of hours (all hours outside of the AM peak), the mean travel times for state 1 (S1) and state 2 (S2) were very similar (within 3 minutes of each other). These are denoted in the table by gray shading. Because such small differences in average travel times are not meaningful enough to the end user to be considered different states, any hour where three
states were suggested but mean travel times between consecutive states differed by less than three minutes were reduced to two states. The model parameters were then re-estimated for this final number of states. In the end, the models for each hour were composed of two states, with the exception of the AM peak hours (6:30 AM-10:30 AM) which remained composed of three states. The final number of states and associated BICs for each hour are shown in the final column in Table 2-1.

Table 2-1: Selection of States

<table>
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<tr>
<th>Hour</th>
<th>Optimal States</th>
<th>Optimal BIC</th>
<th>Constrained States</th>
<th>Constrained BIC</th>
<th>Final States</th>
<th>Final BIC</th>
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<td>1387</td>
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<td>1443</td>
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<td>3580</td>
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<td>3595</td>
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<td>3</td>
<td>5017</td>
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<td>2567</td>
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<td>2622</td>
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<td>1132</td>
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</tr>
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<td>10:30-11:30 PM</td>
<td>3</td>
<td>2398</td>
<td>3</td>
<td>2398</td>
<td>2</td>
<td>2488</td>
</tr>
<tr>
<td>11:30-12:30 AM</td>
<td>3</td>
<td>2162</td>
<td>3</td>
<td>2162</td>
<td>2</td>
<td>2178</td>
</tr>
</tbody>
</table>

Table 2-2: Mean Travel Times by State for Constrained Parameters

<table>
<thead>
<tr>
<th>Hour</th>
<th>S1</th>
<th>S2</th>
<th>S3</th>
</tr>
</thead>
<tbody>
<tr>
<td>4:30 AM-5:30 AM</td>
<td>24</td>
<td>25</td>
<td>29</td>
</tr>
<tr>
<td>5:30 AM-6:30 AM</td>
<td>25</td>
<td>26</td>
<td>31</td>
</tr>
<tr>
<td>6:30 AM-7:30 AM</td>
<td>28</td>
<td>33</td>
<td>37</td>
</tr>
<tr>
<td>7:30 AM-8:30 AM</td>
<td>28</td>
<td>39</td>
<td>46</td>
</tr>
<tr>
<td>8:30 AM-9:30 AM</td>
<td>28</td>
<td>34</td>
<td>42</td>
</tr>
<tr>
<td>9:30 AM-10:30 AM</td>
<td>26</td>
<td>29</td>
<td>34</td>
</tr>
<tr>
<td>10:30 AM-11:30 AM</td>
<td>25</td>
<td>26</td>
<td>28</td>
</tr>
<tr>
<td>11:30 AM-12:30 PM</td>
<td>25</td>
<td>25</td>
<td>29</td>
</tr>
<tr>
<td>12:30 PM-1:30 PM</td>
<td>23</td>
<td>25</td>
<td>--</td>
</tr>
<tr>
<td>1:30 PM-2:30 PM</td>
<td>24</td>
<td>26</td>
<td>30</td>
</tr>
<tr>
<td>2:30 PM-3:30 PM</td>
<td>24</td>
<td>25</td>
<td>27</td>
</tr>
<tr>
<td>3:30 PM-4:30 PM</td>
<td>24</td>
<td>26</td>
<td>29</td>
</tr>
<tr>
<td>4:30 PM-5:30 PM</td>
<td>26</td>
<td>27</td>
<td>--</td>
</tr>
<tr>
<td>5:30 PM-6:30 PM</td>
<td>25</td>
<td>31</td>
<td>31</td>
</tr>
<tr>
<td>6:30 PM-7:30 PM</td>
<td>27</td>
<td>27</td>
<td>31</td>
</tr>
<tr>
<td>7:30 PM-8:30 PM</td>
<td>25</td>
<td>26</td>
<td>28</td>
</tr>
</tbody>
</table>
8:30 PM-9:30 PM  25   26   31
9:30 PM-10:30 PM  25   26   28
10:30 PM-11:30 PM  25   26   31
11:30 PM-12:30 PM  25   26   30

RESULTS

This section first summarizes the travel time reliability findings for each weekday hour. It then provides an in-depth analysis of model results for the AM peak hours.

Overall

Figure 2-4 presents, for each hour of the day and for each state, the probability of the state’s occurrence (top-left), the mean travel time (top-right), the standard deviation of its travel times (bottom-left), and the 95th percentile travel time (bottom-right). Estimates for state 1 are shown in the dashed line, state 2 in the solid line, and state 3 (where applicable) in the bold line. Values are also summarized in Table 2-3.

As can be seen in the plot of each state’s probability, state 1 is by far the most common state encountered during the early morning, the midday, and the late night hours. When this state is active during these hours, the mean travel time tends to be near free-flow, at around 25 minutes, the standard deviation is low, and the 95th percentile is close to the mean. During these off-peak periods, the percent chance of congestion (state 2), generally stays between 10% and 20%. Even when the congested state is active during these hours, the mean travel time is still generally less than 30 minutes, and the 95th percentile travel time generally less than 35 minutes.

At the beginning of the PM peak (4:30 PM-5:30 PM), state 1 and state 2 each have a 50% chance of occurring. During the PM peak hour (5:30 PM-6:30 PM), the probability of congestion increases to 67%. At the end of the PM peak hour (6:30 PM-7:30 PM), the probability of state 1 and state 2 effectively swap; state 1 has a 64% change of occurring and state 2 a 36% change of occurring. Throughout the PM peak, the mean and 95th percentile travel times of each state are consistent. State 1 has a mean travel time of 26 to 27 minutes and a 95th percentile travel time of 27 to 28 minutes, and state 2 has a mean travel time of 30 to 31 minutes and a 95th percentile travel time of 33 to 34 minutes.

The four hours of the AM peak (6:30 AM-10:30 AM) have three active states, as they have both the most congestion and travel time variability. Within these four hours, however, both the relative probabilities of each state and the parameters of each state differ significantly. State 3 (conceptualized as the non-recurrent congestion state) has the greatest chance of occurring at the beginning of the AM peak, between 6:30 AM and 7:30 AM, and between 8:30 AM and 9:30 AM (41% and 39%, respectively). Its likelihood is around 25% during the other two hours. The severity of congestion in this state differs across each hour. It has the highest mean travel time (46 minutes) and 95th percentile travel time (58 minutes) during the 7:30 AM hour, indicating that this is the true AM peak hour. At 8:30 AM, the mean travel time of this state is reduced to 42 minutes, and the 95th percentile travel time to 51 minutes. On the shoulders of the AM peak, the mean travel times of state 3 are 34 and 37 minutes and the 95th percentile travel times are 40 and 44 minutes. State 2 occurs with varying probabilities during the AM peak, ranging from a low of 32% at 8:30 AM to a high of 58% at 7:30 AM. The mean and 95th percentile travel times of state 2 are significantly higher during the AM peak than at any other time period of the day. Even though this time period usually experiences congestion and some
travel time variability, there are days (approximately one out of five) when the corridor operates in the uncongested state, and mean travel times are around 28 minutes.

The information gained from the example plot and accompanying table can be used to provide intuitive and useful information to the traveling public, in ways illustrated in the following section, which focuses on interpreting the results for the AM peak hours.

Figure 2-4: State Probabilities, Mean Travel Times, Standard Deviation, and 95th Percentile Travel Times by Time of Day
As discussed in previous sections, a three-state normal mixture model was selected to measure reliability statistics for the four AM peak hours. Figure 2-5 provides a visual comparison of the relative model fits of the three-state normal mixture model, a two-state normal mixture model, and a lognormal distribution model. These fits are also quantitatively summarized in Table 2-4. It compares the BICs for each model for each hour. Visually, it is clear that for every hour except 8:30 AM, the three-state normal model approximates the data the most closely. This is also reflected in the BIC values, which are the lowest for the three-state normal mixture model. During the 8:30 AM hour, the fits between the three-state and two-state mixture models appear comparable, and their BICs are essentially equivalent.

Figure 2-6 provides a clearer visual comparison of the different travel time distributions within each morning hour by plotting them on the same x- and y-axis scales. It is evident that the two middle peak hours (7:30 AM and 8:30 AM) have the most travel time variability, while the distributions for the shoulder hours are more tightly packed. In particular, there is a large spike in the travel time distribution for the 9:30 AM hour at 25 minutes, which is essentially free-flow for this corridor. In this figure, each bar of the travel time histogram is shaded according to which state the model determined it was the most likely to fall into. It is important to make clear that there are no clearly defined boundaries for each state; rather, for each observed travel time, the model provides the percentage chance that the data point belongs to each state. For some
values (for example, 24 minutes), there is a near 100% likelihood that the travel time belongs in state 1. For others, such as a 46 minute travel time during the 7:30 AM hour, there is a near 50% chance that the data point belongs to state 2 and a near 50% chance it belongs to state 3. As such, these shadings are meant only to be a rough visualization of the component travel times of each state.

Figure 2-5: Lognormal and two- and three-state normal mixture models for AM peak hours

Table 2-4: BICs by distribution model

<table>
<thead>
<tr>
<th>Time Period</th>
<th>3-state normal</th>
<th>2-state normal</th>
<th>Log-normal</th>
</tr>
</thead>
<tbody>
<tr>
<td>6:30 AM-7:30 AM</td>
<td>4322</td>
<td>4346</td>
<td>4330</td>
</tr>
<tr>
<td>7:30 AM-8:30 AM</td>
<td>5017</td>
<td>5053</td>
<td>5034</td>
</tr>
<tr>
<td>8:30 AM-9:30 AM</td>
<td>4856</td>
<td>4856</td>
<td>4910</td>
</tr>
<tr>
<td>9:30 AM-10:00 AM</td>
<td>3876</td>
<td>3954</td>
<td>3981</td>
</tr>
</tbody>
</table>
The desired final output of these analyses is reliability information that can be readily interpreted and consumed by corridor drivers who are planning to make a trip at a certain time. From the information presented above, the following examples convey information that could be provided to drivers on a pre-trip basis, to aid them in their planning process:

- For trips made between 7:30 AM and 8:30 AM, there is a 60% chance of experiencing congestion. If congestion occurs, the expected travel time is 39 minutes and the 95th percentile travel time is 46 minutes. There is also a 25% chance of
experiencing severe, incident-based congestion. If this occurs, the expected travel time is 46 minutes and the 95th percentile travel time is 58 minutes.

- For trips made between 9:30 AM and 10:30 AM, there is a 50% chance of experiencing congestion. If congestion occurs, the expected travel time is 29 minutes and the 95th percentile travel time is 32 minutes. There is also a 25% chance of experiencing severe, incident-based congestion. If this occurs, the expected travel time is 34 minutes and the 95th percentile travel time is 40 minutes.

**SUMMARY**

This case study leverages the methodologies developed by the SHRP2 L10 research team and applies them to three months of five-minute aggregated loop detector data collected on a 26 mile corridor of eastbound I-66 in northern Virginia. The results indicate that normal mixture models reasonably approximate travel time data observed within a given time period. Two-state models seem sufficient to accurately model off-peak hours, while three-state models are needed to capture the variability during the peak hours. Beyond providing a good fit to travel time data, mixture models also output data in a form that can be easily conveyed to help end users better plan for trips.

**REFERENCES**


3. PROBE VEHICLE COMPARISONS

INTRODUCTION

To better understand the implications of the data quality issues on travel times, the team performed a quality control procedure. Probe vehicle runs were conducted along I-66 to amass “ground-truth” data that could be compared with the sensor data. A GPS-based data collection device was used capable of collecting data at 1-second intervals. The sections of roadway along which probe runs were conducted, and details concerning the sensor data collected as part of this effort are described in Table 3-1:

Table 3-1: Overview of Probe Runs

<table>
<thead>
<tr>
<th>Segment</th>
<th>Route</th>
<th>Time Period</th>
<th>Runs</th>
<th>Start and End Mileposts</th>
<th># Sensors</th>
<th>Date</th>
</tr>
</thead>
<tbody>
<tr>
<td>A &gt; B</td>
<td>I-66 EB</td>
<td>PM Peak</td>
<td>1, 2, &amp; 3</td>
<td>68.5 – 74.3</td>
<td>4</td>
<td>April 19, 2011</td>
</tr>
<tr>
<td>C &gt; D</td>
<td>I-66 WB</td>
<td>PM Peak</td>
<td>4, 5, &amp; 6</td>
<td>74.2 – 69.9</td>
<td>3</td>
<td>April 19, 2011</td>
</tr>
<tr>
<td>E &gt; F</td>
<td>I-66 EB</td>
<td>AM Off-Peak</td>
<td>7, 8, &amp; 9</td>
<td>54.4 – 56.3</td>
<td>4</td>
<td>April 20, 2011</td>
</tr>
<tr>
<td>G &gt; H</td>
<td>I-66 WB</td>
<td>AM Off-Peak</td>
<td>10, 11, &amp; 12</td>
<td>56.3 - 54.4</td>
<td>4</td>
<td>April 20, 2011</td>
</tr>
</tbody>
</table>

Along this corridor, as elsewhere in the study region, point detectors are placed at approximately ½ mile intervals. Due to accuracy and maintainability issues with inductive loop detectors and other older sensors, there are no plans to replace failed units which have been deployed on the mainline lanes of NOVA region freeways. Instead, plans are in motion to transition to the use of non-intrusive radar-based detection technologies along the freeways. These sensors are being deployed both as replacements for older failed units, as well as new installations. As a result of a combination of the failure of some older loop detector stations, ongoing roadway construction, and the need to configure many of the newer radar-based units, data is currently available for only about 75 of NOVA’s freeway detectors. Figure 3-1, below, provides a visual indication of the availability of data on I-66 and I-395; darker colored icons indicate working stations, lighter colored icons indicate non-working stations.
Data-Related Issues Associated with NOVA Sensors

As discussed, construction and maintenance-related issues have resulted in a limited number of operational sensors from which data is available for use. In addition, a number of sensors that at first appear to be in working order are actually transmitting speed and/or flow data of questionable quality. For example, Figure 3-1 indicates that there are five (5) working sensors operating in close proximity to one another along I-395. However, a closer analysis of the data output by several of these sensors indicates conditions that are either decidedly irregular, or are simply inaccurate. Examples are shown in Figure 3-2:

![Figure 3-2: Speed/Flow Data from Suspect Sensor Along I-395 (From NOVA PeMS System)](image)

Although the sensor providing the speed and flow data in Figure 3-2 appears to be functioning properly (as reported by the automated system used by the team to collect and analyze data as part of this project), a review of the speed data (Y-axis) and flow data (Z-axis) indicates the following:

- Speeds reported by this sensor are approximately 27 mph at all times of day except during the middle of the night, when traffic speeds increase significantly.

- The reported traffic flows appear fairly normal (with the exception of an apparent issue occurring between approximately 1pm and 5pm on May 10th), except that the peak traffic volume is reported as occurring between noon and 3pm, rather than the typical 4 to 7 pm. A field review of conditions by team members at this location and during this time period does not support this suggested condition.

A review of data collected from other sensors along I-395 (southbound) adjacent to this detector show similar conditions in that the peak traffic flow is reported as occurring between
noon and 3pm, resulting in a concomitant drop in speeds to between 30 and 40 mph. As indicated above, a field review of conditions did not support this reported condition.

Figure 3-3, below, shows similar issues for sensors along I-66.

![Figure 3-3: Speed/Flow Data from Suspect Sensor Along I-66 (From NOVA PeMS System)](image)

As with the sensor data reported in Figure 3-2, data from the sensor displayed in Figure 3-3 indicates the existence of conditions along I-66 that diverge from conventional wisdom concerning the time of day at which the peak travel condition occurs. As per this data, peak volumes and the lowest speeds regularly occur at this location between approximately 2:00 am and 6:30 am, with speeds near 70 mph present during the remainder of the day. Again, a field review conducted by team members indicated that these data do not accurately represent the conditions that really exist.

It is likely that some portion of these data-related issues are the result of the high percentage of imputed detector data being used to represent conditions at many detector stations (e.g., 59% of data used generate the contents of Figure 3-2 are imputed rather than observed). However, an even more significant issue is related to the need for these detectors to be fully calibrated on a system-wide basis so as to ensure they accurately represent real world conditions. Although VDOT is currently in the process of doing this, the team recommends that speed, flow, and estimated travel time data derived from these quantities be used sparingly until this process is complete. Failure to do so may result in decisions based on largely erroneous data, potentially resulting in a significant waste of resources and labor.

**METHODOLOGY**

The primary question the team wanted to answer in this probe-based experiment was: how well do the probe data align with the traffic speed and travel time estimates provided by the sparsely deployed point-based detectors? The primary method for answering this question was to compare data collected at 1-second intervals from a GPS-based data collection device
against speed estimates generated based on data from Virginia DOT sensors deployed along each of the four sections of I-66 described above. As part of this effort, the following analytical approach was used:

For each segment of roadway, graphs were used to compare the speed of the probe vehicle with speeds reported by the sensors. Speeds were displayed on the vertical axis and milepost on the horizontal axis. The solid line represented the speed estimates generated by the sensors (based on aggregate data collected from all lanes of travel), and the dotted line represented the probe vehicle speeds. In cases where data from the sensors was of suspected quality, the line representing the speed estimate provided by that sensor was dashed rather than completely solid. The locations of all the sensors from which data were collected along each roadway was indicated by a solid circle at the mid-point of each segment, accompanied by the sensor’s identification number. We subsequently provided analysis of the differences between these two data sets along each segment.

In addition to analyzing the speed data as described above, the team conducted an analysis of the differences between the travel times experienced by the probe vehicle during each trip versus the estimated travel times generated from the sensor speeds. In situations where unreliable sensor data was present, a combination of observed sensor speeds and imputed speeds was used to fill in the gaps. Results of each analysis were then compared to calculate the average (absolute) error for each segment of roadway, as well as for the complete set of runs as a whole.

DATA ANALYSIS

The speed data from the probe-based runs was compared with the speed estimates generated using the spot speed sensors located along the same sections of roadway.

Data Analysis Along I-66 Inside of I-495 (Eastbound)

Figures 3-4, 3-5, and 3-6 show plots of the instantaneous speeds recorded by the vehicle probe as it traversed I-66 eastbound inside of I-495 at three times on Tuesday April 19th, 2011 plotted against the speeds reported by the detectors along that stretch of roadway (804, 822, 808, and 817) at that those same times.

![Figure 3-4: Segment A > B, Run 1 (I-66 Eastbound - 3:40 PM on Tuesday, April 19th)](image-url)
Comparison of the probe speeds with the sensor-based speeds suggests the following:

- **Sensor 804 (Milepost 68.5 – 70)** – Data generated by this sensor are not consistent with the probe data collected along this roadway segment. The most likely explanation is data quality issues with the sensor. The speed reported by this sensor for most of the day is about 27mph.

- **Sensor 822 (Milepost 70 – 71.05)** – All the data (100%) for this sensor were imputed. The imputed data suggest a sustained free-flow speed which is clearly inaccurate based on the speeds observed by the probe vehicle.

- **Sensor 808 (Milepost 71.05 – 72.7)** – Data generated by this sensor are not consistent with the probe data. Again the explanation is likely to be data quality issues with the sensor. The speed reported by this sensor is about 28mph for most of the day.
Sensor 817 (Milepost 72.7 – 74.3) – This is the one sensor which appears to be providing reliable speed data for the time periods during which the probe runs were conducted. Even so, the probe vehicle speeds are lower, and significantly so for probe runs 1 and 2.

Data Analysis Along I-66 Inside of I-495 (Westbound)

Figures 3-7, 3-8, and 3-9 show plots of the instantaneous speeds recorded by the vehicle probe as it traversed I-66 westbound inside of I-495 at three times on Tuesday April 19th, 2011 plotted against the speeds reported by the detectors along that stretch of roadway (819, 1422, and 806) at that those same times.

Figure 3-7: Segment C > D, Run 4 (I-66 Westbound - 3:27 PM on Tuesday, April 19th)

Figure 3-8: Segment C > D, Run 5 (I-66 Westbound - 4:05 PM on Tuesday, April 19th)
Comparison of these probe data with the sensor-based speeds suggests the following:

- **Sensor 819 (Milepost 74.2 - 72.7)** – This sensor was reporting fairly reliable speeds for the time periods during which the probe runs were conducted. Even so, the probe speeds are lower than those reported by the sensor, especially during the latter portion of probe run #3, during which significant congestion was encountered.

- **Sensor 1422 (Milepost 72.7 – 70.8)** – Data generated by this sensor was not consistent with the probe data due to data quality issues with the sensor. The speed reported by this sensor was about 28mph for most of the day.

- **Sensor 806 (Milepost 70.8 - 69.9)** – All of the data (100%) for this sensor was imputed (estimated). No field observations were generated by the sensor during any of the probe runs. Imputed data for this section of roadway indicates near free-flow speeds which were demonstrated to be inaccurate by the probe vehicle.
Data Analysis Along I-66 Outside of I-495 (Eastbound)

Figures 3-10, 3-11, and 3-12 show plots of the instantaneous speeds recorded by the vehicle probe as it traversed I-66 eastbound outside of I-495 at three times on Wednesday April 20th, 2011 plotted against the speeds reported by the detectors along that stretch of roadway (1139, 1157, 1141, and 1142) at those same times.

Figure 3-10: Segment E > F, Run 7 (I-66 Eastbound – 9:43 AM on April 20, 2011)

Figure 3-11: Segment E > F, Run 8 (I-66 Eastbound – 10:20 AM on April 20, 2011)
Comparison of these probe data with the sensor-based speeds suggests the following:

- **Sensor 1139 (Milepost 54.4 – 54.9)** – Only 15% of the speeds reported by this sensor were actually observed. Consequently, although those speeds are reasonably consistent with the conditions observed by the probe vehicle, it is unclear whether this sensor would provide accurate data under other conditions.

- **Sensor 1157 (Milepost 54.9 – 55.4)** – All of the speeds (100%) reported by this sensor were imputed. Those imputed data suggested sustained free-flow speeds, which is consistent with the conditions encountered by the probe vehicle.

- **Sensor 1141 (Milepost 55.4 – 55.8)** – All of the speeds (100%) reported by this sensor were imputed. Those imputed speeds suggest sustained free-flow conditions, which is consistent with the conditions encountered by the probe vehicle (although the sensor shows slightly higher speeds during 2 of the 3 probe runs).

- **Sensor 1142 (Milepost 55.8 – 56.3)** - As with sensor 1139, only 15% of the speeds reported by this sensor were actually observed. As such, although the sensor suggests the conditions encountered by the probe vehicle, it is unclear whether this sensor would provide accurate data under other conditions.
Data Analysis Along I-66 Outside of I-495 (Westbound)

Figures 3-10, 3-11, and 3-12 show plots of the instantaneous speeds recorded by the vehicle probe as it traversed I-66 westbound outside of I-495 at three times on Wednesday April 20th, 2011 plotted against the speeds reported by the detectors along that stretch of roadway (1143, 1156, 1158, and 1140) at those same times.

Figure 3-13: Segment G > H, Run 10 (I-66 Westbound – 9:34 AM on April 20, 2011)

Figure 3-14: Segment G > H, Run 11 (I-66 Westbound – 9:53 AM on April 20, 2011)
Comparison of these probe data with the sensor-based speeds suggests the following:

- Sensor 1143 (Milepost 56.3 – 55.7) – Only 15% of the speeds generated by this sensor were actually observed. Consequently, although the speeds reported by this sensor are close to those observed by the probe, it is unclear whether this sensor would provide accurate data under other conditions.

- Sensor 1156 (Milepost 55.7 – 55.3) – All (100%) of the speeds reported by this sensor were imputed. The imputed speeds suggest sustained free-flow speeds along this portion of the freeway mainline, which is consistent with the conditions encountered by the probe vehicle.

- Sensor 1158 (Milepost 55.3 – 54.85) – All (100%) of the speeds for this sensor were imputed. Those imputed speeds suggest sustained near free-flow speeds, which is somewhat lower than speed data generated by the probe vehicle.

- Sensor 1140 (Milepost 54.85 – 54.4) - As with sensor 1143, only 15% of the data generated by this sensor were observed. This lack of observed data helps to explain the lower speeds generated by this sensor versus those reported by the probe vehicle.

**COMPARISON OF TRAVEL TIMES – PROBE (MEASURED) VS. SENSOR (ESTIMATED)**

Based on the speed data from the probe vehicle runs and speed estimates provided by the sensors, segment travel times were generated for each of the 12 probe runs described above. Two approaches were used to calculate roadway travel times based on the sensor data.

- Approach 1 – **ALL** of the speed data received by the team from the sensors was used regardless of whether the data was good, imputed, or suspect.
Approach 2 – data from nearby sensors were used in place of the data from the sensors that were flagged (manually) as likely generating suspect data – based on the reporting of very low speeds over significant periods of time:

- Runs 1, 2, and 3 – substituted data for sensors #804 and #808
- Runs 4, 5, and 6 – substituted data for sensor #1422
- Runs 7, 8, and 9 – no substitution of data
- Runs 10, 11, and 12 – no substitution of data

As no substitution of sensor data occurred for runs 7 – 12, Approach 2 was not employed as part of the travel time estimation process along those segments of roadway.

### Travel Times for Runs 1, 2, and 3 (A \(>\) B) – April 19th

<table>
<thead>
<tr>
<th>Start Time</th>
<th>Road</th>
<th>Start MP</th>
<th>End MP</th>
<th>Probe Vehicle Travel Time (Measured)</th>
<th>VDOT Sensor Travel Time (Estimated) Approach 1</th>
<th>VDOT Sensor Travel Time (Estimated) Approach 2</th>
<th>Percent Error App. 1</th>
<th>Percent Error App. 2</th>
</tr>
</thead>
<tbody>
<tr>
<td>3:40 PM</td>
<td>I-66 EB</td>
<td>68.5</td>
<td>74.3</td>
<td>6.3 minutes</td>
<td>7.0 minutes</td>
<td>4.7 minutes</td>
<td>+ 11%</td>
<td>- 25%</td>
</tr>
<tr>
<td>5:23 PM</td>
<td>I-66 EB</td>
<td>68.5</td>
<td>74.3</td>
<td>10.1 minutes</td>
<td>7.0 minutes</td>
<td>4.6 minutes</td>
<td>- 31%</td>
<td>- 54%</td>
</tr>
<tr>
<td>6:18 PM</td>
<td>I-66 EB</td>
<td>68.5</td>
<td>74.3</td>
<td>7.4 minutes</td>
<td>7.1 minutes</td>
<td>4.6 minutes</td>
<td>- 4%</td>
<td>- 37%</td>
</tr>
</tbody>
</table>

### Travel Times for Runs 4, 5, and 6 (C \(>\) D) – April 19th

<table>
<thead>
<tr>
<th>Start Time</th>
<th>Road</th>
<th>Start MP</th>
<th>End MP</th>
<th>Probe Vehicle Travel Time (Measured)</th>
<th>VDOT Sensor Travel Time (Estimated) Approach 1</th>
<th>VDOT Sensor Travel Time (Estimated) Approach 2</th>
<th>Percent Error App. 1</th>
<th>Percent Error App. 2</th>
</tr>
</thead>
<tbody>
<tr>
<td>3:27 PM</td>
<td>I-66 WB</td>
<td>74.2</td>
<td>69.9</td>
<td>7.2 minutes</td>
<td>6.3 minutes</td>
<td>4.0 minutes</td>
<td>- 12%</td>
<td>- 44%</td>
</tr>
<tr>
<td>4:05 PM</td>
<td>I-66 WB</td>
<td>74.2</td>
<td>69.9</td>
<td>4.6 minutes</td>
<td>6.3 minutes</td>
<td>4.0 minutes</td>
<td>+ 37%</td>
<td>- 13%</td>
</tr>
<tr>
<td>6:38 PM</td>
<td>I-66 WB</td>
<td>74.2</td>
<td>69.9</td>
<td>12.2 minutes</td>
<td>6.1 minutes</td>
<td>4.1 minutes</td>
<td>- 50%</td>
<td>- 66%</td>
</tr>
</tbody>
</table>

### Travel Times for Runs 7, 8, and 9 (E \(>\) F) – April 20th

<table>
<thead>
<tr>
<th>Start Time</th>
<th>Road</th>
<th>Start MP</th>
<th>End MP</th>
<th>Probe Vehicle Travel Time (Measured)</th>
<th>VDOT Sensor Travel Time (Estimated) Approach 1</th>
<th>VDOT Sensor Travel Time (Estimated) Approach 2</th>
<th>Percent Error App. 1</th>
<th>Percent Error App. 2</th>
</tr>
</thead>
<tbody>
<tr>
<td>9:43 AM</td>
<td>I-66 EB</td>
<td>54.4</td>
<td>56.3</td>
<td>1.8 minutes</td>
<td>1.7 minutes</td>
<td>N/A</td>
<td>- 6%</td>
<td>N/A</td>
</tr>
<tr>
<td>10:20 AM</td>
<td>I-66 EB</td>
<td>54.4</td>
<td>56.3</td>
<td>1.8 minutes</td>
<td>1.7 minutes</td>
<td>N/A</td>
<td>- 6%</td>
<td>N/A</td>
</tr>
<tr>
<td>10:36 AM</td>
<td>I-66 EB</td>
<td>54.4</td>
<td>56.3</td>
<td>1.8 minutes</td>
<td>1.7 minutes</td>
<td>N/A</td>
<td>- 6%</td>
<td>N/A</td>
</tr>
</tbody>
</table>
Travel Times for Runs 10, 11, and 12 (G > H) – April 20th

<table>
<thead>
<tr>
<th>Start Time</th>
<th>Road</th>
<th>Start MP</th>
<th>End MP</th>
<th>Probe Vehicle Travel Time (Measured)</th>
<th>VDOT Sensor Travel Time (Estimated)</th>
<th>Percent Error App. 1</th>
<th>Percent Error App. 2</th>
</tr>
</thead>
<tbody>
<tr>
<td>9:34 AM</td>
<td>I-66 WB</td>
<td>56.3</td>
<td>54.4</td>
<td>1.7 minutes</td>
<td>1.8 minutes</td>
<td>N/A</td>
<td>+ 6%</td>
</tr>
<tr>
<td>9:53 AM</td>
<td>I-66 WB</td>
<td>56.3</td>
<td>54.4</td>
<td>1.7 minutes</td>
<td>1.8 minutes</td>
<td>N/A</td>
<td>+ 6%</td>
</tr>
<tr>
<td>10:27 AM</td>
<td>I-66 WB</td>
<td>56.3</td>
<td>54.4</td>
<td>1.7 minutes</td>
<td>1.8 minutes</td>
<td>N/A</td>
<td>+ 6%</td>
</tr>
</tbody>
</table>

Travel times collected during the first day of probe data collection (April 19) differed significantly from the estimated travel times generated by the sensor data (using either Approach 1 or 2). For example, for runs 1, 2, and 3 there was an overall absolute average error of 15% for Approach 1 and 39% for Approach 2. Although this might result in a perception that the sensor data along this segment are useful for calculating travel times, it must be remembered that two of the sensors generated suspect speed data – in this case, very low freeway speeds. Incorporating these speeds into the travel time estimation appears to have offset the higher roadway speeds generated by the other two roadway sensors, speeds that were generally much higher than those reported by the probe vehicle. Consequently, incorporation of the likely erroneous slow speeds resulted in travel times closer to those experienced by the probe vehicle – an unintended consequence of the use of this data. Moreover, the nearly identical travel time estimates generated using both approaches over the course of several hours speaks to the likely impact of the considerable amount of data imputation which occurred. The steadiness of these travel time estimates is not ideal for computing reliability, which relies on the ability of the system to detect variability in traffic conditions over time. Reviewing the content of the histogram found in Figure 3-16 (below), which provides a breakdown of PM Peak Period (3 – 7 pm) travel times along the roadway segment used as part of runs 1, 2, and 3 (A > B) for a two month period (March 15th – May 15th) demonstrates a fairly low amount of travel time variability over the 2000+ 5-minute data collection periods for which data was collected.

Travel times collected during the second day of probe runs conform much more closely to the estimates from the sensors, with an average error of 6% in each direction of travel. However, it must be pointed out that nearly all of these data were imputed (only 15% observed data provided by 4 of the 8 sensors from which data was collected). As a result, it is highly unlikely that these sensors would provide accurate travel times under most congested conditions. The full extent of this problem is made clear by the histogram contained in Figure 3-17 (below), which demonstrates that over the course of two months, a total of only 44 (of 2156 total) 5-minute time slices along segment E > F (runs 7, 8, and 9) were reported as having travel times in excess of 2 minutes during the AM peak period. It should be noted that a nearly identical travel time distribution exists for westbound travel times along this segment of I-66 during the AM peak period.
Figure 3-16: I-66 EB PM Peak Travel Times between MP 68.5-74.3 (3/15/11 - 5/15/11)

Figure 3-17: I-66 EB AM Peak Travel Times between MP 54.4 - 56.3 (3/15/11 - 5/15/11)
4. LESSONS LEARNED

OVERVIEW

The team selected Northern Virginia as a case study site because it provided an opportunity to integrate a reliability monitoring system into a pre-existing, extensive data collection network. The data collected on NOVA roadways is already passed to a number of external systems, including RITIS at the University of Maryland, the ADMS at the University of Virginia, and the statewide 511 system. Configuring PeMS to receive NOVA data helped define the requirements for complex traffic systems integration and illustrate what agencies can do to facilitate the process of implementing reliability monitoring.

SYSTEMS INTEGRATION

The process of fully integrating the NOVA data with PeMS took several weeks. While this amount of effort is standard when integrating archived data user systems with traffic data collection systems, there are a number of steps that agencies can take to make this integration go more smoothly and quickly.

For one, it is important that the implementation and maintenance of a traffic data collection system be carried out with a broad audience in mind. Efforts such as the Federal Government’s 2009 “Open Government Initiative” underscore the value of providing public access to government data. Often, increasing access to data outside of an organization can help to further agency goals; for example, providing data to mobile application developers can help agencies distribute information in a way that increases the efficiency of the transportation network. It will also help the agency support contractor’s efforts to implement procured systems, such as travel time reliability monitoring systems.

One of the ways that agencies can facilitate the distribution of data from their data collection system is by establishing one or more data feeds. As discussed in the first chapter, different parties will want to acquire data processed to different levels, depending on the intended use. For example, a mobile application developer may only be interested in heavily processed data, such as route-level travel times. A third-party data aggregator may be interested in obtaining speeds computed from loop detectors, to be fused with other travel time data sources. A traffic engineering firm may prefer raw detector flow and occupancy data that they can quality-check using their own established methods and use to calculate performance measures. Since maintaining multiple data feeds can be a challenge, if agencies want to provide a feed of processed data, it will save resources in the long run to document the processing steps performed on the data. This will allow implementers of external systems to evaluate them and undo them, if needed.

Aside from the processing documentation, maintaining clear documentation on the format of data files and units of data will greatly facilitate the use of data outside of the agency. Additionally, documentation on the path of data from a detector through the agency’s internal systems can be of value to contractors and other external data users. Clearly explaining this information in a text file minimizes the back-and-forth communication between agency staff and contractors and prevents inaccurate assumptions from being made.

METHODOLOGICAL ADVANCEMENT

From a methodological standpoint, this case study focused on implementing a multi-state travel time reliability model developed by the SHRP2 L10 project. The original research
developed this model on AVI travel time measurements in San Antonio, as well as travel times generated by a micro-simulation traffic model on a section of I-66 in Northern Virginia. This effort extended the research by applying it to point speeds generated by multiple loop detectors along a freeway segment.

The methodological findings of this case study are that multi-state normal distribution models can approximate travel time distributions generated from loop detectors better than normal or log-normal distributions. During the peak hours on a congested facility, three states are generally sufficient to balance a good model fit with the need to generate information that can be easily communicated to interested parties. During off-peak hours, two states typically provide a reasonable model fit. The outputs of this method can inform travelers of the percent change that they will encounter moderate or severe congestions and, if they do, what their expected and 95th percentile travel times will be.

**PROBE DATA COMPARISON**

Most public agency managed data processing systems currently rely on fixed sensor infrastructure to support the calculation of roadway travel times and subsequent generation of travel time reliability metrics. Although this state of affairs may change over time as more private sector sources of data become available, this will not happen overnight. To that end, agencies need to consider how to make the best use of the data currently available to them. As part of this use case, we have examined the data available from a network of fixed infrastructure sensors (a combination of single loops and radar-based sensors) going through the process of being modernized by the Virginia DOT. The team’s analysis of the data available from these sensors has yielded a number of findings of potential interest to a wide variety of agencies, particularly those facing maintenance and calibration issues associated with older sensor systems, as well as those agencies with more sparsely spaced spot sensors. Overall, we found that there were five (5) primary factors that accounted for differences between the probe vehicle data and speed / estimated travel times generated based on VDOT sensor data; these factors are detailed below.

Likely one of the most significant, and at the same time most difficult to measure, impacts on sensor based speeds is associated with research that suggests that fixed roadway sensors may not always accurately measure very low speeds during highly congested conditions. Although impossible to definitively evaluate here, it is something that should be taken into consideration as part of all such analysis.

As the Virginia DOT is in the process of modernizing its sensor network in NOVA, the vast majority of sensors are not fully calibrated and/or fully configured so as to properly communicate with back-office data analysis systems. This resulted in the types of data quality issues discussed earlier in the case study. This issue makes clear the need for public agencies to conduct regular sensor maintenance programs in order to ensure that their detection networks are generating the most accurate data possible.

Beyond any issues that spot sensors may have accurately assessing low-speed, stop-and-go traffic conditions, another issue that sensor users must contend with is the problem associated with extrapolating speeds (and subsequently travel times) for a segment of roadway based solely on conditions within the sensor’s field of detection. As such, all speeds and travel times for a segment are based on the assumption that conditions along the segment are identical to those experienced within the sensor’s field of view. As a result, it is likely that any data generated by spot sensors will fail to detect congestion, incidents, etc., that occur outside
of the sensor’s immediate vicinity, with the impact becoming more pronounced the longer the segment.

Related to the problem associated with extrapolating spot sensor data to cover entire segments of roadway is that related to the need to impute data from adjacent sensors or segments of roadway to fill in gaps in sensor coverage. Although not necessarily an enormous problem in cases where data for a single lane of travel is “filled in” based on conditions experienced by adjacent sensor stations, the types of imputation required as part of this case study resulted in speeds being generated for segments of roadway based largely on historical data for a sensor or macroscopic speed and flow data for a section of the roadway network. Although a necessity for computing speed and estimated travel time for the given segment, use of this replacement data further aggravated the data-related issues described above.

Another dynamic impacting the comparison of sensor data with probe vehicle data stems from a basic difference between these data sets:

- Sensor Data – Represents five minute, average conditions across all lanes of travel observed at the sensor location.
- Probe Data – Represents the movement of a single vehicle moving through one lane of travel across the segment being evaluated.

These differences have the potential to result in significant differences in speed/estimated travel time between the two data sources if one lane of travel experiences significant congestion, while the other(s) do not. This is especially true in cases where the probe vehicle is slowed by congestion outside of a sensor’s detection zone, while other lanes of travel are moving at higher, less congested (or even free-flow) rates of speed.

Each of the factors described above almost certainly had some degree of impact on the differences between the probe vehicle speeds we collected and speed / estimated travel times generated based on VDOT sensor data. Moreover, with the exception of the final factor (basic differences between probe and sensor data sets), each of these has the potential to impact the quality of data collected by spot sensor-based fixed data collection infrastructure. As such, public agency staff should take each of these into consideration when making decisions concerning both the deployment of new data collection infrastructure, as well as the maintenance and/or expansion of existing systems.