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DIGITAL ROADWAY INTERACTIVE VISUALIZATION AND EVALUATION NETWORK APPLICATIONS TO WSDOT OPERATIONAL DATA USAGE

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16. ABSTRACT

The combined Washington State Department of Transportation (WSDOT) traffic sensor data and third party data are huge in volume and are highly valuable for system operations, monitoring, and analysis. The current WSDOT traffic data archive systems, however, lack the capability to integrate third party datasets and are not offering the functions needed for real-time performance monitoring, quick operational decision support, and system-wide analysis. The goal of this study was to remove the barriers in the current datasets archived by WSDOT, automate the time-consuming data quality control process, and achieve the integration and visualization of information needed to support decision making. The research findings are not only summarized in this report but are also delivered in a functioning online system named WSDOT Digital Roadway Interactive Visualization and Evaluation Network (DRIVE Net). This WSDOT DRIVE Net system is capable of collecting, archiving, and quality checking traffic sensor data from all WSDOT regions and incorporating third party data, such as those from INRIX, Inc., and weather information into the analytical platform. Roadway geometric data are properly stored in an open-sourced, geospatial database and are seamlessly connected with the traditional transportation datasets. The existing WSDOT data archiving and analysis systems, CD Analyst and FLOW, are successfully recoded and integrated into the WSDOT DRIVE Net system for better efficiency and consistency. A series of loop data quality control algorithms is automated in the backend for detecting malfunction loops and correcting them whenever possible.

With the new data platform empowered by eScience transportation principles, two commonly utilized functions at WSDOT have been implemented to demonstrated the efficiency and utility of this new system. The first is to generate WSDOT's Gray Notebook statistics and charts. This new function will allow WSDOT personnel to produce the tables and figures needed for their annual and quarterly congestion reports in seconds, a significant efficiency improvement over the months previously necessary. The other function is the Level of Service (LOS) map for highway performance assessment. This module follows the Highway Capacity Manual (HCM) 2010 procedure to produce the LOS estimate for each roadway segment every 20 seconds based on real-time traffic measurements. Additionally, a mobile sensing data analysis module was developed as a pilot experiment for reconstructing pedestrian trajectories using the Media Access Control addresses captured from mobile devices.

Traffic engineers and researchers can directly access the WSDOT DRIVE Net system through the Internet. The system has demonstrated its ability to support more complicated analytical and decision procedures for large-scale transportation networks.

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Executive Summary

Traffic sensors have been widely deployed over the state highway network in Washington. Additionally, more and more companies and agencies, such as INRIX, Inc., have developed technologies that can extract “third party” traffic data from vehicle fleets and travel individuals. These third party data greatly complement data from the traffic sensor network of the Washington State Department of Transportation (WSDOT), particularly for rural areas where traffic detectors are sporadic. The combined WSDOT data and third party data are huge in volume and are highly valuable for system operations, monitoring, and analysis. However, the current traffic data archive systems were designed mainly for data storage and off-line analysis. They lack the capability to integrate third party datasets and do not offer the functions needed for real-time performance monitoring, quick operational decision support, and system-wide analysis.

The goal of this study was to remove the barriers in the current datasets archived by WSDOT, automate the time-consuming data quality control process, and achieve the integration and visualization of information necessary to support decision making. The research findings are not only summarized in this report, which describes the data fusion techniques and database design details, but are also delivered in a functioning online system named WSDOT Digital Roadway Interactive Visualization and Evaluation Network (DRIVE Net). This WSDOT DRIVE Net system is capable of collecting, archiving, and quality checking traffic sensor data from all WSDOT regions and incorporating third party data, such as those from INRIX, Inc., and weather information into the analytical platform. Roadway geometric data are properly stored in an open-sourced, geospatial database, and seamlessly connected with the traditional transportation datasets. The existing WSDOT data archiving and analysis systems, CD Analyst and FLOW, were successfully recoded and integrated into the WSDOT DRIVE Net system for better efficiency and consistency. A series of loop data quality control algorithms, including basic thresh-holding, Gaussian Mixture Model (GMM), and spatial/temporal correction, are automated in the backend for detecting malfunction loops and correcting them whenever possible.

A variety of datasets, including freeway loop data, INRIX GPS, Washington Incident Tracking System (WITS), and weather data, are incorporated and archived into well-designed databases. Unlike other prevailing transportation data archiving systems, DRIVE Net is also capable of processing and storing massive amounts of spatial data by using open-sourced spatial

database tools. This significantly alleviates the computational and financial burden of using commercial geographic information system (GIS) software packages and grants maximum flexibility to end users. By properly combining both traditional transportation and spatial data, a more robust GIS-T model is available for large-scale modeling and network-level performance measures following eScience principles.

To develop a more stable yet interoperable platform to process, analyze, visualize, and share transportation data, the previous version of the DRIVE Net system, developed through voluntary efforts, was remodeled by incorporating multiple open-sourced software tools such as OpenStreetMap, OpenLayers, and the R statistics package. The new DRIVE Net system is built over a fat-server, thin-client framework. It requires no additional installation efforts for users. Moreover, its security and reusability are significantly better than the previous design. The new DRIVE Net system is now able to handle more complex computational tasks, perform large-scale spatial processing, and support data sharing services.

With the new data platform empowered by eScience transportation principles, two commonly utilized functions at WSDOT were implemented to demonstrate the efficiency and utility of this new system. The first function was to generate WSDOT's Gray Notebook statistics and charts. Cleaned data were utilized to generate statistics for WSDOT's Gray Notebook. The calculated statistics were presented on an interactive map system. This new function will allow WSDOT personnel to produce the tables and figures needed for their annual and quarterly congestion reports in seconds, a significant improvement over the months previously necessary.

The other function was the level of service (LOS) map for highway performance assessment. This module follows the Highway Capacity Manual (HCM) 2010 procedure to produce an LOS estimate for each roadway segment every 20 seconds on the basis of real-time traffic measurements. To implement this approach, the research team developed a spatial data fusion technique, pixel-based segmentation, and used it to spatially overlay multi-level geometric data and transportation data. Roadway geometric data, GPS probe vehicle-based speed data from INRIX, and fixed traffic sensor data were fused in our calculation process. This new LOS calculation approach was compared with several other algorithms, and the results proved it to be accurate and efficient.

Additionally, a mobile sensing data analysis module was developed as a pilot experiment for reconstructing pedestrian/bicyclist trajectories by using the Media Access Control (MAC) addresses captured from mobile devices. Each pedestrian/bicyclist with a Bluetooth-enabled mobile device was considered to be a moving sensor. Data observers with our phone app designed for collecting Media Access Control (MAC) addresses from mobile device Bluetooth signals recorded MAC addresses and the time when they were observed. These MAC addresses and timestamps were then sent to the STAR Lab server for processing to extract trajectory information. Given the lack of pedestrian/bicyclist movement data and the challenges to collect them, this pilot experiment may have introduced a new and cost-effective method for collecting such data.

In summary, this study shed light on the development of an eScience transportation platform and provided an interoperable data-driven online tool to substitute for WSDOT's existing data systems. The major merits and contributions are listed below:

(1) The DRIVE Net system is significantly enhanced with multiple open-sourced software packages and a robust system design.
(2) This study developed an efficient and effective GIS-T model to integrate massive amounts of transportation data from various sources into the roadway network.
(3) WSDOT's existing data systems (CD Analyst and FLOW) are successfully incorporated into the DRIVE Net system.
(4) More heterogeneous datasets, including INRIX speed data, weather data, and WITS data, have been imported into the DRIVE Net system. The loop sensor data coverage is also greatly expanded.
(5) The WSDOT Gray Notebook has been included as a key component in the DRIVE Net system. The raw loop data are preprocessed through a series of rigorous data quality control processes in an automatic manner and are further imported for congestion statistics calculation. The generated statistics are presented on a digital map system for reporting and visualization.
(6) The HCM 2010 Level of Service (LOS) module is automated in DRIVE Net. INRIX data, loop detector data, and roadway geometric data are fused with a spatial fusion approach, then the K-means clustering algorithm and regression technique are jointly applied to predict LOS for real-time freeway performance monitoring.

(7) A mobile sensing data analysis framework has been developed. This framework includes a prototype mobile phone app for MAC address data collection, a pedestrian trajectory reconstruction algorithm, and a computer module in DRIVE Net that implements the trajectory reconstruction algorithm.

Future endeavors can be undertaken to expand the scope of DRIVE Net to the entire state, design an analytical module for quantifying the benefits of ATM and management lanes, conduct safety performance measurements, and more.

Chapter 1 Introduction

1.1 Problem Statement

The Washington State Department of Transportation (WSDOT) is facing increasing demands on its data infrastructure. Accountability, operations, environmental impact analysis, system design, and implementation decisions require data-driven and data supported decision making. Data and support tools need to be accessible to WSDOT personnel for reporting and public outreach purposes. These include functionalities currently offered by legacy applications such as CD Analyst, databases such as the FLOW archive, and applications to be developed for accountability, operations, and design decision support.

The problem with the FLOW archive and CD Analyst functions that are currently widely used within WSDOT is that they were created almost 20 years ago. They were advanced and efficient when they were designed, but they are simply outdated and are now architecturally awkward and generally unsuited for combination with new functions. Computing power, programming models, Internet functionality, and electronic maps have advanced a great deal since FLOW and CD Analyst were first coded. Now a dynamic, visual, and multiple dataset-based decision making support tool is well within technical means. Given increasing data analysis needs and aging infrastructure, it is time to refresh WSDOT's current data infrastructure and analytical tools.

Because of their age, the current legacy data archival and analysis tools are unable to answer decision support questions related to operations strategies, design requirements, and increased public scrutiny. For example, new traffic control and design decisions, such as those involved with active traffic management (ATM), will require new applications and databases for decision support. Some ATM strategies, such as demand management via tolling and variable speed limits, have very high public visibility. They also span large areas and can affect infrastructure across multiple jurisdictions. Design, operations, and accountability decisions for such large-scale projects require data input from multiple sources, algorithms to compute performance measures, and efficient communications media such as maps, charts, and reports. However, the WSDOT existing data systems are not capable of integrating multiple data sources.

In addition, with the current data archival and analysis tools, assessments of operational performance and future implementation decisions must be performed manually. For example, for performance measures, such as incident rates related to variable speed limit, incident times from the Washington Incident Tracking System (WITS) databases must be matched to variable speed limit records along with any other traffic data of interest, such as volumes and speeds. Generating useful performance measures and analysis is labor intensive and time consuming because of the lack of a suitable platform to process and deliver transportation information efficiently, and thus, limits the WSDOT's ability to respond to legislative and agency requests.

A potential answer to the problems posed by the current databases is a prototype Web-based analytical framework called the Digital Roadway Interactive Visualization and Evaluation Network (DRIVE Net). Developed at the University of Washington (UW) Smart Transportation Applications and Research Laboratory (STAR Lab), DRIVE Net, as it has come to be known, is a first step in attempting to tie together the multiple sources of transportation-related data that are quickly becoming available. A key aspect of the system is an interface that allows sensor data to be overlaid on OpenStreetMap, providing immediate visual representation and analysis. Trends and correlations that would otherwise be concealed in tables become visually apparent when overlaid on a map. Additionally, the OpenStreetMap-based spatial organization of data provides an intuitive interface that is familiar to many users. DRIVE Net is part of a new trend in data-driven decision-making support tools by including data from WSDOT's Northwest Region, the City of Bellevue, and several other entities. However, the functionalities of the current DRIVE Net are limited. The STAR Lab envisions addressing WSDOT's needs by further developing DRIVE Net, not only taking advantage of all WSDOT regions' data and the existing functions of CD Analyst, but also providing a platform for transportation data management, analysis, visualization, and decision making.

1.2 General Background

The concept of a statewide data network is not a new one. Several examples exist, such California's Performance Measurement System (PeMS) and Oregon's Portland Oregon Regional Transportation Archive Listing (PORTAL). The original model for these systems is similar to the

CD-based archive developed in the early 1990s by the Washington State Transportation Center (TRAC) – the FLOW system.

Because of the era during which it was developed, the FLOW system is not a fully functional relational database. It is a series of flat files that are manipulated through a series of stand-alone programs. The stand-alone programs are designed to read those files and produce secondary files. The secondary files are read into additional programs—including conventional spreadsheets containing basic Macro functionality, which in turn produce a variety of analytical outputs used by WSDOT. The combined series of analytical programs goes by the name of CD Analyst.

The CD Analyst suite of programs has been developed over an 18-year period. It produces a large number of key accountability reports for WSDOT and also performs the basic analysis of freeway performance reporting for WSDOT. Unfortunately, the CD Analyst suite of programs has grown organically over that 18-year period, with that growth always focused on the provision of new analytical capabilities needed to meet specific WSDOT reporting needs. Because available funds have always been focused on adding specific analytical capabilities, the inherent data structure has never been modified to allow easier and more flexible access to the collected data. As a consequence, the system has not taken advantage of many of the improvements in computing technology which have occurred since the mid-1990s. The result is that, while the current WSDOT data system functions, it is neither as efficient nor as flexible or accessible as needed.

The DRIVE Net system has evolved from two major STAR Lab research efforts, the Google-map-based Arterial Traffic Information (GATI) system (Wu, 2007) and the Development of a Statewide Online System for Traffic Data Quality Control and Sharing (Wang et al., 2009) project sponsored by the WSDOT and Transportation Northwest (TransNow). Freight management functions have been added through the Developing a GPS-based Truck Performance Measures Platform (McCormack, 2010) project sponsored by WSDOT and TransNow. Additional datasets and modules have been added on a test basis. These modules are generally operating on a reduced number of datasets, because of either data availability or analysis complexity. Test modules include freeway level of service (LOS) and link emissions mapping applications.

The DRIVE Net framework is designed upon a scalable and modular architecture. This architecture is intended to make the addition of various analytical modules as easy as possible so that future upgrades will require minimal effort. A series of Extract, Transform and Load (ETL) programs collect, format, and store the data in the appropriate databases. As new data sources are added, existing ETL tools can be adopted if the data source is similar to an existing data source, or new ETL logic can be written as needed. Once data have been loaded into databases, many data formatting inconsistencies, such as collection periods, can be reduced through database functions and aggregation within queries. This allows analyses at a flexible resolution level while maintaining compatibility with established 5-minute based analyses, such as those conducted by CD Analyst.

DRIVE Net has also been designed from the beginning to present analytical results in a visual and map aware manner. This allows functions such as the emissions model to take underlying traffic data, apply a traffic emissions model, and then display a color-coded map for viewing the results. This ability will allow the current functionalities of CD Analyst, as well as future functionalities, to be visualized.

The addition of other datasets, such as WITS, weather, and INRIX data, will provide new analytical and data quality control options. Incident data from these sources can be used to flag affected analyses in order to reduce inaccuracies due to abnormal traffic. Simply flagging results that may be affected by incidents that happened on the selected route(s) at the selected time(s) could have profound implications for the quality of data analyses.

1.3 Research Objectives

The primary goal of this study is to provide a data-driven, online transportation platform as a substitute for the previous CD Analyst to provide WSDOT Gray Notebook statistics calculations and to incorporate more diverse and heterogeneous sensor data sources. In addition, DRIVE Net will be able to automate the Highway Capacity Manual (HCM) 2010 method calculations for freeway performance measures and to implement a mobile sensing data analysis framework for reconstructing pedestrian trajectories. This e-Science platform will not only serve to archive the tremendous amount of historical transportation data, but will also provide several visualization and modeling tools to help users better understand the large sets of transportation data, and thus make more informed decisions. The detailed research objectives are listed below:

- Enhance the current DRIVE Net system by improving system design and increasing sensor data coverage.
- Integrate WITS, weather, and INRIX data into DRIVE Net and apply them for analytical functions.
- Expand the current data coverage of freeway loop detectors statewide.
- Incorporate CD Analyst functions into DRIVE Net by re-coding its core functions.
- Develop an automated function to compute statistics and charts needed to produce the WSDOT Gray Notebook.
- Develop an example module to show how DRIVE Net's databases and analytical functions may be applied to measure freeway performance with the HCM 2010 method.
- Develop a mobile sensing data analysis framework with a prototype mobile phone app for MAC address data collection and pedestrian trajectory reconstruction.

Chapter 2 Literature Review

In the past decades, a considerable number of online transportation platforms for data sharing, archiving, and analysis have been developed for transportation agencies and the public. Typical examples of them are described as follows:

2.1 Freeway Performance Measures Systems (PeMS)

Established in 1998, PeMS is a freeway performance measurement system jointly developed by the University of California, Berkeley, California Department of Transportation (Caltrans), and the Partners for Advanced Transportation Technology (PATH). With support from Caltrans and local agencies, the system integrates various traffic data sources, including traffic detectors, census traffic counts, incident logs, vehicle classification data, toll tag-based data, and roadway inventory. These traffic data have been automatically collected and archived for over ten years, and real-time information is updated from over 25,000 detectors (Chen et al., 2001; Chen et al., 2003). As a critical component of Caltrans performance measurement system, PeMS provides a variety of freeway evaluations in terms of speed, occupancy, travel time, vehicle miles traveled, vehicle hours traveled, and vehicle hours of delay. The success of PeMS for freeways has triggered the development of a similar system for arterial performance evaluation. Following the basic principle of PeMS, the Arterial Performance Measurement System (APeMS) has been implemented to estimate intersection travel time, control delay, and progression quality on arterials every 5 minutes by using mid-block loop detectors (Tsekeris et al., 2004; Petty et al., 2005). Unlike the open availability of PeMS, APeMS usage is designated for stakeholders, and it is not accessible by the public.

2.2 Regional Integrated Transportation Information System (RITIS)

RITIS is an automated data archiving and integration system developed by the Center for Advanced Transportation Technology Laboratory (CATT Lab) at the University of Maryland. The focus of RITIS, one of several online transportation archive systems, is to improve transportation safety, efficiency, and security by fusing and mining transportation-related data in Maryland, Virginia, and the District of Columbia. The system provides both real-time and historical data to users with access credentials, including incident, weather, radio scanner, and other sensor data. Numerous visualization and analysis tools have been developed to enable interactive exploration and analysis of performance measures from archival data. DOT or public safety employees can possibly use the RITIS service by applying online. The system is not accessible to the general public (CATT lab, 2013).

2.3 Portland, Oregon, Regional Transportation Archive Listing (PORTAL)

Originally established in 2004 with a simple user interface and only one data source—freeway loop detectors—PORTAL has evolved significantly over the past eight years. In addition to the loop detector data from the Portland-Vancouver metropolitan region, PORTAL 2.0 now archives approximately 1 terabyte of transportation data, including weather, incident, freight, and transit data. The system takes advantages of Adobe Flash and Google Maps technologies to display transportation data spatially. Additionally, various graphical and tabulated performance information is available on the website, such as incident reports, transit speed maps, traffic counts, vehicle miles traveled, and vehicle hours traveled (Tufte et al., 2010).

2.4 Freeway and Arterial Systems of Transportation (FAST) Dashboard

The FAST dashboard, released online in September 2010 (http://bugatti.nvfast.org), is a Web-based system developed to control and monitor traffic in the Las Vegas and Nevada metropolitan areas (Xie and Hoeft, 2012). In collaboration with the Nevada Department of Transportation (NDOT), the system collects and archives real-time traffic data retrieved from loop detectors, radar detectors, and Bluetooth sensors deployed on freeways and ramps. Traffic data including lane occupancy, volume, and speed data are further processed as the major data sources for performance measurement. Also integrated into the system are incident data in report format collected from the general public, and weather data shared by the NDOT Road Weather Information System.

The performance measures used by the FAST dashboard include average speed, traditional travel time performance measures, delay volume, and temporal and spatial extension of congestion. Meanwhile, the website is updated every 1 minute to display the real-time traffic map. By ensuring the delivery of timely and accurate information to traffic managers, operators, and planners as well as the general public, the FAST dashboard significantly enhances the interchangeability of traffic data, helps improve the freeway and arterial system, and optimizes operation strategies in the southern Nevada region.’

2.5 Applications in Washington State

In Washington state, a great effort has also been made to develop applications to supply traffic data for traffic monitoring and research activities. Completed in 2002, The Traffic Data Acquisition and Distribution (TDAD) project provided a traffic data repository for a chosen wide area, such as King County in Washington. The interactive user interface enabled transportation researchers and agencies to query historical data by time and location. This was not very common in the early 21^{st} century.

Established in 2006, the DRIVE Net system has evolved from two major STAR Lab research projects, the Google-map-based Arterial Traffic Information (GATI) system (Wu, 2007) and the Development of a Statewide Online System for Traffic Data Quality Control and Sharing (Wang et al., 2009) project sponsored by WSDOT and Transportation Northwest (TransNOW), the USDOT University Transportation Center for federal region 10. In 2008, the system was named the Digital Roadway Interactive Visualization and Evaluation Network (Ma et al., 2011). More functions have been implemented and integrated into the system over time, such as a freight management module (Ma et al., 2011), incident induced delay calculations (Yu et al., 2013), arterial travel time estimation (Wu et al., 2011) and emission data analysis (Ma et al., 2012). DRIVE Net provides users with the capability to store, access, and manipulate data, which benefits not only transportation practitioners and researchers but also the public by providing both historical and real-time transportation information and numerous performance measures in the broader context of an interdisciplinary framework.

Chapter 3 Study Data

DRIVE Net builds upon existing databases controlled by the STAR Lab. A variety of data sources are digested and archived into the STAR Lab server from WSDOT and third party data providers through different data acquisition methods.

There are four ways to use the data archive service, as illustrated in Figure 1:

1. Direct upload

Users can upload data into the database through the DRIVE Net website. This model is suitable for receiving data from those who do not maintain online databases. Typical datasets used in this study include INRIX data and weather station data.

2. Periodic download via Web services

A scheduled fetch job is run to download data at predefined intervals via File Transfer Protocol (FTP), Hypertext Transfer Protocol (HTTP), Simple Object Access Protocol (SOAP), or Representational State Transfer Principles (RESTful) interfaces. This method is currently used for the acquisition WSDOT freeway loop data.

3. Active data acquisition

For those agencies with specialized needs or who do not allow public access, the research team will construct a satellite server—a form of "information appliance"—bundling hardware, software, and data processing services into a single provisionable platform. These satellite servers elegantly solve several problems related to bootstrapping a data sharing network. First, system administrators rarely create holes in their firewalls for connections with remote machines. The appliance, however, can be deployed inside the agency's firewall and still connect to remote servers by using port 80 or port 22, which are usually unrestricted. Second, specialized software for establishing a Web service, in order to use the periodic download method, is difficult to install and configure. Even if a comprehensive software suite is written, the cost of providing technical support to users would be prohibitive. However, installing the software on behalf of a customer on computers over which the STAR Lab has complete control is far more straightforward. Finally, the appliance grants access to STAR Lab researchers and technicians as well as participant agency staff. This allows multi-agency shared access, which can simplify troubleshooting and upgrade deployment. This method is currently used to retrieve the roadway geometric data and WITS data from WSDOT.

4. Direct data archiving

The data are generated from the data collection devices and enter into the data warehouse by several communication protocols, such as General Packet Radio Service (GPRS) and Global System for Mobile Communications (GSM). Mobile sensor data are transmitted into DRIVE Net with this method.

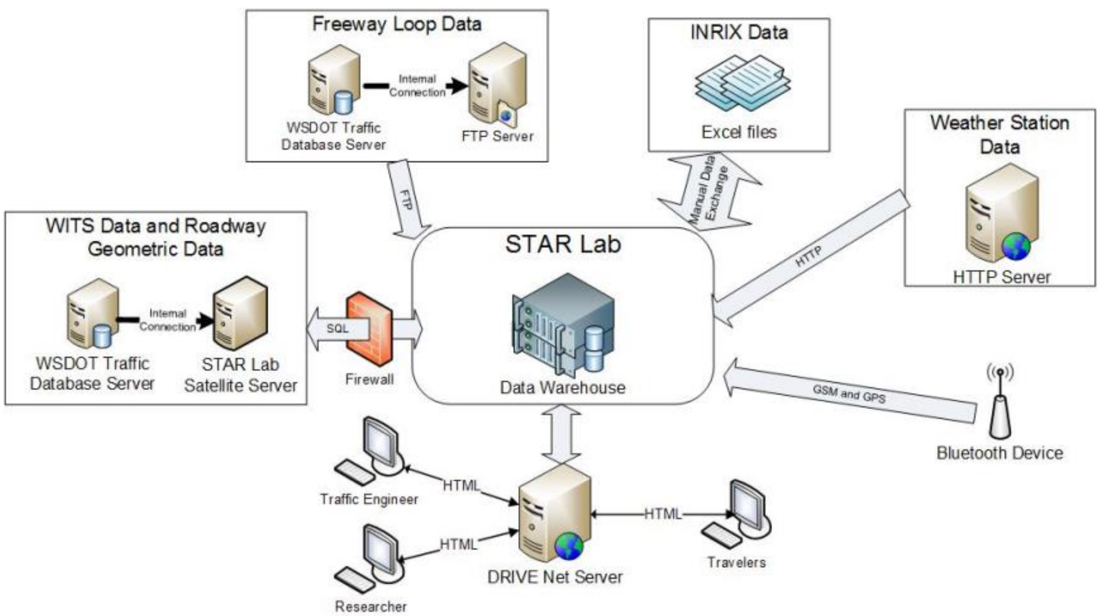


Figure 3-1 Data Acquisition Methods for the DRIVE Net System

Detailed information about each data source is described in the following sections.

3.1 Freeway Loop Data

Inductive loop detectors are widely used to monitor freeway performance in the United States because of their reliability and durability (Klein et al, 2006). An inductive loop detector is a conductive coil embedded in the pavement, and it detects a moving vehicle passing over it with electromagnetics. The signal is then transmitted to a roadside cabinet, which stores the vehicle presence information and also sends the signal to the traffic management center via cable. Volume and occupancy are two key indicators that traffic detectors can collect during a fixed time interval (20 seconds or 5 minutes). WSDOT maintains and manages loop detectors in both Washington state highway and Interstate freeways. Washington divides the state into six regions: Northwest, North Central, Eastern, South Central, Southwest, and Olympic. For instance, there are approximately 4200 single or dual loop detectors installed in the Northwest Region, and they aim to monitor traffic condition around the Seattle metropolitan area.

WSDOT stores both 20-second and 5-minute loop detector data using an online FTP website for downloading. The 5-minute loop detector data are aggregated from 20-second loop data for long-term analysis and archiving. A computer program written in Microsoft Visual C# was developed to periodically retrieve loop data from the posted FTP website, and the downloaded data are automatically imported into Microsoft SQL server databases for further processing.

Single loop detectors can detect only whether a vehicle is present or absent. When several vehicles pass over a single loop detector during a certain time interval, the detector is able to count the number of vehicles and the percentage of time when the detector is occupied. Unlike single loop detectors, a dual loop detector is composed of two single loop detectors, which are placed a short distance apart. By measuring the arrival time difference between the two loops, the roadside traffic controller can calculate each vehicle’s speed. The vehicle’s length can be also estimated by using the calculated vehicle speed and the on-time measurement from either the front loop or the rear loop.

For both 20-second and 5-minute data aggregation intervals, three types of loop data are collected. The key information is listed in Table 3-1 and Table 3-2.

Table 3-1 20-Second Freeway Loop Data Description

Table: SingleLoopData and StationData (Single Loop)

Columns	Data Type	Value Description
LOOPID	smallint	Unique ID number assigned in order of addition to LoopsInfo table
STAMP	datetime	24-hour time in integer format as YYYYMMDD hh:mm:ss (in 20-second increments)
DATA	tinyint	Indicate whether a record is present or not
FLAG	tinyint	Validity flag (0-7): 0=good data; otherwise, bad data
VOLUME	tinyint	Integer volume observed during this 20-second interval
SCAN	smallint	Number of scans when a loop is occupied during each period (60 scans per second multiplied by 20 seconds per period equals 1200 scans)

Table: TrapData (Dual Loop)

Columns	Data Type	Value Description
SPEED	smallint	Average speed for each 20-second interval (e.g., 563 means 56.3 mile per hour)
LENGTH	smallint	Average estimated vehicle length for each 20-second interval (e.g., 228 means 22.8 feet)

WSDOT primarily uses the 5-minute aggregation level loop data for freeway performance measures (Wang et al., 2008). The key information for 5-minute loop data is shown in Table 3-2.

LoopID is the unique ID that matches each cabinet with loop data. Several loops could connect to each cabinet. For each cabinet, these loop data are aggregated as a loop group, namely a loop station, for which the volume is the sum of total volumes for the associated loops, and the occupancy (or scan) is the average of total occupancies (scans) for the associated loops. In addition, to facilitate locating and categorizing each loop, each loop is assigned to a cabinet with spatial information (e.g., milepost). The key information is listed in Table 3-3.

Table 3-2 5-Minute Freeway Loop Data Description

Table: STD_5Min and STN_5Min (Single Loop)		
Columns	**Data Type**	**Value Description**
LOOPID	smallint	Unique ID number assigned in order of addition to LoopsInfo table
STAMP	datetime	24-hour time in integer format as YYYYMMDD hh:mm:ss (increased by 5 minutes)
FLAG	tinyint	Good/bad data flag with 1 = good and 0 = bad (simple diagnostics supplied by WSDOT)
VOLUME	tinyint	Integer volume observed during each 5-minute interval
OCCUPANCY	smallint	Percentage of occupancy expressed in tenths to obtain integer values (6.5% = 65)
PERIODS	smallint	The number of 20-second readings incorporated into this 5-minute record (15 is ideal, less than 15 almost always indicates that volume data are unusable unless adjusted to account for missing intervals).
Table: TRAP_5Min (Dual Loop)		
Columns	**Data Type**	**Value Description**
SPEED	smallint	Average speed for each 5-minute interval (e.g., 563 means 56.3 mile per hour)
LENGTH	smallint	Average estimated vehicle length for each 5-minute interval (e.g., 228 means 22.8 feet)

Table 3-3 Cabinet Data Description

Columns	Data Type	Value Description
CabName	varchar	Unique ID for each cabinet
UnitType	varchar	Type for each loop (i.e. main, station, speed and trap)
ID	smallint	Unique ID number assigned in order of matching the loop data table
Route	varchar	The state route ID (e.g. 005=Interstate 5)
direction	varchar	Direction of each state route
isHOV	tinyint	Bit indication whether loop detector is on an HOV lane (1=HOV, 0=not HOV)
isMetered	tinyint	Bit indication whether loop detector is on a metered ramp (1=metered, 0=not metered)

Although WSDOT provides a preliminary data quality assurance procedure to flag erroneous loop data, this procedure is still unable to capture other possible errors, such as loop detector sensitivity issues (Corey et al., 2011). Because of the environmental changes around loop detectors over time, the actual detection zone of these loops may increase or decrease, and these changes will consequently affect the accuracy of speed calculations. Zhang et al. (2003) stated that approximately 80 percent of WSDOT dual-loops suffer from severe sensitivity problems. It is of critical importance to detect and correct possible loop errors before conducting freeway performance measurement. A detailed loop data quality control mechanism will be discussed later in this report.

3.2 INRIX Data

As a leading traffic data provider, INRIX combines multiple data sources, including GPS-equipped devices and cell phones. INRIX tracks more than 30 million probe vehicles and more than 400 additional data sources (INRIX, 2012). To aggregate and fuse heterogeneous transportation data, INRIX developed a series of statistical models to compute real-time traffic information such as speed and travel time based on measurements from GPS devices, cellular networks, and loop detectors. The resulting speed data were aggregated into 5-minute intervals for 2008, 2009, and 2010 and into 1-minute intervals for 2011 and 2012. WSDOT purchases the data, and they are further archived into the database in the STAR Lab. INRIX data cover almost the entire roadway network in Washington, including freeways, highways, and most arterials and side streets. The key information for INRIX data is presented in Table 3-4.

Table 3-4 INRIX Data Description

Columns	Data Type	Value Description
DateTimeStamp	datetime	24-hour time in integer format as YYYYMMDD hh:mm:ss
SegmentID	varchar	Unique ID for each segment-Traffic Message Channel (TMC) code
Reading	smallint	Average speed for each segment

INRIX has adopted the Traffic Message Channel (TMC), a common industry convention developed by leading map vendors, as its base roadway network. Each unique TMC code is used to identify a specific road segment. For example, in Table 3-5, TMC *114+0509* represents the WA-522 road segment with start location (*47.758321, -122.249705*) and end location (*47.753417, -122.277005*). However, that fact that WSDOT follows a linear referencing system based on mileposts poses challenges to matching the two different roadway layouts for data fusion.

Table 3-5 TMC Code Examples

TMC	Roadway	Direction	Intersection	Country	Zip	Start Point	End Point	Miles
114+05099	522	Eastbound	80th Ave	King	98028	47.758321,-122.249705	47.755733,-122.23368	0.768734
114-05095	522	Westbound	WA-523/145th St	King	98115	47.753417,-122.27005	47.733752,-122.29253	1.608059

3.3 WITS Data

Traffic incident data are collected and maintained by Washington State's Incident Response (IR) Team in the Washington Incident Tracking System (WITS). WITS includes the majority of incidents that happen on freeways and Washington state highways, which totaled 550, 376 by March 2013. For each incident, the Washington State IR team logs details such as incident location, notified time, clear time, and closure lanes. The DRIVE Net team obtained the WITS datasets from 2002 to 2013 and integrated them into the DRIVE Net database. Several key columns are listed in Table 3-6.

Table 3-6 WITS Data Description

Columns	Data Type	Value Description
SR	varchar	State route ID, e.g., 005=Interstate 5
Direction	varchar	Route direction (NB=northbound, SB=southbound, WB=westbound, EB=eastbound)
MP	float	Milepost
Notifited_Time	datetime	The time when an incident was reported to the Incident Response (IR) program
Arrived_Time	datetime	The time when an IR truck arrived at the incident location
Clear_Time	datetime	The time when the incident had been fully cleared and all IR crews left the incident scene
Open_Time	datetime	The time when all lanes became open to the traffic and IR crews may still be on the incident scene

3.4 Weather Station Data

Weather data are retrieved from the National Oceanic and Atmospheric Administration (NOAA) weather stations in the region. The University of Washington Atmospheric Sciences Department hosts a website that records all the weather statistics from 209 weather stations in Washington state every hour. The DRIVE Net team developed a Java-based computer program to fetch the weather report in an automatic manner through the HTTP connection. The retrieved data are then imported into a database in the STAR Lab. The key information of the weather data is shown in Table 3-7.

Table 3-7 Weather Data Description

Columns	Data Type	Value Description
name	varchar	The weather station identifier
timestamp	datetime	24 hour time in integer format as YYYYMMDD hh:mm:ss
visibility	smallint	Visibility in miles
temp	smallint	Temperature in degrees Fahrenheit
dewtemp	smallint	Dewpoint temperature
wind_direction	smallint	Direction wind is coming from in degrees; from the south is 180
wind_speed	smallint	Wind speed in knots
pcpd	smallint	Total 6-hr precipitation at 00z, 06z, 12z and 18z; 3-hr total for other times. Amounts in hundredths of an inch.

Each weather station is associated with a pair of latitude and longitude. In this case, weather data can be visualized on a mapping system.

3.5 Roadway Geometric Data

WSDOT's GIS and Roadway Data Office (GRDO) produces and maintains the GeoData Distribution Catalog online at http://www.wsdot.wa.gov/mapsdata/geodatacatalog/. The geospatial data in the format of an ESRI Shapefile is available to the general public, promoting data exchange and data sharing. Various roadway geometric datasets are available, including number of lanes, roadway widths, ramp locations, shoulder widths, and surface types. State route ID and locations marked by mileposts and accumulated mileage are also included in the WSDOT linear referencing systems. For DRIVE Net, these geometric data were stored in a spatial database for further processing. It is critical to connect roadway geometric data with traditional transportation data. Chapter 4 discusses such a geospatial platform to undertake this task.

3.6 Mobile Sensing Data

The DRIVE Net team developed an in-house Bluetooth sensor, also known as the Media Access Control Address Detection System (MACAD). Bluetooth is a short-range communication protocol initiated by Spatial Interests Group (SIG) for inter-device communications. Nowadays, more and more electronic manufacturers embed such technology into their products. The protocol utilizes a unique 48-bit Media Access Control (MAC) address to distinguish different devices. Because earlier Bluetooth technology adopted a frequency-hopping protocol for device discovery, the devices create a detection overhead of up to 10.24 seconds, causing spatial errors in detection and therefore travel time measurements. A detailed description of the Bluetooth-based data technology is covered in Chapter 7.

A communication module is incorporated into our designed Bluetooth data collection devices.. This module synchronizes to Coordinated Universal Time (UTC) over the GPS network and transfers latitude and longitude to the server through the Global System for Mobile (GSM) cellular system. Therefore, the key information from Bluetooth devices includes a timestamp, a pair of geospatial coordinates, and a unique MAC address. To conduct further travel time estimation or pedestrian tracking tasks, MAC address matching must be conducted.

Chapter 4 DRIVE Net 3.0: System Design and Implementation

Despite many years of development, several challenging problems remained unsolved in the previous version DRIVE Net 2.0. One critical issue was that the earlier versions had little geo-processing power, which made it difficult to store, analyze, and manipulate geographic data. Previous solutions included manually recording series of spatial locations (latitude and longitude) for lines and polygons in a relational database. However, this ad hoc method was inefficient, unreliable, and did not meet the needs of modeling complex spatial relationships.

Additionally, DRIVE Net 2.0 had severe bugs and was vulnerable to massive page visits because of incompatibility issues among the development tools. Google Web Toolkit (GWT), one of the major tools adopted in this earlier version, allowed developers to write in Java, and the GWT compiler translated Java code into JavaScript. Although GWT is a widely used tool for developing JavaScript front-end applications, it has a steep learning curve and requires developers to constantly keep up with new technologies. Huge amounts of time and effort are demanded to maintain and update the system because of the rapidly changing features of the GWT. Therefore, a more productive and straightforward development process was desired to ensure the stability of such online platforms. Another concern related to the inclusion of Google Maps in DRIVE Net 2.0 was the licensing model revision announced by Google, Inc. in early 2012 (Google, 2012). It stated that only the first 2,500 geocoding Web services would be offered free daily. Access to Google Maps would not be granted if a system continuously exceeded usage limits. Therefore, potential maintenance costs forced the developers to change the DRIVE Net system to a more flexible yet reliable alternative Web-mapping product, such as OpenLayers and OpenStreetMap (OpenLayers, 2013; OpenStreetMap, 2013). These led to the development of DRIVE Net 3.0, described in this section.

4.1 Geospatial Database Design

Because of the increasing amount of study data, multiple servers are configured to archive these data. To better balance computational resources and allow fast data access, transportation data and geospatial data are stored separately. The transportation data are managed by Microsoft SQL Server 2010, and all the databases are indexed and optimized on the basis of projected needs. However, the traditional method for handling geospatial datasets is to utilize commercial GIS software packages. Unfortunately, transportation agencies have to spend considerable amounts of time and financial resources purchasing and maintaining the software (Sun et al., 2011). In addition, because most commercial software is not designed as open architecture, transportation agencies have to provide the spatial data in strict accordance with the format of GIS files used by the commercial software. These restrictions incur inconveniences and reduce flexibility for both users and developers. Moreover, file-based data management systems have inherent disadvantages for processing tremendous amounts of data efficiently. Fortunately, the emergence of new geospatial database techniques can alleviate the burden of file-based geospatial data management and analysis. Similar to the traditional Relational Database Management System (RDBMS), geospatial databases can optimize the geospatial data management and analysis by using Structured Query Language (SQL) techniques and spatial indices. In addition, geospatial databases enable a variety of geo-processing operations that traditional relational, non-spatial databases cannot complete—for example, whether two polylines intersect, or whether points fall within a spatial area of interest. For this study, non-spatial relational databases were used to store traffic-related information such as loop detector data and INRIX data. This created a critical issue: how to best represent and manage the dynamic transportation data in a context of hybrid spatial and non-spatial databases. Especially when more and more location-aware transportation data are available for advancing Big Data initiatives, this issue is becoming more pressing.

For the new system, PostgreSQL with extender PostGIS and pgRouting was adopted to maintain geo-data and perform spatial modeling, as outlined in Figure 4-1. Those three products are all free, open source, and well-supported by their active communities. Although some commercial software such as ArcGIS/ArcServer could perform the same jobs, open source projects are generally more academic in nature, despite the fact that commercial products usually have expensive license and usage restrictions. The rest of this section introduces more details about PostgreSQL, PostGIS, and pgRouting.

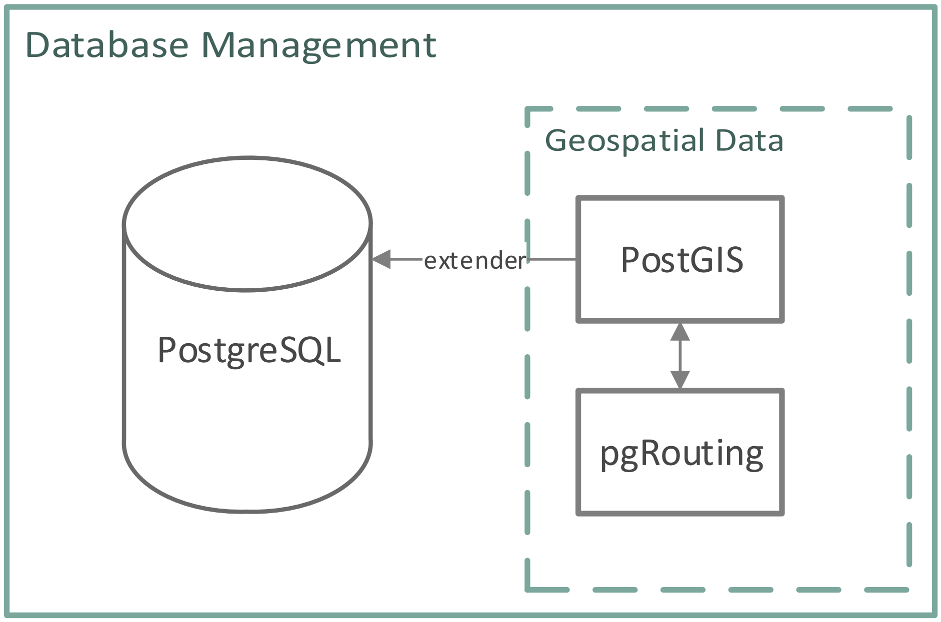


Figure 4-1 PostgreSQL, PostGIS, and pgRouting

PostgreSQL is a sophisticated and feature-rich object-relational database management system under an open source license (PostgreSQL, 2013). Its powerful functions and efficient performance make it the most popular open source database, and it is able to compete against well-known commercial products such as Oracle, IBM DB2, and Microsoft SQL server. Some advanced and unique features distinguish it from others, including table inheritance, support for arrays, and multiple-column aggregate functions. Moreover, the active global community of developers continually updates PostgreSQL with the latest database technology.

With PostgreSQL as a tabular database, PostGIS is a spatial database extender built on PostgreSQL (Obe, 2011). The PostgreSQL/PostGIS combination offers support to store, maintain, and manipulate geospatial data, making it one of the best choices for spatial analysis. Besides the geo-data storage extension, PostGIS has nearly 300 geo-processing operators or functions. The ability to analyze geographic data directly in the database by SQL sets distinguishes PostGIS from commercial competitors. For example, the following spatial query creates a polygon buffer with a size of 10,000 feet:

Select ST_Buffer(the_geom, 10000) from county_polygon

pgRouting is an extension of PostGIS/PostgreSQL geospatial database that provides a set of routing-related SQL functions (pgRouting, 2013). Various routing algorithms are supported by pgRouting, including shortest path Dijkstra (Dijkstra, 1959), shortest path A* (Hart et al., 1968), shortest path shooting*, traveling salesperson problems, and driving distance calculation. Meanwhile, its open source framework makes it convenient for developing and implementing user-specified routing algorithms. More advanced algorithms such as Multimodal Routing support, Two-Way A*, and time-dependent/dynamic shortest path will be included in the near future.

4.2 System Design

The new system adopts the "thin-client and fat server" architecture with three basic tiers of Web application: presentation tier, logic tier, and data tier, as shown in Figure 4-2. The presentation tier includes the user interface terminal through which users interact with the application. The logic tier, which is also called the computational tier, is the core component of the DRIVE Net system. It performs computations to assist in customized analysis and decision making based on users' interactive input. The data tier organizes and supports data requested for analysis. Normally the client handles the user interface while the server is responsible for the data. The significant difference between "thin-client and fat server" and "fat-client and thin server" is the shifted responsibility for the logic/computational tier (Lewandowski, 1998). In fat server systems, the server fully takes over the logic/computation tier while the client only hosts the presentation tier for displaying the user interface and dealing with user interactions.

There are three reasons to adopt the thin-client architecture: First, no plug-in and installation are required at the client side except a basic browser, which ensures the highest level of compatibility. Given that the system is designed for customers with constrained network functions, minimal requirements on the client side are most desirable. Second, there are fewer security concerns since all the data and computational tasks are manipulated and performed on the server side, and the client is only responsible for user interaction and results presentation. Third, mature frameworks for building thin client Web applications could be re-used to boost development productivity. However, thin-client architecture does have its drawbacks. One major disadvantage is that the performance of the system depends solely on the server and, as a result, excessive user requests greatly affect system efficiency. This has become more manageable in recent years with the continuous advancement of cloud computing technologies such as Amazon Web Service, whose the cloud servers are fully designed to improve system performance.

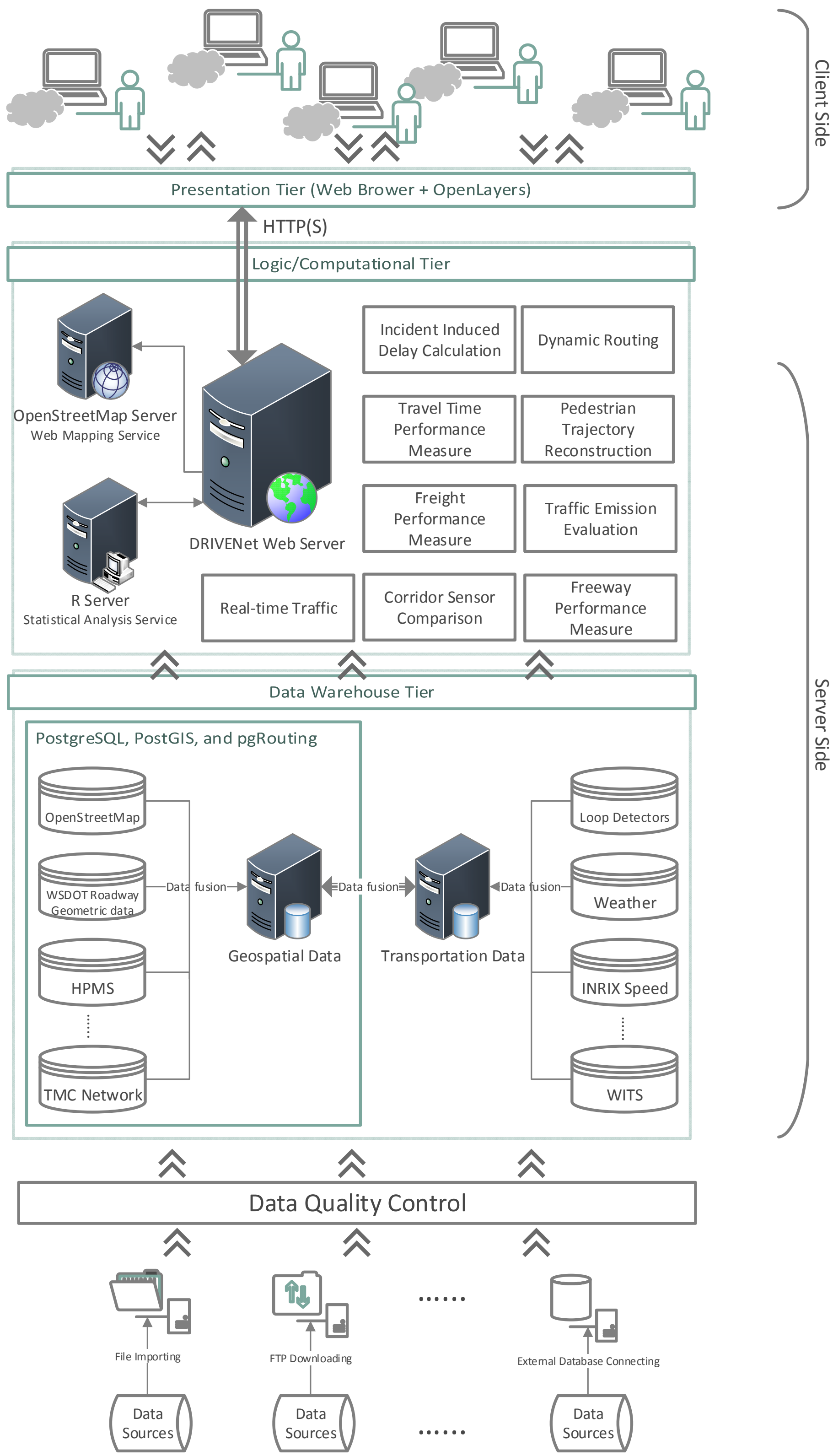


Figure 4-2 DRIVE Net 3.0 Architecture

The data communication flows in the DRIVE Net system can be summarized as follows:

1. *The end-user sends an HTTP(S) request to the Web server.*

2. *The Web server looks into the request and retrieves the related data information from the data warehouse.*

3. *The warehouse sends back the requested data and the Web server performs the computational tasks by using either the built-in analytical tools or external statistical modules provided by R Server.*

4. *If geospatial analysis is involved, the Web server connects to the OpenStreetMap Server and requests the map.*

5. *Analysis results as well as the map are then returned to the client. The Web browser displays the results or visualizes the returned objects on the map.*

4.3 System Implementation

As mentioned in the previous section, the DRIVE Net architecture has been redesigned to meet challenges. To reduce costs and boost productivity, multiple open source products are utilized. Relying on open source products, the DRIVE Net team not only takes advantages of code-sharing and collaboration with a broad community of developers but also contributes to open source projects. The core open source products combined into the DRIVE Net system are explained in the remainder of this section.

4.3.1 OpenStreetMap and OpenLayers

OpenStreetMap (OSM) is a collaborative project that has created a comprehensive worldwide map that is free to use and editable (Haklay et al., 2008). With the outlook that geospatial data should be freely accessible to the public, University College London established the OSM project in July 2004, and it is one of the most prominent and famous examples of Volunteered Geographic Information, a concept introduced by Goodchild (2007, 2008). The process of maintaining OSM data is termed crowdsourcing and is being used by a number of other commercial companies such as Google and TomTom. In crowdsourcing, a term defined by Brabham as an “online and distributed problem-solving and production model,” labor-intensive tasks are distributed to large groups of users, and this has allowed volunteers to create and update geospatial data on the Internet. By January 2013, OSM had over one million registered contributors and 20,000 active users worldwide, and the number continues to rise dramatically (Wood, 2013). Besides governments, OSM has obtained strong support from commercial companies. For instance, Yahoo Maps made its vertical aerial imagery available to OSM as a backdrop for map production in 2006, and Microsoft Bing Maps donated part of its satellite imagery to the OSM in 2010 (Microsoft, 2010).

One major reason for DRIVE Net to choose OSM is its low cost in comparison to commercial datasets, as well as its data sharing nature. With the Open Data Commons Open Database License (ODbL), developers are free to use, distribute, and modify the OSM data as long as OSM and its contributors are credited (OpenStreetMap, 2013). Using OSM to replace Google Maps helps DRIVE Net avoid potential charges by Google, Inc in the future that might eventually prevent the project from growing. In addition, in keeping with the theme of eScience, the DRIVE Net developers prefer open source products over commercial ones because they can help share ideas, drive innovation, and boost productivity for the entire community.

High-resolution and qualitative geographic information such as that shown in Figure 4-3 makes OSM an appealing replacement for Google Maps. Recent research confirms the good quality of OSM and its ability to compete against commercial geodata, especially for urban areas. Zielstra and Hochmair (2011) used the commercial datasets NAVTEQ and TeleAtlas, as well as the freely available dataset TIGER/Line, to quantify the coverage of OSM in the United States. The results indicated that "there is strong heterogeneity of OpenStreetMap data for the U.S., in terms of its completeness," A similar study was done in Germany by Zielstra and Zipf in 2010 (Zielstra et al., 2010). The paper states that some projects already replaced proprietary data with rich OSM data in larger cities. In the U.K., Haklay (2010) performed a comparison with the Ordinance Survey (OS) Meridian dataset by evaluating the accuracy, completeness, and consistency of the positions and attributes. The analysis concluded that "OSM information can be fairly accurate," with a positional accuracy of about 6 meters and an approximately 80 percent overlap of motorway objects in comparison to the OS dataset.

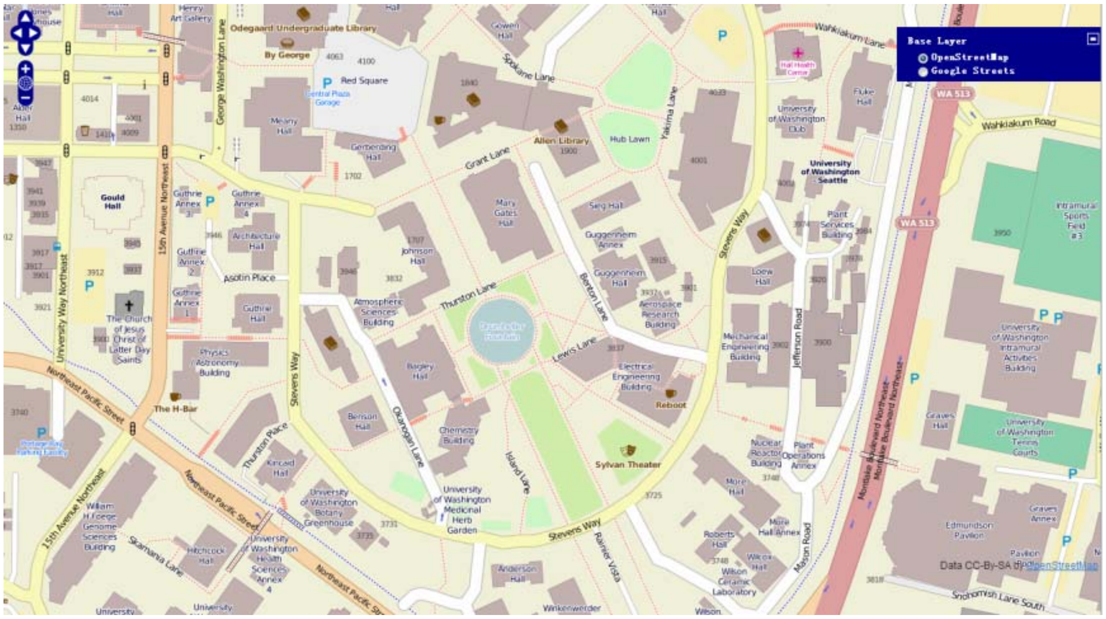


Figure 4-3 High Resolution OpenStreetMap near the University of Washington

Figure 4-4 shows how clients dynamically interact with OpenStreetMap in the DRIVE Net system and the backend processes. When a Web server receives clients' request for a map, it transmits the request to the OSM mapping server for retrieving map contents. The OSM mapping server renders the map with specified geospatial information and sends it back to the Web server. The Web server then passes the map contents to clients. On the client side, OpenLayers provides the service to obtain map images from servers and display map tiles on the screen (Haklay et al., 2008). OpenLayers is an open-source JavaScript library running on the client side that helps users interact with dynamic maps from disparate services. A number of extra features are provided by OpenLayers. Specifically, it allows developers to lay numerous data on top of map layers, such as vector layers, markers, and pop-up windows, as Figure 4-5 demonstrates.

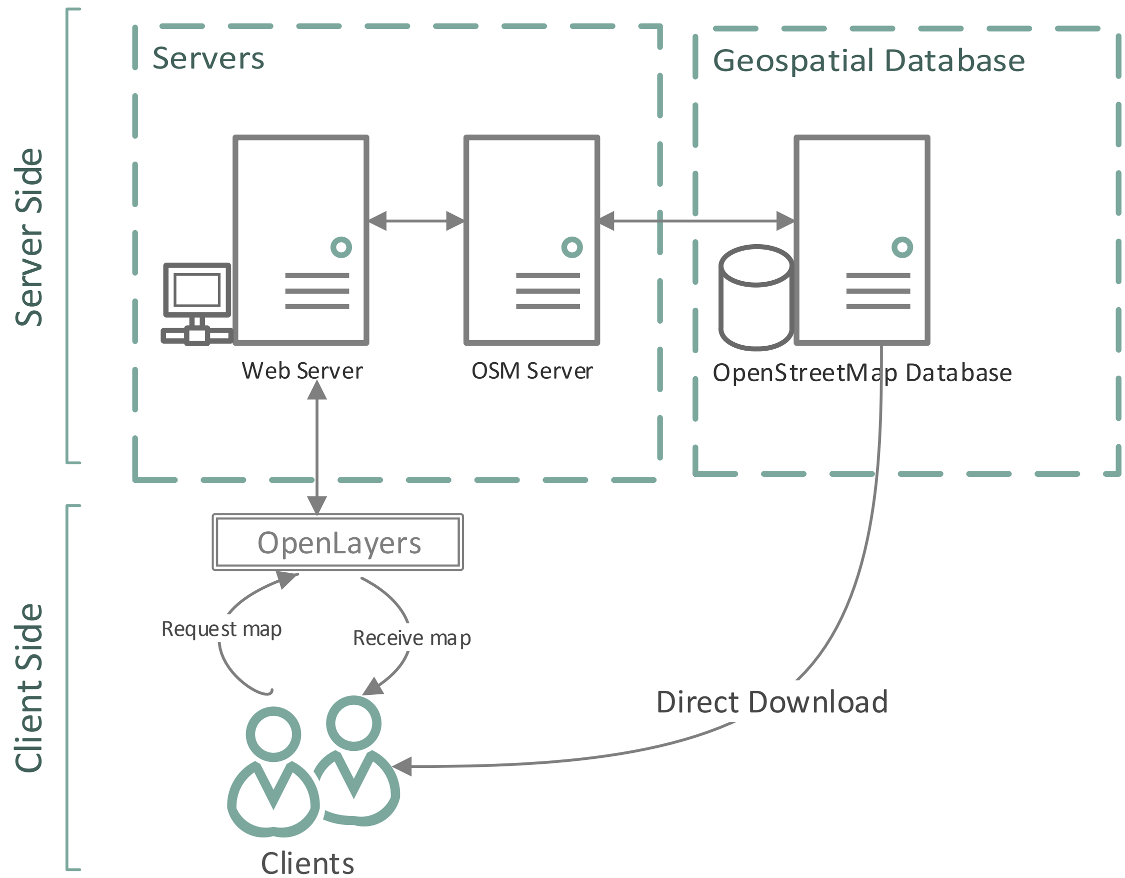


Figure 4-4 Communication Mechanism for OpenStreetMap

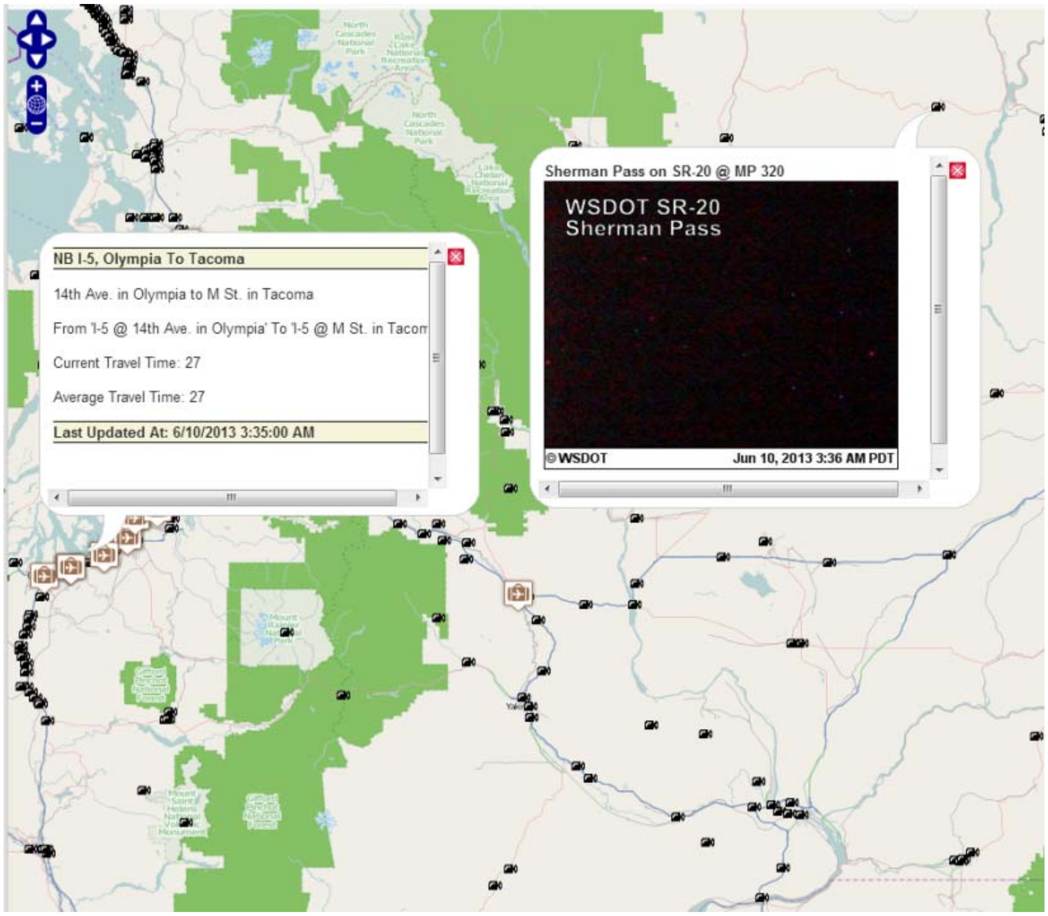


Figure 4-5 Multiple Layers on Top of a Map

4.3.2 R and Rserve

R is a free and powerful statistical analysis tool utilized by more than two million people for machine learning, statistical modeling, and data visualizations (R, 2013). With thousands of active contributors from academia, R keeps evolving with the latest efficient and innovative algorithms. Meanwhile, R provides excellent tools for creating graphics, which enable users to gain better insights via data visualization. Rserve, a TCP/IP server connecting to R, integrates R into the DRIVE Net system so that it takes full advantages of R's statistical computation capability (Rserve, 2013). Several modules in the system use the combination of Rserve and R as the major tool for statistical analysis and data visualization, as Figure 4-6 demonstrates. By integrating R and its countless statistical and graphic packages, DRIVE Net offers an easy and customizable interface for performing complex analysis and data visualization for users, even those without any background knowledge of R scripts.

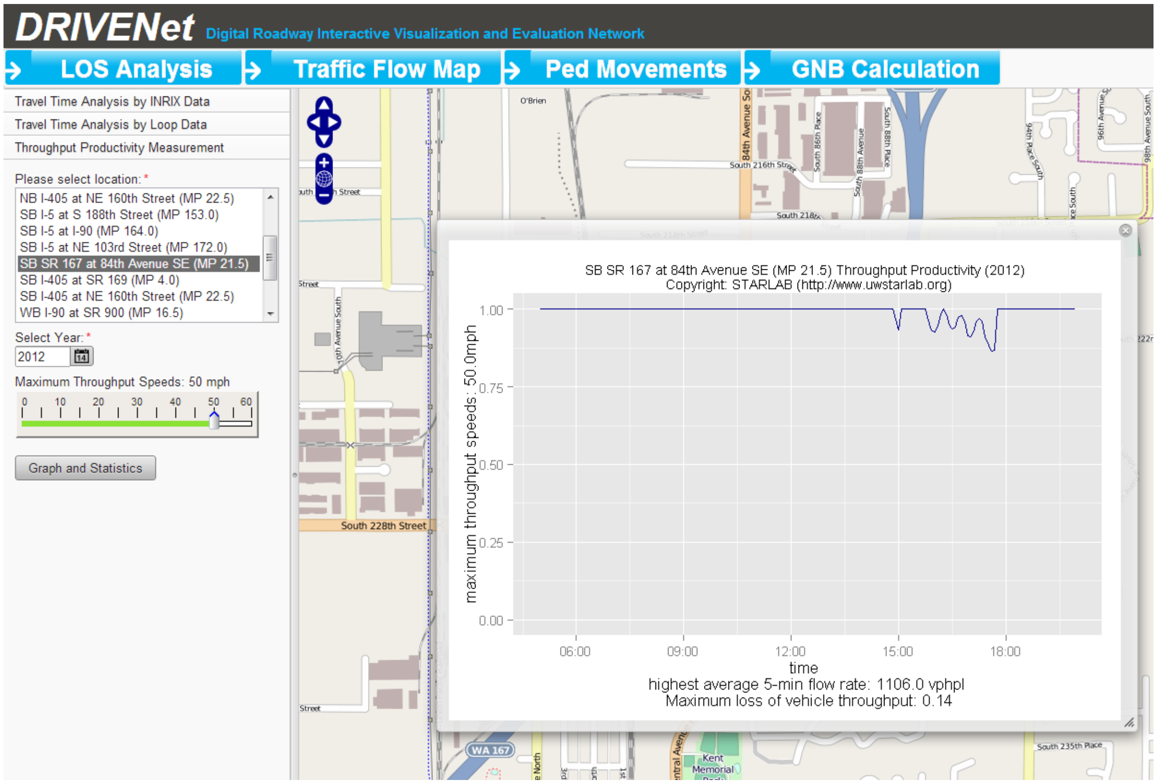


Figure 4-6 Travel Time Performance Measurement

Chapter 5 HCM 2010 Freeway Performance Monitoring

To demonstrate the data sharing, integration, visualization, and analysis capabilities of the DRIVE Net eScience transportation platform, a pilot research effort on automating network-wide, real-time freeway performance measurement was undertaken. It is described in this chapter.

5.1 Background

Real-time freeway performance measurement helps quantitatively describe traffic conditions to transportation researchers, operators, planners, and the general public in a timely manner. With network-wide, real-time information, decision makers can not only quickly evaluate the quality of service on transportation facilities and identify congestion bottlenecks, but can also promptly coordinate facility management and refine policy and investment decisions. The ultimate goal of measuring freeway performance is to improve transportation mobility and accessibility.

The most widely used guidance for measuring freeway performance is the HCM 2010, which has been undergoing constant revision since 1944 (Kittelson, 2000). The 2010 HCM, published by the Transportation Research Board of the National Academies of Science, is a collection of state-of-the-art methodologies for quantifying the quality of service on transportation facilities. One important concept introduced by the HCM is level of service (LOS), which represents a qualitative ranking of traffic performance ranging from **A** to **F**. LOS **A** represents the best traffic operational condition, while **F** is the worst. In this study the HCM 2010 methods were applied to quantify freeway performance. Although every DOT collects real-time traffic data as well as roadway geometric data, there is no universal procedure for utilizing available datasets and automating network-wide freeway operational analysis. FREEVAL 2010, a computational engine executed in Microsoft Excel, is one alternative for freeway facilities analysis (HCM, 2010). However, FREEVAL requires users to manually input geometric and traffic demand information for each segment, which can be extremely cumbersome when analyzing long roadway segments across multiple periods. With DRIVE Net's significant computational power and comprehensive data (such as mainline loop detector data, freeway geometric factors, INRIX speed, etc.), it provides a mature platform from which to perform real-time LOS analysis for freeway segments. Because of the limited information on ramp geometry, on-ramp volumes, off-ramp volumes, and weaving volumes, this study focuses only on quantifying traffic operational performance for basic freeway segments.

5.2 Challenge

The methodology in HCM 2010 has limitations. First, HCM methods can be applied to local oversaturated conditions, but not when system-wide oversaturation occurs. Second, some special conditions are not taken into account, such as road segments near toll plazas, free-flow speed above 75 mph, or free-flow speeds below 55 mph. Although the HCM recommends potential alternative tools to fill these gaps, most of them are commercial simulation tools. Given the cost and technical challenges, it is not an ideal solution to perform such real-time analyses in DRIVE Net.

Measuring network-wide performance poses challenges for integrating multiple geospatial data layers. Different GIS data layers have different line segments, even when they share the same route, start point, and end point. For example, in Figure 5-1, the same route on I-5 northbound from milepost 0 to milepost 10 is segmented into different lines in different GIS data layers. One possible solution is to use a line-to-line vector overlay, as Figure 5-2 shows. However, the operation of a network-wide multi-layer overlay on the fly is inefficient and time-consuming. Better spatial data fusion techniques are needed to efficiently and accurately integrate multiple geo-data sources.

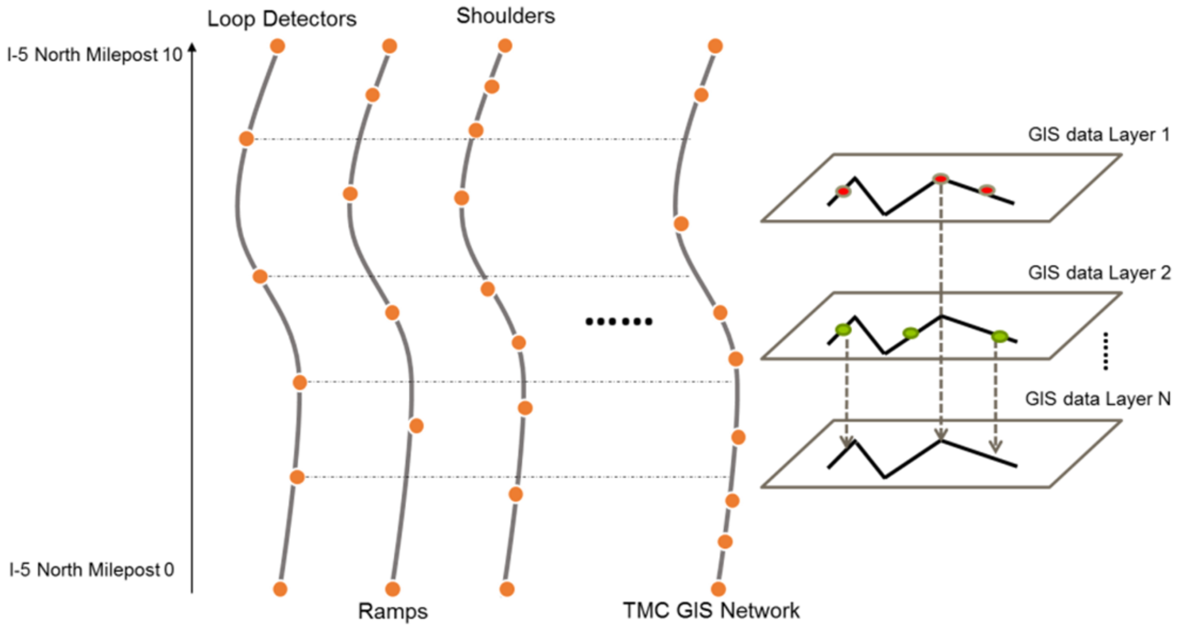


Figure 5-1 Geospatial Data Fusion Challenge

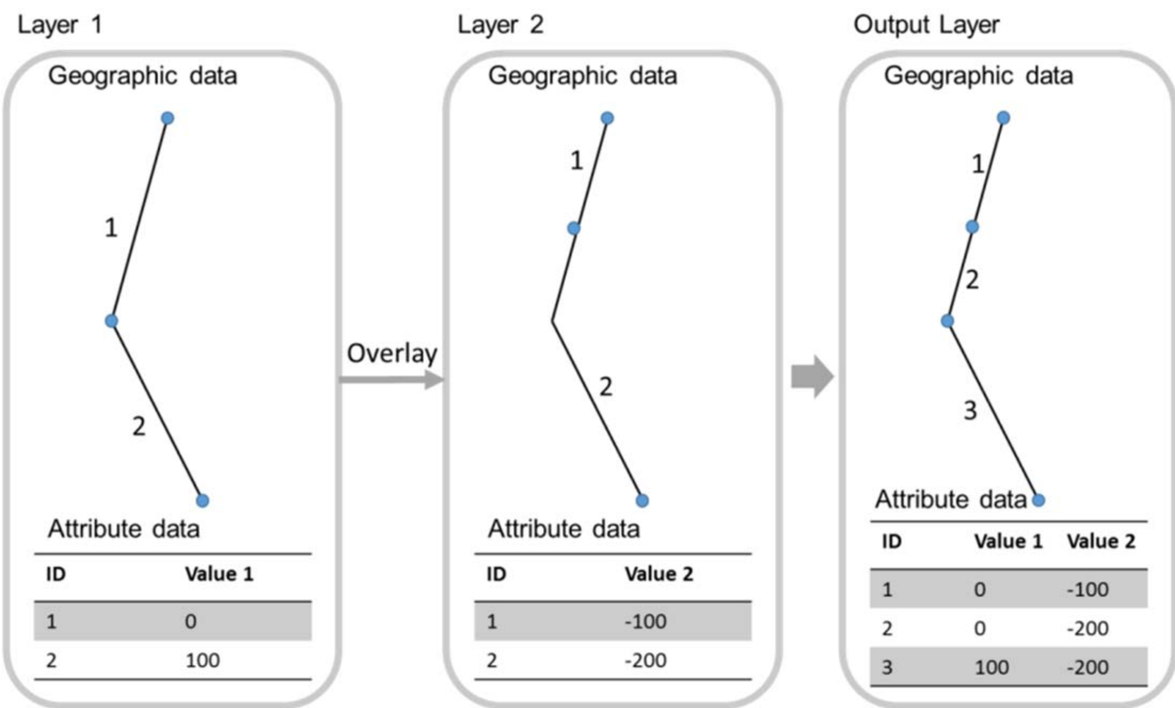


Figure 5-2 Vector Overlay

The objective of this case study was to automate freeway performance measurement in a consistent, efficient, and accurate manner, given existing resources that included geometric factors, loop detector data, and INRIX speed data. The DRIVE Net platform was utilized to implement the automation, not only because of its interoperable data framework but also because of its customizable computing power. The rest of this chapter elaborates on the spatial modeling framework for network-wide freeway performance measurement.

5.3 Modeling Framework

The modeling process was divided into two main phases, as shown in Figure 5-3. In the first stage, the roadway network was segmented by using an innovative spatial data fusion technique called pixel-based segmentation. Once the segmented network had been formed, three different methods were applied to compute LOS in phase 2, namely, the HCM 2010 Method, HCM 2010 Method with INRIX Speed Data, and Multi-regime Prediction Method.

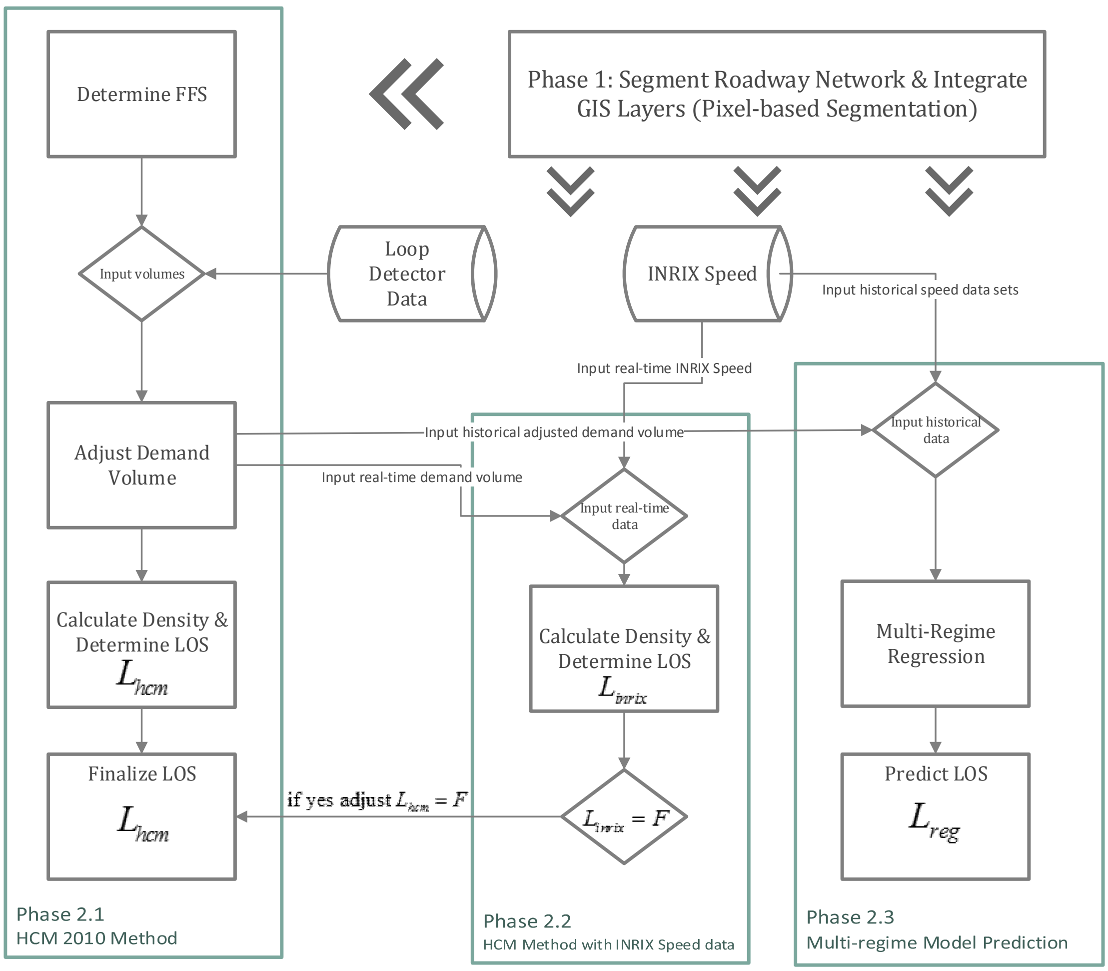


Figure 5-3 HCM2010 Modeling Framework

5.3.1 Segment Roadway Network and Integrate GIS Layers

With heterogeneous datasets, multi-layer geospatial data processing is necessary in order to superimpose multiple GIS layers to generate an output layer. To calculate performance measurements, a fundamental network layer has to be prepared, in which each basic roadway segment has the same attribute data as input value. In particular, the HCM 2010 requires the roadway to be segmented uniformly. Uniform segments must share the same attribute data, including geometric features and traffic features. In GIS, vector overlay is the common and major solution for combining both the geographic data and attribute data from multiple input GIS layers, as presented in Figure 5-2. However, in our case, the network-wide large volume spatial data made the overlay analysis time consuming and computationally intensive. Additionally, if a new GIS layer was imported into the DRIVE Net data warehouse, it would not be realistic to re-perform the entire series of overlay operations.

Therefore, pixel-based segmentation, a novel method for modeling the geospatial data, was proposed. It borrows from the concept of pixels in digital imaging. A *pixel* is generally treated as the fundamental unit of a digital photo, extracted from the words "PICture ELement" (Wikipedia, 2013). In a digital image, millions of pixels are combined together to resemble the subject of the image. The quality of the image greatly depends on the total number of pixels used, which is defined as *resolution*. As Figure 5-4 illustrates, the more pixels an image contains, the more details it is able to reveal.

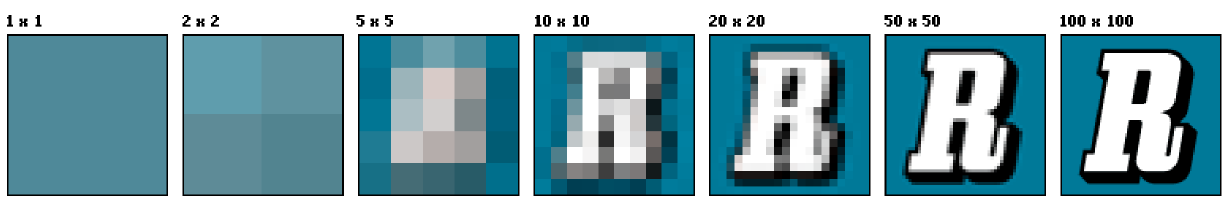


Figure 5-4 Image Resolution (Wikipedia, 2013)

Similarly, pixel-based segmentation subdivides a roadway network into basic segments of equal length, called line pixels. The length of a line pixel defines the resolution of the segmentation. The shorter the pixel length is, the more details the output network contains. For instance, in Table 5-1, I-5 northbound with start milepost 140.4 and end milepost 140.9 is subdivided into five basic segments of equal length (0.1 mile each). The output network attribute data use the combination of route ID, start milepost, and end milepost as a unique key to link with the geographic data. With the geographic data already segmented into equal line pixels, the process of superimposing multiple GIS layers can be accomplished with the attribute data only. Because the Linear Referencing System (LRS) that WSDOT has adopted to identify the locations of features is based on state route ID and feature distance in miles from route beginning (WSDOT's Linear Referencing System, 2013), it is easy and fast to retrieve corresponding features given the route ID, start milepost, and end milepost.

Table 5-1 Examples of Segmented I-5

Route	Start MP	End MP	DIR	Shoulder width	Rdwy width	Num Lanes	Avg width	Urban Rural	Terrain	TRD	Upper Ramp MP	Lower Ramp MP
5	140.4	140.5	North	10	48	4	12	U	Level	0.8333	141.64	138.04
5	140.5	140.6	North	10	48	4	12	U	Level	0.8333	141.64	138.04
5	140.6	140.7	North	10	48	4	12	U	Level	1	141.64	138.04
5	140.7	140.8	North	10	48	4	12	U	Level	1.1666	141.64	138.04
5	140.8	140.9	North	10	48	4	12	U	Level	1.1666	141.64	138.04

Pseudo code for integrating attribute data from multiple GIS layers can be found below:

```
function integrateGISLayers
    for each route r in network
        for k = 0; k < r.length; k = k + pixel_length
            start_mp = k;
            end_mp = k + pixel_length;
            for each input GIS Layers l
                # look up attribute data of l
                # given routeid, start_mp and end_mp
                outputLayer[r, start_mp, end_mp, l]
                    = getAttributeDate(I, r, start_mp, end_mp);
            end
        end
    end
    output outputLayer;
```

The pixel-based segmentation was used in this study for the following reasons: First, it separates the attribute data from geographic data. In comparison to vector overlay operations, the integration of attribute data based on LSR is more efficient, fast, and easy to implement. Second, the fixed segmentation will make it convenient to integrate more GIS layers into an existing network in the future, as long as the pixel resolution remain the same. Third, the value of pixel resolution is flexible, which allows us to select the level of accuracy to achieve. If the line pixel is infinitely close to 0, the output attribute table will capture perfect details no matter how many GIS layers are imported. In reality, pixel size 0.1 mile is a good choice for balancing efficiency and accuracy.

5.3.2 Calculate LOS using the HCM 2010 methodology

Because of limitations in available datasets, this study focused only on LOS calculations for basic freeway segments. The HCM 2010 provides a comprehensive method for analyzing LOS, as shown in Figure 5-3, Phase 2.1. Notice that no measured free flow speed (FFS) was available for the entire network layer; rather, FFS was computed by lane width adjustment and lateral clearance adjustment in this study. The HCM 2010 is unable to handle system-wide oversaturated flow conditions, and focuses only on analyzing under-saturated flow conditions. Over-saturated flow conditions are discussed in the next section.

Step 1: Input Data

In this step, demand volume, number and width of lanes, right-side lateral clearance, total ramp density, percentage of heavy vehicles, peak hour factor, terrain, and the drive population factors are retrieved from the DRIVE Net data warehouse.

Demand Volume

Real-time demand volumes are mainly estimated from loop detectors. The system automatically fetches all the cabinets between the Nearest Upstream Ramp (NUR) and the Nearest Downstream Ramp (NDR), and then it queries the corresponding latest 15-minute flow. Demand volume is calculated by using the following equation:

$$V = 4 \times median(\{latest\ 15minute\ flow\ |cabinet\ between\ NUR\ and\ NDR\}) \quad (5\text{-}1)$$

V: $hourly\ volume\ (veh/h)$

The median is selected to measure the central tendency, since it naturally eliminates the outliers. It is then multiplied by 4, which projects into hourly volume. For instance, in Figure 5-5, there are six cabinets between the upstream and downstream ramps. The 15-minute flows fetched are shown as 500, 100, 450, 450, and 550. Hence, hourly volume for the segments between the upstream and downstream ramps is equal to 450×4=1800 *veh/h*. Notice that if no cabinets/loop are detectors between the upstream and downstream ramps, the system will assume that there is no demand volume input for segments and will use real-time INRIX speed and a historical regression model to predict LOS, which will be discussed later in this chapter.

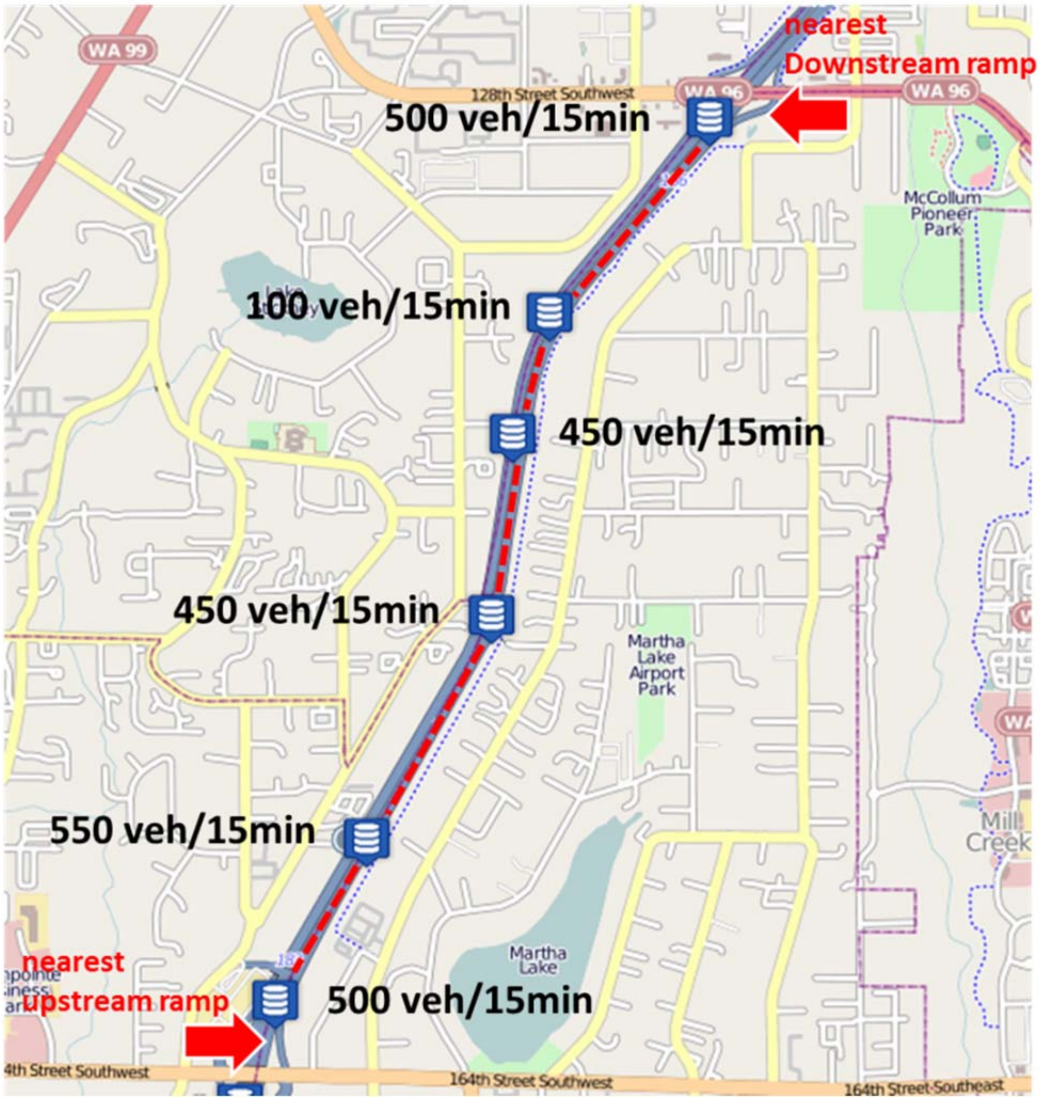


Figure 5-5 Nearest Upstream and Downstream Ramps

Total Ramp Density (TRD)

Total ramp density (TRD) is defined as the total number of ramps (both on and off with one direction) within 2 miles of the midpoint of the segment under study. Given the study segment start milepost and end milepost, the following equation could be used to calculate TRD:

$$midpoint = \frac{start\ milepost + end\ milepost}{2}$$

$$TRD = total\ number(\{ramps \mid ramp\ route = segment\ route\ \textbf{and}\ ramp\ milepost\ beween\ (midpoint + 3) and\ (midpoint - 3)\})/\ 6\ miles \qquad (5\text{-}2)$$

Other Input Data

The geometric data, including number and width of lanes, right-side lateral clearance, and terrain, are originally downloaded from the WSDOT Roadway Datamart for GIS (Roadway Datamart, 2013). Geospatial data fusion is performed by using the methods introduced in the previous section. Because no site-specific data are available for the remaining features, default values recommended by NCHRP Report 599 (Zegeer et al., 2008) are used.

Table 5-2 Default Values for Basic Freeway Segments

Required Data	Default Values
Peak Hour Factor	Urban: 0.92, Rural: 0.88
Driver Population Factor	Urban: 1.0, Rural: 0.975
Percentage of heavy vehicles (%)	Urban: 5%, Rural: 12%

<u>Step 2: Determine Free-Flow Speed</u>

Because the site-specific measured FFS is not available, the following equation, developed by HCM 2010, is used to estimate FFS. Lane width, right-shoulder lateral clearance, and ramp density are taken into account to adjust the Base Free-Flow Speed (BFFS). The estimated FFS is then rounded to the nearest 5 mph as HCM suggests. The adjustment value can be found in HCM 2010.

$$FFS = 75.4 - f_{LW} - f_{LC} - 3.22\ TRD^{0.84} \qquad (5\text{-}3)$$

where

$$FFS = estimated\ free\ flow\ speed\ in\ mph$$
$$f_{LW} = lane\ width\ adjustment\ in\ mph$$
$$f_{LC} = lateral\ clearance\ adjustment\ in\ mph$$
$$TRD = total\ ramp\ density\ adjustment\ in\ mph$$

<u>Step 3: Adjust Demand Volume</u>

Demand volume obtained from loop detectors must be converted into service flow rate under equivalent base conditions. According to the HCM 2010, the base conditions for a basic freeway segment are specified as follows:

- 12-ft lane widths
- 6-ft right shoulder clearance
- 100 percent passenger cars in the traffic stream
- level terrain.

A driver population of regular users familiar with the roadway is then used for the conversion:

$$v_p = \frac{V}{PHF \times N \times f_{HV} \times f_p} \tag{5-4}$$

where

$$v_p = adjusted\ demand\ volume\ under\ base\ conditions\ in\ pc/h/ln$$

$$V = hourly\ demand\ volume\ under\ prevaling\ conditions\ in\ veh/h$$

$$PHF = peak\ hour\ factor$$

$$N = numer\ of\ lanes$$

$$f_{HV} = heavy\ vehicle\ adjustment\ factor$$

$$f_p = driver\ population\ adjustment\ factor$$

The heavy-vehicle adjustment factor can be calculated by the following equation:

$$f_{HV} = \frac{1}{1+P_T(E_T-1)+P_R(E_R-1)} \tag{5-5}$$

where

$$f_{HV} = heavy\ vehicle\ adjustment\ factor$$

$$P_T = percentage\ of\ trucks\ and\ bus\ in\ the\ traffic\ stream$$

$$P_R = percentage\ of\ recreational\ vehicles\ in\ the\ traffic\ stream$$

$$E_T = passenger\ car\ equivalent\ factor\ for\ trucks\ and\ bus$$

$$E_R = passenger\ car\ equivalent\ factor\ for\ recreational\ vehicles$$

As HCM suggests, the proportion of recreational vehicles in the traffic stream is small and close to 0 in many cases. Hence, in this study, P_R was set to be 0 as the default value. The value of passenger car equivalent factors E_T and E_R are also recommended by HCM 2010 on the basis of the type of terrain or grades.

Step 4: Calculate Density and Determine LOS

Given the FFS from **Step 2** and adjusted volume v_p from **Step 3**, the average passenger car speed S can be found in Figure 5-6 or computed by the speed-flow equation in Table 5-3. Then the density D_{hcm} can be derived:

$$D_{hcm} = \frac{v_p}{S} \tag{5-6}$$

Once the density has been computed, the LOS L_{hcm} can be determined from Table 5-4.

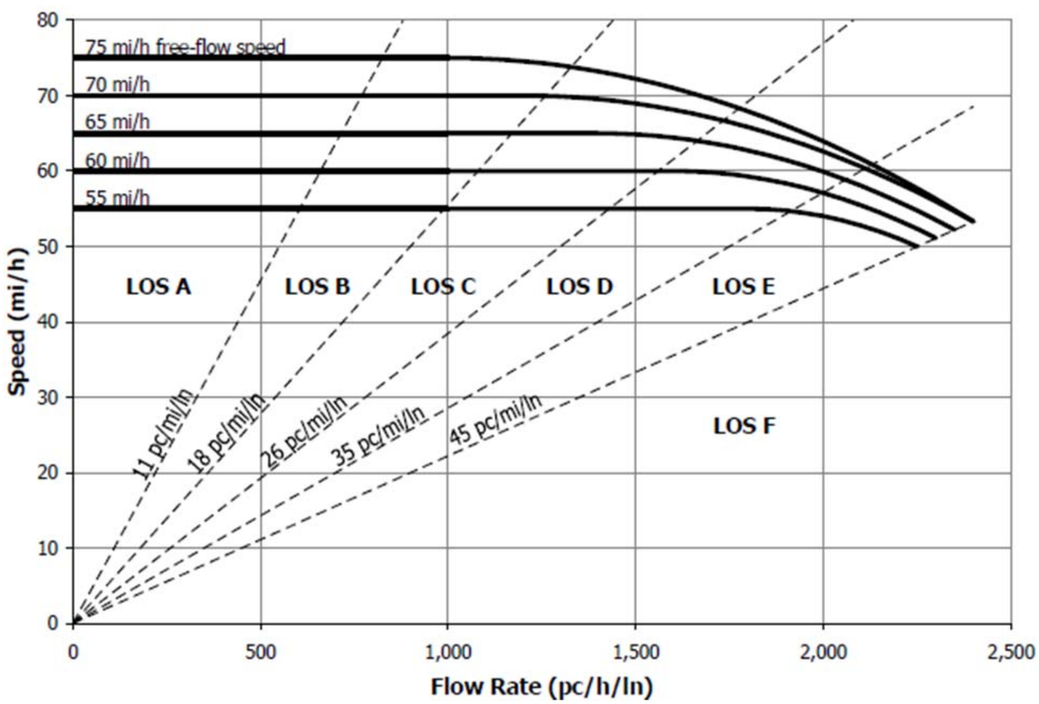


Figure 5-6 HCM Speed-Flow Model (HCM, 2010)

Table 5-3 Speed-Flow Equations (HCM, 2010)

FFS (mi/h)	Break-Point (pc/h/ln)	Flow Rate Range: ≥0 ≤ Break-Point	Flow Rate Range: >Break-Point ≤ Capacity
75	1,000	75	$75 - 0.00001107 (v_p - 1{,}000)^2$
70	1,200	70	$70 - 0.00001160 (v_p - 1{,}200)^2$
65	1,400	65	$65 - 0.00001418 (v_p - 1{,}400)^2$
60	1,600	60	$60 - 0.00001816 (v_p - 1{,}600)^2$
55	1,800	55	$55 - 0.00002469 (v_p - 1{,}800)^2$

Notes: FFS = free-flow speed, v_p = demand flow rate (pc/h/ln) under equivalent base conditions.
Maximum flow rate for the equations is capacity: 2,400 pc/h/ln for 70- and 75-mph FFS; 2,350 pc/h/ln for 65-mph FFS; 2,300 pc/h/ln for 60-mph FFS; and 2,250 pc/h/ln for 55-mph FFS.

Table 5-4 LOS Criteria for Basic Freeway Segments

Density	LOS
11	A
18	B
26	C
35	D
45	E

5.3.3 Incorporate the Real-Time INRIX Speed into LOS Calculation

One of the limitations of the HCM method is that it cannot analyze system-wide oversaturated conditions. In other words, once the demand is greater than the capacity, HCM is unable to estimate space mean speed as well as density. However, in reality, it is critical to identify oversaturated conditions spatially and temporally so that operators and planners can understand bottlenecks (formation, propagation, and dissipation) in their facilities. As suggested by Figure 5-7, in oversaturated conditions traffic speeds drop dramatically, typically below 35 mph. To fill the gap of analyzing oversaturated conditions, INRIX speed data are incorporated into the LOS calculation. With the demand volume still obtained from loop detectors and adjusted by the HCM 2010 methodology, INRIX speed S_{inrix} is used to estimate the density as shown below:

$$D_{inrix} = {v_p}/{S_{inrix}}$$

$$\delta = \begin{cases} 1 \; if \; D_{inrix} \leq 45 \\ 0 \; if \; D_{inrix} > 45 \end{cases}$$

$$D_{hcm} = \delta \cdot D_{hcm} + (1 - \delta) \cdot D_{inrix} \tag{5-7}$$

where

$$D_{inrix} = density\ calcuated\ by\ INRIX\ speed$$

$$D_{hcm} = density\ calcuated\ by\ HCM\ methods$$

$$v_p = adjusted\ demand\ volume\ under\ base\ conditions\ in\ pc/h/ln$$

$$S_{inrix} = real\ time\ INRIX\ speed$$

Additionally, using INRIX speed to estimate LOS provides ground-truth data by which to judge the feasibility of HCM methodologies, as discussed in section 5.4.

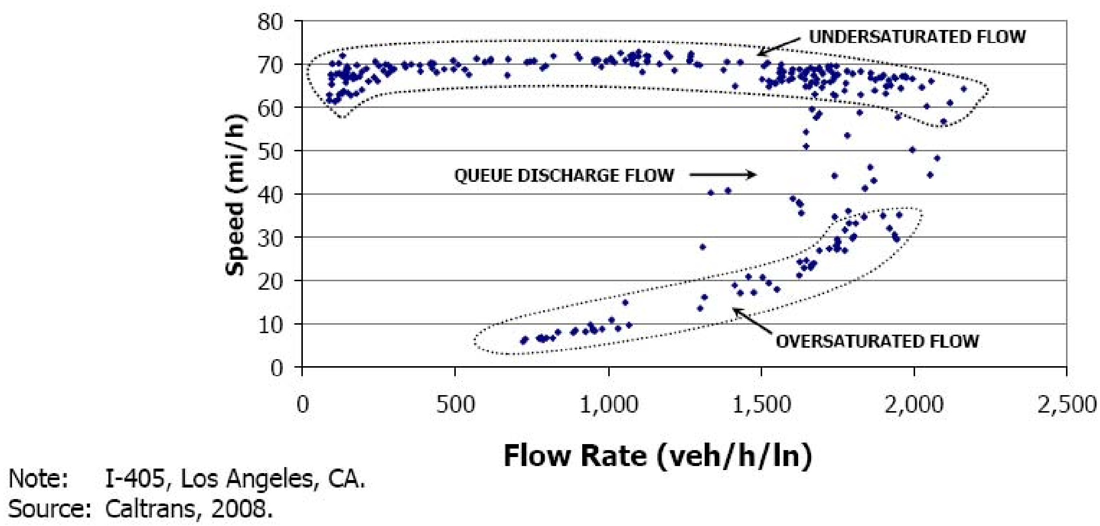


Figure 5-7 Undersaturated, Queue Discharge, and Oversaturated Flow (HCM, 2010)

5.3.3 Develop Empirical Speed-Density Regression Equations to Predict LOS

The quality of traffic data greatly influences the accuracy of performance estimation and as among the primary concerns in this analysis. Data quality issues involve at least (1) missing data, (2) suspicious or erroneous data, and (3) inaccurate data (Turner, 2001). Erroneous data are those that do not follow accepted principles or go beyond thresholds, while inaccurate data contain inexact values due to measurement error. In this study, these three types of errors were all treated as invalid traffic data entries. The data quality issues involved two major challenges: (1) how to identify the bad data and (2) how to compensate for the invalid data input.

Many efforts have been made to develop comprehensive and sophisticated data quality checking methods. In practice, the threshold approach is often adopted to ensure that sensor values fall within a reasonable range. The combination of volumes, speed, and occupancies provides a relatively straightforward yet robust way to check data error. Jacobson et al. (1990) developed an algorithm that uses volume-to-occupancy ratios to examine the reliability of loop detector data. In addition, time series of traffic samples can be used for comparison. For example, Chen et al. (2003) proposed a diagnostics algorithm to efficiently find malfunctioning single-loop detectors on the basis of the sequence of volume and occupancy measurements for an entire day. Ishak (2003) developed a fuzzy-clustering approach to measure uncertainties in freeway loop detector data. Moreover, measuring spatial relationships between detectors also turns out to be an effective tool for accurately detecting errors. Kwon et al. (2004), for instance, utilized the strong measurement correlations between upstream and downstream sensors to detect spatial configuration errors.

All those advanced algorithms demonstrate robust solutions in identifying quality issues related to loop detectors. A related question is how to estimate real-time density or LOS when the input demand volume is invalid. With the relatively comprehensive speed dataset from INRIX, this research focused on predicting real-time density, given historical traffic data and real-time speed, as the solution to dealing with invalid input volume.

Empirical speed-density relationships provide the most abundant source of data for performing predictions. Over the past few decades, a great deal of research has been done on developing speed-density models. Because of its data-driven nature, a multi-regime model based on cluster analysis (Sun et al., 2005) was adopted to fit empirical speed-density observations. This method first applies a *K*-means algorithm to traffic datasets, which naturally partitions the data into homogenous groups. It then applies a series of single-regime models to find the one that best fits the data, such that breakpoints can be automatically determined. Notice that Sun's method chooses the *k* value by trial and error; in this study, the optimal number of clusters was determined by the average Silhouette criterion instead of trial and error. For conceptual testing purposes, only linear, logarithmic, and exponential models were included. Pseudo code for building a multi-regime traffic model can be found below:

```
function PerformSpeedDensityRegression
     # Given traffic datasets observations
     # Choosing k using the Sihouette
     k = DetermineKbySihouette(observations);
     clusters = kmeans(observations, k);
     for each cluster c in clusters
          # three basic functions chosen to fit c
          lmReg = lm(c.speed ~ c.density, data = c);
          logReg = lm(c.speed ~ ln(c.density), data = c);
          expReg = lm(c.speed ~ exp(c.density), data = c);

          #choose the regression model fits best
          bestReg = max(lmReg.Rsquare, logReg.Rsqaure, expReg.Rsquare);
          output bestReg;
     end
```

5.4 Implementation Result

The aforementioned modeling framework was implemented in a real-world network for pilot testing purposes. The I-5 northbound corridor in Seattle, Washington, from milepost 140 to milepost 195 was selected as the study site. It is the primary travel route connecting Tacoma and Everett through downtown Seattle, and it has the most comprehensive traffic data available. Figure 5-8 shows cabinets 140 deployed by WSDOT along the corridor. In the next several subsections, network segmentation and data preprocessing are briefly introduced, followed by an explanation of LOS results computed from the three proposed methods: the HCM 2010 method, the HCM 2010 method with INRIX speed data, and the multi-regime regression method. The satisfactory results further confirm the reliability and feasibility of the proposed modeling framework.

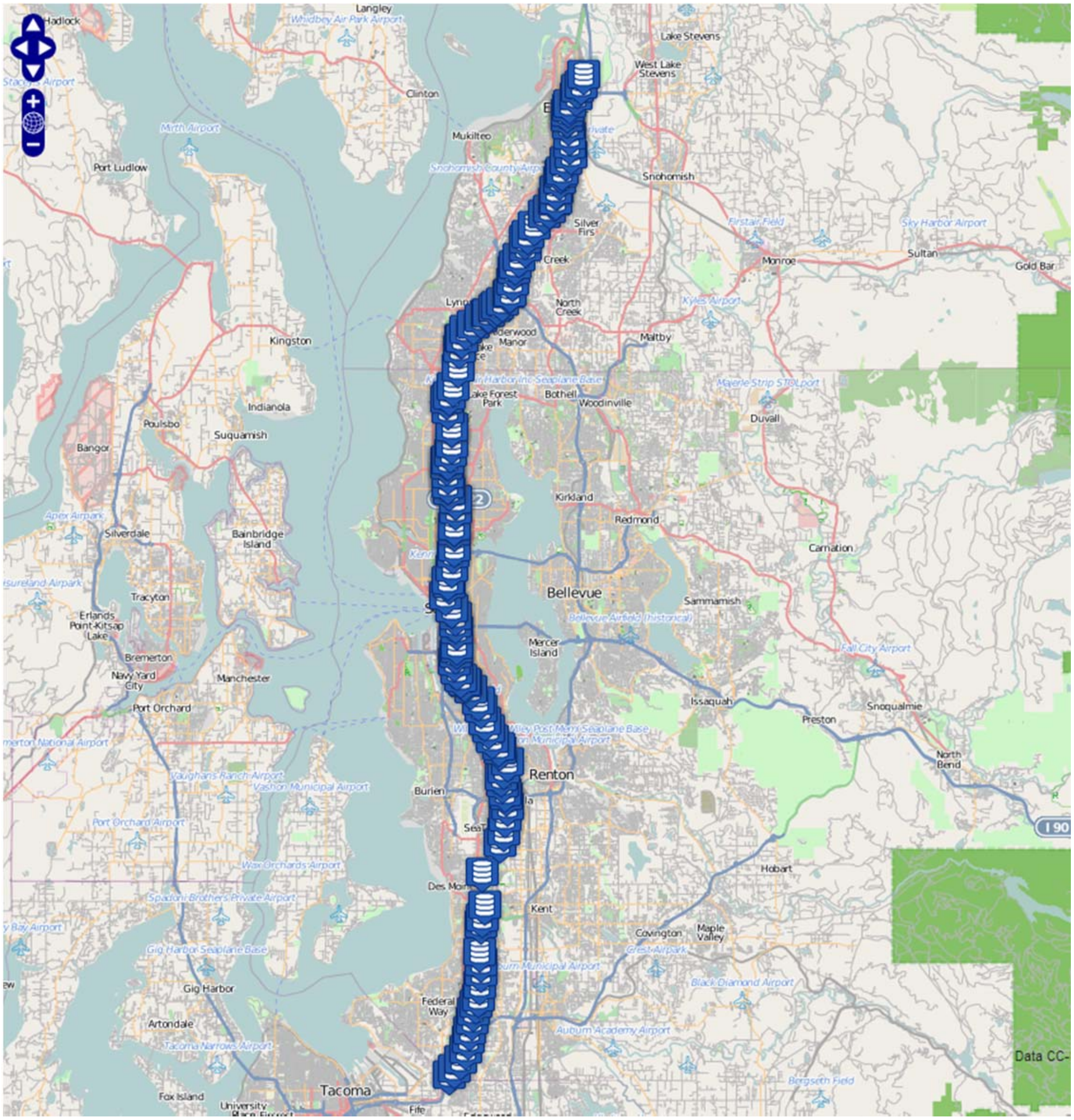


Figure 5-8 I-5 Northbound Corridor (Tacoma - Everett)

5.4.1 Network Segmentation

By applying pixel-based segmentation to the geographic data, introduced in section 5.3, the corridor was subdivided into 550 basic freeway segments with pixel length of 0.1 mile. The corresponding attribute data were then fused according to route ID (I-5), start milepost, and end milepost. Table 5-5 presents the sample attribute data. Notice that the roadway geometric data are relatively static and not updated very often. It is more efficient and effective to pre-process the attribute data fusion instead of running it on the fly.

Table 5-5 Fused Attribute Data

Route	Start MP	End MP	DIR	Shoulder width	Rdwy width	Num Lns	Avg width	Urban Rural	Terrain	TRD	Upper Ramp MP	Lower Ramp MP
5	140.4	140.5	North	10	48	4	12	U	Level	0.8333	141.64	138.04
5	140.5	140.6	North	10	48	4	12	U	Level	0.8333	141.64	138.04
5	140.6	140.7	North	10	48	4	12	U	Level	1	141.64	138.04
5	140.7	140.8	North	10	48	4	12	U	Level	1.1666	141.64	138.04
5	140.8	140.9	North	10	48	4	12	U	Level	1.1666	141.64	138.04

5.4.2 Volume and Speed Data Sets

Real-time volume data are collected from single loop detectors every 20 seconds, and INRIX speed data are aggregated every 1 minute on the basis of GPS data, respectively. Both datasets are archived in the DRIVE Net database. For pilot testing purposes, two-day observations were extracted and utilized in the latter computation. The two traffic datasets were further aggregated into 15-minute time intervals, as recommended by the HCM. Data quality control techniques were applied to ensure data accuracy. For example, several thresholds were set to eliminate obvious outliers. Comprehensive data quality control is critical to the DRIVE Net system. For more detail, please refer to (Wang et. al., 2009).

Figure 5-9 shows the scatter plot of adjusted volume v_p vs. speed S_{inrix} as well as density, D_{inrix} vs. speed S_{inrix}, for a total of 95,040 observations. Notice that the service volume, v_p , used in Figure 5-9 was under base conditions, converted from real-time traffic counts following the HCM 2010 methods.

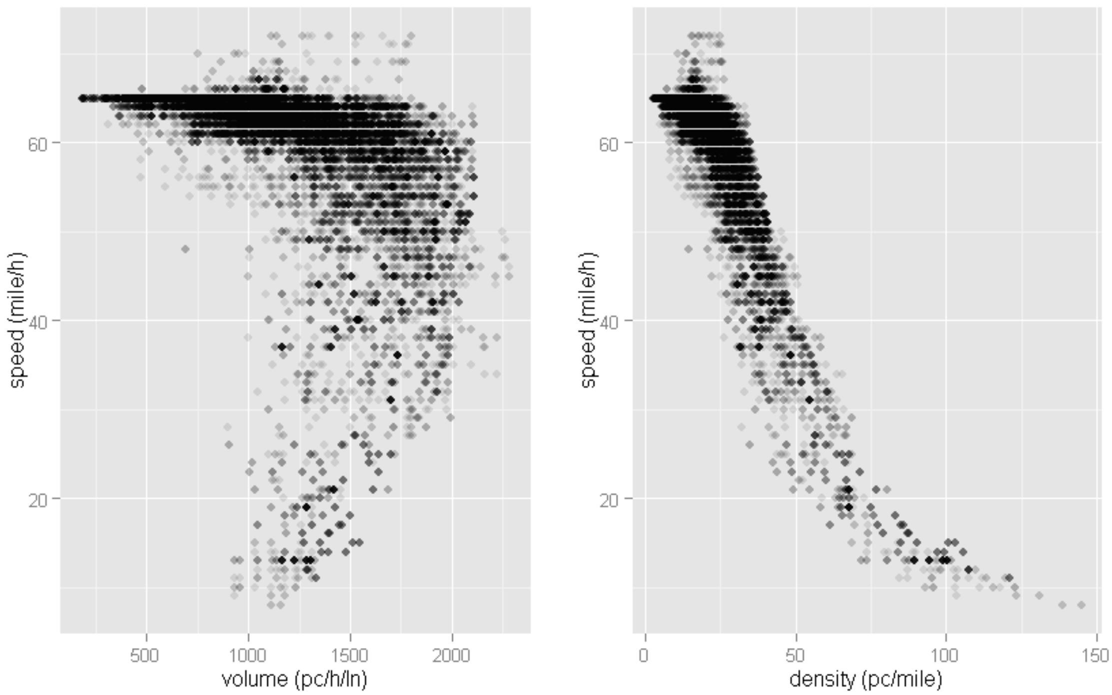


Figure 5-9 INRIX Speed, Adjusted Volume, and Density

5.4.3 HCM Method with/without INRX Speed Data

The HCM method with volume only and HCM method with volume and speed were applied to compute L_{hcm} and L_{inrix} , respectively. Because the HCM method is unable to analyze oversaturated conditions (LOS = **F**), the comparison between L_{hcm} and L_{inrix} was conducted for undersaturated flow only. Of the total 92,400 observations that fell into the undersaturated conditions, 83.83 percent of L_{hcm} was equivalent to L_{inrix}, a total of 77,458 data points. The match rate increased to 98.98 percent if adjacent LOS's were treated as approximately equal (e.g., LOS **A**≅LOS **B**). The fact that these two methods were highly consistent in estimating LOS delivers suggests the following: (1) the proposed methodologies such as pixel-based segmentation can generate satisfactory accuracy; (2) using INRIX speed data to determine oversaturated conditions is feasible and cost effective; and (3) the quality of INRIX speed data is proved to some extent, given the consistency between results computed with both HCM methods in Phase 2.1 (without INRIX speed data) and Phase 2.2 (with INRIX speed data).

Table 5-6 and Figure 5-10 compare the LOS category counts produced by the two methods. Note that LOS computed by using INRIX speed usually underestimated service quality. These results are consistent with recent research on transportation sensor comparisons conducted by Dr. Yegor Malinovskiy from the UW STAR Lab, who found that INRIX speed data usually have a smaller standard deviation and tend to underrate traffic conditions.

Table 5-6 LOC Count by Phase 2.1 (without INRIX Speed Data) and Phase 2.2 (with INRIX Speed Data)

LOS	HCM Method	HCM Method with INRIX Speed
A	37430	35994
B	30343	25188
C	18677	20324
D	5756	8077
E	194	2817
F	2640	2640

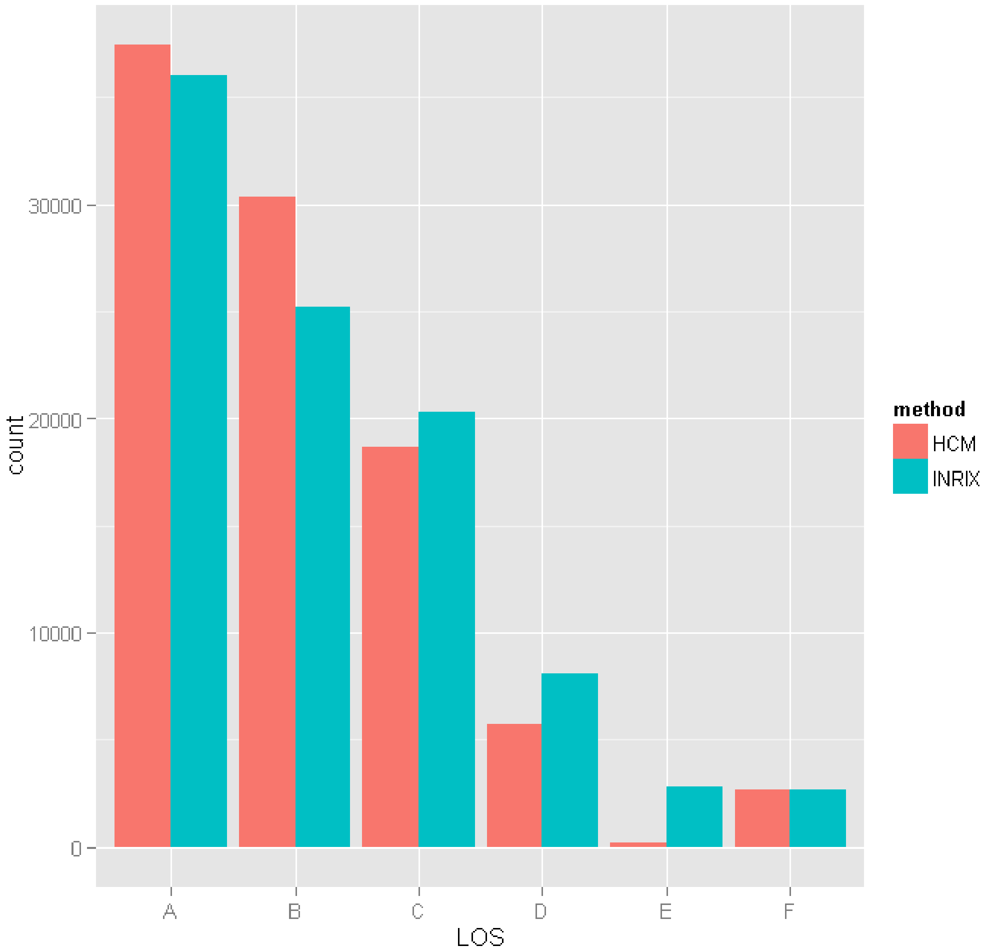


Figure 5-10 LOS by Phase 2.1 (without INRIX Speed Data) and Phase 2.2 (with INRIX Speed Data)

5.4.4 Regression Analysis

To compensate for missing or low quality data, an empirical multi-regime density-speed model was used to predict density in this study. During the implementation, the two-day datasets were divided evenly into a training set (November 07, 2011) and a testing set (November 08, 2011) to avoid overfitting to test conditions.

```
function PerformSpeedDensityRegression
    # Given traffic datasets observations
    # Choosing K using the SilHouette
    K = DetermineKbySilhouette(observations);
    clusters = kmeans(observations, K);
    for each cluster c in clusters
        # three basic functions chosen to fit c
        lmReg = lm(c.speed ~ c.density, data = c);
        logReg = lm(c.speed ~ ln(c.density), data = c);
        expReg = lm(c.speed ~ exp(c.density), data = c);

        #choose the regression model fits best
        bestReg = max(lmReg.Rsquare, logReg.Rsqaure, expReg.Rsquare);
        output bestReg;
    end
```

Following the procedures described in the pseudo code above, the *K* value was chosen to be 2 by using the Silhouette. According to suggestions from Sun et al. (2005), using the original data for the *K*-mean algorithm would outperform the normalized data. Hence, this study applied the *K*-mean algorithm to the training set without normalization. The clustering results can be found in Figure 5-11 and Table 5-7. As expected, Cluster 1 had high speed and low density, which represents a free-flow regime, while Cluster 2 had lower speed and high density, which represents congested-flow regime.

Three single-regime models, namely, linear, logarithmic, and exponential functions, were then used to fit Cluster 1 and Cluster 2, respectively. The one with the greatest *R squared value* was chosen to represent the empirical speed-density relationship. The following equation shows the final two-regime model obtained from the training set:

$$u = \begin{cases} 66.3237 - 0.1851k \; if \; k \leq 24.6 \\ \exp(4.657 - 0.02169k) \; if \; k > 24.6 \end{cases} \tag{5-8}$$

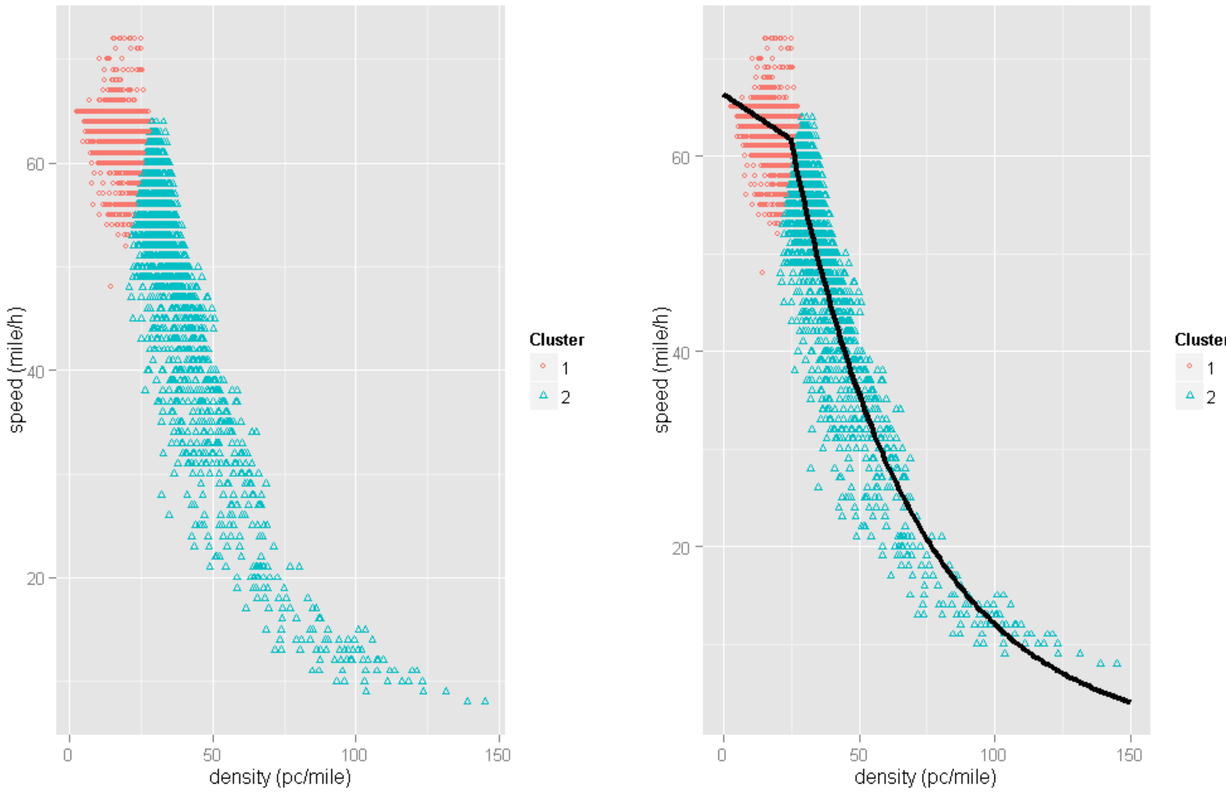


Figure 5-11 Training Set: Two Clusters by K-means Algorithm Analysis

Table 5-7 Training Set: Clustering Centers by K-means Algorithm

I-5 Northbound	Speed (mile/h)	63	53
	Density (pc/mile)	16.94186	32.87736
	Percentage	80.27%	19.73%

As Figure 5-11 shows, the two-regime model fit the training set quite well. A comparison between the ground-truth value L_{inrix} and predicted value L_{reg} for both training set and testing set was further conducted. The testing set yielded an even lower error, as indicated in Table 5-8. If adjacent levels were treated as approximately equal, both training error and test error were less than 5 percent (shown as an accuracy of ± 1 in Table 5-8). This proves the feasibility and accuracy of the proposed modeling framework.

Table 5-8 Test Results

Date Set	Accuracy	Accuracy of ± 1
Training Set	57.7%	95.38%
Test Set	59.84%	95.01%

5.4.5 Data Visualization

Figure 5-12 shows the user interface designed for the freeway performance measurement module. The control panel is located on the left side, while the interactive map is on the right. Users are free to input date, time, route ID, route direction, start milepost, and end milepost and to query the corresponding LOS map by clicking the button "LOS Map". As long as the system receives the user request, it will show the LOS map based on criteria described in the color legend on the left. As Figure 5-13 shows, the LOS map gives a straightforward way to demonstrate LOS spatially, which enables users to easily identify bottlenecks. Additionally, a related statistics report can be prepared and automatically displayed for downloading if users click the button "Statistics Report". The report includes detailed information such as segments, geometric factors, speed, density, and LOS, which enables users to further analyze the data.

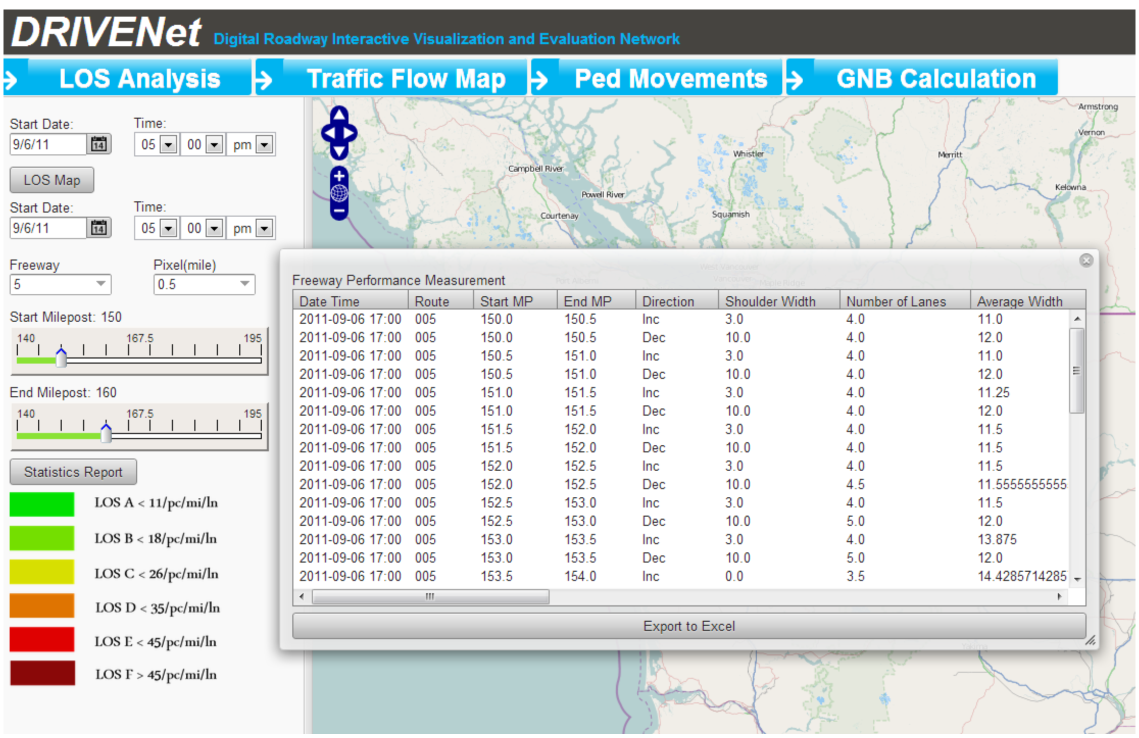


Figure 5-122 User Interface Design

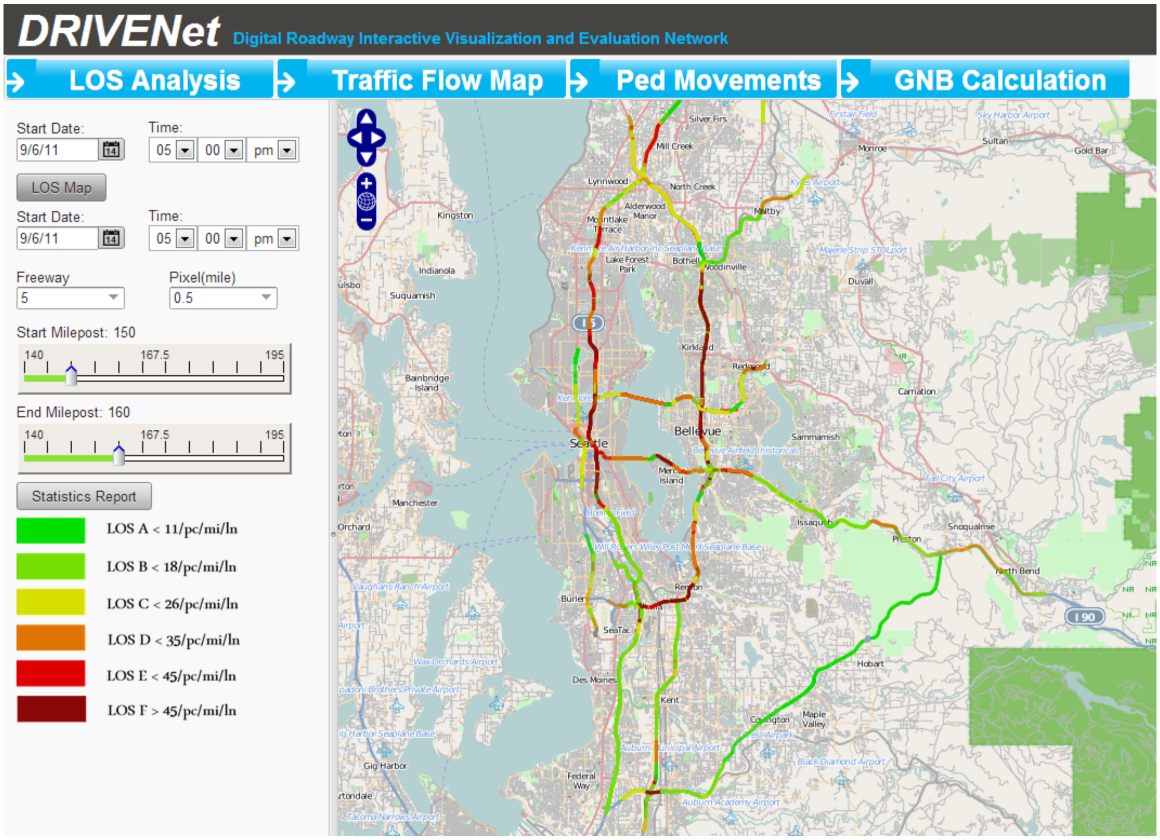


Figure 5-133 Data Visualization: LOS Map

Chapter 6 Computational Methods for WSDOT Gray Notebook (GNB) Statistics Calculation

As a primary accountability reporting tool, WSDOT's Gray Notebook has been updated quarterly and annually since 2001. The report summarizes multiple aspects of the Washington state transportation system, including safety, rest areas, ferry vessel and terminal preservation, travel information, wetlands protection, commercial vehicle information systems and networks, and trucks, goods and freight (WSDOT, 2013). To better monitor and alleviate congestion, WSDOT also publishes its congestion report annually. The Department utilizes various detectors to collect transportation data, which are then analyzed for reporting purposes. Such congestion reporting assists the public and WSDOT officials in gaining a better understanding of whether its existing congestion mitigation countermeasures are effective (WSDOT, 2012). The statistics generated from the congestion report are incorporated into the WSDOT Gray Notebook.

Traditionally, processing massive transportation data and calculating congestion measures are labor-intensive tasks that require intensive efforts to coordinate among different partners. In addition, the complexity of congestion analysis requires the expertise of various disciplines, so WSDOT has to spend a great deal of manpower and time to produce the congestion report each year. However, the DRIVE Net system can address these issues by integrating multiple data sources, conducting desired analytical functions, and presenting the congestion report via a map-based, online platform.

This chapter describes how the loop detector data are first preprocessed through a comprehensive data quality control procedure to detect, remedy, and correct erroneous records. Next, the processed data are further incorporated into a computational engine for Gray Notebook statistics calculation. The generated performance indicators are then visualized by the DRIVE Net system and used to generate all the necessary reporting and graphic functions required by WSDOT.

6.1 Freeway Loop Data Quality Control

Data quality control (DQC) was a key component in this research because quality data yield reliable information on which smart decision making depends. Early DQC work, such as that conducted by Ingram (1976) and Chen and May (1987), focused on raw inductive loop detector output. Specifically, detector level errors include chatter (rapid cycling of the detector), crosstalk (adjacent sensors actuating together), and failed on/off sensors, among others. Over time, many of these early, detector-level diagnostics have been incorporated into the detectors themselves, controller software, and practice. It is important to remember that these basic diagnostics, while well-known and accepted for loop detectors, may apply to other detectors that do not have the history of inductive loop detectors. For the next level of DQC, blocks of data from a sensor are used to determine whether the results it presents are within expected boundaries. A number of such threshold methods were developed during the 1990s. Good summaries of these methods were compiled by Turochy and Smith (2000) and May et al. (2004). Threshold-based methods can be thought of as drawing lines on a chart and discarding data that lie beyond the lines. For example, a maximum volume threshold would discard data that reported volumes greater than the threshold maximum value. Current DQC research has two branches: the first uses network information to identify errors and the second has returned to the event roots used in earlier research. Network-based DQC methods focus on volume correction, typically relying on conservation of vehicles between sensor stations, as in the work done by Wall and Dailey (2003).

Loop detector data are used to compute Gray Notebook statistics. A two-step data quality control procedure is proposed: first, the raw loop data should be subjected to a series of error detection tests to identify missing and erroneous data. These data should then be flagged for further corrections and remedies. Several statistical algorithms were developed to estimate the missing data and replace those erroneous records. The corrected data should be periodically stored in the database for Gray Notebook calculation. The 20-second loop data and 5-minute data should all be processed for quality control purposes.

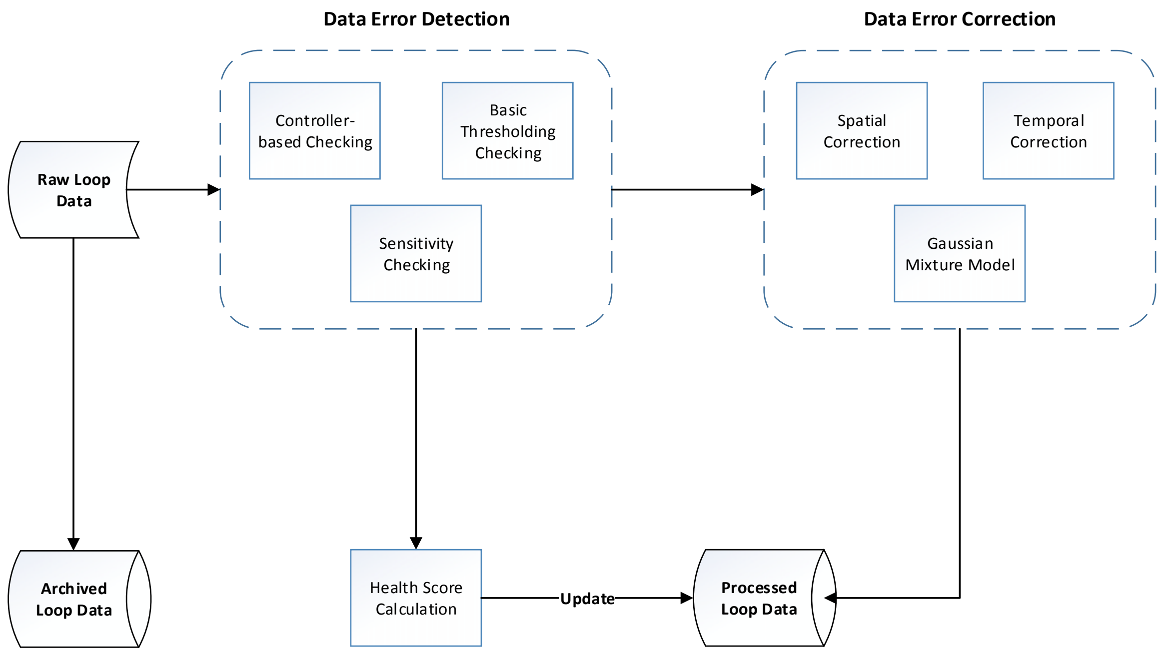


Figure 6-1 Loop Data Quality Control Flow Chart

Figure 6-1 shows how incoming loop detector data are processed in the DRIVE Net DQC procedure. Shortly after the raw data arrive, the first data quality control checks are performed. The research team found it very important to maintain the raw data in addition to the processed data. Keeping the original raw data allowed the research team to improve the data quality control algorithms and quantify their efficacy. It also served as an insurance policy against false positives in the DQC algorithms.

6.1.1 Data Error Detection

The first step is to utilize the controller-equipped error detection mechanism to identify data errors. WSDOT's loop detector cabinets are able to provide simple data quality checking on the hardware end, and to flag errors directly with each record. These errors include short pulses, loop chatter, and values outside of allowable volume/occupancy ranges, and they include a flag for operator-disabled loops (Ishimaru and Hallenbeck, 1999). To be specific, the existing columns in the raw loop data include several flags to indicate the status of each record. For instance, the "Data" column in the 20-second loop database is an indicator of missing data. This data quality control procedure focuses on daily loop data for preliminary checking. If more than 90 percent of the records for a particular loop detector are considered to be "good data" by the controller, then this loop can be used for freeway performance monitoring.

The raw loop data are then further transferred to a series of error detection procedures. The simplest approaches are the threshold-based methods. They are designed to check whether the incoming data are valid and within expected bounds. This is an important step because some sensors feeding the DRIVE Net system report -1 for the volume as an error flag, which can cause calculation errors if this value is not corrected and converted into a bad data flag. These threshold criteria are listed below according to Chen et al. (2003):

a. For each time interval, the volume is zero while the occupancy is greater than zero.
b. For each time interval, both volume and occupancy are zero (between 5:00 AM and 8:00 PM).
c. For each time interval, the occupancy exceeds 0.35.

The loop data samples are retrieved from 5:00 AM to 8:00 PM, as it is hard to judge the loop data quality beyond this time range using the above three criteria. For a given day, there are 3240 20-second records and 216 5-minute records per detector. For each loop detector, the number of records belonging to error type (a), (b), and (c) are denoted as N_a, N_b, N_c respectively, and the criteria to check the status of a loop detector for any date are expressed as:

$$flag = \begin{cases} 0 & \text{if } \frac{N_a}{N} < p_a, \frac{N_b}{N} < p_b, \frac{N_c}{N} < p_c \\ 1 & otherwise \end{cases} \tag{6-1}$$

where N is the number of time intervals of daily loop data (3240 for 20-second loop data and 216 for 5-minute loop data), and $p_i (i = a, b, c)$ is the percentage threshold belonging to error type a, b, or c.

The above DQC procedures have inherent shortcomings for detecting systematic errors such as over-sensitivity and under-sensitivity. To better capture those errors, a statistical Gaussian Mixture Model (GMM) was proposed by Corey et al. (2011). The GMM analysis is performed monthly, using intervals from only one vehicle to simulate the event data the method was originally designed to use. Three parameters are determined by the GMM fitting algorithm: distribution weight, distribution mean on time, and distribution on time variance. Short vehicles, which make up the majority of the vehicle population, should be represented by the largest modeled distribution weight, and their average length divided by speed is represented by the distribution mean on time. When the distribution weights or means are too high or low, the data are flagged. If the error is not too extreme, correction factors may be calculated and implemented. The GMM analysis produces an error type and a correction factor that can be used to adjust the occupancy values of loop detector data suffering certain error types. The error type identification indicates whether the loop detector data are good, suffering from software correctible errors, or in need of technician attention. Note that the GMM analysis is capable of identifying errors that thresholds cannot. Specifically, thresholds cannot capture small to medium sensitivity level errors because the occupancy values generated correspond to either faster or smaller vehicles for under-sensitivity or slower or larger vehicles for over-sensitivity.

With the above three primary data quality checking processes, each loop detector's health score can be calculated. The health score is defined as the percentage of good records for daily loop data. For example, consider the following scenario: there are 340 records with high occupancies on a particular day for 20-second loop data, and 100 records are flagged as "bad" by the cabinet. The loop detector has no sensitivity issue. In this case, the overall health score for this loop detector is calculated as: 1-(340+100)/ 3240=86.4 percent. The statistics are updated daily into loop data databases for further reference. By having such a flexible data quality indicator, transportation engineers and planners are able to determine which data should be included in the freeway performance measures.

Table 6-1 is an example of updated data quality health scores.

Table 6-1 Data Quality Health Score Table

Year	Month	Day	LoopID	HealthScore	isZeroVol	isZeroVolOcc	isHighOcc	isGap
2012	10	14	22	0.75	0	0	0	0
2012	10	15	22	0.8	0	0	0	0
2012	10	16	22	0.81	0	0	0	0

20-second loop data on October 14, 2013, were examined to test the accuracy of the proposed error detection approach. A total of 10,143 loop detectors were found. A variety of errors were distributed, as shown in Table 6-2:

Table 6-2 Error Type Summary for 20-Second Loop Data on October 14, 2013

Error Type	Count	Percentage
isZeroVol	63	0.6%
isZeroVolOcc	907	8.9%
isHighOcc	34	0.3%
isGap	1820	17.9%
isDisc	0	0%
Sensitivity	3834	37.8%
Total	6658	65.5%

In this table, isZeroVol indicates the scenario in which the loop volume was zero while occupancy was nonzero. isZeroVolOcc means that both volume and occupancy were zero. isHighOcc denotes that the loop occupancy exceeded the maximum allowable range. isGap and isDisc are the loop error detection results from cabinets, indicating whether loop data were missing or erroneous as a result of hardware-level failures. Sensitivity is determined by the GMM model, which ascertains whether each loop detector suffers from over-sensitivity or under-sensitivity issues. Note that loop sensitivity issues can be tangled with other error types. Therefore, although 65.5 percent of loop data were considered "bad" data, the actual number of malfunctioning loops would be lower than this percentage.

6.1.2 Data Error Correction

Not every loop data record can be corrected. If more than half of daily loop data are marked erroneous or missing, then this loop detector will be considered malfunctioning and cannot be used for further freeway performance calculations. For loop detectors with a health score of more than 50 percent, several possible data correction approaches can be applied.

(1) Spatial Correction

The spatial correction method refers to using the data from adjacent "good" loop detector(s) to estimate the existing "bad" loop data. Two scenarios are commonly seen for spatial correction:

Scenario 1: Imputation using adjacent loop(s) on multiple lanes

Several other loop detectors may be mounted on the adjacent lanes of the "bad" loop detector. Those "good" loops can then be used to estimate the missing or erroneous loop data. Figure 6-2 depicts this scenario.

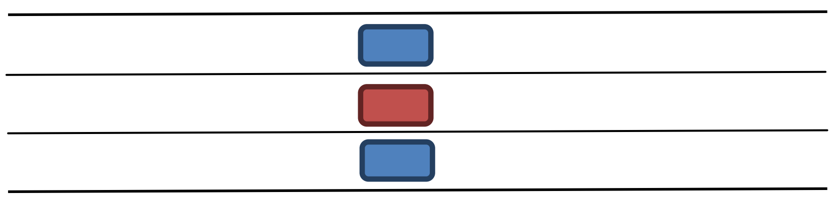


Figure 6-2 Imputation Using Adjacent Loop(s) on Multiple Lanes

The blue rectangle represents the "good" adjacent loops, and the red rectangle represents the malfunctioning loop detector. Assuming that the number of lanes is N, then the corrected volume and occupancy for the malfunctioning loop can be written as:

$$V_i = \frac{\sum_{j \neq i}^{N} V_j}{N-1} \tag{6-2}$$

$$O_i = \frac{\sum_{j \neq i}^{N} O_j}{N-1} \tag{6-3}$$

Scenario 2: Imputation using upstream (downstream) adjacent loops

If the adjacent loops in the same location are malfunctioning as well, then the downstream and upstream loop detectors can be utilized to remedy the missing or erroneous loop data. This scenario is shown in Figure 6-3.

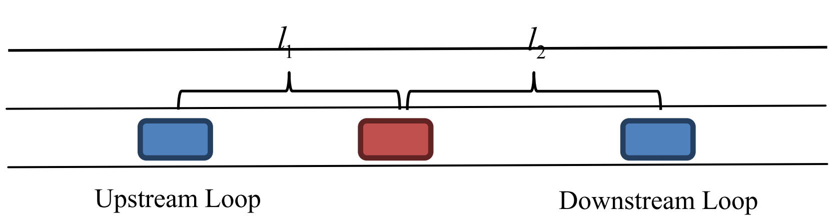


Figure 6-3 Imputation Using Upstream (Downstream) Adjacent Loops

Suppose that the distance between the most adjacent upstream "good" loop and the malfunctioning "good" loop is l_1, and similarly, the distance between the most adjacent downstream loop and the malfunctioning loop is l_2. The estimated volume and occupancy for the malfunctioning loop can be interpolated as:

$$V = \frac{l_2}{l_1 + l_2} V_{down} + \frac{l_1}{l_1 + l_2} V_{up} \tag{6-4}$$

$$O = \frac{l_2}{l_1 + l_2} O_{down} + \frac{l_1}{l_1 + l_2} O_{up} \tag{6-5}$$

The maximum searching distance was 2 mi (or 3.2 km) in this study. If there is only one downstream or upstream loop detector within this range, then the erroneous or missing data of the malfunctioning loop will be substituted with the data from the good loop detector.

(2) <u>Temporal Correction</u>

The temporal correction method is straightforward. The erroneous or missing data are estimated from the most temporally close loop data. The maximum allowable temporal range is defined as 10 minutes. In other words, if no good loop data can be found 10 minutes ahead or beyond the time when the erroneous or missing data were recorded, then the erroneous data are uncorrectable. Otherwise, the bad loop data can be recovered by averaging all the "good" loop data. The temporal correction method is only applicable in certain circumstances, since if a loop detector is systematically malfunctioning, the loop data should be temporally unusable, and therefore cannot be used for temporal correction.

(3) <u>GMM Correction</u>

As mentioned in the previous section, the GMM process is intended to simulate the distribution of occupancy by using multiple Gaussian distributions, which allows calculation of the ratio between the normal occupancy and biased occupancy. This ratio is defined as the correction factor. However, the GMM model is not able to capture loop volume errors. If the loop volume can be corrected by either the temporal or spatial correction methods, then the average speed for single loop detector can be calculated by using the Athol's speed estimation approach (Athol, 1965) as:

$$V(t) = \frac{N(t)}{T \cdot o(t) \cdot g(t) \cdot c(t)} \tag{6-6}$$

where t denotes the t-th time interval, N is the traffic volume retrieved from the loop detector, o is the percentage of time that a loop is occupied by vehicles in each time interval, T is the duration of each time interval (either 20 seconds or 5 minutes), c is the correction factor generated by the GMM model, and g is called g factor, which is determined by the effective vehicle length. In Washington state, a g factor of 2.4 is used (Ishimaru and Hallenbeck, 1999).

6.1.3 Implementation

The aforementioned loop data detection and correction algorithms are automated with the Java and R programs. Because of the massive amount of loop data, only 5-minute loop data are corrected. The corrected loop data are imported into a Microsoft SQL server 2012 for Gray Notebook calculation. To ease the execution of the DQC process, graphic user interfaces have been developed for internal use only, as shown in Figure 6-4 and Figure 6-5.

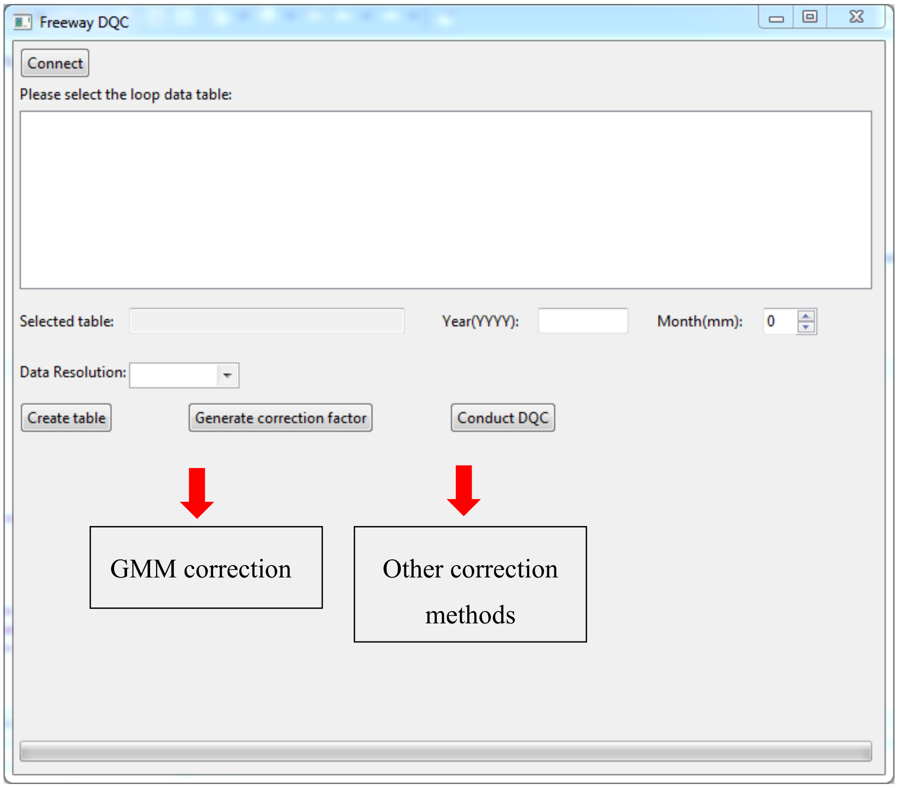


Figure 6-4 GUI for Loop Data Error Detection

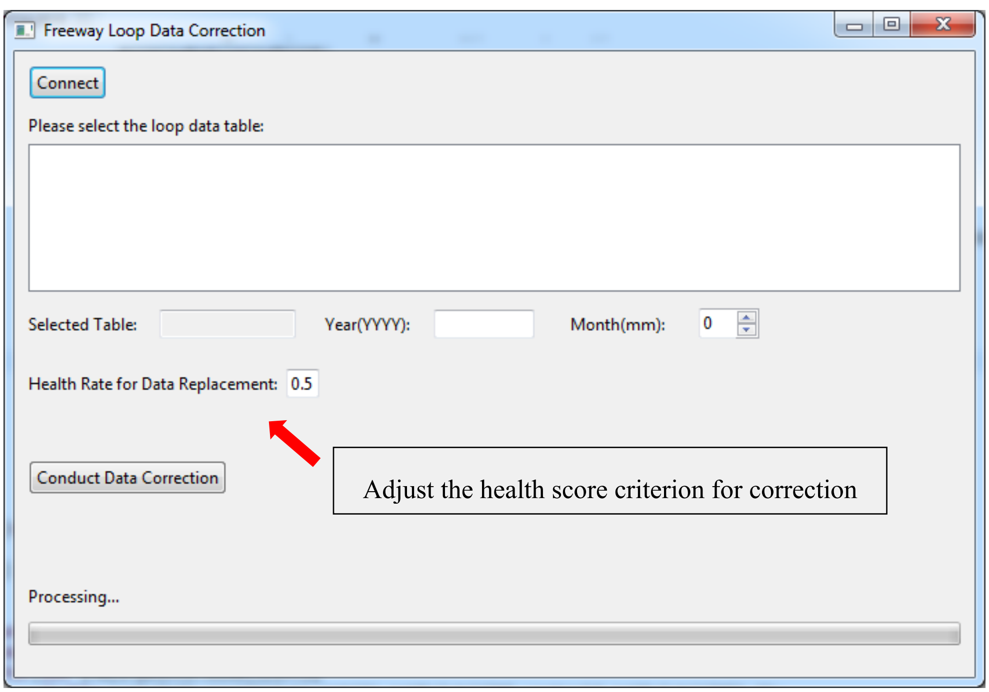


Figure 6-5 GUI for Loop Data Error Correction

6.1.4 A Simplified GIS-T Model

To better highlight the benefits of the DRIVE Net system, a simplified GIS-T was developed. Loop detector data are initially imported into a transportation data warehouse with the automatic DQC program described previously. Simultaneously, freeway network geometric data from WSDOT's GIS workbench are also converted into the geospatial database. To locate each loop detector along each specific route, a lookup table containing each cabinet's latitude and longitude information is created. Each route's attributes, such as number of lanes, direction, and width of the shoulder lane, are kept in the geospatial database. Figure 6-6 demonstrates how a loop detector can associate with each freeway geometric feature:

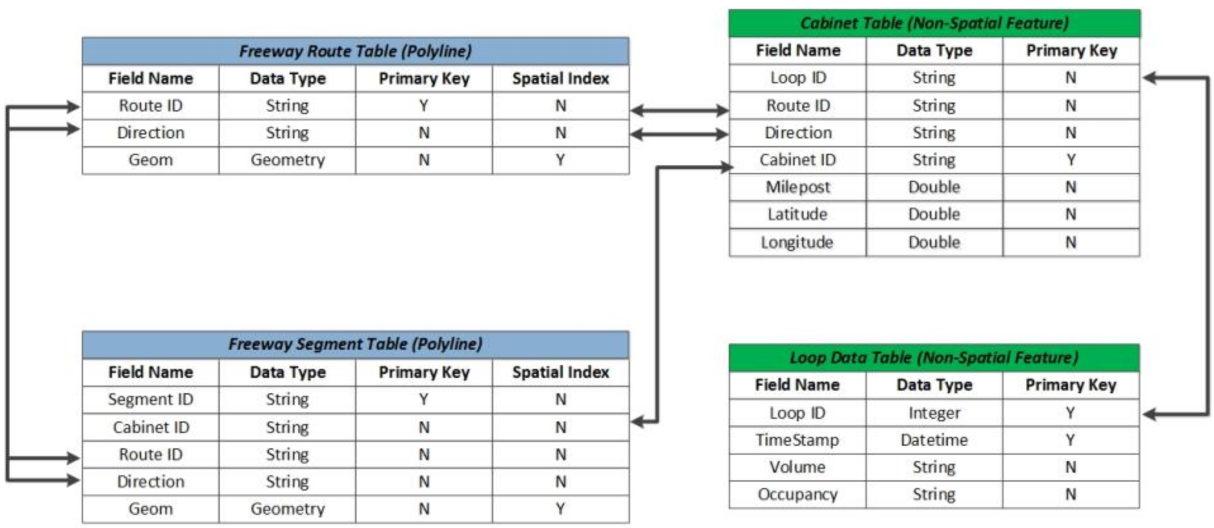


Figure 6-6 Freeway GIS Data Model

The freeway route table and cabinet table share common fields of Route ID and Direction. In addition, each cabinet has its own location information (i.e., latitude and longitude), and it can be spatially joined with each route. Therefore, a route is further segmented into a series of shorter links with detailed cabinet information. Similarly, loop data table and cabinet tables can be integrated by using the common field of Loop ID. In this case, a connection between roadway geometric data and loop data is established. The merit of this freeway GIS data model is that it offers a loose-coupled structure for transportation geospatial analysis, and this is particularly suitable for massive transportation data analysis, since transportation data can be separately managed in multiple databases operating under different jurisdictions and with varying levels of access and control.

6.2 WSDOT Gray Notebook Statistics Design and Implementation

With the processed loop detector datasets, statistics for WSDOT's Gray Notebook (GNB) can be calculated by leveraging the power of eScience. This section documents the development of GNB statistics for the DRIVE Net system.

6.2.1 Summary of WSDOT Congestion Report

A major component of the GNB are the freeway performance monitoring results that WSDOT annually collects statewide. To meet this target, WSDOT has purchased private sector, probe-based speed data to assist in generating the WSDOT congestion report. WSDOT also uses loop detector data from 6800 loop detectors, gathered from 26 commuter routes in the Puget Sound area, to calculate congestion conditions. Travel time analysis and throughput productivity evaluation are two important sections in the WSDOT congestion report.

For travel time analysis, travel times and travel reliability are two important performance indicators for commuters. Key information includes the average peak travel time, the 95 percent reliable travel time, the duration of congestion, the percentage of weekdays when average travel speeds are below 36 mph, and the maximum throughput travel time index (MT^3I). The congestion performance of each route for the current year is compared with that of a baseline year. The average peak travel time is the average travel time during the peak 5-minute intervals for all weekdays of a whole year. The duration of congestion is defined as "the period of time during which average trip speeds fall below 45 mph (75 percent of the posted speed)" (WSDOT, 2013). MT^3I is used to compare travel times on routes with different lengths, and it can be calculated as the ratio between average peak travel time and maximum throughput speed travel time. Maximum throughput speed travel time can be obtained by using the length of a route divided by the maximum throughput speed. However, in reality, the maximum throughput speed is dynamic and hard to acquire because of multiple contributing factors. To simplify the calculation of freeway congestion metrics, 85 percent of the posted speed is adopted as the maximum throughput speed.

For the throughput productivity evaluation, vehicle throughput is the total vehicle hourly volume on a segment at a point location, and the lost throughput productivity is thus defined as "the difference between the highest average 5-minute flow rate observed during the year and the flow rate that occurs when vehicles travel below the maximum throughput speeds" (WSDOT, 2013).

6.2.2 WSDOT Gray Notebook Statistics Implementation on DRIVE Net

The traffic information collected from loop detectors is the main source of data for computing travel time on corridors as well as vehicle throughput productivity. The critical steps for estimating travel time are summarized as follows:

Step 1 – Corridor Segmentation

In Step 1, corridors are segmented on the basis of cabinet locations. The midpoints of the cabinets are used to naturally break the corridor down into segments. For instance, as Figure 6-7 depicts, the corridor is divided into three segments, d_1, d_2, and d_3 by splitting it up at midpoints of three cabinets. The speed of each segment is then taken from the nearest loop detectors.

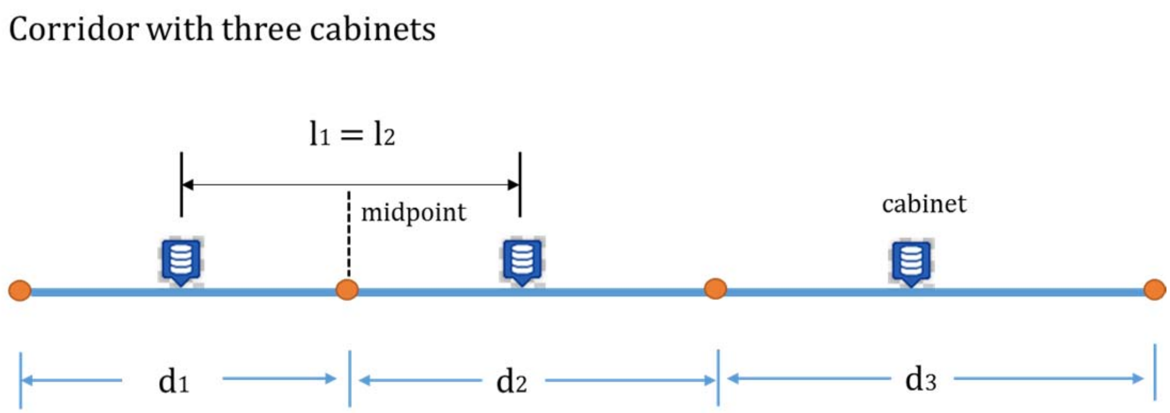


Figure 6-7 Corridor Segmentation

Step 2 – Five-Minute Interval Travel Time Computation

The traffic data are aggregated into speed values in 5-minute intervals. The lengths of segments are computed on the basis of the mileposts of the cabinets. Once the speed and length for segments are known, the travel time on entire corridor can be estimated by summing all the segments' times. The system further prepares the 5-minute travel time of the corridors for all weekdays in the year selected.

$$corridor\ travel\ time = \sum_{i=1}^{n} d_i / s_i \quad (6\text{-}7)$$

where

$$n: total\ number\ of\ segments\ on\ the\ corridor$$

$$d_i: distance\ of\ segment\ i$$

$$s_i: speed\ of\ segment\ i$$

Step 3 – Determination of Peak Time

For each 5-minute interval between 5:00 to 10:00 (morning) or 14:00 to 20:00 (evening), the system averages travel time for all weekdays of the whole year. The 5-minute time slot with the highest observed average travel times for morning/evening, respectively, is then determined as the peak time of the commuter AM/PM rush.

Step 4 – Travel Time Reliability Analysis

Once the peak 5-minute interval has been determined, average travel time, 50th percentile travel time, 80th percentile travel time, 90th percentile travel, time and 95th percentile travel can be found from the dataset prepared in Step 2. The system further calculates the MT^3 index, peak period VMT, and duration of congestion to compare travel time among corridors with different lengths.

Similarly, for throughput productivity analysis, the cabinets close to the 16 monitored locations are used to provide volume and speed information. For each location, the system averages the 5-minute flow rate as well as speeds for all weekdays in the year. The highest observed average 5-minute flow rate, V_o, passing through a location is then defined as the optimal throughput. Using this value as the basis, throughput productivity is computed with Equation (6-8).

$$throughput\ productivity = \begin{cases} 1, & speed \geq maximum\ throughput\ speed \\ 1 - V/V_o\ , & speed < maximum\ throughput\ speed \end{cases} \qquad (6\text{-}8)$$

where

$$V_o: optimal\ throughput$$

$$V: 5 - minute\ flow\ rate$$

Chapter 7 Development of a Mobile Sensing Data Analysis Framework for Pedestrian Trajectory Reconstruction

Automatic pedestrian data collection has been challenging because of the freedom of pedestrians' movements and the lack of effective pedestrian sensors. Presently, pedestrian data collection has relied largely on manual counts or using video images. These approaches are both expensive and time consuming. To address this issue, the research team developed a mobile sensing approach for collecting pedestrian movement data. This approach will become increasingly attractive because of the ubiquitous use of mobile devices and their frequent need to communicate wirelessly. By capturing mobile devices' Media Access Control (MAC) addresses and re-identifying them, the movements of people carrying those devices can be identified. In this task, a mobile app was developed for volunteers who will be willing to help collect pedestrian data. The app will turn a volunteer's mobile device into a moving sensor. The sensor will collect MAC addresses and their timestamps and then send these data, together with the volunteer's GPS location data to the DRIVE Net server computer at the STAR Lab. These data will be processed by a computer module that implements a pedestrian trajectory reconstruction algorithm, developed in this study on the DRIVE Net platform, to estimate the routes of the detected pedestrians.

7.1 Introduction

7.1.1 Problem Statement

Present pedestrian data collection approaches are limited to surveys, which are either administered on location or via broad distribution, manual counts, which involve field data collection by personnel, or automatic spot counts, achieved by either infra-red trip-line sensors or, in the case of cyclists, inductance loops. Video-based data collection methods that are capable of counts as well as localized route choice are also under development (Kong et al., 2006 and Malinovskiy et al., 2008). Aside from expensive, stated preference surveys, none of these approaches provides network-wide travel information. Furthermore, because of the costs of many of these approaches, communities often conduct studies only annually, picking a particular day of the year to act as a surrogate for overall performance (Alta Planning and Design, 2006).

Not only is this approach likely to produce non-representative results because of climate variations, but it also does not provide a clear trend line that can be analyzed for effective improvements in infrastructure or policy.

Development of a cost-effective data collection paradigm that relies on existing mobile phone infrastructure would alleviate many of these concerns and provide continuous, rich data. This is a chance to quickly address the current disconnect between community planning and available, active travel knowledge, while opening doors for additional investigations into epidemiological issues, cultural behavior, economic impacts, and community evacuation strategies.

7.1.2 Mobile Sensing

As the concept of ubiquitous computing develops from its nascent vision (Weiser, 1991), the applications of such an infrastructure are quickly coming to light. Conceptual work has begun, laying the necessary foundation that will be used to support the structure, functions, and limitations of a ubiquitous network. Specifically, mobile device sensors carried by users are envisioned to become important sources of data for everything from traffic conditions and noise pollution to air quality and population health (Cuff et al., 2008; Abdelzaher et al., 2007; Lane et al., 2010; Kanjo, 2009; Kansal, 2007). Although the full potential of ubiquitous sensing may be still on the horizon, a few applications and experiments that use ubiquitous computing devices have begun to appear. Most current approaches focus solely on internal features of the device, treating it as a probe, primarily collecting information about its location and speed. However, extensions to this paradigm have begun to treat the devices as sensors, able to collect external environment data such as noise, air quality, and the presence of surrounding devices. Thus, the devices are examined as primarily location probes and, increasingly, environmental sensors.

In the transportation field, much of the focus for collecting data from ubiquitous devices has been on the MAC identifiers broadcast by the Bluetooth protocol. Many Bluetooth devices, such as headsets, are, by default, set in the discovery mode and can be discovered by other Bluetooth devices inquiring for Bluetooth connections. Research regarding pedestrian and bicyclist travel data collection via Bluetooth is far more limited. In one of the earliest studies, O’Neill et al. (2006) focused on correlating “gatecounts,” or trip-line counts of pedestrians and Bluetooth devices detected in the area of the count. In this study, they found that about 7 percent of pedestrians were detected carrying Bluetooth devices. The number of devices detected grew linearly with the number of pedestrians present. Network approaches to multi-modal data collection using Bluetooth have also received relatively little attention. A conference proceeding by Barberis et al. (2006) outlined the concept of Bluetown, a fully integrated data collection network based on Bluetooth beacons. The authors suggested creating an ad-hoc network of Bluetooth sensors that would be tied into groups by central nodes, capable of relaying acquired travel time information from each sensor into a main database.

7.1.3 Pedestrian Trajectory Reconstruction

Point sensor data are limited to providing the behavior of a given network in just a few sample points. Re-identification approaches effectively allow one to study the entire network as a whole. Some of the most available and important re-identification-based data include origin-destination pair data, which are a key component to both long- and short-term forecasting efforts. These data have traditionally been collected with surveys; however, the increasing capacity to reliably re-identify individuals automatically by using the approaches described above is allowing this information to be collected without the subject's knowledge or input. This allows the collection of observed preference (instead of stated preference). However, it also relies on implied consent (at best) to collect such data. Because many of the identifiers collected are unique, it becomes relatively easy to tie a particular device to a particular point in space-time. Furthermore, since collecting origin-destination data primarily involves determination of home and work locations, it becomes increasingly easy to tie an individual to a particular device, thus violating their locational privacy.

Besides origins and destinations, imputation of intermediate points is also of interest, in particular when route choice, infrastructure effectiveness, and road pricing questions are studied. Imputation of intermediate points allows one to create trajectories, or travel diaries, for each observed entity within the network. This information has great potential for use in the new generation of activity-based models currently being built and used as transportation and land-use forecasting tools. However, the imputation of trajectories will yield more issues related to compromising individual privacy. That is, in addition to knowing home and work locations, it is potentially possible to impute places of worship, shopping habits, and a host of other individual behavior characteristics. Because many models rely on a variety of indicators to improve predictive power, there is a greater conflict between building accurate models and imputing or otherwise obtaining increasingly invasive data. As the possibility of MAC-based, network-wide re-identification becomes more apparent, these privacy issues must be addressed. In addition, the inherent uncertainties within the data collection method must be mitigated. A framework for pedestrian trajectory reconstruction was developed as an important module in the DRIVE Net system.

7.2 Mobile Sensing Data Device Development

7.2.1 System Design

Bluetooth is a short-range communications protocol developed by Special Interests Group (SIG) for inter-device communications. Presently, most electronic devices such as cell phone handsets/headsets, laptop computers, and electronic organizers support the Bluetooth protocol. The protocol itself consists of a device to broadcast a unique 48-bit Media Access Control (MAC) address to devices within range. The broadcast happens at varying frequencies and random intervals (frequency hopping within a 10.24-second time window), allowing for multiple devices to connect to each other. This protocol was designed for short-range, multi-device communications and is therefore optimized for such purposes, creating some challenges for its use for additional purposes, such as travel time collection based on Bluetooth MAC address matching.

Bluetooth device detection is subject to several sources of error, which undermine the overall travel-time measurement accuracy. First, the frequency hopping protocol allows up to 10.24 seconds in device discovery time, which may result in a location error of approximately 170 meters (558 ft) at 30 km/h to 570 meters (1870 ft) at 100 km/h (62 mph) at each detection point for highway travel-time data collection. These errors can affect the travel-time data accuracy significantly if the link is short because the location errors are relatively high for the link distance. A second error factor derives from the variety of Bluetooth devices, antenna types, and geometric configurations that are possible. Additional errors may result from non-vehicle-based devices within the analyzed corridor—these could be pedestrians, bicycles, or other vehicles that are not of interest but are still recorded.

The project's device design consists of five main components: (1) a Bluetooth chipset that constantly scans the available 79 channels, (2) a WiFi chipset that scans the WiFi spectrum, (3) a 16 MHz ARM processor that records MACs, (4) another 16-MHz ARM processor that takes care of communications, and (5) a communications module that synchronizes to Coordinated Universal Time and transmits data in near real-time (GPS + GSM). The device is housed in a weatherproof enclosure that provides a port for an external antenna, as shown in Figure 7-1. This provides an excellent base for testing mounting locations and various antennae, as it can be mounted to signposts and signal posts , as also shown in Figure 7-1, and will accept a wide range of antenna types. The current design allows the device to function for up to a week without external power using one 6-cell LiPo pack (15.6Ah capacity @ 3.7V), running the sensing board only. The device accommodates up to two battery packs at a time, resulting in a maximum runtime of two weeks without external or solar power.

Figure 7-1 MACAD Evolution

Solar power compatibility has also been considered in the design, and a solar power module has been designed and tested. The device operates using the power provided by the battery, which is, in turn, charged by the solar panel. Preliminary testing indicated that the discharge rate is lower than the received solar power input rate, meaning that continuous operation is possible.

7.2.2 Communication Design

Once mounted, the device synchronizes to UTC time using the communications module. In addition to synchronizing over the GPS network, the system also sends its exact coordinates via GSM. These coordinates are then used for automatic geospatial organization of deployed sensor units. This initialization routine is repeated at regular intervals to prevent clock drift (Quayle et al., 2010) and ensure that the device is functioning properly and has not been tampered with. Once the synchronization and location recording is complete, the device begins data collection, recording bypassers' MAC addresses and their respective timestamps. As data are collected, they are sent over the GSM network to a server in the STAR Lab, where the MACs are kept for a specified period (currently 60 minutes). If a matching MAC is received during this period, a travel time is calculated, the MAC address is deleted, and the data are uploaded to the DRIVE Net system for data sharing, modeling, and online analysis. This approach to data collection allows for real-time information flow to users while maintaining a level of privacy. Figure 7-2 illustrates the overarching structure of the data collection effort.

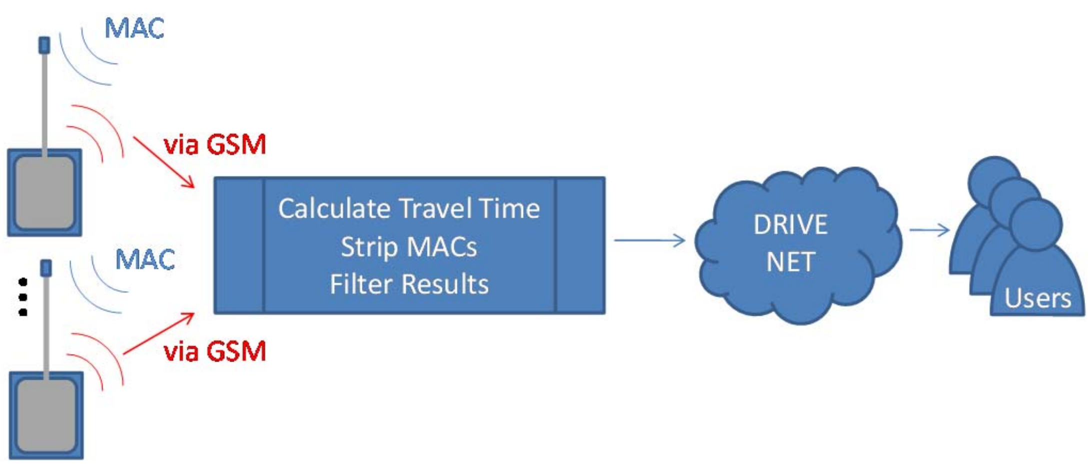


Figure 7-2 Bluetooth Data Collection and Distribution Diagram

7.3 Mobile-node Data Collection Paradigm Applications

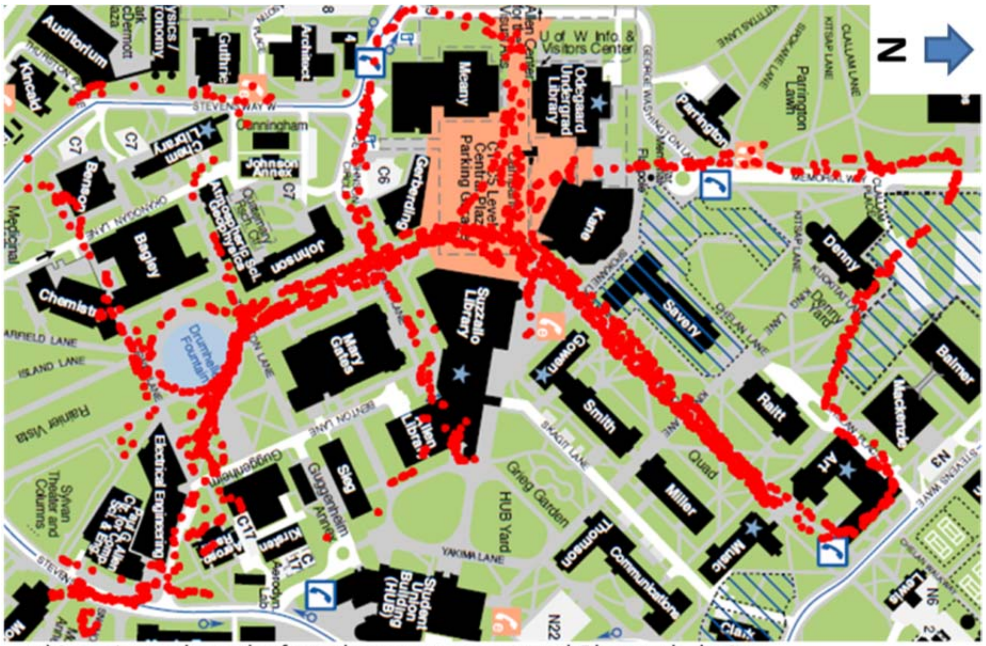
7.3.1 Pedestrian Route Estimation Application

Most smartphones on the market have Bluetooth and GPS functionality, making them perfect platforms for the mobile monitoring paradigm. Google's Android operating system is quickly becoming one of the most popular mobile device platforms, in part because of the open source nature of the development environment, which allows end users to create apps with minimal inconvenience and effort. In light of this, a small app was written for the Android operating system that continuously scans for surrounding Bluetooth devices and records the current GPS coordinates of the device. WiFi-based location services were turned off to ensure that no errors could result from hand-offs and switches between GPS and WiFi. Figure 7-3 shows a Motorola Droid phone running the software, displaying a detected MAC (of a device belonging to the author), while still finding its current location. This particular device is equipped with a Class 2 Bluetooth chipset, granting a range of around 10 m for detection of surrounding Bluetooth devices.

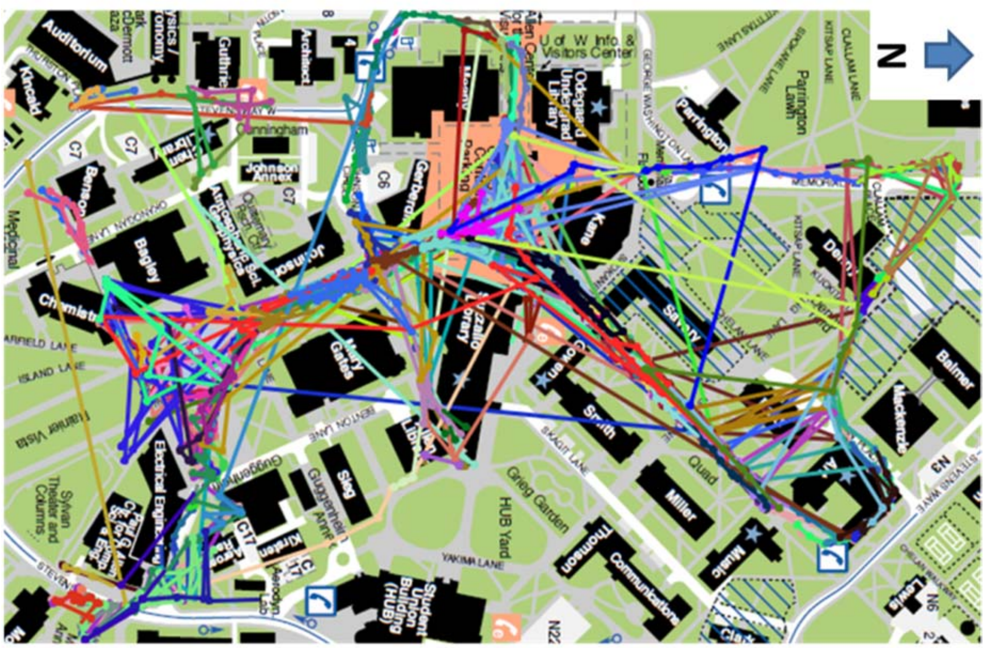
Figure 7-3 A Motorola Droid Handset Running the Mobile Monitor Ppplication
(Phones used in study courtesy of Dr. Alan Borning)

7.3.2 Study Site

Four Motorola Droid phones were used in the experiment. Four volunteers (hereafter called “observers”) walked for 50 minutes from 1:10pm to 2:00pm on April 20, 2011 (sunny, warm) at the University of Washington central campus, encountering Bluetooth devices along the way. The locations of Bluetooth encounters (which are shown by the paths) are shown in Figure 7-4a. During the 50-minute experiment, 546 unique devices were discovered by all four observers. Main thoroughfares had higher concentrations of devices, reflecting higher pedestrian volumes encountered by the observers. The collected sightings were then compiled to create device trajectories, shown in Figure 7-4b. The trajectories were created by plotting the coordinates at which the MAC address had been seen. Two types of trajectories were observed: ones that resulted from the observer following a particular device and walking alongside (shoaling) and ones where a device was seen momentarily by more than one observer (encounters). These encounters often occurred at longer distance intervals and could result in trajectories that were unrealistic if plotted without network knowledge, as can be seen in Figure 7-4.



a) Locations where the four observers encountered Bluetooth devices



b) Collected Bluetooth device trajectories

Figure 7-4 Trajectories on the UW Campus on April 20, 2011, 1:10pm to 2:00pm, Collected by Four Observers

7.4 Developing a Pedestrian Trajectory Reconstruction Algorithm to Reduce Data Uncertainty

7.4.1 Inference of Plausible Paths

Spatial uncertainty occurs when the exact location of a detected MAC device is unknown. In addition, the exact location of the device is never truly known because of the nature of the protocol (related to the temporal uncertainty discussed above); however, the largest uncertainty is not where in the given detection zone a device is currently located, but which route a given device owner has taken in between a set of sensors. As shown in Figure 7-4, a straight line is used to connect two mobile sensors because of the spatial uncertainty, but the route information between these sensors is not known. This issue is of significantly higher interest within the mobile sensing paradigm, as there are no pre-defined travel corridors. Therefroe, an innovative means of asserting the most likely path taken by the detected device must be developed.

Plausible paths can be inferred in a number of ways. The simplest approach is to assume that the shortest path is the path always taken. Under such a construct, the MAC sightings data obtained can be assigned to a known network of available links, and the shortest paths between each consecutive sighting of the device can be found. These shortest paths can then be stitched together to provide a complete plausible trajectory for the individual. This approach is illustrated in Figure 7-5 a-c. The green circle represents the first sighting, the red dot represents the last sighting and the blue dots are intermediate ones. However, as can be seen in the figure, a number of possible paths may be available to choose from, particularly on a network such as an urban grid system. Furthermore, the longer the distance interval between sightings, the more options that exist. In Figure 5-19c, a completely plausible path is shown (in red and orange) between all the points. Without additional information, there is nothing to suggest that this path is any less likely than another. However, under the mobile sensing paradigm, we do have additional information about other travelers. This information can help us determine whether some routes are preferred over others, that is, "popular paths." This information can be leveraged to create better guesses regarding the plausible paths between MAC sightings, thus reducing overall spatial uncertainty.

Figure 7-5(a-d) shows the concept in action. The pink highlight color represents *a priori* path popularity (darker = more popular). Additional popularity information can be gleaned from sections of the trajectory shown in Figure 7-5(a-b). Because mobile sensors often move with the very entities they are trying to detect, two types of interactions are common: (1) following behavior, in which the mobile sensor and the sensed entity are moving along the same path and or direction; (2) encounters, in which the mobile sensor briefly encounters the sensed device either passing in an opposite direction, at an intersection, or the like. Leveraging this duality, one can obtain path popularity values either from the trajectories that have high resolution or from the “following behavior” ones. The “encounter” segments of trajectories can then be reinforced by using the popularity information gleaned from the high resolution trajectories. Figure 7-5c shows the additional path popularity information that can be obtained from the “certain” segment of the trajectory. The remaining “uncertain” portion of the trajectory can then be estimated by using a shortest path algorithm on a network where the links are weighted not only by distance but also by the popularity of a given path. Figure 7-5 d shows the final computed trajectory, which follows the most popular paths while also being one of the shortest paths available.

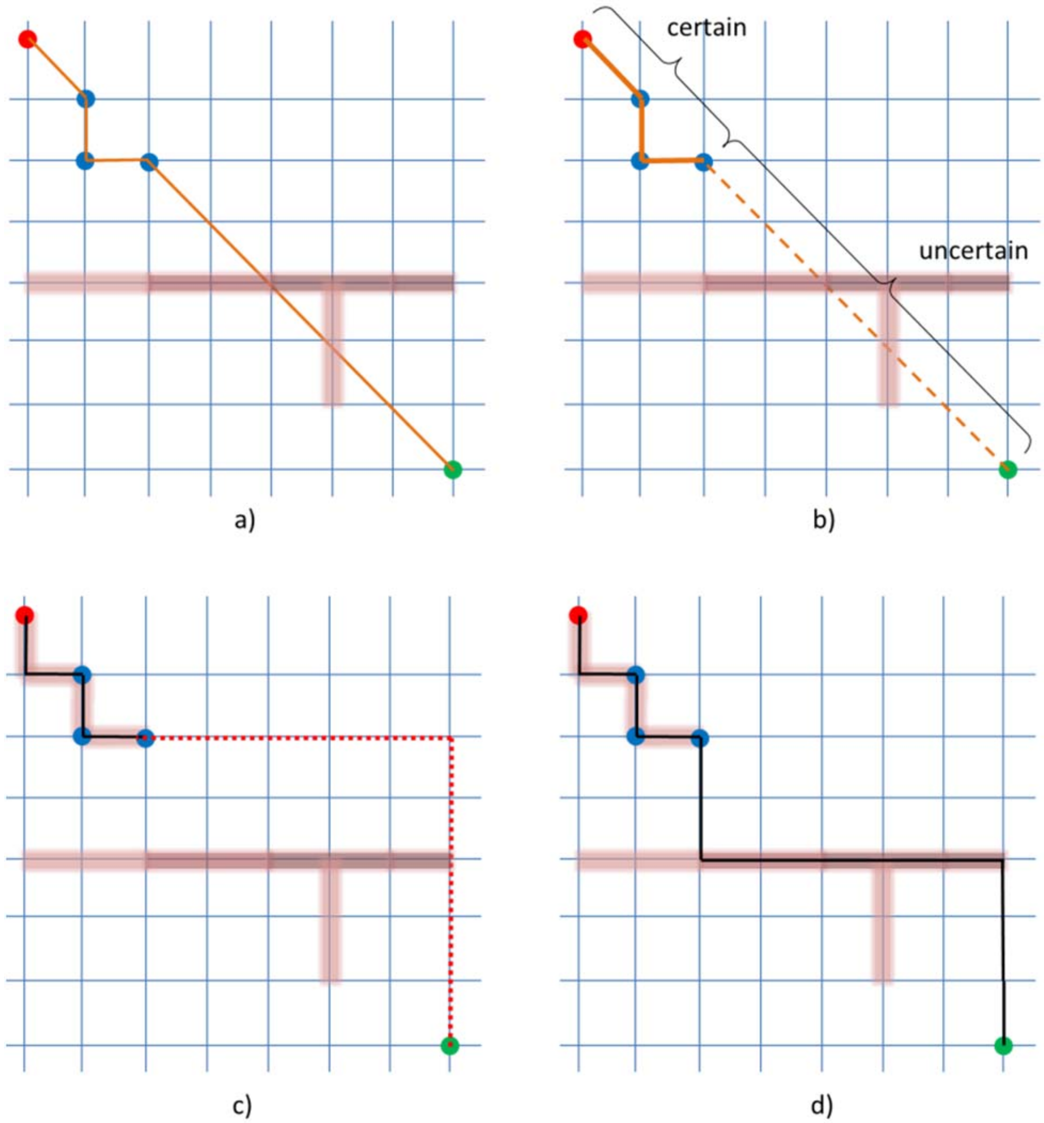


Figure 7-5 Inference of Plausible Paths

This concept was implemented in the DRIVE Net system. A diagram of the implemented system is shown in Figure 7-6. The primary pre-processing of data occurs within the MAC Matching and Filtering Engine. The PG Routing Engine is an open-source routing library that is capable of running shortest path algorithms on Postgresql databases. The routable GIS network was obtained from King County and modified to limit the network to the University of Washington Seattle campus only. Additional links were also inserted to better represent the extent of the network. The GIS files were then loaded into the Routable Network contained in the primary DRIVE Net PostgreSQL database. When MAC trajectories become available, route popularities are calculated, and the corresponding weights in the Routable Network are updated on the basis of a cost function that is designed to consider distance, popularity, and potentially other factors. Likely routes (plausible paths) are calculated for all MACs seen on the basis of the Routable Network link weights. Additional details follow in the next sections.

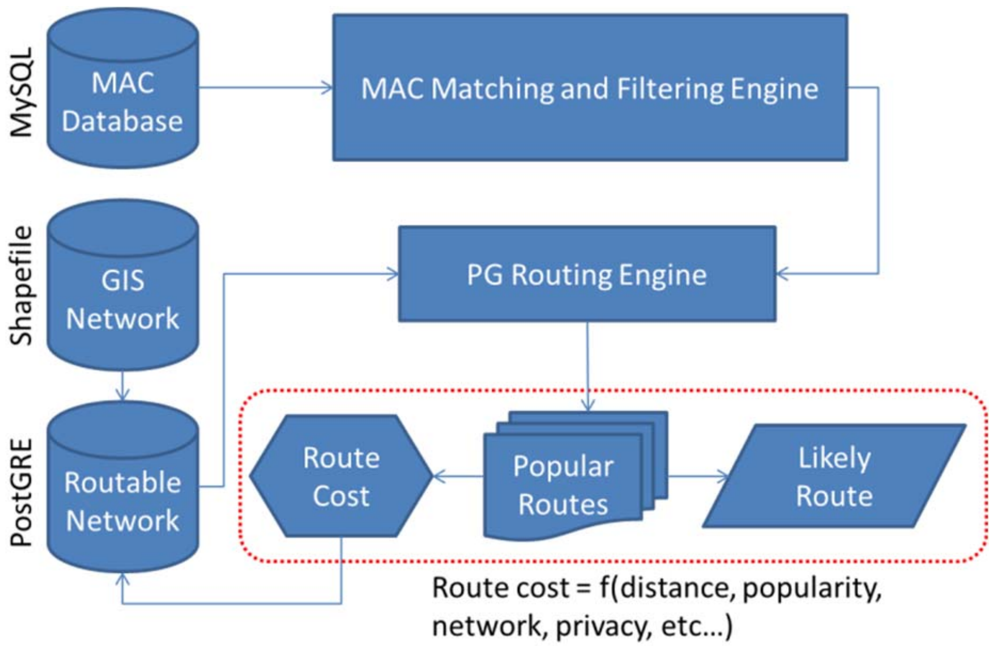
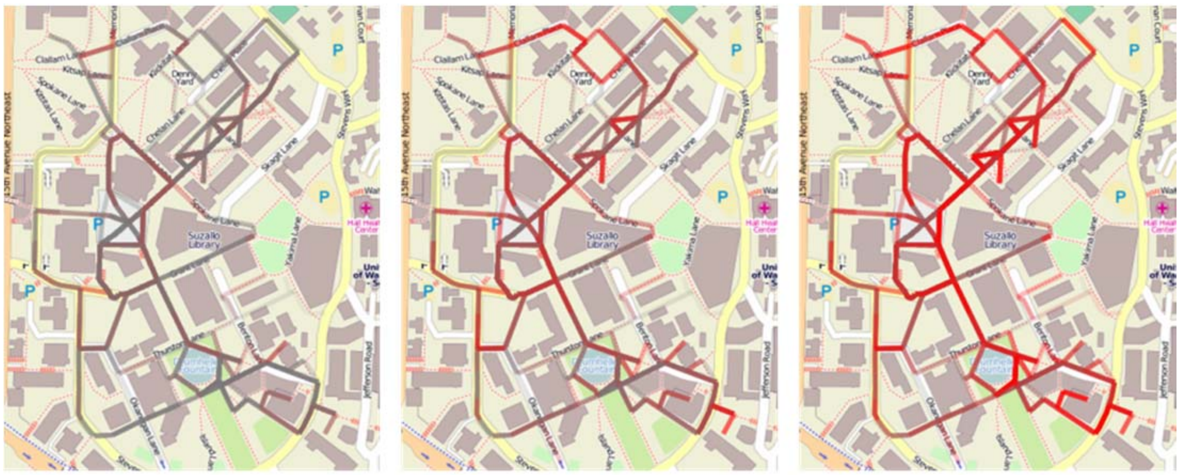


Figure 7-6 Diagram of Route Imputation System

7.4.2 Popular Routes Estimation

To estimate popular routes, the trajectories obtained must be split into "certain" and "uncertain" sections, whereby the "certain" sections are able to reinforce the "uncertain" ones. To do so, some mechanism for distinguishing between which trajectories act as reinforcement and which need to be reinforced must exist. A threshold-based algorithm is the simplest means of accomplishing this task—if there is a gap of greater than a certain distance threshold between two consecutive sightings, then that portion of the trajectory is uncertain. Figure 7-7 shows the Routable Network (University of Washington Seattle campus) with popular routes highlighted in red (deeper red color means increasing popularity). These data were obtained from the experiment described in Section 7.3.2. It can be seen that increasing the distance threshold increases the popularity of paths; this is reasonable, as more paths are deemed “acceptable” and are assigned to the network. Also note that the relative popularity appears to be similar.



a) thresh= 20m b) thresh= 50m c) thresh= 100m

Figure 7-7 Distance Threshold (in meters) for Certain/Uncertain Path Discrimination

7.4.3 Routing Cost Function

The routing cost determines the weights of the links within the Routable Network by adjusting the inherent distance of the link in accordance with other parameters deemed important, i.e., popularity. The basic form of the function is as follows:

$$
\begin{aligned}
&if \quad \left(\alpha g(p) + \sum_{i=1}^{n} \beta_i h(\ldots) < 0\right) \\
&then\ w \\
&\qquad = d + max\left\langle \alpha g(p) + \sum_{i=1}^{n} \beta_i h(\ldots) \middle| -\gamma d \right\rangle \\
&\text{else } w \\
&\qquad = d + min\left\langle \alpha g(p) + \sum_{i=1}^{n} \beta_i h(\ldots) \middle| \gamma d \right\rangle
\end{aligned}
\tag{7-1}
$$

where w is the new link weight, d is the link distance, $g(p)$ is a function of the popularity p, and $h(\ldots)$ is a function that incorporates other potential factors (privacy, link centrality, attractions, etc..). α is the route popularity weight, β is the weight of respective parameters included in $h(\ldots)$, and γ is the maximum allowable proportion of distance that can be affected by all factors. This ensures that the maximum allowable decrease in link weight is not more than γd. This formulation allows the function to be extended to incorporate a range of possible parameters that would affect route choice, as outlined in Hoogendoorn and Bovy (2004). In the current implementation, *g(p)* is assumed to be a simple quadratic function, first starting at zero, growing positive, then reducing and becoming negative. This is meant to represent the individual's desire to walk on populated paths, but not ones that are too crowded. The current definition of the *g(p)* is as follows:

$$g(p) = \frac{\gamma d p^2}{(LOS_E/2)^2} - \frac{\gamma d p}{LOS_E/4} \tag{7-2}$$

$$LOS_E = 15 * d * t * \ BT \tag{7-3}$$

where BT is the percentage of people with Bluetooth-visible devices, t is the time interval length in minutes, d is the link length, and γ is the maximum allowable proportion of distance that can be affected by all factors, as before. The constant 15 comes from the HCM LOS determination, where LOS E is defined as 15ppl/ft/min. LOS E is considered to be the turning point at which pedestrian density becomes a detractor. Thus, *g(p)* is set up to intersect the x axis, at LOS_E, or $15*d*t*BT$, or the total number of people needed to be present on a given link during the study interval to cause LOS E. The remaining constraint was the vertex, which was placed at $LOS_E /2$ and γd.

By using this cost function, it becomes possible to update the link costs within the graph to better represent the routing decisions made by the owners of detected MACs. The following section explains the final stage of route assignment.

7.4.3 Plausible Route Calculation

Leveraging the existing network, newly weighted link costs from the routing cost function, and the PGRouting shortest path algorithm, it becomes possible to place the detected trajectories onto the network. Figure 7-8 shows the trajectories from the campus experiment described in Section 7.3.2 and their corresponding mapping to the network, complete with imputed intermediary points. Each route is calculated on the basis of querying the network route between each of the timepoints contained within a trajectory for a given MAC address' trip. The pseudocode for this operation is as follows:

```
ImputeUncertainTrajectory(Trip t) {

      foreach Trajectory trajectory in t:

      foreach (consecutive) TimePoint p1 and p2 in t:

                  newPoints  = getUncertainTrajectory(a,b);
            trajectory.updatePoints(newPoints);

      end;
end;
}
```

The `getUncertainTrajectory(a,b)` function obtains the shortest path on the weighted network with PGRouting, while `updatePoints(newPoints)` ensures that the obtained intermediate points fit into the trajectory according to their proper timestamp and location. Trajectories are stored in a Java TreeMap data structure to ensure that the timepoints are kept in consecutive order.

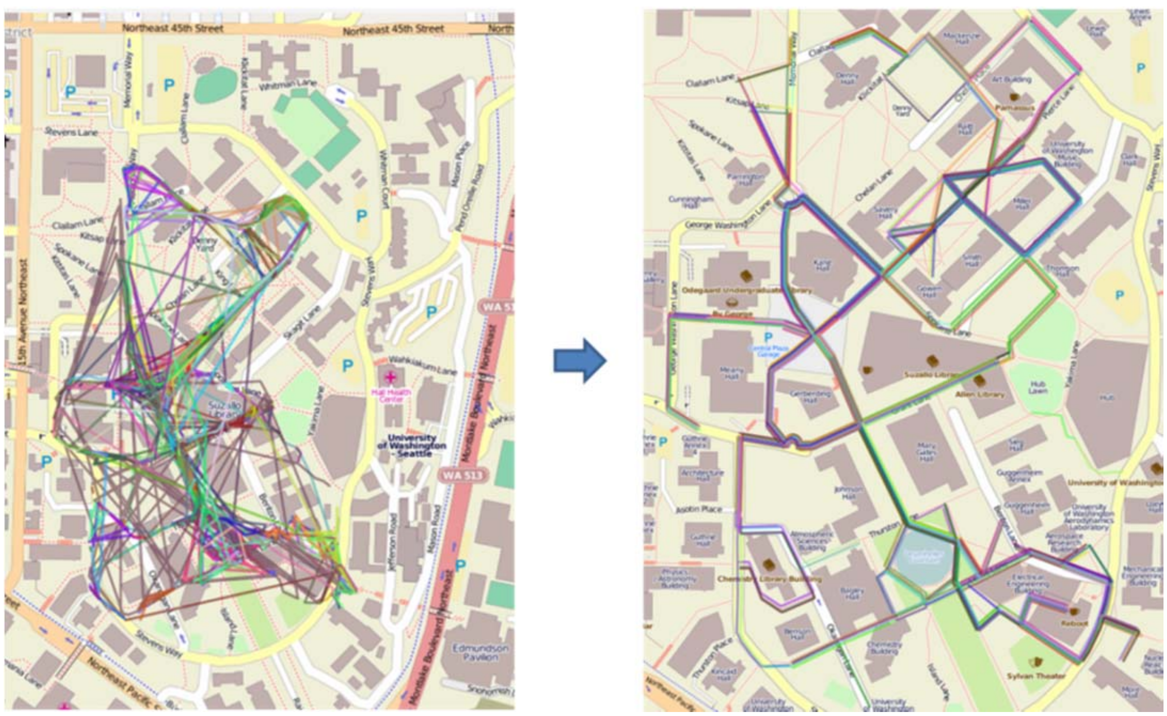


Figure 7-8 Imputed Plausible Paths from the Campus Experiment Conducted April 20, 2011

Although the obtained paths were, at the very least, more plausible than those from direct interpretation of MAC sightings, we still watned to determine how much contribution the method provided. In addition, we wanted to determine how much additional explanatory power the popular route information contained. An additional campus test, described in the next section, was conducted to answer these questions.

7.5 Verification

Verification of plausible path imputation is difficult, as the true paths of the entities in question are not known and cannot be easily obtained. Although simulation is often resorted to in such cases, it was important to understand how the proposed methodology fared in collecting actual data. Therefore, an experiment to compare static MAC readers and mobile ones was created. The main concept behind the verification test was to match MACs between static and mobile sensors. The set of MACs seen by each static sensor in an assumed range and the set of MACs seen by mobile devices restricted by GPS coordinates to the corresponding range were compared. First, the comparison was made without path imputation and then with path imputation. The difference in the total matches was considered to be the effectiveness of the algorithm in reducing spatial uncertainty.

7.5.1 Experiment Description

On the basis of the relative route popularity information obtained from the April 20, 2011, experiment described in Section 7.3.2, a set of eight static sensors was mounted on the University of Washington Seattle campus. Figure 7-9 shows the sensor locations. These locations were meant to cover the primary gates as well as destinations on campus. However, note that complete coverage was not necessary for verification. Four MACAD v3.0 devices (one omni-directional antenna, ranging up to 100 m) and four Blip Track Bluetooth devices (two-directional and one omni-directional antennae, ranging up to 100 m) were used. BlipTrack sensors were used at locations 1, 2, 3, and 4, and the remainder were covered by UW MACAD v3.0 devices.

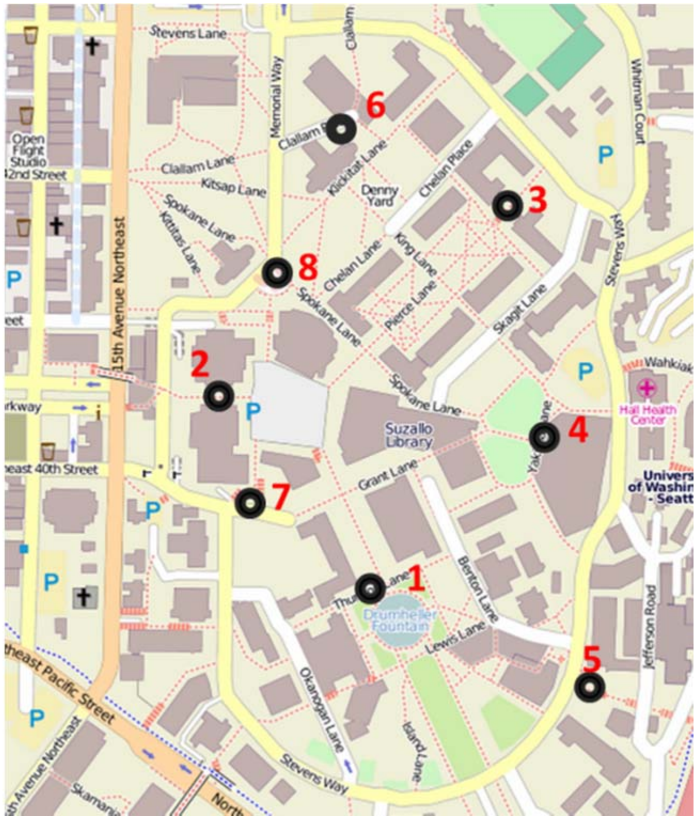


Figure 7-9 Static Sensor Mounting Locations on the University of Washington Campus

Eight volunteers were asked to participate and were given equipment identical to that of the April 20, 2011, experiment, described in Section 7.3.2. However, instead of roaming freely, the volunteers (observers) were asked to complete two rounds of visits to each sensor by following predetermined itineraries, shown in Table 7-1. These itineraries were meant to minimize the potential of multiple volunteers visiting the same sensor concurrently and had to be repeated twice. The experiment took place on March 4, 2013, from 11:00am to 1:30pm. Volunteers were also asked to roughly count pedestrians for 5 minutes at sensors corresponding to the parity of their assigned identificagtion (i.e., observer #3 counted at sensors 1, 3, 5, and 7). These counts were used to roughly estimate the penetration of Bluetooth-visible devices within the population.

Table 7-1 Observer Sensor Visit Itineraries

Obs 1	2	6	5	3	4	8	7	1
Obs 2	4	8	1	7	5	3	6	2
Obs 3	5	2	7	6	8	4	1	3
Obs 4	3	1	4	8	6	7	2	5
Obs 5	1	4	8	2	7	5	3	6
Obs 6	6	7	3	5	1	2	8	4
Obs 7	8	3	6	4	2	1	5	7
Obs 8	7	5	2	1	3	6	4	8

7.5.1 Results

The data collected by the mobile observers are shown in Figure 7-10b. In comparison to the previous experiment data (shown in Figure 7-10a), the coverage expanded to multiple routes, as expected—the volunteers were free to choose their own routes between the eight sensors. However, there was also a drop in the total number of detected devices—546 unique devices on April 20, 2011, vs. 450 unique devices on March 4, 2013. This may be explained by the slightly different timing of the experiment (held later in the day), or by the fact that half of the time by the observers were static, counting pedestrians at sensor locations.

a) 4/20/2011 mobile device detections   b) 3/4/2013 mobile device detections

Figure 7-10 Comparison of Heatmaps of MAC Devices Detected on the UW Campus

Overall, the mobile sensors picked up more unique devices than the static sensors, with static sensors picking up 343 unique devices during the same time interval (vs. 450 via mobile). Of those, 228 addresses were shared between the sensor types, with 565 MACs detected in total by both static and dynamic sensors. Flow between each of the eight static sensor locations was calculated by matching MACs seen at sensor pairs. The flows are displayed as ray charts, with thicker rays depicting higher volumes in Figure 7-11. Figure 7-11 also shows the percentage of the unique MAC addresses captured at each location. These do not sum up to 100 percent, as many MACs were seen by multiple sensors.

Similar analyses could be conducted for the mobile sensors, if an effective range was chosen as a surrogate for the sensor’s range. For example, we could choose 75 m as the effective range (smaller than the actual range), thereby considering all MACs found by mobile devices within 75 m of a sensor to belong to that particular sensor group. Thus, we could achieve the same pairwise comparisons by using dynamic sensor-collected data. Although the sample size for pairings would be significantly smaller because of the zone cut-off (90 mobile pairings vs. 409 static pairings), the general trend would remain the same. Table 7-2 shows the results between a normalized comparison of the raw (un-routed) mobile sensor pairings and static sensor pairings. On average, the error was less than 5 percent, meaning that, in general, the mobile sensors were able to capture the same pairwise travel trends as the static sensors.

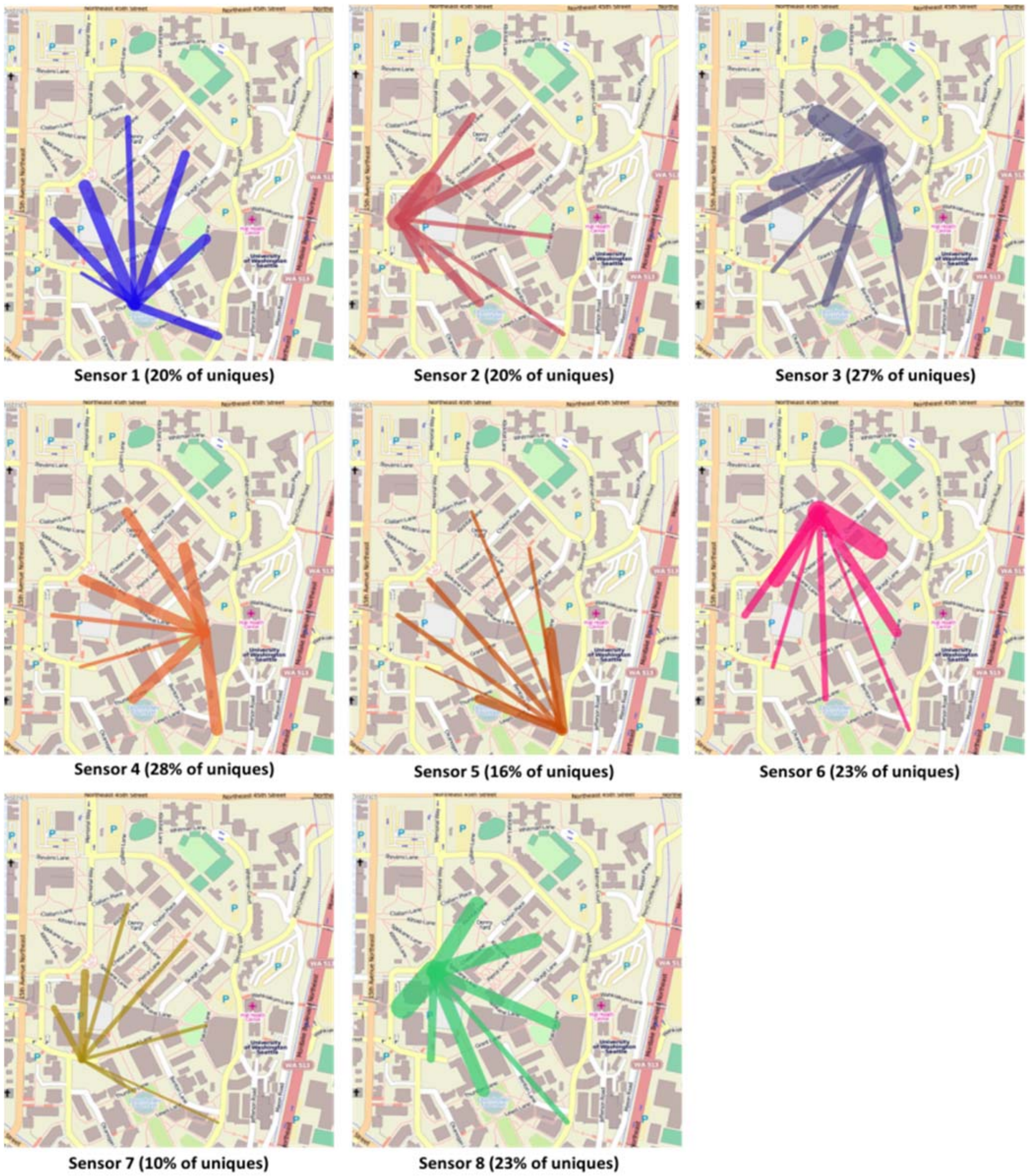


Figure 7-11 Ray Charts Depicting Pairwise Flows for Each Static Sensor Location

In addition to comparing flows, the sets of seen MACs can also be compared to determine whether there is an overlap between the MACs seen by the static sensors and the MACs seen by mobile sensors in the same zones. Evaluation of path imputation is also possible, as the imputation technique places certain MACs in locations where they were not detected but would be expected to have visited given the path reconstruction. Figure 7-12 shows the percentage of static MACs matched by the mobile paradigm with and without path imputation, with the popularity weight held constant at zero. The distance threshold of zero represents the baseline condition in which no path reconstruction is performed. It can be seen that path reconstruction, even without popularity imputation, provides benefit in terms of the matched MACs (3.5% more correct matches, or about a 10 percent improvement on average).

Table 7-2 Relative Errors in Pairwise Flows for Mobile and Static Bluetooth Data

	1	2	3	4	5	6	7	8	Average Absolute Error %
1 - Drumheller Fountain		7.8%	0.1%	9.7%	1.1%	2.5%	17.0%	13.7%	7.4%
2 - Red Square Entrance	2.5%		1.4%	3.6%	7.5%	0.3%	13.7%	1.8%	4.4%
3 - Quad Music Hall	5.0%	1.9%		1.4%	2.1%	1.8%	7.4%	6.0%	3.7%
4 - The HUB	11.1%	2.4%	7.1%		2.5%	5.7%	4.8%	1.5%	5.0%
5 - CSE/More Hall	5.8%	12.1%	6.3%	5.7%		6.3%	9.3%	1.7%	6.8%
6 - Paccar Hall	5.0%	0.9%	2.0%	1.2%	2.4%		2.3%	4.8%	2.7%
7 - Meany Hall Lower	1.9%	7.6%	2.6%	2.4%	1.3%	8.6%		2.3%	3.8%
8 - Memorial/Flagpole	10.8%	3.0%	3.8%	2.3%	0.5%	5.9%	7.5%		4.8%

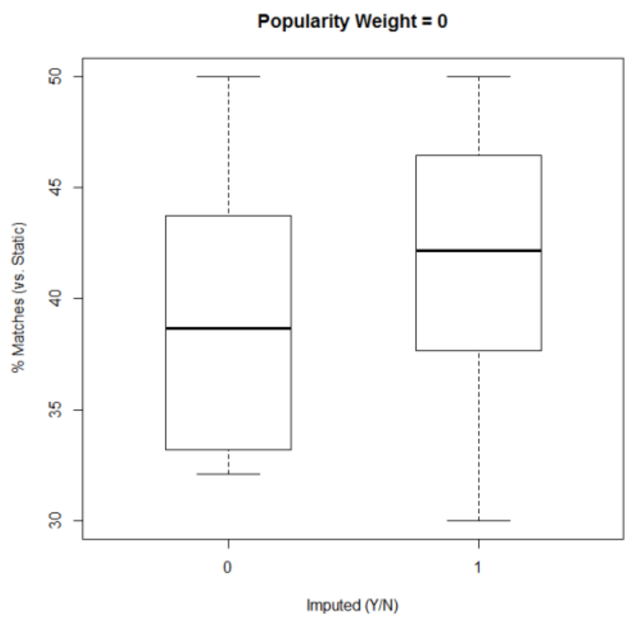


Figure 7-12 Percentage of Correctly Matched MACs without and with Path Reconstruction

Examining the variations due to the popularity function, with weights (alpha) ranging from 1250 to 5000, showed that some additional benefit can be had at the higher alpha values, with up to 4 percent more matches at alpha values of 5000. However, the lowest variance was observed at a popularity weight of 2500.

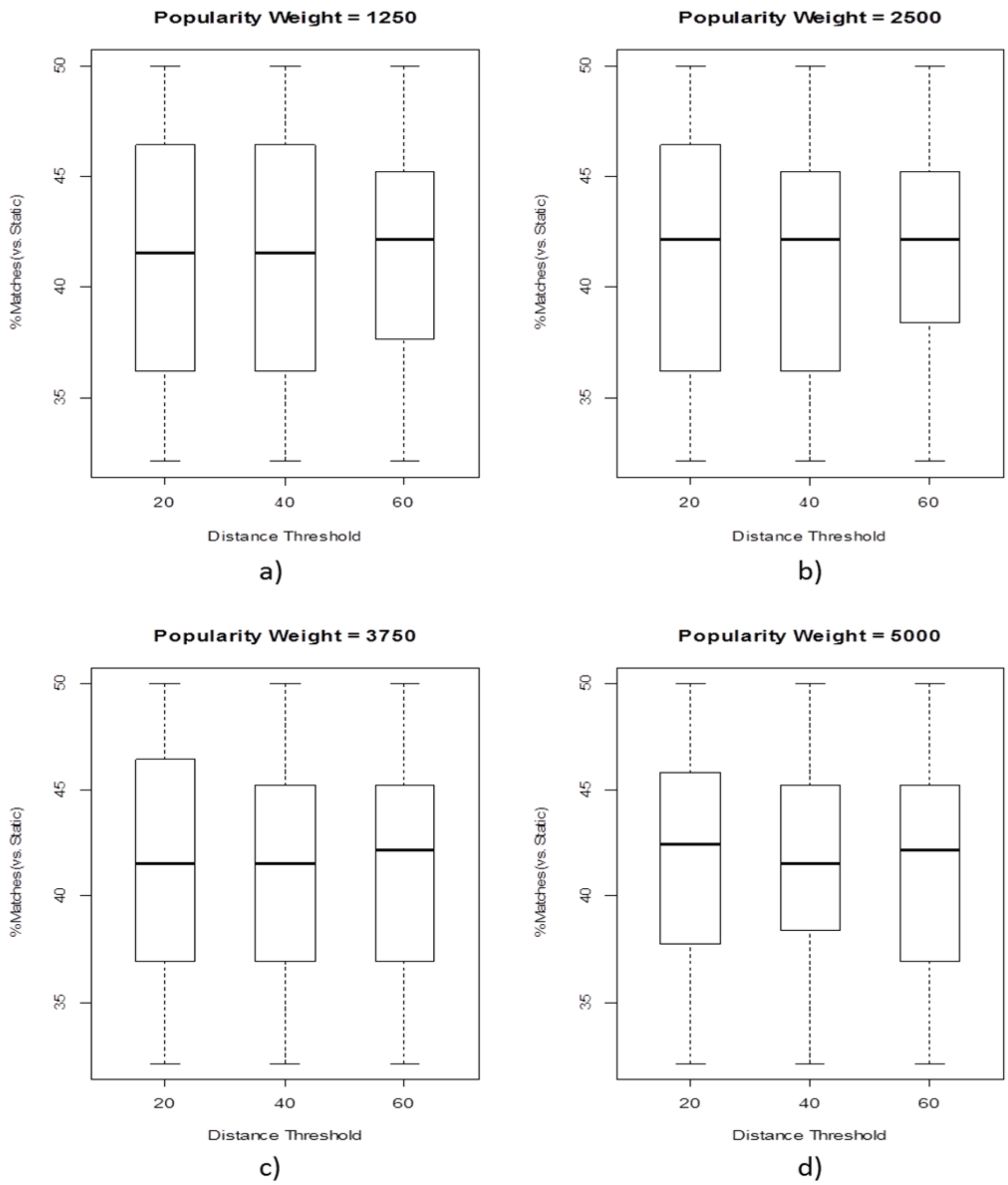


Figure 7-13 a) Percentage of Correctly Matched MACs by Distance Threshold with Popularity Weights of 1250 to 5000

While these gains are modest at best, the aim of this task was not to provide an optimal means of trajectory reconstruction but rather to develop a framework for collecting and evaluating mobile MAC data. In this experiment, it was shown that mobile MAC data are capable of capturing data that are representative of the movements detected via static sensors. Furthermore, it is possible to reconstruct trajectories of individuals traversing the network while concurrently increasing the accuracy of the mobile MAC data.

Chapter 8 User Manual

When the site is first accessed, DRIVE Net defaults to the welcome screen (Figure 8.1). Background knowledge and contact information can be found on the default page. After clicking the green Button "WSDOT DRIVE Net," users are able to interact with the WSDOT DRIVE Net with the interface shown in Figure 8-2. At any time, the user may access the LOS Analysis, Traffic Flow Map, Pedestrian Movements, or GNB Calculation features by clicking the appropriate tab visible at the top of the screen (labeled "A" in Figure 8-2).

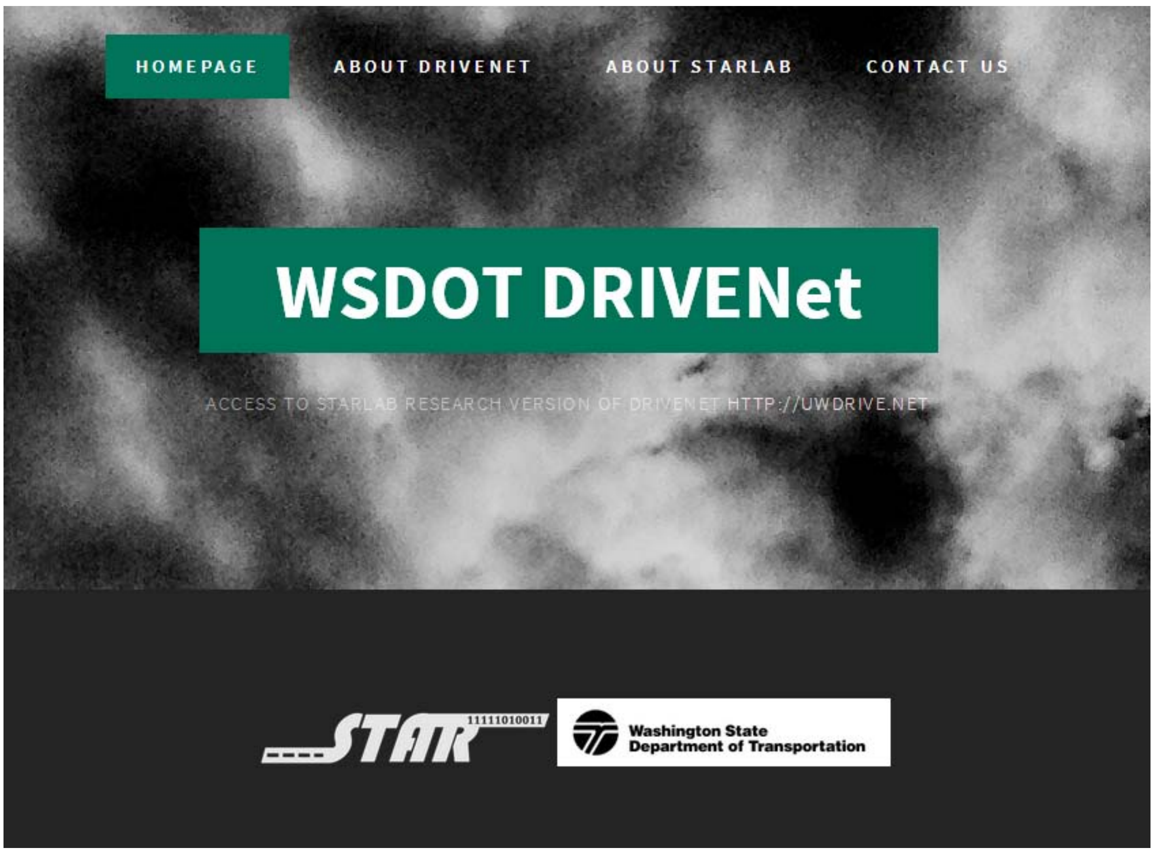


Figure 8-1 DRIVE Net Screen

8.1 LOS Analysis

The DRIVE Net Level of Service (LOS) tool can produce regional maps and targeted summary statistics for five major travel corridors in the Puget Sound region based on HCM 2010 procedures. The user need only to supply date, location, and desired resolution—all remaining data are contained in the DRIVE Net database.

A LOS map can be displayed for the Puget Sound region by selecting a start date and time in the region labeled "B" in Figure 8-2, and clicking the "LOS Map" button. The LOS map legend is, labeled "E" in Figure 8-2. To compute the LOS for a specific roadway segment and view summary statistics, first select a date, route, start and end milepost, and resolution in the region labeled "C" in Figure 8-2. Note that the LOS results will be returned for each "pixel" in the selected roadway section. This means that if a pixel size of 0.1 mile is entered in the pixel size dropdown box, then each mile of roadway will be divided into 10 segments with a size 0.1 mile, and LOS will be computed for each segment respectively. The current start or end milepost is displayed when the associated sliding control is clicked. Next, click Statistics Report to display summary statistics for that segment and date, shown as "D" in Figure 8-2. Summary statistics can be exported as a Microsoft Excel file by clicking on the Export to Excel button shown in Figure 8-3.

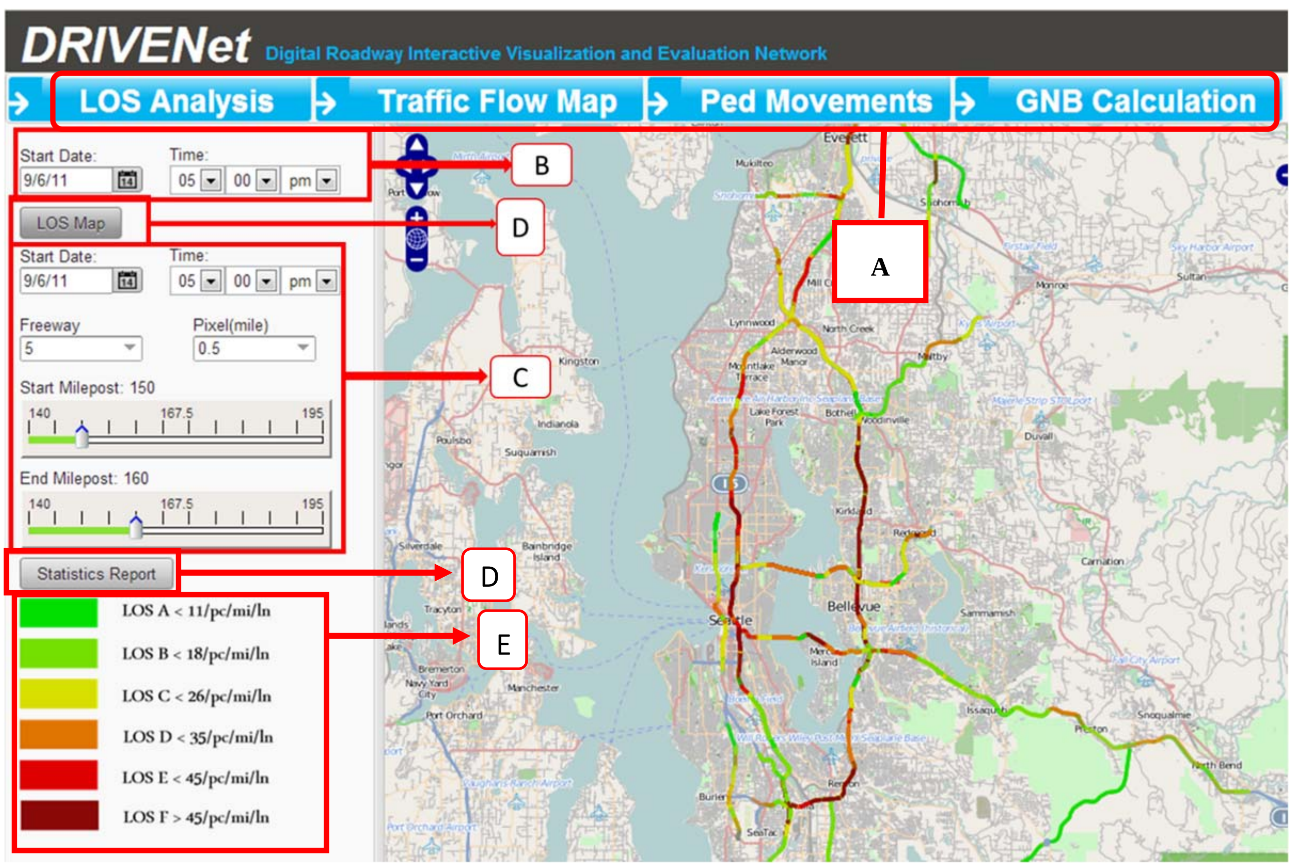
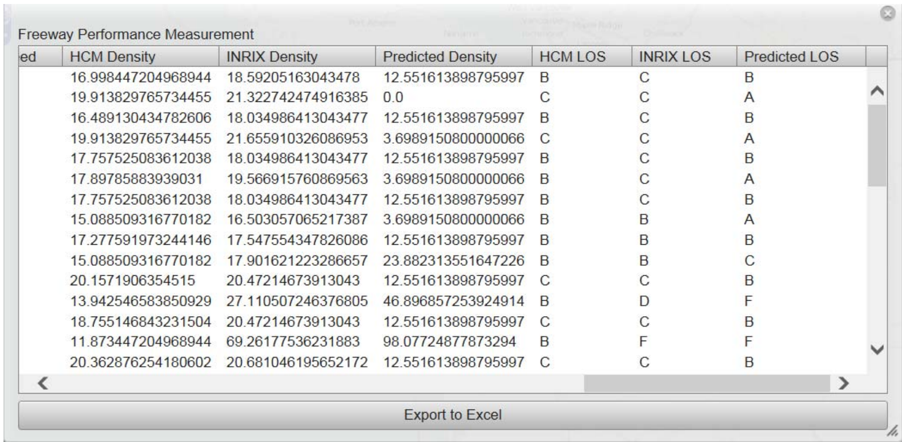


Figure 8-2 DRIVE Net LOS Analysis Screen



Freeway Performance Measurement

ed	HCM Density	INRIX Density	Predicted Density	HCM LOS	INRIX LOS	Predicted LOS
	16.998447204968944	18.59205163043478	12.551613898795997	B	C	B
	19.913829765734455	21.322742474916385	0.0	C	C	A
	16.489130434782606	18.034986413043477	12.551613898795997	B	C	B
	19.913829765734455	21.655910326086953	3.6989150800000066	C	C	A
	17.757525083612038	18.034986413043477	12.551613898795997	B	C	B
	17.89785883939031	19.566915760869563	3.6989150800000066	B	C	A
	17.757525083612038	18.034986413043477	12.551613898795997	B	C	B
	15.088509316770182	16.503057065217387	3.6989150800000066	B	B	A
	17.277591973244146	17.547554347826086	12.551613898795997	B	B	B
	15.088509316770182	17.901621223286657	23.882313551647226	B	B	C
	20.1571906354515	20.47214673913043	12.551613898795997	C	C	B
	13.942546583850929	27.110507246376805	46.896857253924914	B	D	F
	18.755146843231504	20.47214673913043	12.551613898795997	C	C	B
	11.873447204968944	69.26177536231883	98.07724877873294	B	F	F
	20.362876254180602	20.681046195652172	12.551613898795997	C	C	B

Export to Excel

Figure 8-3 Summary LOS Analysis Screen

8.2 Traffic Flow Map

In this screen, the user can view a color coded traffic speed map of the Puget Sound region for a given time and aggregation level. First, select the data source by clicking on either INRIX or Loop Traffic Flow Map in the area labeled "A" in Figure 8-5. Note that loop detector data are only available for state and interstate highways. Also, because INRIX data are only available at the 5-minute aggregation level, there is no aggregation option if the INRIX Traffic Flow Map option is selected. Because INRIX data are available for the entire state, select a WSDOT region to display (see map in Figure 8-4). Next, select a date, time, and aggregation level in the region labeled "B" in Figure 8-5. Click the Show Traffic button to display the traffic map, with colors corresponding to the legend, labeled "C" in Figure 8-5. An example traffic flow map is shown in Figure 8-6.

Abbreviation	WSDOT Region
SC	South Central
SW	Southwest Region
EA	Eastern Region
OL	Olympic Region
NC	North Central
NW	Northwest

Figure 8-4 WSDOT Region Map

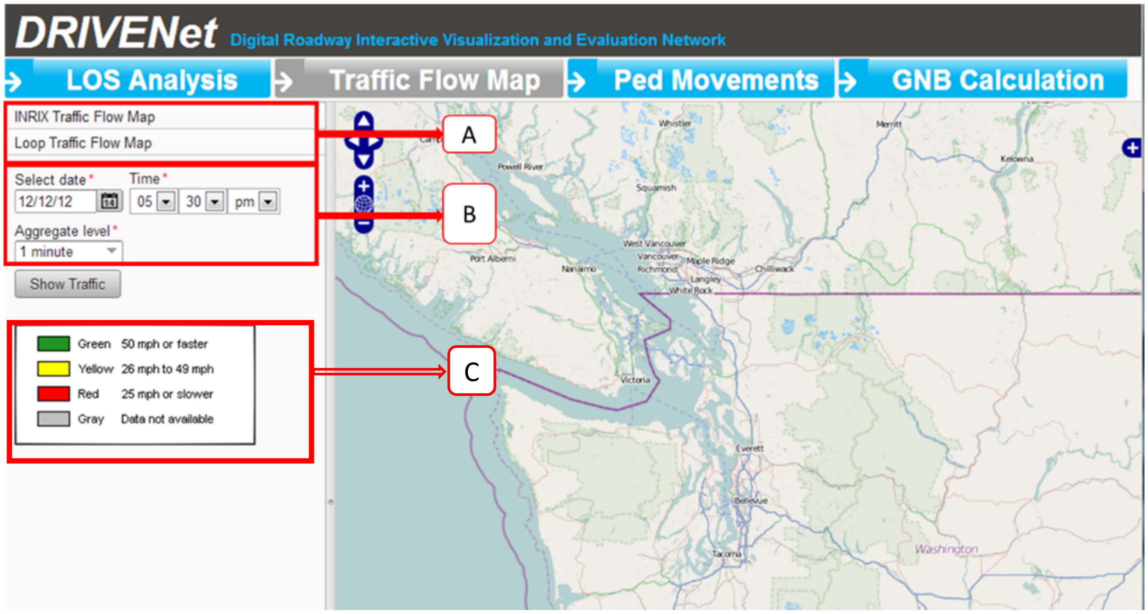


Figure 8-5 DRIVE Net Traffic Flow Map Screen

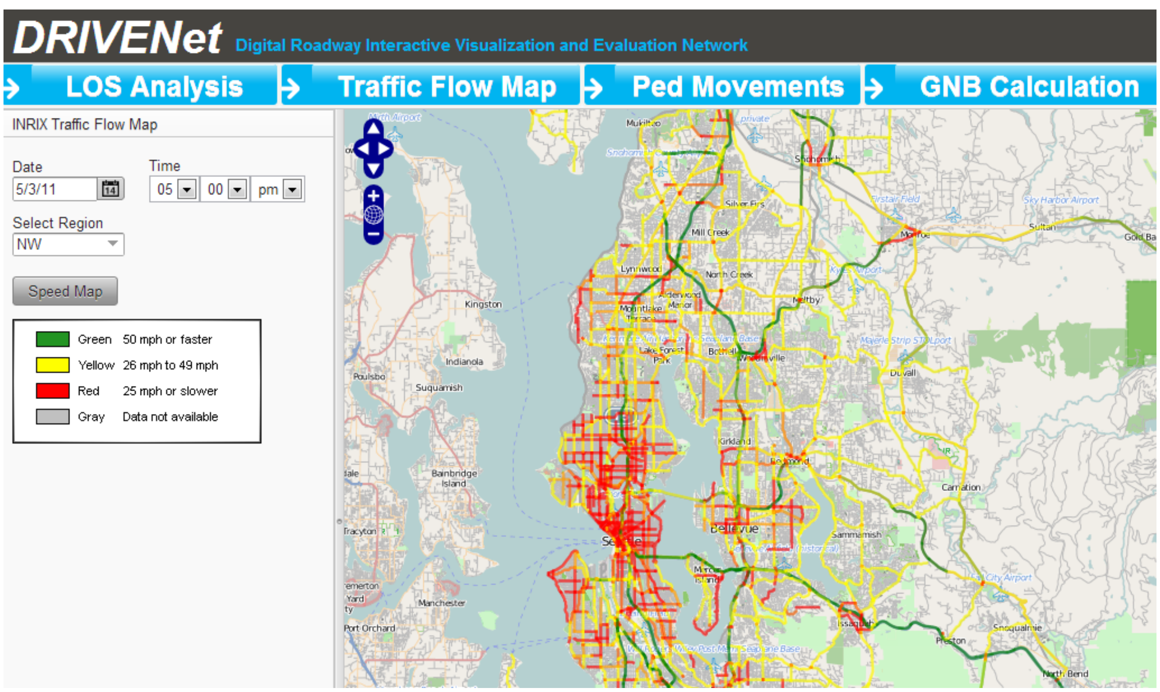


Figure 8-6 Traffic Flow Map Generated in DRIVE Net

8.3 Pedestrian Analysis

In this screen, the user can conduct pedestrian trajectory analysis by using Bluetooth data collected on the University of Washington campus. With user-selected experiment date and analysis parameters, DRIVE Net generates plausible paths and likely pedestrian routes.

The Bluetooth data used in this section of DRIVE Net were collected by STAR Lab researchers in two separate events, using both static and mobile "opportunistic" sensors. The first step is to select an experiment date in the box labeled "A" in Figure 8-6. Note that the 2013 dataset encompasses both a larger time period and a greater number of sensors.

To estimate popular routes, the trajectories obtained must be split into "certain" and "uncertain" sections, whereby the "certain" sections are able to reinforce the "uncertain" ones. For example, if the observations along a path are spaced closely enough to ensure with reasonable certainty that the points can be connected into a single continuous route, this route can then be used to infer possible paths for other, more sparse observations. A threshold-based algorithm is the simplest means of accomplishing this task. If there is a gap of greater than a certain distance threshold between two consecutive sightings, then that portion of the trajectory is uncertain. This distance threshold is set by using the slider labeled "B" in Figure 8-7. Clicking the Generate Popular Paths button reconstructs pedestrian paths on the basis of the threshold distance, which can then be used to infer paths for less frequent observations.

Next, select popularity weights by using the sliders in the region labeled "C" in Figure 8-7. The popularity weight assigns additional likelihood to a frequently used path on the basis of the previously imputed popular paths. Clicking on the Compute Plausible Paths button will generate paths for each origin/destination in the Bluetooth data.

Selecting the Show Detections box in the region labeled "D" in Figure 8-7 displays a heat map of mobile Bluetooth device encounters. To view origin/destination data collected with static Bluetooth sensors, click the desired sensor in the region labeled "E" in Figure 8-7. This will display color-coded bars emanating from the selected sensor to the other static detectors, with thickness corresponding to the relative pedestrian volume between each origin/destination. To view data from multiple sensors, hold down the Ctrl key and select all desired sensors.

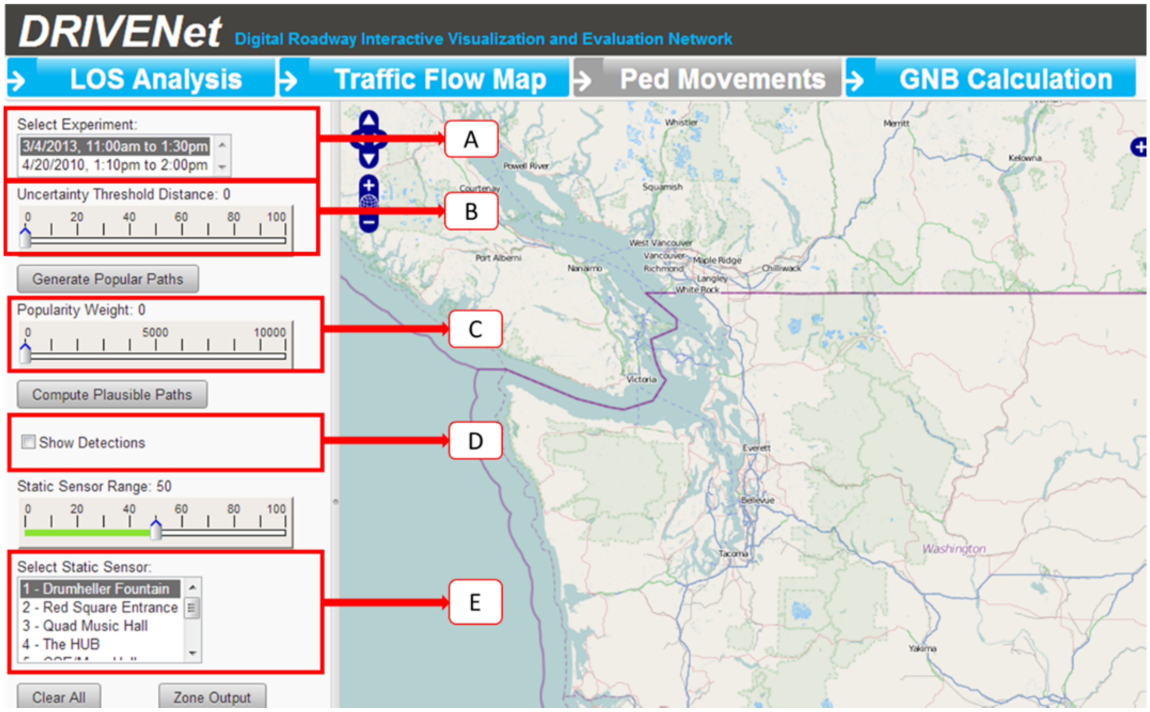


Figure 8-7 DRIVE Net Pedestrian Analysis Screen

8.4 Gray Notebook Calculations

There are three options on the GNB Calculation screen: travel time analysis using INRIX data, travel time analysis using loop data, and throughput productivity measurement. Start by clicking on one of these options in the region labeled “A” in Figure 8-8. The appropriate options will then be displayed in the region labeled “B” in Figure 8-8, magnified in Figure 8-9 below.

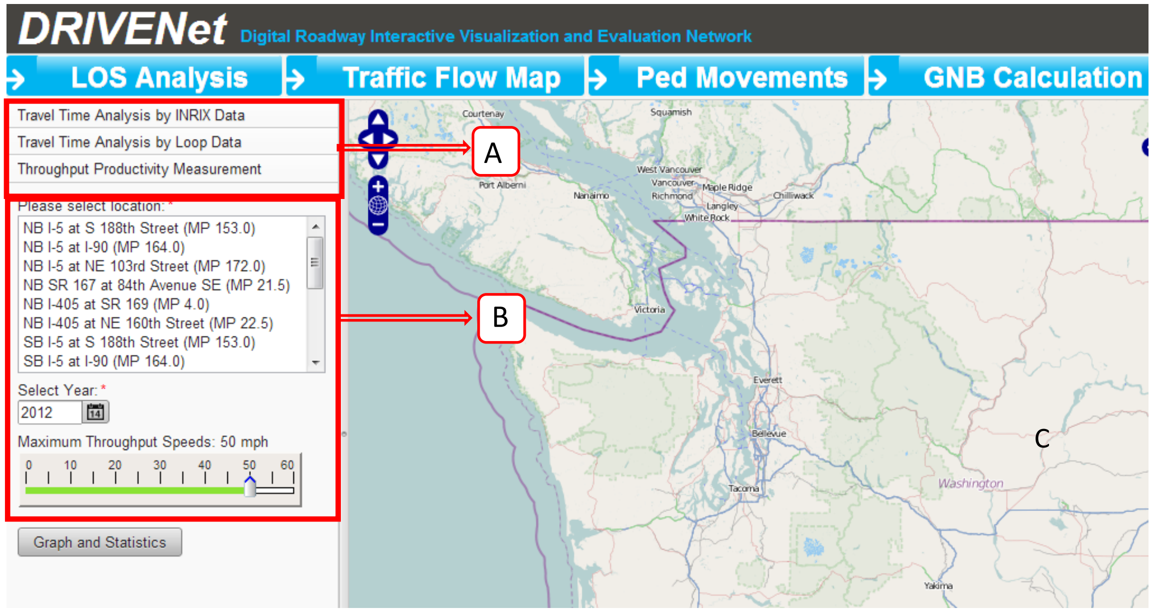


Figure 8-8 DRIVE Net Gray Notebook Calculations Screen

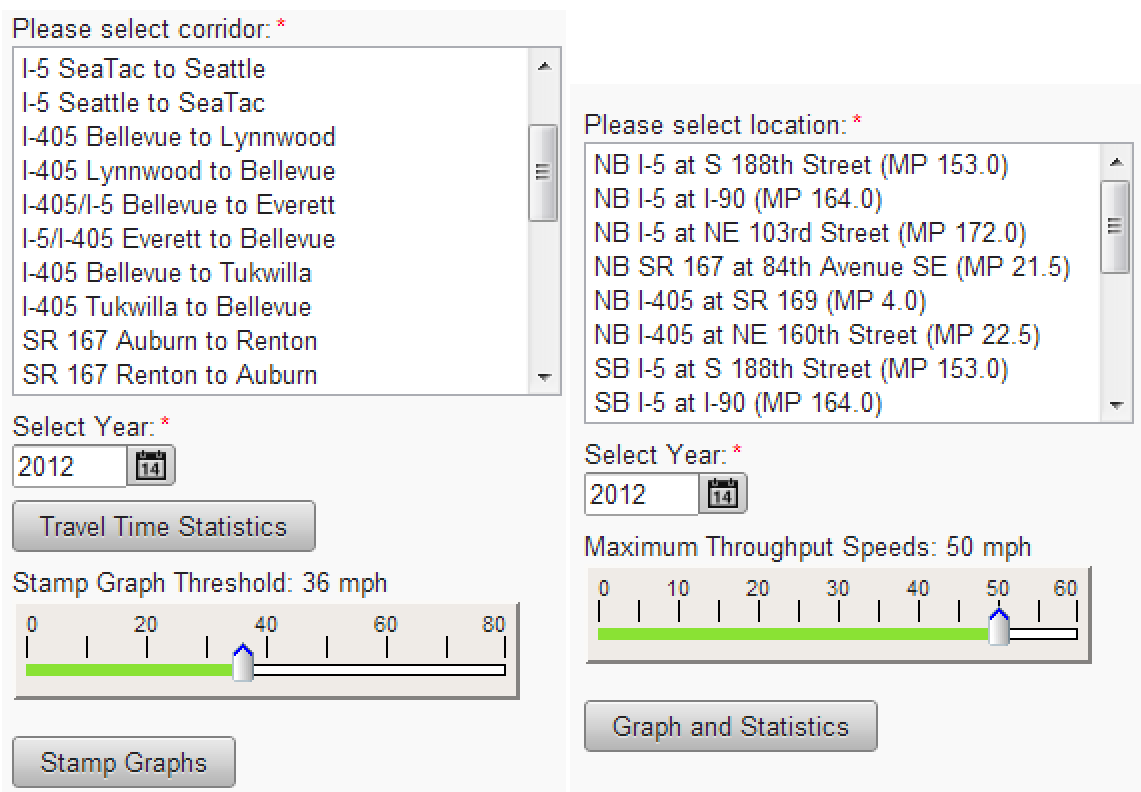


Figure 8-9 Travel Time Analysis Options (left) and Throughput Productivity Options (right)

8.4.1 Throughput Productivity

Throughput productivity can be computed for each travel direction at eight locations in the Puget Sound region, for a total of 16 locations. WSDOT measures throughput productivity by using the difference between the highest observed flow rate for that road section and the flow rate when the traffic speed falls below the maximum throughput speed (i.e., under-congested conditions). DRIVE Net computes this quantity as the throughput ratio, or the ratio of the current throughput performance to the maximum throughput. The maximum throughput speed is a user input field, but in general it should be set to the speed at which the highest 5-minute volume for the year was observed. When the traffic speed is above the maximum throughput speed, it is assumed that there is no loss in performance, and the throughput ratio is equal to 1.

To estimate throughput productivity in DRIVE Net, start by selecting a location (right, Figure 8-9). This will highlight the selected location in the map. Next, select an analysis year and maximum throughput speed (right, Figure 8-9). Finally, click the Graph and Statistics button to display a throughput productivity summary for the selected location and analysis year. Figure 8-10 shows the summary statistics for a location on northbound I-405. Results can be exported as a Microsoft Excel® file by pressing the Export to Excel button on this screen. The summary graph shows throughput performance for the highest observed 5-minute traffic volume for the selected year, as shown in Figure 8-11.

Throughput Productivity Statistic

Location:	EB I-90 at SR 900 (MP 16.5)	
Year:		2012
Maximum Throughput Speed:		50
Highest Flow Rate:		1749
Maximum Loss of Vehicle Thro		0
Time	**Throughput Ratio**	**Loss of Vehicle Throughput**
05:00	1	0
05:05	1	0
05:10	1	0
05:15	1	0
05:20	1	0
05:25	1	0
05:30	1	0
05:35	1	0
05:40	1	0
05:45	1	0
05:50	1	0
05:55	1	0
06:00	1	0

Figure 8-10 Throughput Productivity Summary Statistics

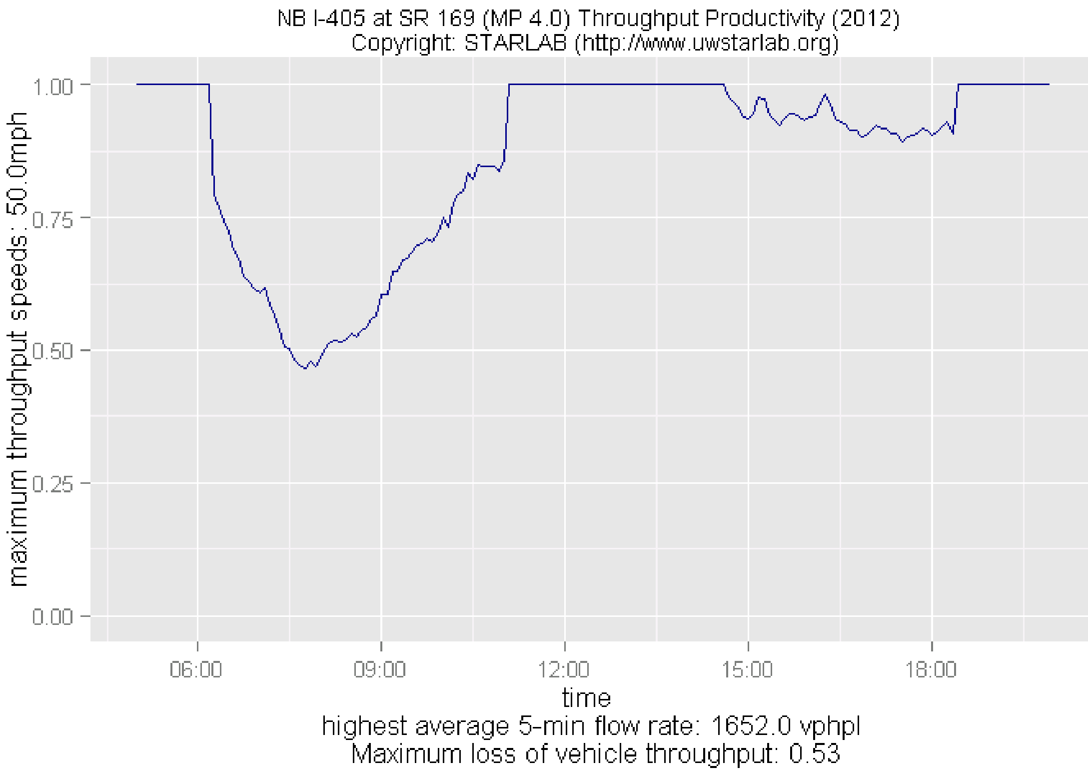


Figure 8-11 Throughput Productivity Graph for Northbound I-405 at SR 169, Based on a Maximum Throughput Speed of 50 MPH

8.4.2 Travel Time Analysis

DRIVE Net can be used to estimate travel time and reliability measures for 26 Puget Sound commuter routes. The following measures can be estimated by using either loop or INRIX data:

- Mean travel time
- Median travel time
- 80th, 90th, and 95th percentile travel time
- Maximum throughput travel time
- Travel time index
- Planning time index
- Buffer index.

In addition, DRIVE Net can be used to estimate the average travel speed for a corridor, which is used to estimate the number of days for which congestion is present at any given time of day.

For travel time using INRIX or loop data, start by selecting a corridor and travel year (left, Figure 8-9). The stamp graph threshold selector (left, Figure 8-9) sets the traffic speed threshold below which traffic conditions are considered to be congested. For example, on a corridor with a 60 mph speed limit, traffic may be assumed to be congested if the speed drops below 36 mph. Clicking on the scroll button will display the current speed threshold. Clicking the Travel Time Statistics button will display a summary of travel time for the selected corridor (Figure 8-12). These results can be exported to Excel by clicking the Export to Excel button, as shown in Figure 8-12. Clicking the Stamp Graph button will display a plot with the percentage of days with an average speed below the stamp graph threshold on the y-axis and time of day on the x-axis, as shown in Figure 8-13.

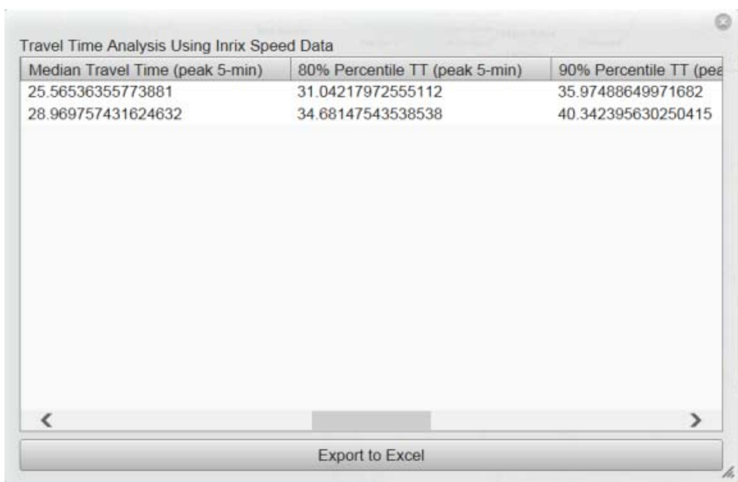


Figure 8-12 Travel Time Statistics Results for the Bellevue to SR 524 Corridor

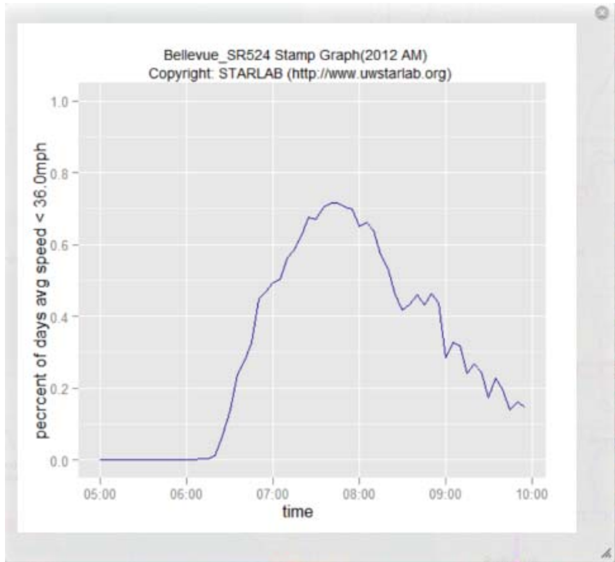


Figure 8-13 Stamp Graph for the Bellevue to SR 524 Corridor, Morning Period

Chapter 9 Conclusions and Recommendations

9.1 Conclusions

Modern technology is creating a significant increase in the amount and types of data available to describe the condition, use, and performance of the state's transportation system. While many new data sources are being captured, these datasets are not being used to WSDOT's full benefit, as these new datasets cannot be easily combined with each other or with WSDOT's existing data systems. Consequently, WSDOT has a significant need for a tool that has the data storage and analysis capability to allow fast, multi-data source analysis in support of WSDOT's project planning, scoping, design, construction, performance analysis, reporting, and system maintenance activities.

This study enhanced the stability and reliability of the current DRIVE Net system. The new DRIVE Net system has the capability to archive, process, and analyze massive volumes of transportation data. Thanks to the power of open-sourced technologies, the new system can seamlessly and efficiently integrate geospatial data (roadway geometry datasets) with traditional loop detector data, weather data, incident data, and INRIX GPS data. In comparison to the previous DRIVE Net system, the new system not only provides reporting and visualization service, but also acts as a functioning archiving platform to collect state-wide loop detector data and flexibly incorporate third party datasets such as WITS data and INRIX data.

The DRIVE Net system not only serves as an online data archiving and visualization platform, but it also acts as a powerful analytical toolkit for decision makers. The diverse datasets from various sources and the multiple scales in temporal, spatial, and categorical aspects allow quantitative studies on a variety of transportation issues. To automate the analysis functions, supporting software modules must be developed on the DRIVE Net platform. Each analysis module requires programming the corresponding data processing and computation algorithms. The implementation of the HCM 2010 LOS demonstrates the feasibility of DRIVE Net for network-level modeling. INRIX data and loop data were integrated to calculate freeway critical traffic density, and a novel spatial data mining approach was developed to overlay multiple roadway geometric data together. To address data quality issues, a K-means clustering algorithm and regression technique were proposed to estimate freeway LOS under oversaturated conditions. The proposed system outperformed several other traditional algorithms for LOS calculation in terms of accuracy and practicability. The network-level LOS measurements are colored in a regional map system through DRIVE Net.

DRIVE Net can also help WSDOT personnel in publishing and reporting annual and quarterly freeway performance measurements in the WSDOT Gray Notebook. Loop data quality control is critical before data analysis is conducted. In the updated DRIVE Net system, 5-minute loop data are subjected to a series of error checking approaches that include basic thresholding for volume and occupancy, hardware-level detection, and statistical methods. The identified erroneous and missing data are imputed with a three-step correction procedure: spatial imputation, temporal imputation, and Gaussian Mixture Model (GMM) imputation. The entire data checking and correction procedure is automated with Microsoft Visual C#, and the raw and corrected data are imported into the Microsoft SQL server 2012. The processed data are then utilized to calculate Gray Notebook statistics, which help in monitoring and evaluating traffic performance in Washington.

Another important application of DRIVE Net is to collect, process, and visualize pedestrian route information using mobile sensors. Self-designed Bluetooth sensors were used in this study to collect pedestrian movement data. A mobile app was also developed for users to facilitate data collection. The generated data are sent back and archived into DRIVE Net through MAC address matching and filtering. Because of spatial uncertainty, the movement of each pedestrian with a mobile device cannot be fully understood. This is to say, the route details between a set of check points recorded by the Bluetooth devices is not known. However, an algorithm to address that spatial uncertainty was proposed in this study. This algorithm resorts to a routing cost function to depict the spatial uncertainty and to find a route that minimizes total routing costs. For validation purposes, eight static Bluetooth sensors were mounted on the University of Washington Seattle campus, and eight volunteers participated in pedestrian tracking. The errors were less than 5 percent. To help visualize the estimated routes, the proposed algorithm was successfully implemented into DRIVE Net with the PGRouting open-sourced library.

9.2 Recommendations

To facilitate future research, the following recommendations are made:

(1) With the advent of the "Big Data" concept, efficiently processing a huge amount of transportation data will be a critical challenge for transportation agencies. Cloud computing techniques should be adopted to alleviate the computational burden and help achieve real-time freeway performance measurement.

(2) To reduce the space required to store a large amount of data, they can be aggregated spatially and temporally. The aggregation procedure can be handled by multidimensional data models with predefined hierarchies of aggregation levels. Relational Online Analytical Processing (ROLAP) and Multidimensional OLAP (MOLAP) are two major technologies that may be used to aggregate the data while maintaining query performance. Another option for handling a large dataset is data compression. Data compression functionality is quite mature, and many database packages, such as IBM's DB2 and Microsoft's MS SQL, provide functions that can easily reduce space usage.

(3) Future efforts should be made to utilize DRIVE Net for evaluating operational strategies, such as active traffic management (ATM) and High Occupancy Toll (HOT) (Zhang et al., 2013). Such before-and-after analyses will provide solid data support in helping WSDOT better allocate and manage its limited resources for the most critical transportation facilities.

(4) The current thresholding method for the pedestrian trajectory reconstruction module can be improved by using several artificial intelligence approaches, such as Fuzzy Logic or Decision Tree algorithms.

(5) Rather than focusing on static corridors and locations, future work should involve enabling travel time reliability analysis for dynamic corridors and locations. The start point and end point of corridors could be selected by individuals, which could serve different purposes. Similarly, throughput productivity estimation could be applied to the entire network rather than being restricted to 16 locations.

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