Use of Mobile Data for Weather-Responsive Traffic Management Models

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16. Abstract

The evolution of telecommunications and wireless technologies has brought in new sources of traffic data (particularly mobile data generated by vehicle probes), which could offer a breakthrough in the quality and extent of traffic data. This study reviews the Weather- Responsive Traffic Management Models (WRTM) models which were developed in previous FHWA funded weather-related projects and identifies the components within WRTM framework where mobile data could be incorporated, mainly, (i) supply-side model calibration; (ii) demand-side calibration; (iii) model validation; and (iv) on-line implementation. This report summarizes the unique properties of mobile data in contrast to traditional traffic data, particularly regarding its much wider geographic coverage and travel time information. The different types of mobile data which could be offered from major vendors are also discussed.

The study finds that vehicle trajectory data serves best for the purpose of improving WRTM models, from calibration of supply and demand side relations and model validation to the case of the on-line TrEPS implementation. A framework for how to implement the integration of mobile data and WRTM models was also developed. In this project the process of following the framework and incorporating mobile data into WRTM models is demonstrated by a case study. DYNAMSART (DYnamic Network Assignment-Simulation Model for Advanced Road Telematics), a DTA simulation-based TrEPS, is selected for this study. Vehicle trajectory data, collected by vehicles equipped with TomTom GPS devices circulating in New York City area during a two-week period, is also used.

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We are grateful to the data providers who have shared information about the status of their current sources of mobile data and plans to improve quality and coverage. Several firms provided sample data to the team. These included TomTom; Inrix; Nokia (formerly Navteq) and AirSage. TomTom also provided Northwestern University with a more detailed sample for research purposes.

Several research assistants at Northwestern University's Transportation Center have contributed to this effort, especially in terms of network preparation and calibration, especially Omer Verbas, Ali Zockaie, and Lan Jiang.

The authors remain solely responsible for all work, findings, conclusions and recommendations presented in this report.

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Executive Summary

Adverse weather impacts on freeway traffic operations have become a growing concern for roadway management agencies. Dealing with adverse weather requires not only sensing of traffic conditions but also the ability to forecast the weather in real-time for operational purposes. FHWA and the research community have developed a series of weather-responsive traffic management (WRTM) models that make it possible to manage weather-related traffic events better. Weather-sensitive Traffic Estimation and Prediction System (TrEPS) has been developed in the previous studies, and has been proven to be capable of modeling the effects of weather on traffic more realistically. A key driver of a TrEPS for weather-related management applications is the availability of real-time data on prevailing conditions, both weather data and traffic data. Traditionally model calibration and implementation rely on traffic data collected from fixed sensors with limited geographic coverage. The evolution of telecommunications and wireless technologies has brought in new sources of traffic data (particularly mobile data generated by vehicle probes), which could offer a breakthrough in the quality and extent of traffic data. It is believed that the combination of weather-sensitive TrEPS and mobile data will make it practical to improve the accuracy and relevance of WRTM models.

This study reviews the WRTM models which are developed in previous FHWA funded weather-related projects, and identifies the components within WRTM framework that mobile data could be incorporated, mainly, (i) supply-side model calibration; (ii) demand-side calibration; (iii) model validation; and (iv) on-line implementation. It summarizes the unique properties of mobile data as contrast to traditional traffic data, particularly as having much wider geographic coverage and travel time information. The different types of mobile data which could be offered from major vendors are discussed. It is found that vehicle trajectory data serves the best for the purpose of improving WRTM models, from calibration of supply and demand side relations, model validation, to the case of the on-line TrEPS implementation. A framework of how to implement the integration of mobile data and WRTM models is developed. In this project the process of following the framework and incorporating mobile data into WRTM models is demonstrated by a case study. DYNAMSART (DYnamic Network Assignment-Simulation Model for Advanced Road Telematics), a DTA simulation based TrEPS is selected for this study. Vehicle trajectory data provided by TomTom is used, which is collected by vehicles equipped with TomTom GPS devices circulating in New York City area during a two-week period.

The principal procedures of off-line calibrating and validating supply and demand side WRTM models using mobile data are introduced and implemented by using TomTom vehicle trajectory data. It is found that in cases where the mobile data allow estimation of the same types of traffic variables and parameters as more conventional sensor data, the procedures already developed can be used with little modification, e.g., supply-side model calibration; while in some other cases, mobile data which contain richer information, especially in the form of vehicle trajectories, is particularly more useful for modeling drivers' behavior in route choice, e.g., demand-side model calibration. It is also validated by observations from mobile data, that the TrEPS model calibrated using mobile data together with weather data and some traditional fixed sensor traffic data, is also capable of capturing the adverse impact on traffic flow, especially in terms of speed and travel time.

The work accomplished in this study advances the state of art and state of practice of incorporating mobile data in Weather-Responsive Traffic Management models. The procedures of using mobile data in calibrating and validating those models, presented in this study, provides a framework of combining weather-sensitive TrEPS and new sources of traffic data. Additional effort is necessary, when more types of mobile data become available, to show the applicability of mobile data in on-line implementation of TrEPS.

Chapter 1. Introduction

1.1 Background

Weather events such as precipitation, fog, high winds and extreme temperatures cause low visibility, slick pavement, reduced roadway capacity and other hazardous conditions on roadways. Research studies show that the disruptive effect of inclement weather on traffic has a direct impact on safety - about 28% of all highway crashes and 19% of all fatalities involve weather-related conditions as a factor. Additionally, adverse weather accounts for about 25% of delays on freeways due to reduced service capacity, diminished reliability, and greater risk of accidents.

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Adverse weather impacts on freeway traffic operations have become a growing concern for roadway management agencies. Dealing with adverse weather requires not only sensing of traffic conditions but also the ability to forecast the weather in real-time for operational purposes. To mitigate the impacts of adverse weather on highway travel, the Federal Highway Administration (FHWA) Road Weather Management Program (RWMP) has been involved in research, development and deployment of weather responsive traffic management (WRTM) strategies and tools. Figure 1-1 presents the FHWA's overall WRTM framework. In a project completed in 2006, the Road Weather Management Program used data from Seattle, Minneapolis and Baltimore to develop statistical models and adjustment factors to quantify the impacts of weather on traffic flow (*Hranac et. al. 2006*). One of the challenges remaining is to integrate those models into decision support systems to help improve the performance of the transportation system during inclement weather conditions.

In order to reduce the impacts of inclement weather events and prevent congestion before it occurs, weather-related advisory and control measures could be determined for predicted traffic conditions consistent with the forecast weather, that is, anticipatory road weather information. This calls for integrated real-time WRTM and a Traffic Estimation and Prediction System (TrEPS). Because the dynamics of traffic systems are complex, many situations necessitate strategies that anticipate unfolding conditions instead of adopting a purely reactive approach. Real-time simulation of a traffic network can predict future conditions and thus help design and implement more effective traffic operations including various types of control measures (*Jayakrishnan et al. 1994*; *Mahmassani 2001*). Predicted future traffic states can be described in terms of flows, travel times, and other time-based performance characteristics. These are used in the on-line generation and real-time evaluation of a wide range of measures, including information to users, VMS displays, coordinated signal timing for diversion paths, as well as weather-related interventions (through variable speed limits, advisory information, signal timing adjustments and so on).

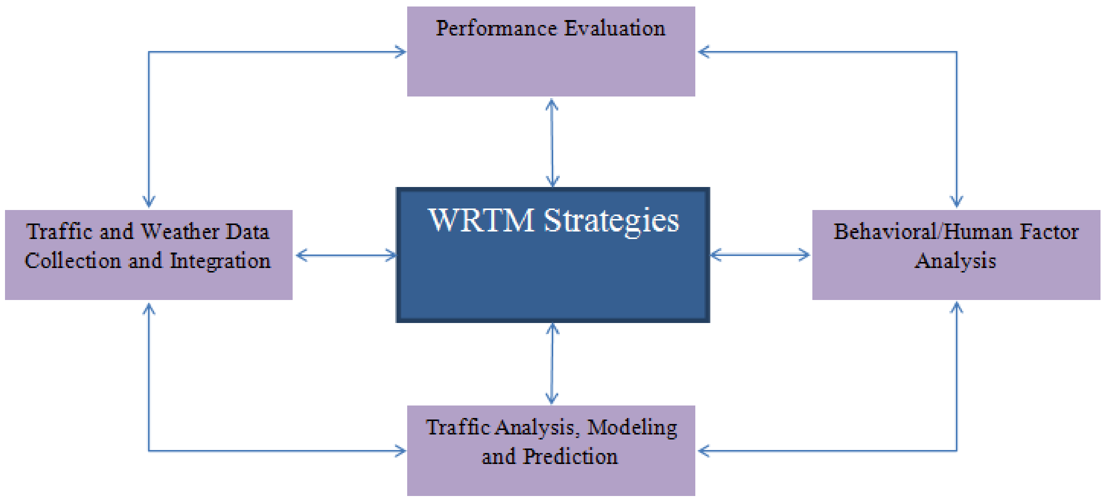

Figure 1-1. Framework for Weather Responsive Traffic Management (WRTM) Program (Source: Krechmer, et al., 2010)

In a recently completed FHWA project, a methodology for incorporating weather impacts in Traffic Estimation and Prediction Systems (TrEPS) is developed (*Mahmassani et al., 2009*). The project addressed both supply and demand aspects of the traffic response to adverse weather, including user responses to various weather-specific interventions such as advisory information and control actions. The methodology was incorporated and tested in connection with the DYNASMART-P simulation-based DTA system, thereby providing a tool for modeling the effect of adverse weather on traffic system properties and performance, and for supporting the analysis and design of traffic management strategies targeted at such conditions. In a follow-on FHWA project, work is advanced towards actual implementation through calibration, implementation and evaluation of weather-responsive traffic estimation and prediction systems (*Mahmassani et al., 2012*). In that project, the weather-sensitive TrEPS model (DYNASMART-X) is applied, calibrated and tested in several major US cities (Chicago, IL; Salt Lake City, UT; New York, NY; and Irvine, CA). The study findings confirmed that the proposed models successfully capture the weather effects on traffic. The study highlighted the important role network models and simulation methodologies can play in the further development and deployment of WRTM strategies, and the process through which such tools could be made more effective in helping agencies attain their objectives within available resources.

A key driver of a TrEPS for weather-related management applications is the availability of real-time data on prevailing conditions, both weather data and traffic data. The former is addressed through the Road Weather Connected Vehicles Program, while the latter typically relies on sensors deployed by the operating agency. These sensors are tied to the infrastructure; while different technologies may be used for detection and communication, their deployment tends to be limited to a portion of the freeway system in a given area, with very limited to non-existent coverage for urban arterials and streets. In addition to their use as an essential input for the online implementation of the estimation and prediction system, traffic data are required for the off-line calibration of the network and related procedures. These include both demand-side quantities (e.g. origin-destination trip matrix) and supply-side relations (e.g. speed-density relations). In all applications so far, these data issues have proven to be the main bottleneck and challenge that needs to be overcome in adoption and deployment of advanced modeling and management tools. Mobile data obtained through GPS or cellular-assisted location information from smart phones and/or specialized devices, have long held considerable promise given their independence from infrastructure-based devices and because their information reflects travel by actual users. These systems offer the potential for consistent coverage of the entire network, including arterials, local streets and freeways. However, the availability of such data has remained elusive largely because of the structure of the industry (telecommunications) and the relatively low value or priority previously ascribed to traffic uses of those data. With the rapid spread of smart phones, the picture is changing dramatically. The purpose of the current project is to examine the potential value of mobile sources of data for WRTM and then demonstrate how these data might be integrated into WRTM models.

1.2 Emergence of Mobile Data

The transportation data marketplace became an actual ‘marketplace’ over the last ten years. This reflects a change in technology and a change in public versus private roles. Traditional sources of data for public sector applications – fixed sensors (primarily loop detectors and side view radar) – are well known and relatively low in cost since they are owned and operated by public entities. These installations provided accurate volume, occupancy, speed, and density data that have served metropolitan areas quite well for operations, planning, and traveler information. Many cities provide web-based traffic data archive systems that are freely available to public (e.g., PeMS in California).

But, fixed sensors also are limited geographically, with few located along arterials and very few in rural areas. They also require maintenance meaning that some jurisdictions have spotty data. The evolution of telecommunications and wireless technologies has opened up a world of opportunity to collect traffic data. These technologies support probe-based systems that rely on GPS-based data or cellular location systems. These offer broader coverage, with the potential to cover major arterials. They also have the ability to measure traffic in nontraditional patterns – such as might occur before or during a major weather event. On the other hand, evaluation of these sources has not always been consistent and they do miss data elements such as occupancy that traditional fixed sensors can provide. Localized deployments of other technologies including Bluetooth and license plate readers provide additional resolution for specific geographic regions. These technologies also serve to validate probe data installations.

The public sector has shown great interest in using these new data systems to expand coverage and particularly to offset the costs of installation and maintenance of fixed detection systems. Several states have contracted for both pilot programs and statewide data for evaluation and integration. In 2007, The Minnesota Department of Transportation carried out a field test around Minneapolis in collaboration with the telecom operator Sprint PCS network, to estimate travel times and travel speeds and compare against ground truth measures (Liu et al., 2008). In 2008, the California Department of Transportation, together with UC Berkeley, Nokia Research Center, and NAVTEQ, launched the Mobile Millennium project which aims to design, test and implement a state-of-the-art system to collect traffic data from GPS-equipped mobile phones and estimate traffic conditions in real-time (Herrera et al., 2010). Realistically, the questions of quality, accuracy, and confidence remain for the available data sources, particularly as applied to the public sector use.

The pace of change continues rapidly with significant increases in the volume of probe data for individual firms (for example AirSage has announced adding a second wireless firm as an additional source of data) and new market entrants – TomTom is one example. Also networks built on Bluetooth technologies have been proposed. Automobile companies are a potential source of these data, with GM's OnStar system and Ford's Sync providing examples. Similarly, firms such as Google, Apple, and Microsoft have shown an interest in collecting location and speed data from their customers. Google Maps has the functionalities to show both historical and real-time traffic conditions (with color coded speed categories) on every single street, and recently it has added the ability to estimate travel time of user specified journeys. The data that Google used to estimate traffic is gathered through third-party services and through information from cell phone (with Android OS) users who have opted in to the 'My Location' feature on Google Maps. Google would then be able to tell, for instance, if there were several Android owners moving slowly on the freeway and determine that there was traffic slowing them down. The more people opting into the service in the area, the better the traffic information available will be. Similarly, Inrix (courtesy of Microsoft Corp.) collects trillions of bytes of information about roadway speeds from nearly 100 million anonymous mobile phones, trucks, delivery vans, and other fleet vehicles equipped with GPS locator devices. The data collected is processed in real-time using Bayesian statistical methods, creating traffic state estimation for major freeways, highways and arterials across the United States and many other countries around the world.

Though different parties have demonstrated the wide application of mobile data in the transportation field, particularly in term of traffic state estimation and prediction, its application with newly developed WRTM models has never been studied. Realizing the great potential inside this area, this project is aimed at developing a systematic framework of incorporating mobile data into weather-sensitive TrEPS, from off-line calibration to on-line implementation.

1.3 Structure of Final Report

The remainder of this report is organized as follows. Chapter 2 provides a thorough review of WRTM models that are developed in previous FHWA funded weather-related projects. An overview of Traffic Estimation and Prediction System (TrEPS) is presented in the first, followed by its capability of capturing weather effects on traffic. The review is focused on DYNASMART weather-sensitive TrEPS. Chapter 3 introduces the unique properties of mobile data as contrast to traditional traffic data. Then it identifies the potential areas where mobile data could be incorporated. It systematically maps the different components of WRTM models onto different data needs and sources – for calibration of different supply and demand side relations, and in the case of the on-line TrEPS. A framework of how to implement the integration of mobile data and WRTM models is also developed. Chapter 4 describes the urban road network selected to conduct the calibration and validation of TrEPS models using mobile data. For that selected network, its configurations in the simulation-based DTA model (DYNASMART) format is presented. Chapter 5 describes the calibration and validation of weather-sensitive TrEPS model using vehicle trajectory data. Detailed procedures and results for incorporating mobile data in calibrating the supply side parameters, i.e., traffic flow model parameters and weather adjustment factors, and the demand-side parameters, i.e., time dependent OD matrices for the simulation analysis, are presented. Chapter 6 presents the conclusions, including lessons learned and recommendations for next steps needed to advance the state of the art and of the practice of using mobile data for WRTM models.

Chapter 2. Review of WRTM Models

2.1 Overview of Traffic Estimation and Prediction System

The most critical component at the core of weather-sensitive TrEPS model is a real-time traffic estimation and prediction system which provides real-time estimates of traffic conditions, network flow patterns and routing information, and predicts future traffic conditions. DYNASMART-X (*Mahmassani et al., 1998; Mahmassani and Zhou, 2005*) and DynaMIT-R (*Ben-Akiva et al., 2002*), both developed largely under FHWA support, use a mesoscopic simulation-based dynamic traffic assignment (DTA) approach for real-time traffic estimation and prediction, in which individual particles (vehicles) move according to local speeds determined consistently with (macroscopic) relations among averages of speed and density. The TrEPS model selected in this study for demonstration purpose is DYNASMART.

As an online TrEPS, DYNASMART-X interacts continuously with multiple sources of real-time information, such as loop detectors, roadside sensors, and vehicle probes, which it integrates with its own model-based representation of the network traffic state. The system combines advanced network algorithms and models of trip-maker behavior in response to information in an assignment-simulation-based framework to provide: (1) estimates of current network traffic conditions; (2) predictions of network flow patterns over the near and medium terms, in response to various contemplated traffic control measures and information dissemination strategies; and (3) anticipatory traveler and routing information to guide trip-makers in their travel (*Dong et al., 2006*). The system includes several functional modules (for OD estimation, OD prediction, real-time network state simulation, consistency checking, updating and resetting functions, and network state prediction), integrated through a flexible distributed design that uses CORBA (Common Object Request Broker Architecture) standards, for real-time operation in a rolling horizon framework with multiple asynchronous horizons for the various modules (*Mahmassani et al., 2004*).

The functionality of DYNASMART-X is achieved through judicious selection of modeling features that achieve a balance between representational detail, computational efficiency and input data requirements. These features include (*Mahmassani et al., 2004*):

- A simulation-based dynamic traffic assignment system, with microsimulation of individual user decisions in response to information, and mesoscopic traffic flow simulation approach.
- Multiple user classes in terms of (1) operational performance (e.g. trucks, buses, and passenger cars), (2) information availability and type, and (3) user behavior rules and response to information.
- Representation of traffic processes at signalized junctions, under a variety of operational controls, including real-time adaptive signal policies and coordination schemes.
- Consistency between predicted network states, supplied information, and user decisions.

- State prediction capabilities in a rolling horizon implementation with simultaneous multiple horizons.
- Capability for optimal path assignment and integrated system management.
- Compatibility with different ITS architectures (e.g. centralized vs. distributed)
- Distributed software implementation using CORBA for flexible and scalable execution in a distributed environment.

The DYNASMART TrEPS platform is comprised of four components: (1) the graphical user interface, or GUI, (2) the database, (3) the algorithmic modules that perform the DTA functional capabilities, and (4) the set of CORBA programs used to implement the scheduler and the data broker. The algorithmic component is the main entity in the system in terms of performing the TrEPS functions, and consists of the following modules: (a) state estimation, (b) state prediction, (c) OD estimation, (d) OD prediction, and (e) consistency checking and updating. The purpose of the state estimation module (RT-DYNA) is to estimate the current traffic state in the network. The state prediction module (P-DYNA) on the other hand provides future network traffic states for a pre-defined horizon. The OD estimation module (ODE) is responsible for estimating the coefficients of a time varying polynomial function that describes the OD demand in the current stage. The OD prediction module (ODP) utilizes these to calculate the demand that is generated from each origin to each destination at each departure time interval of the current and future stages. Finally, the consistency checking modules are responsible for minimizing the deviation or discrepancy between what is estimated by the system and what is occurring in the real world, in an effort to control error propagation. A schematic view of the DYNASMART-X system as implemented is shown below in Figure 2-1. The arrows represent the data flows between its modules and components.

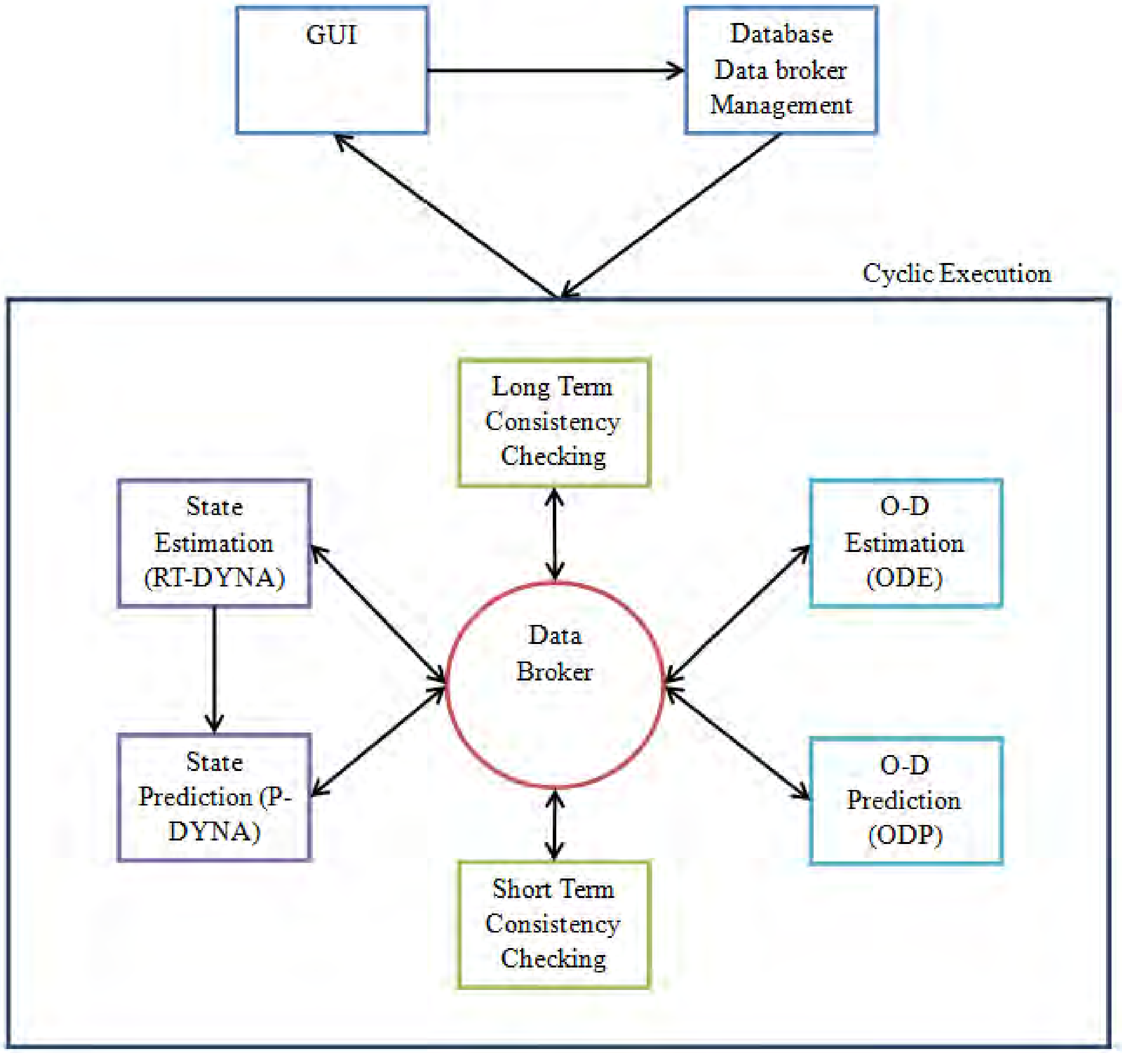

Figure 2-1. DYNASMART-X TrEPS structure (Source: Mahmassani, et al., 2004)

Note that RT-DYNA and P-DYNA are essentially near-identical copies of the same simulation assignment code, executed in a different manner and with different dynamic inputs. However, the core simulation logic is essentially identical, and is shared with the off-line DTA tool (DYNASMART-P) used primarily for analysis and evaluation to support operational planning decisions. In this study, efforts were focused on incorporating mobile data in the context of off-line calibration, validation, and evaluation of weather-sensitive DTA models (DYNASMART-P), while the conceptual framework of online implementation will also be addressed. Since the on-line and off-line tools share the same core simulation logic, the methodologies and functionalities made in DYNASMART-P to incorporate mobile data to capture the effect of adverse weather would then seamlessly be extended to the on-line DYNASMART-X TrEPS.

2.2 Modeling Weather Effects

2.2.1 Overall Conceptual Framework

A conceptual modeling framework has been proposed to explicitly incorporate the weather effect on demand and supply of transportation road network system into the analysis (Figure 2-2). In a previous FHWA project (*Mahmassani et al., 2009*), the principal supply-side and demand-side elements affected by adverse weather were systematically identified and modeled in the Traffic Estimation and Prediction System (TrEPS) framework. The models and relations developed were calibrated using available observations of traffic and user behavior in conjunction with prevailing weather events. The proposed weather-related features have been demonstrated through successful application to a real world network, focusing on two aspects: (1) assessing the impacts of adverse weather on transportation networks; and (2) evaluating effectiveness of weather-related advisory/control strategies in alleviating traffic congestion due to adverse weather conditions.

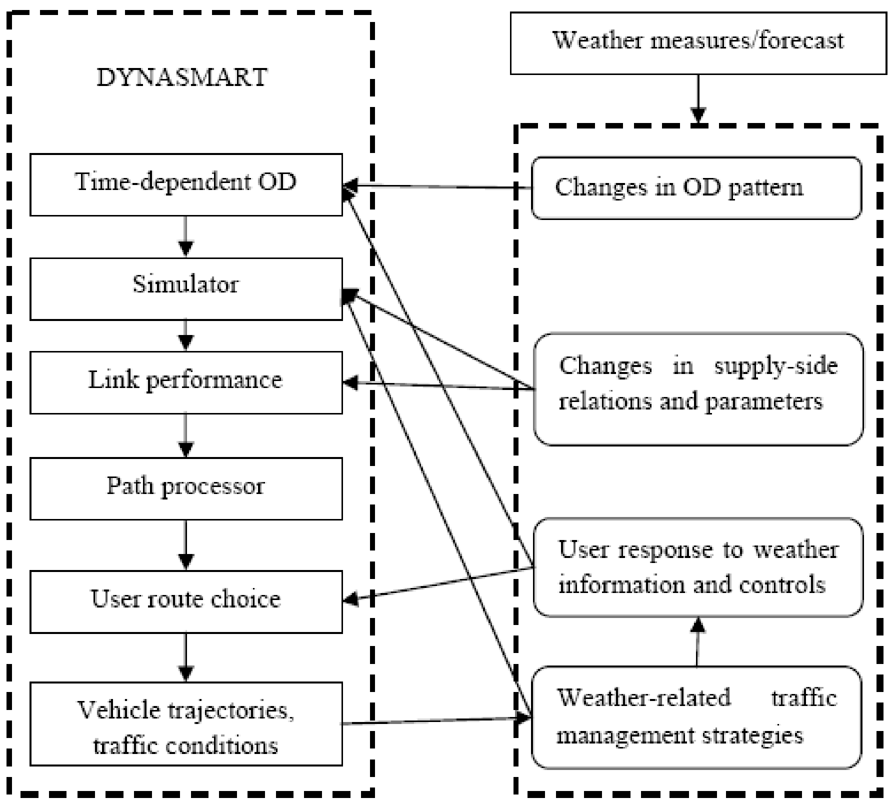

Figure 2-2. Conceptual framework of integration of WRTM and TrEPS (Source: Mahmassani, et al., 2009)

In a recent study titled "Implementation and Evaluation of Weather Responsive Traffic Estimation and Prediction System", systematic procedure for calibrating and validating weather sensitive TrEPS model are proposed and implemented (*Mahmassani et al., 2012*). The supply-side parameter calibration includes the estimation of parameters in the traffic flow model (i.e., speed-density relation) and the weather adjustment factors (WAF). The demand-side parameter calibration for that study includes several considerations: the base-case OD matrix estimation, changes in dynamic OD trip patterns due to weather conditions, user responses to information and various advisory/control operations schemes, and so on. In that study, four major U.S. cities, New York (Long Island), Salt Lake City, Chicago and Irvine, were selected for calibrating and validating weather related TrEPS. The application to those real world networks shows that the proposed model can be used to successfully evaluate weather impacts on transportation networks and the effectiveness of weather-related variable message signs and other strategies.

In the following three sections, the weather impacts on supply-side relations and parameters and travel demand patterns, as well as on-line implementation of weather-sensitive TrEPS are discussed in details. This will provide the required backdrop for discussing the role of mobile data in this process.

2.2.2 Modeling Weather Effect on Supply Side

Adverse weather conditions can significantly reduce the operating speed and thus the capacity in a given road segment (*HCM 2000*). According to the literature, most inclement conditions can be classified into one of three types: “rain”, “snow” and “other” (wind, fog etc.). These in their turn differ in intensity (light versus heavy). Specifically, light rain does not have noticeable impact on traffic flow compared to heavy rain (10% to 15% reduction in capacity). Similar to rain, heavy snow is reported to have a potentially large impact on the operating speed (*Ibrahim and Hall, 1994*). Studies also show that a 30% drop in capacity is attributed to heavy snow compared to a 10% reduction in the case of light snow. The main reason behind such drop is the search for a greater lateral clearance and longer headways since the lane markings are obscured by snow accumulation. In reviewing previous research efforts, Rakha et al. (2007) reported the influence of rain and snow conditions on travel speed as summarized in Table 2-1and Table 2-2.

Table 2-1. Empirical evidence of rain effects on speed

	Speed Reduction		
Researcher	Ibrahim and Hall	Kyte et al.	Smith et al.
Location	Toronto, Ontario	Idaho	Hampton Roads, Virginia
Year	1994	2001	2004
Light Rain	1.2-8 mph	5.9 mph	3-5%
Heavy Rain	3-10 mph	5.9 mph	3-5%

Source: Rakha et al., 2007

Table 2-2. Empirical evidence of snow effects on speed

	Speed Reduction			
	Freeway		Arterial	
Researcher	Ibrahim and Hall	Kyte et al.	Maki	Perrin
Location	Toronto, Ontario	Idaho	Minneapolis, Minnesota	Salt Lake City, Utah
Year	1994	2001	1999	2001

	Speed Reduction			
	Freeway		Arterial	
Light Snow	0.6 mph	10.19 mph	N/A	13%
Heavy Snow	23-26 mph	10.19 mph	40%	25-30%

Source: Rakha et al., 2007

Although the effect of adverse weather on traffic flow may appear evident and easy to perceive, it is still important to develop an accurate quantitative description of the effect for modeling purposes. Hall and Barrow (1988) studied the effect of adverse weather conditions on the flow-occupancy relationship using freeway traffic data in Ontario, Canada. They found that adverse weather affects the flow-occupancy function by reducing the slope of the curve corresponding to uncongested traffic state. Similar findings, that the maximum flow rates of highways are reduced by inclement weather, were obtained by Ibrahim and Hall (1994). They also observed that adverse weather causes a downward shift in the speed-flow function. These weather effects are modeled statistically using regression analysis, and the results are quantitatively documented for both rainy and snowy conditions. Rakha et al. (2008) studied the impacts of inclement weather on some key traffic stream parameters for several different metropolitan areas in the United States. They calibrated Van Aerde traffic flow model using loop detector data and concluded that the impacts of weather on traffic increases as the rain and snow intensities increase. In their study, they also proposed and developed so-called Weather Adjustment Factors (WAF), which are applied multiplicatively to the clear-condition parameters to reflect the weather impact. The WAF is closely related to three variables that characterize the severity of weather condition, namely, visibility, rain intensity, and snow intensity. Specifically, a linear functional form can be used to model and represent the WAF (*Rakha et al., 2008*).

Mahmassani et al. (2009) identified seven principal model components on the supply side within the DYNASMART TrEPS framework that could be adjusted to capture weather effects on traffic patterns, if appropriate data is available for calibration. These components include:

1. <u>Speed-density model for freeway sections (and ramps)</u>

   Both the functional form and the parameter values (free mean speed, jam density, breakpoints for multiple regime models) may be affected by weather, and may be affected differently by the characteristics of different weather instances. Hranac et al. (2006) summarized changes in the so-called fundamental diagram observed at a limited number of locations (e.g. Twin Cities, Minnesota).

2. <u>Speed-density model for signalized arterials and unsignalized approaches</u>

   Empirical evidence collected through the calibration experience with DYNASMART in various cities strongly suggests different functional forms for the speed-density relations for arterials than for freeways. For instance, the latter exhibit distinct multi-regime features that are not present in arterial data. In addition, there is considerably more variation in both functional form and parameter values for arterials than for freeways.

3. <u>Service rates and section capacities for freeways and ramps</u>

   It is not well understood in the traffic simulation community that service rates and capacities play at least as important a role as the speed-density relation parameters in governing traffic flow under highly congested conditions, when queuing phenomena become critical in determining traffic propagation. Hence specifying these parameters correctly is an essential aspect of calibrating these models. Such parameters will naturally be affected by weather of varying characteristics. Reductions ranging from 5%

to 35% have been reported in the literature, and provide a starting point for the modifications addressed in this study.

4. Saturation flow rates, section capacities and turning service rates at signalized junctions

   Under normal weather condition, the default values of saturation flow rates are consistent with accepted highway capacity manual practices. Yet, these values will be dramatically affected by inclement weather conditions.

5. Saturation flow rates and operational parameters at unsignalized junctions

   Controls at unsignalized junctions include yield signs, stop signs and roundabouts. Weather effects on these facilities are likely to be of greater magnitude than at signalized intersections given the reliance of unsignalized junctions on human interaction in sharing the right of way, which becomes more difficult under adverse weather.

6. Operational characteristics associated with incidents and their impact

   Adverse weather magnifies the impact of traffic incidents, increasing their severity and possibly their duration as well. It is suggested that higher severity, longer duration, and possibly greater frequency of occurrence, be used in devising incident scenarios under adverse weather.

7. Operational characteristics of work zones and other special events

   Work zones typically affect the maximum speed as well as the capacity of the directly affected sections, as well as those that carry traffic in the opposite direction for certain work zone geometries (see DYNASMART-P User's Manual, Mahmassani et al., 2009). Given the significance of weather events that occur in conjunction with work zones in most parts of the country, it would be important to revisit the entire approach to modeling work zones in order to enable better representation of traffic flow in and around work zones under adverse weather conditions.

In the recently completed project (*Mahmassani et al., 2012*), the above-mentioned Weather Adjustment Factor (WAF) approach is adopted and calibrated using field data collected from four different networks across the United States. The calibrated models are provided as input into TrEPS model, and the results show that the use of WAFs successfully captures the weather effects on both link speeds and flows.

2.2.3 Modeling Weather Effect on Demand Side

Inclement weather can affect the dynamics of demand on the transportation system directly. As drivers can reschedule or cancel their trips/activities according to the change of weather conditions, the demand level under adverse weather is usually reduced, while the demand before and immediately after adverse weather period can increase. In addition, the impact of weather on travel demand can be complex, as different types of trips can have different levels of exposure to weather impacts. Work commutes that occur during the morning and afternoon peak, for example, would only be affected by the most severe and extreme weather, while leisure trips are more likely to be rescheduled to a more favorable time of the day or even the week in order to avoid inclement weather.

The impact of adverse weather on travel demand has been proved in the literatures. Ibrahim and Hall's (1994) found that traffic flow is reduced by 10 to 20 percent as a result of heavy rain, and little or no effect on flow was observed under light rain conditions. Compared to rain, snow shows a more significant impact on traffic volume. Hranac et al. (2006) summarized the observations from different sources in the literature as shown in Table 3 below.

Table 2-3. Empirical evidence of snow effects on traffic volume

	Traffic Volume Reduction		
	Freeway		Arterial
Author	Hanbali and Kuemmel	Knapp	Maki
Location	Illinois, Minnesota, New York, Wisconsin	Iowa	Minnesota
Year	1992	1995-1998	1999
Light Snow	7-31%	N/A	N/A
Heavy Snow	11-47%	16-47%	15-30%

Source: Hranac et al., 2006

According to Mahmassani et al. (2009), the demand side dimensions and parameters that determine how traffic patterns may be affected by adverse weather consist of two principal categories: (1) those that affect the dynamic OD pattern in the network, and (2) those that affect the distribution of flows in the network, especially in response to information and/or various traffic controls. Hence, changes in destination, departure time or trip cancellation (and, if dealing with a vehicle rather than person OD pattern, changes in mode choice as well) would be reflected in the dynamic OD pattern. On the other hand, route diversions in response to information, route choice decisions based on pre-trip or en-route information, response to various advisory messages and the like would be in the second category. While, of course, we can view the first category as resulting from individual decisions as well, modeling such mechanisms directly would be considerably more complicated (and require a much richer, and unfortunately lacking, empirical survey basis) than trying to capture their net result by inferring the dynamic OD pattern.

One of the advantages of an on-line TrEPS system is its ability to adaptively estimate and predict OD and associated flow patterns as the latter are unfolding. The hybrid Kalman Filter approach with structural temporal effects developed for DYNASMART-X (*Mahmassani and Zhou, 2005*), along with the consistency checking and updating modules, are intended to capture changes in dynamic OD patterns resulting from weather-related adjustments in trip making. As such, both the overall levels of demand, their distribution across OD pairs as well as over time should be captured by the existing system. The main limitation is that the traffic models may not capture traffic propagation correctly under adverse weather, hence introducing a potentially important source of error in the overall estimation and prediction process (which will affect the OD predictions as well since the latter are linked to the observed measurements through the DTA model and resulting link proportion matrix).

2.2.4 Conceptual Framework for On-line Implementation

To effectively manage the flow of traffic during inclement weather conditions, many agencies implement a wide variety of WRTM strategies. In general, based on pre-defined operational procedures for different weather types and severities, corresponding strategies are employed in response to prevailing weather conditions. Because the dynamics of traffic systems are so complex, however, WRTM strategies selected based on such general rules may not always perform as expected. This calls for integration of WRTM and a real-time Traffic Estimation and Prediction System

(TrEPS), which allows incorporating predicted traffic conditions under different strategies into the selection of appropriate WRTM strategies. The real-time TrEPS model interacts continuously with loop detectors, roadside sensors and vehicle probes, providing real-time estimates of traffic conditions, network flow patterns and routing information. Based on the current network state, a prediction is then generated for the traffic under future weather conditions and weather-related interventions providing the predicted effect of WRTM strategies on the real world network.

An overall framework of the implementation of WRTM strategies using the weather-responsive TrEPS model is presented in Figure 2-3. The framework comprises three components: WRTM Strategy Repository, Scenario Manager and DYNASMART-X. The WRTM Strategy Repository contains a set of available WRTM strategies defined for different weather situations. Based on existing guidelines and practices adopted by local operating agencies, several alternatives could be identified and included in each weather category. For example, when the rain intensity exceeds a certain threshold, different combinations of individual advisory/control method (e.g., VMS, VMS + speed limit, and VMS + signal timing) might be considered as available implementation options. In case of a snowfall, decisions might involve choosing between different routing and scheduling options for snow plow operations. When the Scenario Manager receives the prevailing weather conditions and the future weather information, it firsts generates the weather scenario input file (i.e., weather.dat) for the next prediction horizon that will be simulated in DYNASMART-X. Next, it retrieves available WRTM strategies based on the specified weather condition from the WRTM Strategy Repository. Users might choose two or more strategies under consideration. The Scenario Manager then creates a set of input files for each strategy (e.g., VMS.dat, WorkZone.dat, control.dat, etc.) and supplies them to DYNASMART-X along with the weather scenario file. In DYNASMART-X, based on the estimated current traffic conditions using real-time traffic surveillance data, the future traffic conditions are predicted for different scenarios. The predicted network performance measures produced under different intervention scenarios will allow the traffic manager to evaluate effectiveness of each strategy and select the best WRTM strategy for the current situation.

The weather-responsive TrEPS model would also help decision-making in modifying plans for various roadside events such as road construction, pavement works and planned special street events. When such events encounter unexpected adverse weather conditions, the traffic manager can simulate different weather and traffic management scenarios to assess the impact of weather conditions on traffic and decide how to modify the current plan to minimize the congestion and risk of accident.

Evaluating effectiveness of various WRTM strategies would require several instances of implementation and measurement. As we observe only the outcome associated with selected WRTM strategy, it would take time until we have a sufficient number of similar occasions for which different scenarios are tested and outcomes are collected. In this case, historical data and past experiences need to be used to assess the performance of the selected strategy. The evaluation procedure can also be facilitated by the use of the TrEPS model framework. Figure 2-4 presents the post-process of the real-time WRTM implementation in the context of the same framework shown in Figure 2-3. After applying the selected WRTM strategy, DYNASMART-X obtains the traffic surveillance data and estimates the resulting network state. This can be viewed as the network performance outcomes produced under the implemented WRTM strategy and used by the traffic manager to assess its effectiveness. If it is considered necessary to modify/discard the selected strategy or add a new strategy, the Scenario Manager will help update the WRTM Scenario Repository accordingly. The updated strategies for the experienced weather situation are stored in the repository and will be retrieved on demand next time the similar weather event occurs.

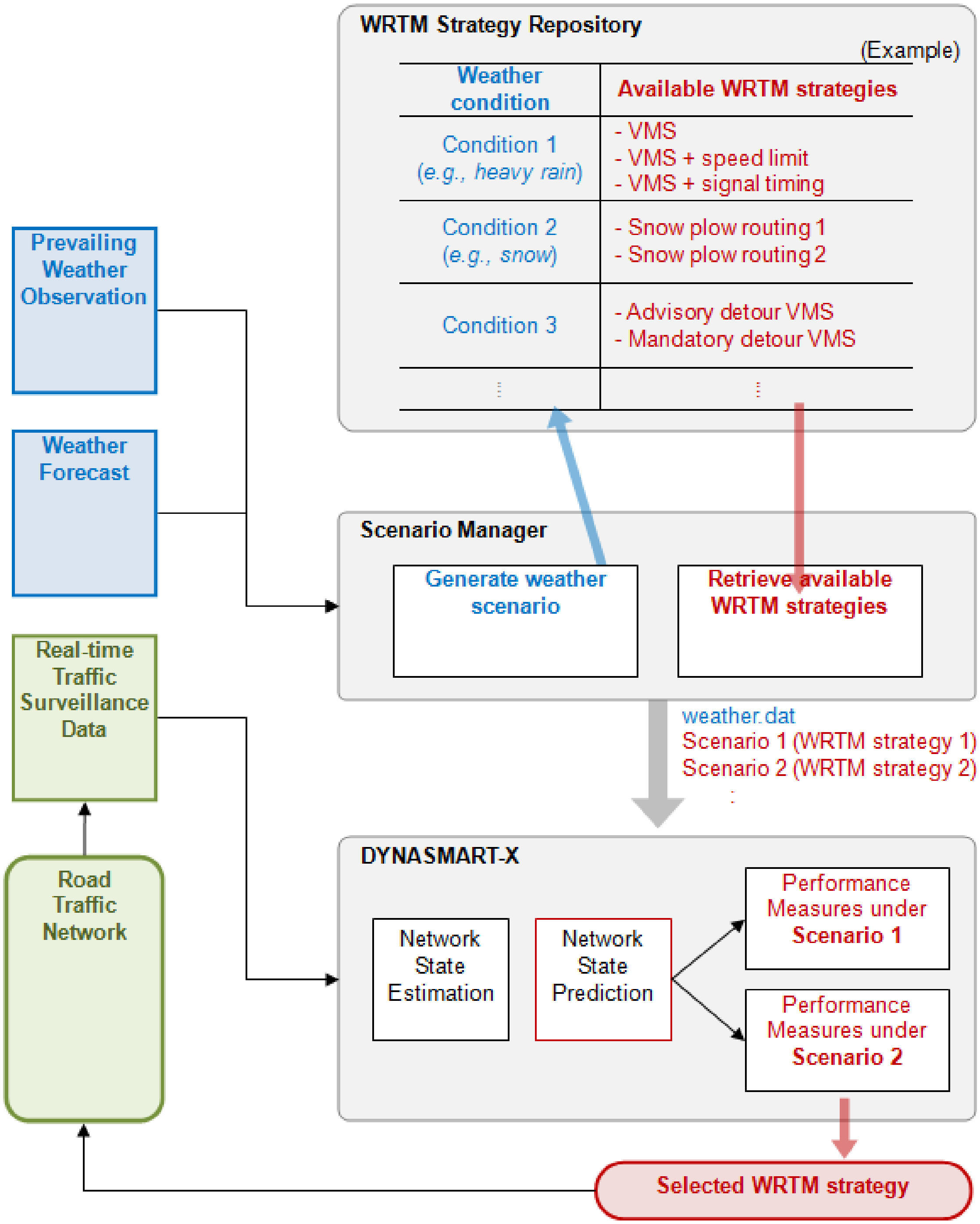

Figure 2-3. Framework for Implementing WRTM strategies using TrEPS models (Source: Mahmassani, et al., 2012)

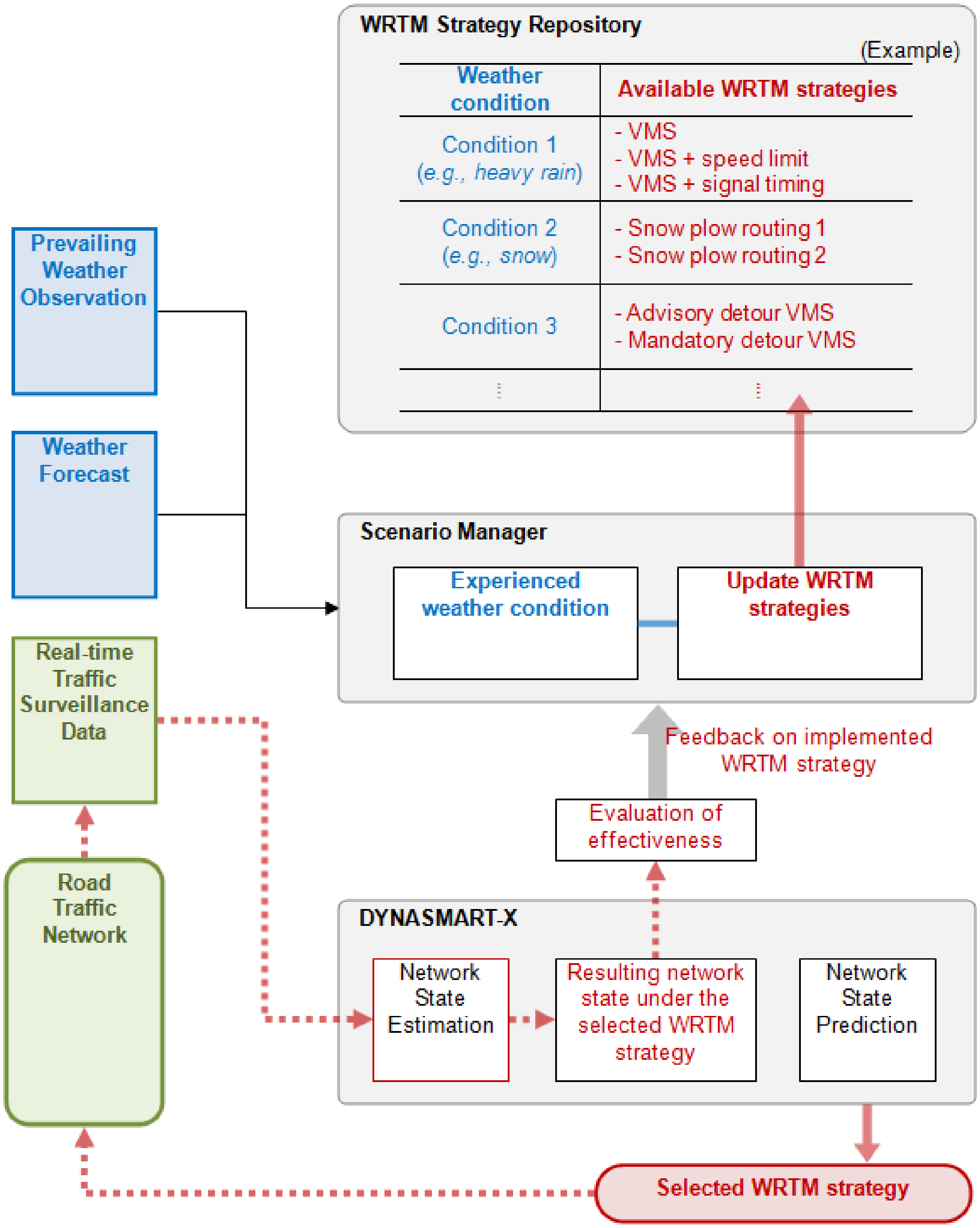

Figure 2-4. Framework for Evaluating WRTM strategies using TrEPS models (Source: Mahmassani, et al., 2012)

Chapter 3. Incorporating Mobile Data to WRTM Models

3.1 Properties of Mobile Data

The development of Intelligent Transportation Systems (ITS) requires high quality traffic information in real-time. The use of traditional on-road sensors (e.g. inductive loops) for collecting data is necessary but not sufficient because of their limited coverage and expensive cost of implementation and maintenance. In the past few decades, the evolution of telecommunications and wireless technologies has opened up a world of opportunity to collect traffic data in alternative ways. These technologies support probe-based systems that rely on GPS-based data or cellular location systems. These offer broader coverage, with the potential to cover major arterials.

Mobile data exists in different forms, with different contents, and can be collected in different ways. According to the data collection method, mobile data can be categorized into three major classes:

1. Floating car data collected by electronic transponders. In this method, electronic transponders (tags) are placed on vehicles and electronic devices for reading those tags are placed along the roadway to determine when each vehicle passes those locations. The Automotive Vehicle Identification (AVI) technique is one such example which is covered widely in the literature (Travel Time Data Collection Handbook, 1998). Other examples include electronic toll data collected at toll booths, blue tooth data collected by roadside blue tooth receivers, etc.
2. GPS based mobile data. In this case, probe vehicles are equipped with GPS receivers and two-way communication to receive signals from earth-orbiting satellites. The positional information determined from the GPS signals is transmitted to a control center to display real-time position of the probe vehicles. Usually GPS mobile data mainly come from certain types of vehicles, particularly fleet management services, e.g. taxis and trucks. The Connected Vehicle program conducted by U.S. DOT is now offering a new opportunity for collecting GPS based mobile data.
3. Cell phone based mobile data. Every switched-on mobile phone becomes a traffic probe in the network. The location of the mobile phone is usually determined by means of triangulation or by the hand-over data stored by the network operator, and then travel time speed data can be estimated over a series of road segments before being converted into useful information by traffic centers. As contrast to the first two categories, cell phone based mobile data requires no hardware in cars and no specific infrastructure needs to be built along the road.

In terms of format, mobile data can be classified into two types: (1) aggregated data, and (2) individual trajectories. Aggregated mobile data is an outcome of data fusion process conducted by traffic information providers, which usually contains travel time and speed information in either historical or real-time format. On the other hand, individual trajectory data is relatively raw, and is made up of a series of vehicle locations and corresponding arrival times. In this study, we focus our discussion on trajectory data because of its richness in information and high degree of suitability for application to WRTM models, as explained in the rest of this report.

A trajectory is the path followed by the moving entity through the spatial area over which it moves. Because a path requires a certain amount of time to traverse, time and position are the two essential aspects of a trajectory (*Giannotti and Pedreschi, 2008*). The information contained in trajectory data can be far beyond these two variables. The characteristics that can be extracted from trajectory data include the following:

- Time, i.e. position of this moment on the timescale;
- Position of the vehicle in space;
- Trip origins and destinations ;
- Direction of the vehicle's movement;
- Speed of the movement;
- Dynamics of the speed;
    - Periods of constant speed, acceleration and deceleration
    - Characteristics of these periods: start and end times, duration, initial and final positions, initial and final speeds, etc.
- Change of the direction (turn);
- Accumulated travel time and distance.

When groups of trajectory data are available on the same route, more information can be extracted, including:

- Mean, median and maximal speed/travel time;
- Variance of speed/travel time;
- Inferred volumes / probe vehicle density.

Overall, mobile data differ dramatically in nature from traditional fixed sensor data. The advantages and some shortcomings of mobile data are summarized in the Table 3-1.

Table 3-1. Pro and Cons of Mobile Data

Advantages	Disadvantages
• low or no cost in installation and maintenance; • wide geographic coverage (freeways and arterials); • finer resolution (individual vehicle and shorter measurement time interval); • contain travel time information; • not affected by traffic interruptions or bad weather conditions.	• fewer experience of analyzing data; • technology is not as mature as fixed sensors; • no occupancy or traffic density information.

Source: Northwestern University, May 2012

These unique properties of mobile data make it practical to be incorporated into traffic analysis and help improve the accuracy and relevance of WRTM models. For example,

- Mobile data can provide detail on roads not currently equipped with fixed sensors, thus improving the calibration of these models during severe weather events.
- These data also can provide accurate real time information that reflects shifts in routes and origins and destinations during (or just prior) to weather events. These shifts in traffic patterns can support Traffic Estimation and Prediction (TrEPS) models that make it possible to use WRTM tools to support management decisions during major weather events such as hurricanes, tornadoes, or blizzards.
- Mobile data also provide opportunities to assess the impacts of operational changes before and after certain actions.

3.2 Mobile Data Sources

The mobile traffic data market is now growing worldwide with a wide range of applications and benefits. This would not only improve traffic management but would also help satisfy the growing demand of drivers who are willing to pay service providers as long as they have access to relevant real-time information. Currently, several service providers have integrated mobile data from cellular phones within their raw traffic data sources. Most often, these companies also rely on multiple sources coming from fixed sensors and fleet companies (e.g. taxi fleets with GPS). One of the current limitations of mobile data for WRTM application is that most currently available mobile data sources have been tailored for production and distribution of real-time travel time data. While mobile data has the potential to provide much richer detail, e.g., locations and fine resolution timestamps, such detailed data is scarce in the current market. In this project, the mobile data products that are offered by four major vendors, namely AirSage, Inrix, Navteq and TomTom, are studied and summarized. The results are included in Appendix A.

3.3 Selection of WRTM models for Incorporating Mobile Data

The contents of mobile data vary widely in their characteristics – and thus vary in how they best fit the needs of weather related modeling. Models to support analysis and deployment of WRTM strategies fall in two categories: those intended for off-line analysis and design of such strategies and evaluation of their deployment effectiveness in particular areas; and those intended to support on-line application of these strategies for weather-related traffic management. Both off-line and on-line tools entail supply-side and demand-side models; the former reflect performance relations that determine traffic dynamics under the influence of weather, while the latter capture user choices and behavior in response to weather-related control or management measures, as well as other behaviors both as travelers (e.g. route, mode and departure time choice) and drivers (e.g. car following). In cases where the mobile data allow estimation of the same types of traffic variables and parameters as more conventional sensor data, the procedures already developed can be used with little modification, while in some other cases, mobile data which contain richer information, especially in the form of vehicle trajectories, will be particularly useful for modeling drivers' behavior in route choice or response to various WRTM measures. Table 3-2 presents a mapping of different types of mobile data on different WRTM model components.

Table 3-2. Use of mobile data in WRTM models

Model Components			Types of Mobile Data		
			travel times	speeds	inferred volumes
off-line calibration	Supply Parameters (Meso)	Traffic Flow Model: speed-density relations	*	***	***
		Weather Adjustment Factors: traffic flow model parameters, maximum or service flow rates, speed limit margin, etc.	*	***	***
	Behavior Parameters (Micro)	Car-following Model	**	***	*
		Gap-acceptance Model	*	***	***
		Lane-changing Model	*	***	***
	Demand Parameters (Meso & Micro)	Time-dependent OD matrix	**	**	***
		Demand adjustment factors under different weather conditions	**	**	***
		Vehicle Class Composition	**	***	***
On-line Traffic State Measurement	Supply Side Consistency Checking	Minimize discrepancy between observed and simulated travel time	***	*	*
		Minimize discrepancy between observed and simulated link speeds	*	***	*
	Demand Side Consistency Checking	Minimize discrepancy between observed and simulated OD demand	*	*	***
Evaluation of WRTM Strategies	Performance Measures	Link-level measures	**	***	***
		OD or Path Travel times	***	***	***
		Vehicle diversion rates or compliance rates	***	***	***

Note: number of stars reflects greater suitibility of corresponding data type for particular model component.
Source: Northwestern University, January 2012

One of the tasks of this study is to select a suitable set of WRTM tools into which the mobile data could be incorporated, and demonstrate the process using available data sources. The major criterion for selection is for those tools likely to have the greatest impact on the effectiveness of WRTM strategies and programs through greater application and deployment. In addition, the considerations when selecting WRTM models include:

1. Criticality to WRTM application;
2. Readiness and ease of adaptation for use in connection with mobile data;

3. Magnitude of likely improvement in models and resulting WRTM due to mobile data availability;
4. Obstacle-removing potential of mobile data in connection with use of those models; and
5. Likely impact in terms of increased use of these tools and deployment of WRTM.

Given the essential role of prediction in weather-related traffic management, the components of Traffic Estimation and Prediction System (TrEPS) models, which incorporate the effect of weather predictions on traffic congestion and thus form the basis for WRTM interventions to mitigate the effect of bad weather, would be a logical priority candidate for this demonstration. In the following three sub-sections, the potential applications of mobile data in weather-sensitive TrEPS (DYNASMART) are introduced, from supply side model, demand side model, to on-line implementation.

3.3.1 Supply Side Model

Two supply side models in weather-sensitive DYNASMART are selected for mobile data application, namely the modified Greenshields traffic flow model and weather adjustment factor model. The former is used for traffic propagation, with parameters modified to reflect prevailing weather conditions using the latter model. Systematic procedures for calibrating these two models have been developed and tested in the previous studies (*Mahmassani et al., 2009, 2012*), using weather data and fixed sensor traffic data only. With supplementary information obtained from mobile data, that procedure could be refined in order to improve accuracy.

Modified Greenshields Traffic Flow Model

Two types of modified Greenshields models are used in DYNASMART for traffic propagation (*Mahmassani and Sbayti, 2009*). Type 1 is a dual-regime model in which constant free-flow speed is specified for the free-flow conditions (1st regime) and a modified Greenshields model is specified for congested-flow conditions (2nd regime) as shown in Figure 3-1.

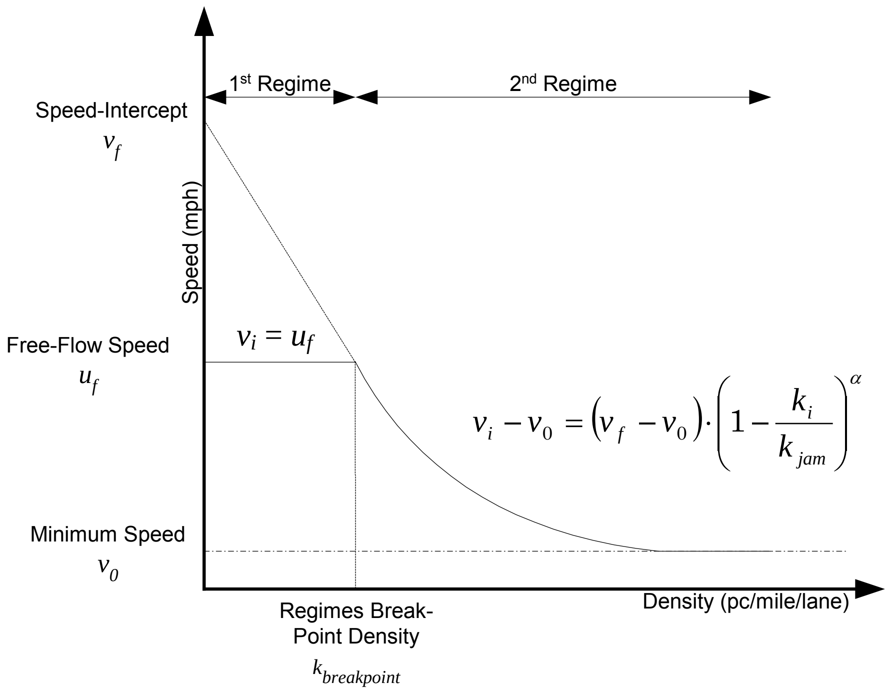

Figure 3-1. Type 1 modified Greenshields model (dual-regime model) (Source: Mahmassani and Sbayti, 2009)

In mathematical form, the Type 1 modified Greenshields model is expressed as follows:

$$v_i = \begin{cases} u_f & 0 < k_i < k_{breakpoint} \\ v_0 + (v_f - v_0)\left(1 - \dfrac{k_i}{k_{jam}}\right)^{\alpha} & k_{breakpoint} < k_i < k_{jam} \end{cases} \tag{3-1}$$

where v_i = speed on link *i*

v_f = speed-intercept

u_f = free-flow speed on link *i*

v_0 = minimum speed on link *i*

k_i = density on link *i*

k_{jam} = jam density on link *i*

α = power term

$k_{breakpoint}$ = breakpoint density

Type 2 model uses a single-regime to model traffic relations for both free- and congested-flow conditions as shown in Figure 3-2.

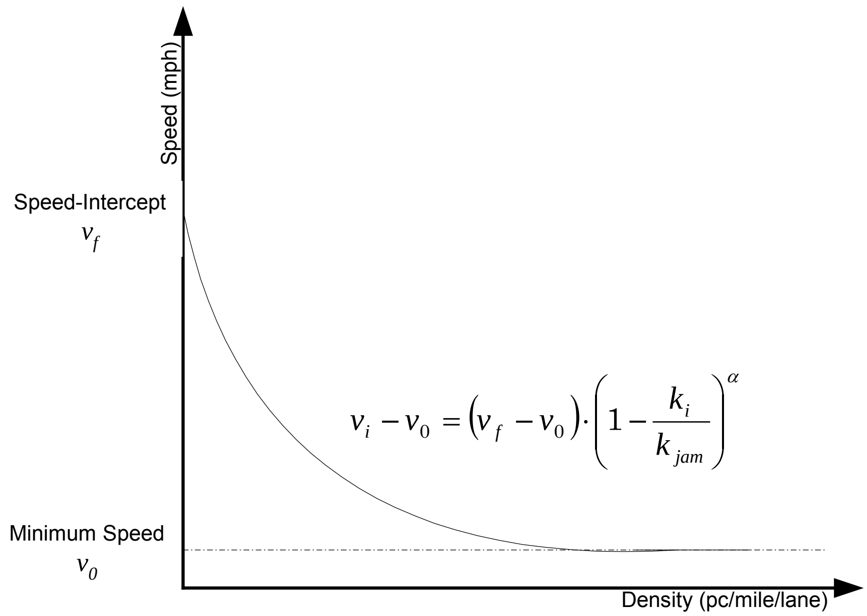

Figure 3-2. Type 2 modified Greenshields model (single-regime model) (Source: Mahmassani and Sbayti, 2009)

In mathematical form, the type 2 modified Greenshields model is expressed as follows:

$$v_i - v_0 = (v_f - v_0) \cdot \left(1 - \frac{k_i}{k_{jam}}\right)^{\alpha} \tag{3-2}$$

Dual-regime models are generally applicable to freeways, whereas single-regime models apply to arterials. The reason why a two-regime model is applicable for freeways in particular is that freeways have typically more capacity than arterials, and can accommodate dense traffic (up to 2300 pc/hr/ln) at near free-flow speeds. On the other hand, arterials have signalized intersections, meaning that such a phenomenon may be short-lived, if present at all. Hence, a slight increase in traffic would elicit more deterioration in prevailing speeds than in the case of freeways. Therefore, arterial traffic relations are better explained using a single-regime model.

Weather Adjustment Factor

In DYNASMART, supply-side parameters that are expected to be affected by the weather condition are identified as presented in Table 3-3. The inclement weather impact on each of these parameters is represented by a corresponding weather adjustment factor (WAF) such that

$$f_i^{Weather\ Event} = F_i \cdot f_i^{Normal} \tag{3-3}$$

where $f_i^{Weather\ Event}$ denotes the value of parameter *i* under a certain weather event, f_i^{Normal} denotes the value of parameter *i* under the normal condition and F_i is the WAF for parameter *i*.

Table 3-3. Supply Side Properties related with Weather Impact in DYNASMART

Category	*i*	Parameter Description
Traffic flow model[1]	1 2 3 4 5	Speed-intercept (mph)[1] Minimal speed (mph) Density break point (pcpmpl)[1] Jam density (pcpmpl) Shape term alpha
Link performance	6 7 8	Maximum service flow rate (pcphpl or vphpl) Saturation flow rate (vphpl) Posted speed limit adjustment margin (mph)
Left-turn capacity	9	g/c ratio
2-way stop sign capacity	10 11 12	Saturation flow rate for left-turn vehicles (vphpl) Saturation flow rate for through vehicles (vphpl) Saturation flow rate for right-turn vehicles (vphpl)
4-way stop sign capacity	13 14 15	Discharge rate for left-turn vehicles (vphpl) Discharge rate for through vehicles (vphpl) Discharge rate for right-turn vehicles (vphpl)
Yield sign capacity	16 17 18	Saturation flow rate for left-turn vehicles (vphpl) Saturation flow rate for through vehicles (vphpl) Saturation flow rate for right-turn vehicles (vphpl)

1) only available in dual-regime model

The WAF is assumed to be a linear function of weather conditions, and is expressed in the following form

$$F_i = \beta_{i0} + \beta_{i1} \cdot v + \beta_{i2} \cdot r + \beta_{i3} \cdot s + \beta_{i4} \cdot v \cdot r + \beta_{i5} \cdot v \cdot s \qquad (3\text{-}4)$$

where

F_i	weather adjustment factor for parameter *i*,
v	visibility (mile),
r	precipitation intensity of rain (inch/hr),
s	precipitation intensity of snow (inch/hr), and
$\beta_{i0}, \beta_{i1}, \beta_{i2}, \beta_{i3}, \beta_{i4}, \beta_{i5}$	coefficients to be estimated.

3.3.2 Demand Side Model

Same as supply-side models, travel demand information is of crucial importance as an input for dynamic traffic assignment (DTA) models. On the demand side, DYNASMART is flexible in the way it accepts loading information (time-varying rates prevailing over specified intervals, numbers of vehicles in discretized time slices, individual vehicle schedules). There are two methods for DYNASMART to generate vehicles. The first method is to specify Origin-Destination (O-D) matrices among origin-destination zones at different time intervals. This method considers the aggregated dynamic properties of demand level and demand distribution between different zones, for any loading period; however, it requires calibrating the time-varying O-D matrices. The second vehicle loading method is to specify the itineraries (origin and destination) of all vehicles with or without their corresponding travel plans. In this format, users can specify a trip plan (chain) for each traveler. The data required are the intermediate stops considered by each traveler, and the corresponding activity durations. In the other FHWA funded WRTM-related TrEPS project, a bi-level optimization method (Figure 3-3) is used to capture the time-dependent travel pattern (*Verbas et al., 2011*). It is a sensor-based OD estimation method which uses street sensors such as loop detectors together with traffic-assignment models. In the upper level of the bi-level framework, the sum of squared deviations of the simulated link flows from the corresponding observed values is minimized; in the lower level a dynamic traffic assignment problem is solved. The process is iterated until convergence in the reduction of root mean square errors (RMSE) of the estimated link-flows is achieved.

Several approaches for estimating time-dependent OD trip tables using mobile data have been discussed in the literature and could be used in this project. One approach developed by Calabrese et al. (2011) relies on a reference OD table and mobile data only. The method consists of two separate steps, namely a trip determination step and an OD estimation step. Within the trip determination step, mobile data are filtered and analyzed to identify individual trips. Those trips are then aggregated according to their origin, destination, and departure time, in preparation for OD matrix estimation in the next step. In the OD estimation step, the total number of trips is obtained by scaling up the observed number of trips through a scaling factor K. The accuracy of this estimation approach relies heavily on the quality of sample mobile data and the value of the scaling factor K, which accounts for the share of trackable probes among the total number of trip makers. Calibration of the scaling factor requires an independent reference OD flow table source, for example, census data. Another approach proposed by Kim and Jayakrishnan (2010) maintains the bi-level optimization structure, and uses trajectory data as supplementary data to traditional link counts data, to enhance the accuracy of estimation results. The proposed methodology does not require a historical reference OD table and uses a path-based OD estimation approach. However, the sampling rate of vehicle trajectories needs to be estimated, if the penetration rate of probe data is not given explicitly. Zhou and Mahmassani (2006) utilized automatic vehicle identification (AVI) counts data and proposed a dynamic OD estimation method to extract point-to-point split fraction information from those data without estimating market penetration rates and identification rates of AVI tags. Depending on the availability of mobile data sources, the most appropriate methodology could be selected for implementing dynamic OD estimation using mobile data.

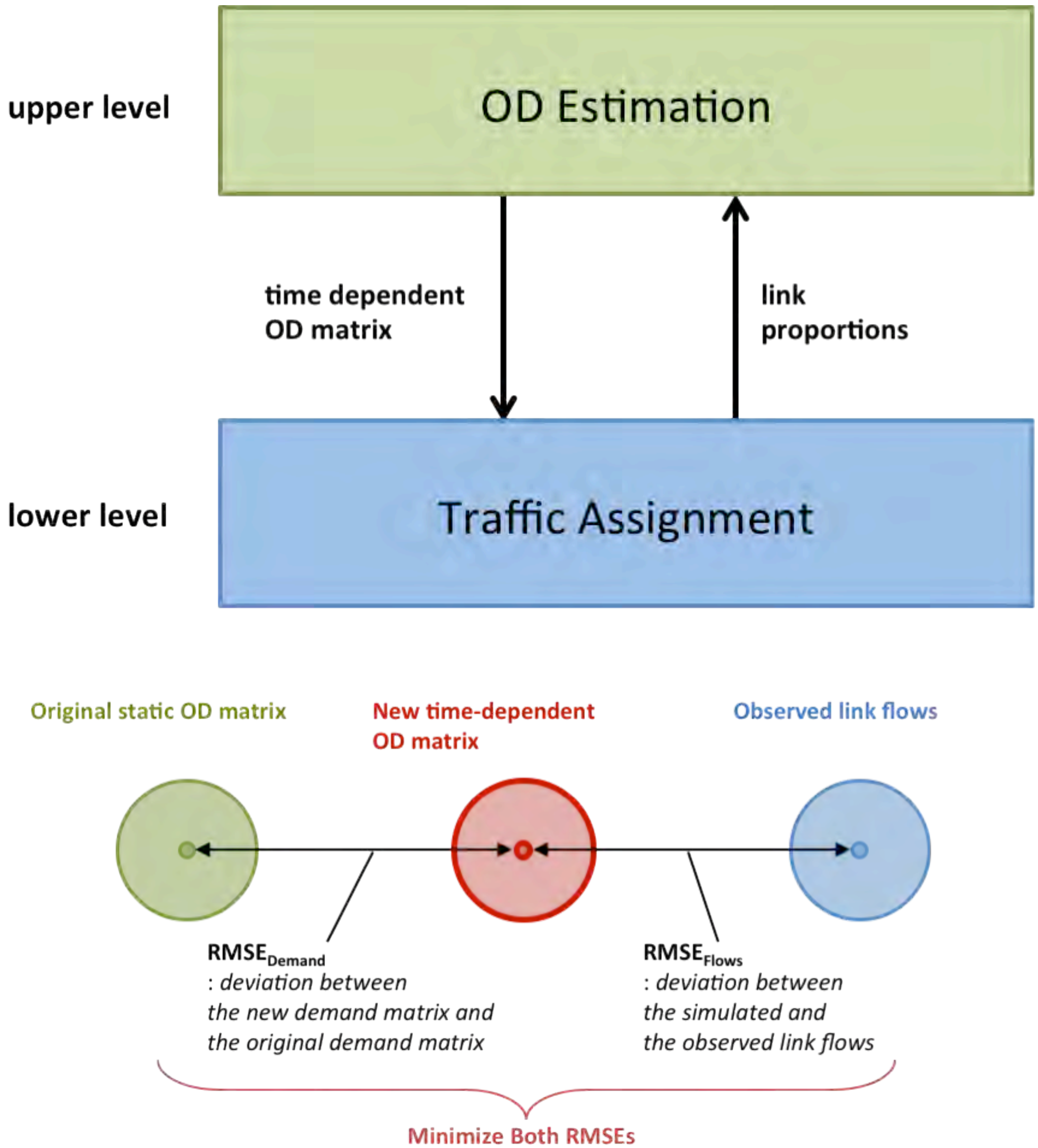

Figure 3-3. OD Estimation (bi-level optimization) framework (Source: Northwestern University, March 2012)

3.3.3 On-line Implementation

The on-line traffic demand estimation and prediction module within TrEPS provides time-dependent traffic demand matrices for dynamic traffic assignment and associated network traffic simulation. Within the module, it seeks to estimate time-dependent OD trip demand patterns at the current stage, and predict demand volumes over the near and medium terms in a general network, given historical demand information and real-time traffic measurements from various surveillance devices. A recursive real-time OD demand estimation and prediction framework is developed by Zhou and Mahmassani (2007). The real-time traffic information is usually in the format of occupancy and volume observations collected from loop detectors on specific links. With the help of mobile data, the on-line implementation process could be enhanced, as more real-time traffic information becomes available. The advantages of incorporating mobile data in on-line TrEPS implementation arise in three areas: (1) wider geographic coverage of real-time information; (2) finer resolution of data; (3) availability of travel time information, which is absent in traditional data.

3.4 Implementation Framework

Demonstrating the use of mobile data in WRTM models involves a systematic procedure, from data collection, information extraction, to model calibration, DTA simulation, and model validation. This section introduces a detailed implementation plan for incorporating mobile data. Figure 3-4 illustrates a framework for using mobile data in weather-sensitive TrEPS models. The red blocks in the figure highlight the components where mobile data could contribute in addition to traditional traffic data, in terms of improving the accuracy of model calibration and evaluation. It should be noted that the detailed implementation procedure depends on the availability of mobile data, i.e., what types of data are available, and what information could be extracted from those data.

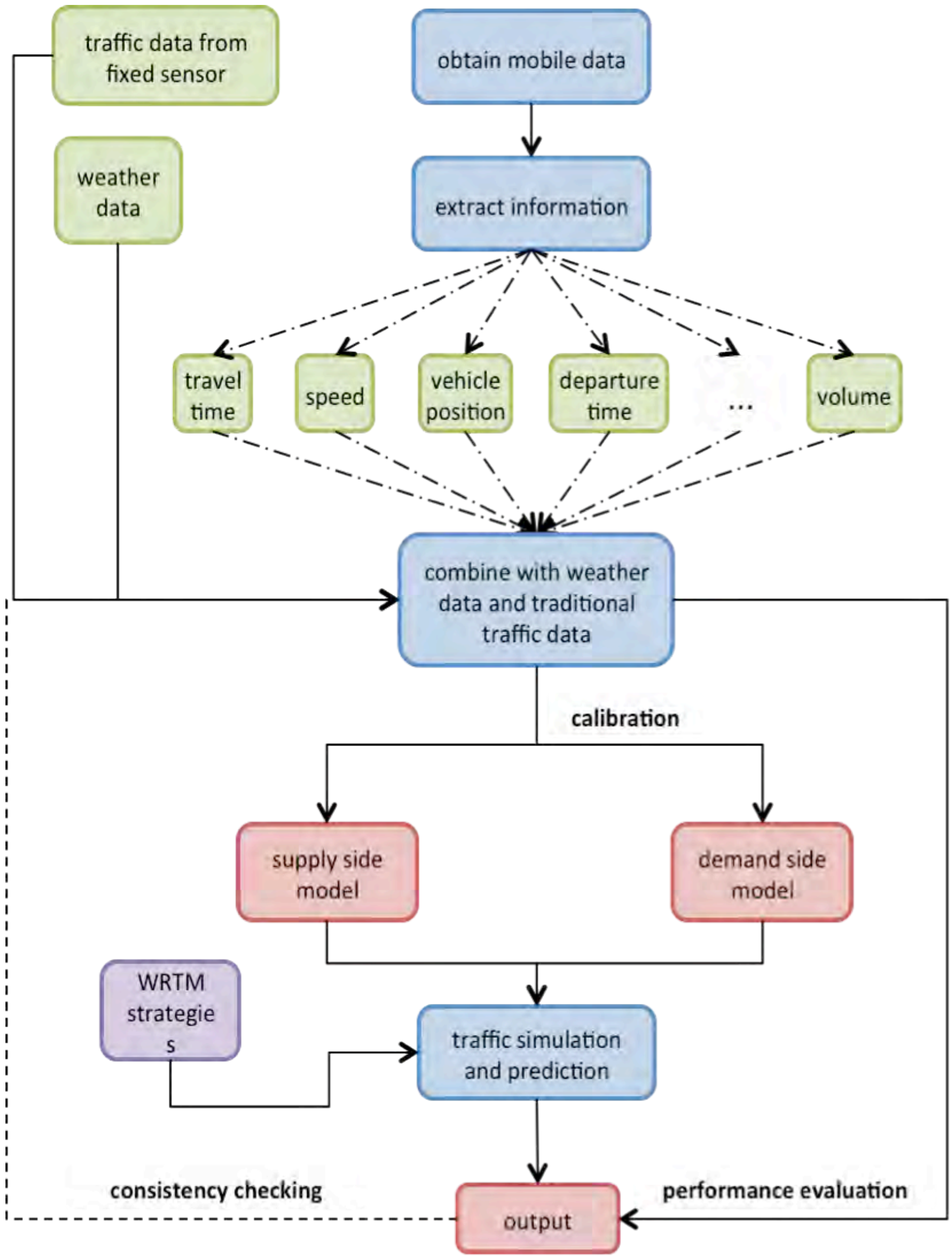

Figure 3-4. Framework for incorporating mobile data into WRTM models (Source: Northwestern University, March 2012)

Chapter 4. Study Network

The first step in demonstrating the use of mobile data in the WRTM framework is selecting a site/area network that will provide the test bed for the demonstration. The selection is the outcome of joint consideration of data availability as well as network development effort. As a result, the selection falls naturally into the four candidate networks that are prepared and tested in the recently completed project, i.e., Chicago, New York City, Salt Lake City, and Irvine. Notwithstanding the project team's effort to obtain mobile data from different data vendors, the only available mobile data source that can be utilized in this project consists of vehicle trajectory data collected by TomTom GPS devices in the New York City area. Therefore, the study network selected consists of the portion of the New York City regional network that encompasses the geographic area covered by the TomTom trajectory data.

Networks used in simulation-based DTA applications, including DYNASMART, are typically built on the basis of existing static networks, which often do not contain necessary information such as cycle and green times and allowed movements at each phase at signalized intersections, or definition of each movement at a node (e.g. left turn, right turn, U- turn, and through movement). Thus, in addition to data provided by static networks, information from many other external sources is necessary to achieve an accurate representation of the real-world network. Figure 4-1illustrates the overall process for building and converting networks for the DYNASMART application. The main tool for this conversion is software called DYNABUILDER, which is capable of converting many networks from different platforms into a DYNASMART-P network. As DYNABUILDER also requires input files in a certain format, the pre-processing steps are conducted using several different codes and macros to format the GIS or other sources of data. A snapshot of the New York City network in DYNASMART format is displayed in Figure 4-2, together with detailed descriptive information on nodes, links, zones, and demand.

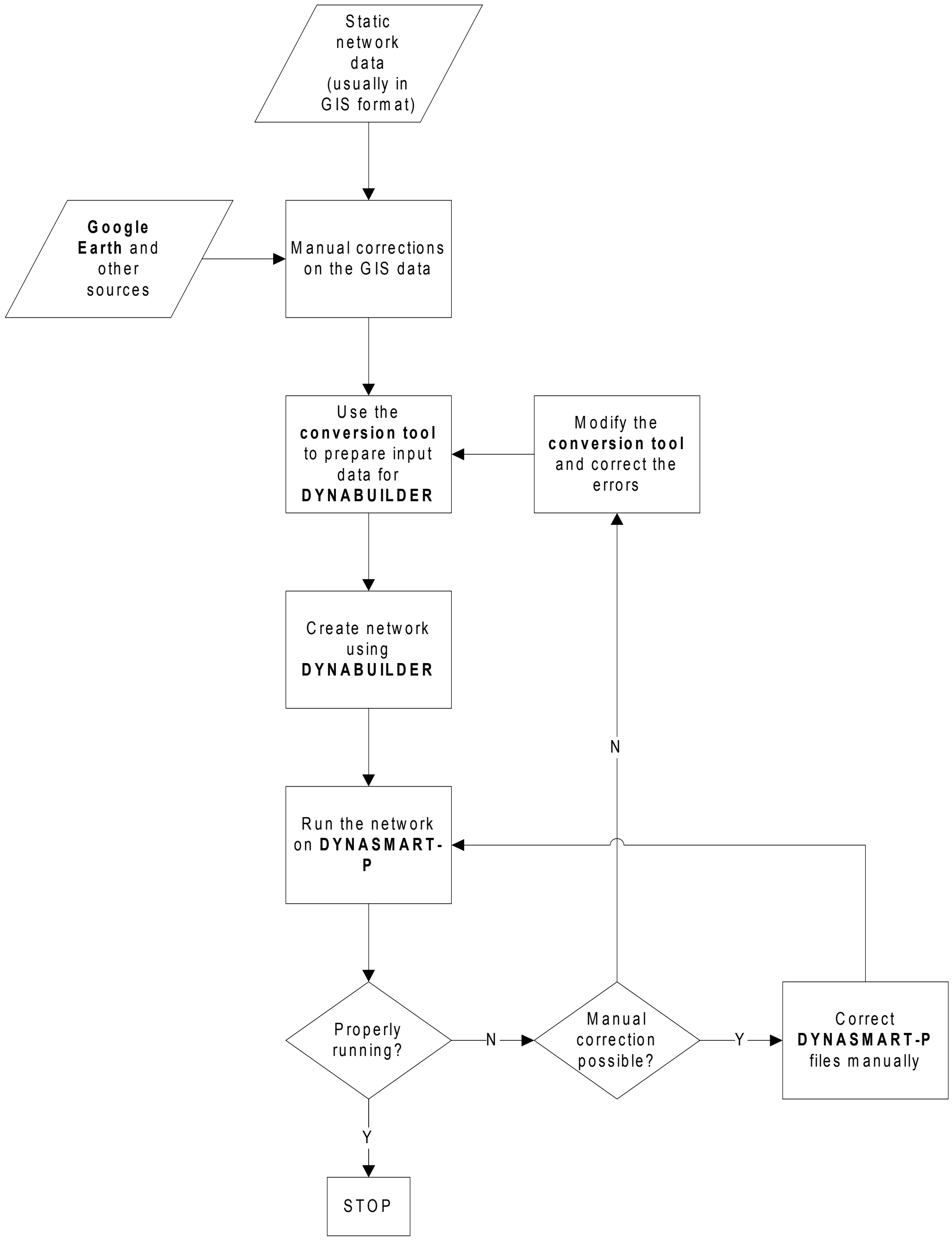

Figure 4-1. Flowchart for the Conversion from the Static to the Dynamic Network Model (Source: Northwestern University, May 2012)

Network Description

- 21,734 links,
  - 1,531 freeways,
  - 14 links with tolls,
  - 31 highways,
  - 139 HOV facilities,
  - 2,087 ramps,
  - 17,945 arterials,
- 9,390 nodes,
  - 1,722 signalized intersections,
- 1,886 zones,
  - 1,876 internal,
  - 10 external,
- Demand period,
  - 6 am - 11 am,
  - 43links with observations used in calibration.

Figure 4-2. Network Configuration and Description for New York Network (Source: Northwestern University, July 2012)

Chapter 5. Calibration and Validation of Weather-sensitive TrEPS Model Using Mobile Data

5.1 Data Collection

5.1.1 Weather Data

Currently, there are two major sources of historical weather data. The first is the National Weather Station archives collected at the National Climatic Data Center (NCDC), and the second is the roadway surface weather data archived by FHWA's *Clarus* project. As a research initiative, the *Clarus* system will be ending and transitioning to an NOAA-based system in 2013. Both of these sources collect and archive weather data at fixed locations, either at regional airports (ASOS stations) or at roadsides. The content of weather data from NCDC includes visibility, temperature, precipitation intensity level, and wind speed, while *Clarus* data usually contains some additional information like humidity and road surface temperature. The resolution of the data from these two sources differs, with 5-minute for NCDC data, and 20-minute for *Clarus* data. The distributions of weather stations (ASOS and *Clarus*) in the New York area are presented in Figure 5-1, showing a comprehensive geographic coverage. It is usually reasonable to assume, for the areas within 10 miles of a weather station, that the weather condition can be represented by the data recorded at that corresponding station.

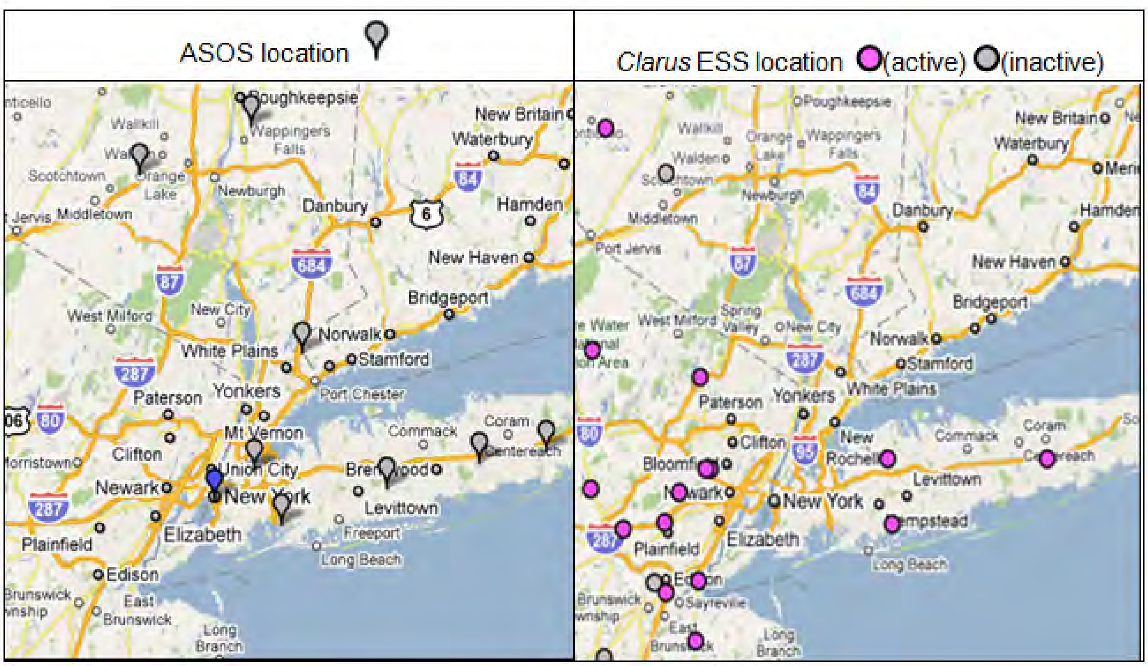

Figure 5-1. Distribution of Weather Stations in New York area (ASOS and *Clarus* (ESS)) (Source: Google Maps, accessed April 2012)

The historical weather data from *Clarus* are only available from 2009. In the contrast, ASOS data has a larger archived database, and the time coverage of data varies among different stations (Table 5-1). Moreover, ASOS data have a finer resolution (5 minute), which make them more suitable for use in conjunction with traffic detector data collected and aggregated over 5-minute intervals.

In addition to data collected from fixed sensors, road side weather data is becoming available from vehicles equipped with mobile sensors. For example, Minnesota DOT is contributing mobile weather data from their maintenance vehicles to the *Clarus* system. Also, the scope of Connected Vehicles program conducted by U.S. DOT includes collecting real-time road weather information from mobile sensors.

Table 5-1. Airports with ASOS Stations and Available Time Periods for Data (New York City)

No	Airport	Location	ICAO code	ASOS data
1	La Guardia Airport	Queens, NY	KLGA	2000 - present
2	John F. Kennedy International Airport	Queens, NY	KJFK	2000 - present
3	Republic Airport	Farmingdale, NY	KFRG	2005 - present
4	Long Island MacArthur Airport	Islip, NY	KISP	2000 - present
5	Brookhaven Airport	Shirley, NY	KHWV	2005 - present
6	Francis S. Gabreski Airport	Westhampton Beach, NY	KFOK	2005 - present

Source: Northwestern University, April 2012

5.1.2 Fixed Sensor Traffic Data

Traffic data plays an important role in both supply-side and demand-side model calibration. Traditional traffic data are obtained from loop detectors at fixed locations, which contain speed, occupancy, and vehicle count information. Despite substantial efforts to obtain traffic data from the New York area, we were not able to identify a comprehensive data source for all desired items. Fortunately, the items missing are not unique to the New York region, as they pertain to the traffic flow aspects under certain weather adjustment factor (WAF) across similar areas. Accordingly, to advance the progress in estimating model parameters for the New York network, other sources of traffic data have been investigated focusing on adjacent states such as New Jersey, Pennsylvania, and Maryland, Based on the data availability and the general characteristics (e.g., social/geographical characteristics and weather pattern), data from the Baltimore area were retained for this purpose. We believe that these data can be a good representative of New York data as Baltimore is a large metropolitan area with a similar geography (i.e., located on the northeast coast). Furthermore the I-95 Corridor through Baltimore and Maryland is heavily traveled by drivers from New York and New Jersey.

One advantage of mobile data is that it allows us to update the original parameters (in this case from the Maryland area) with local mobile data from New York even as the latter does not have suitable fixed sensor locations. We develop and apply a Bayesian updating scheme for this purpose in the next section, whereby a priori estimates based on fixed sensors are updated using more recent local mobile data.

The traffic data are collected from loop detectors installed on freeways along I-695 and the time period covers 2010 and 2011. Locations of the weather station and selected detectors are presented in Figure 5-2.

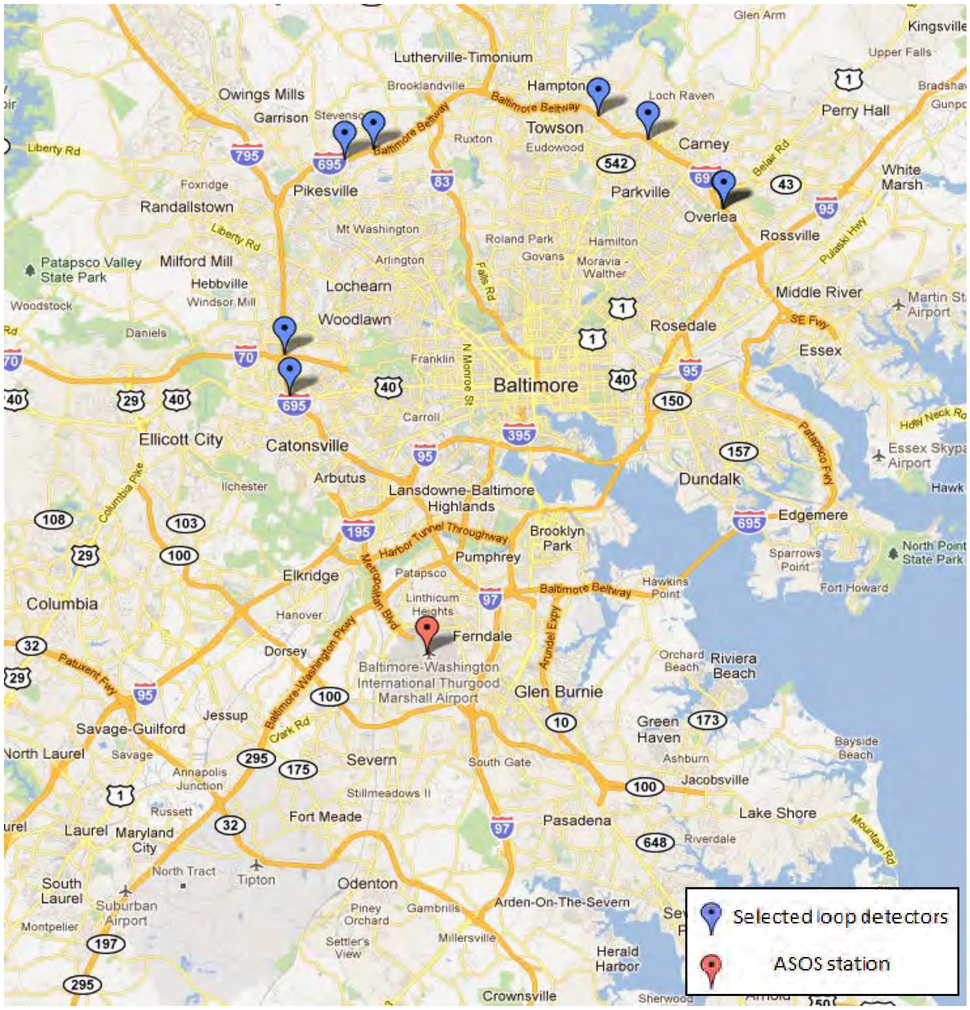

Figure 5-2. Locations for Selected Detectors and ASOS Station in Baltimore (Source: Google Maps, accessed May 2012)

For the demand-side calibration, hourly traffic volume data are obtained from New York State Department of Transportation's Traffic Data Viewer website (http://www.dot.ny.gov/tdv). Its web interface is displayed in Figure 5-3. The traffic volume data are collected by the count stations installed along selected road segments, and are available for the period of 2001 to 2009.

Figure 5-3. NYSDOT Traffic Data Viewer web interface (Source: NYSDOT, May 2012)

5.1.3 Mobile Data

Throughout this project, the project team was actively communicating with different data vendors to obtain trajectory data. Given that the project scope did not explicitly include dedicated mobile data collection, purchase or preparation, the focus was on illustrating what could be accomplished with mobile data, recognizing that a complete validation would require additional resources for data acquisition and network calibration and validation. Fortunately, TomTom was willing to allow use of trajectory data purchased for another project to be used for this effort as well. The mobile data provided by TomTom was originally used as part of the SHRP2 L-04 work on travel time reliability ("Incorporating Reliability in Operations and Planning Models"). With TomTom's permission, the same dataset was shared with this project for weather related traffic modeling research. The data are recorded and stored in the format of vehicle trajectories. They are collected by vehicles equipped with TomTom GPS devices circulating in the New York City area during a two-week period (2010/05/02 – 2010/05/17). Examples of trajectories in GIS map format are shown in Figure 5-4. The geographical coverage of the data is represented by the purple area.

An average number of 10000 trips are collected each day within the study area in that two-week period. The information within each trajectory file includes:

- A GIS format map of New York City area, including link length, speed limit information.
- Trajectory ID and probe ID
- Trip start time
- All the links that are traversed in the trip, and times when entering each link
- Travel time of each link, and total travel time of the trip

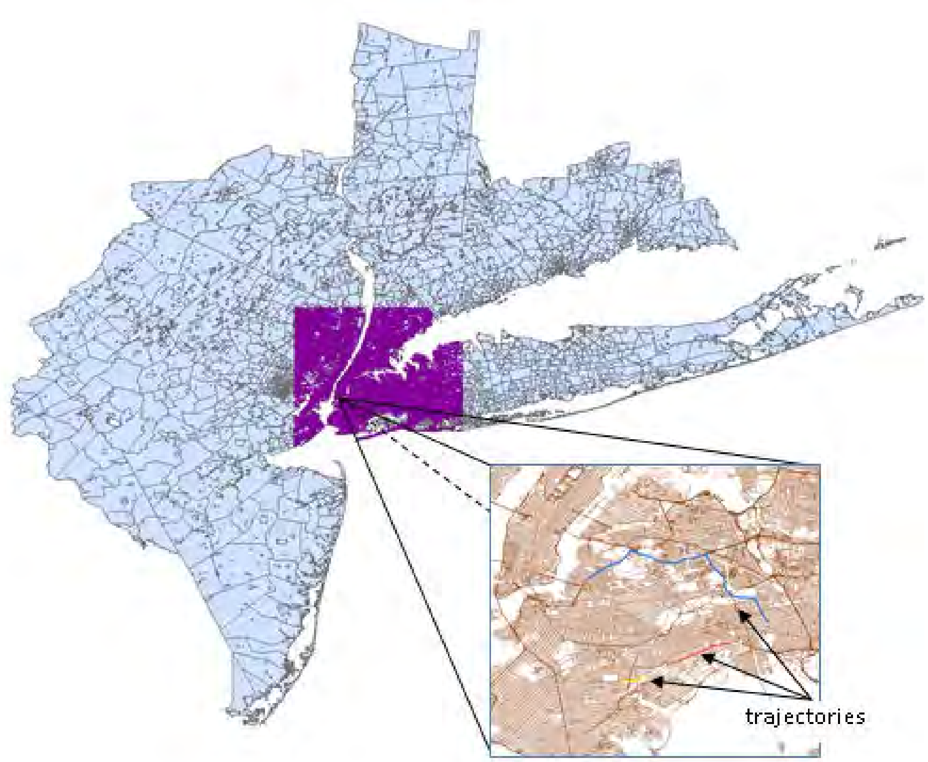

Figure 5-4. Examples of vehicle trajectories in New York network obtained from TomTom (Source: TomTom, June 2012)

5.2 Supply-side Parameter Calibration

5.2.1 Calibration using Fixed Sensor Traffic Data

Weather Categorization

When different sources of data are collected, the next step of the demonstration process is to integrate those input data, essentially to match weather data with traffic data. After that, for model calibration purpose, the integrated data will be divided into groups according to different weather categories.

The weather categories were defined based on the precipitation type and the intensity. With a normal weather as the base case, in which no precipitation is observed, three levels of precipitation intensities (light, moderate and heavy) are used for both rain and snow.
Table 5-2 shows these seven weather categories and the corresponding precipitation intensity ranges: normal (no precipitation), light rain (intensity less than 0.1 in./hr), moderate rain (0.1 to 0.3 in./hr), heavy rain (greater than 0.3 in./hr), light snow (less than 0.05 in./hr), moderate snow (0.05 to 0.1 in./hr), and heavy snow (greater than 0.1 in./hr). The values for the intensity range are based on the literature (*Hranac et al., 2006; Maze et al., 2006*).

Table 5-2. Weather categorization

Weather Condition (precipitation intensity (inch/hr))						
normal (no precipitation)	**light rain** (< 0.1)	**moderate rain** (0.1 - 0.3)	**heavy rain** (> 0.3)	**light snow** (< 0.05)	**moderate snow** (0.05 - 0.1)	**heavy snow** (> 0.1)

Traffic Flow Model Calibration using Fixed Sensor Data

The two-regime traffic flow model for freeways can be calibrated extensively using fixed sensor data unless such data is not available. The calibration work can be done by nonlinear optimization approach. The detailed procedures are as follows:

1. Plot the speed vs. density graph, and set initial values for all the parameters, i.e. breakpoint density (k_{bp}), speed-intercept (v_f), minimum speed (v_0), jam density (k_j), and the shape parameter (α), based on observations.
2. For each observed density (k_i), calculate the predicted speed value ($\hat{v}_i$) using Eq.

$$v_i = \begin{cases} u_f & 0 < k_i < k_{breakpoint} \\ v_0 + (v_f - v_0)\left(1 - \frac{k_i}{k_{jam}}\right)^{\alpha} & k_{breakpoint} < k_i < k_{jam} \end{cases}$$

(**(3-1**)

and the parameters initialized in Step 1.

3. Compute the squared difference between observed speed value (v_i) and predicted speed value ($\hat{v}_i$), for each data point, and sum the squared error over the entire data set.
4. Minimize the sum of squared error obtained in Step 3, by changing the values of model parameters.

The goodness-of-fit of the nonlinear regression model can be measured by the root mean square error (RMSE) as shown in Eq. ($RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(v_i - \hat{v}_i)^2}$ (**5-1**), where $\hat{v}_i$ is the predicted/modeled value and v_i is the observed value for the i^{th} observation in the sample with the size of N. The smaller the RMSE is, the better the model represents the data.

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(v_i - \hat{v}_i)^2} \quad (5\text{-}1)$$

Examples of calibrated speed-density curves for New York network are presented in Figure 5-5. It is observed that the overall speed for both uncongested and congested regimes decreases as the weather conditions become severe. The same procedure is carried out for several different locations on highways using Baltimore area loop detector data, and the calibration results are tabulated in Appendix B.

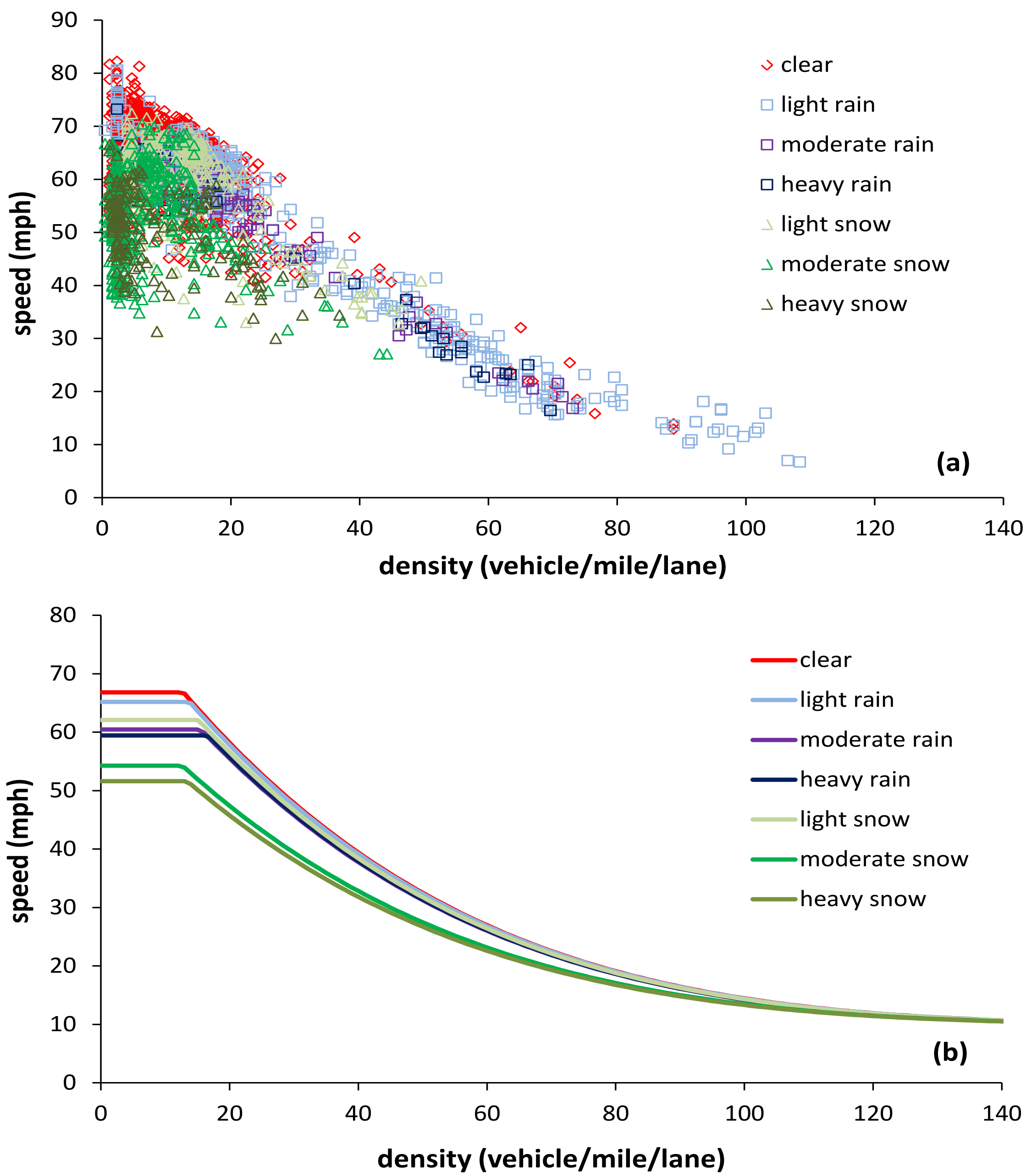

Figure 5-5. Type 1 modified Greenshields models calibrated using fixed sensor data under different weather conditions (Source: Northwestern University, May 2012)

Unlike freeways, very few arterials have loop detectors installed. No fixed sensor traffic data have been found on any arterials in the New York networks. Before the introduction of mobile data, the one-regime traffic flow models on arterials are usually inferred from those of some other well-calibrated networks with similar characteristics, e.g., same speed limit, same number of lanes. When mobile data becomes available, this problem can be partial solved, as travel speed information on arterials can be extracted from either aggregated mobile data or vehicle trajectories. However, the other important variable (density) required for calibrating the traffic flow model, is difficult to obtain directly, and needs to be inferred from other data sources.

Weather Adjustment Factor Calibration

Once traffic flow models for different weather conditions (i.e., normal, light rain, moderate rain, etc.) are obtained, a multiple linear regression analysis is performed to obtain the WAF for each parameter based on observed rain intensities, snow intensities and visibility levels. A detailed description of the calibration procedure is provided below. The procedures are same for both freeways and arterials.

1. For each weather condition *c*, calculate the WAF for each parameter i such that $F_i = f_i^c / f_i^{Base} \quad \forall c$, where Base denotes the normal (no precipitation) weather.
2. Assign F_i to corresponding traffic-weather data such that each observation has a structure similar to the following: {time, traffic data (volume, speed, density), weather data(v, r, s), WAF($F_1,\cdots,F_i$)}.
3. For each parameter i, estimate coefficients $\beta_{i0}, \beta_{i1}, \beta_{i2}, \beta_{i3}, \beta_{i4}, \beta_{i5}$ by conducting the regression analysis using Eq. ($F_i = \beta_{i0} + \beta_{i1} \cdot v + \beta_{i2} \cdot r + \beta_{i3} \cdot s + \beta_{i4} \cdot v \cdot r + \beta_{i5} \cdot v \cdot s$ (**3-4**) given F_i as a dependent variable and weather data (v, r, s) for all observations as independent variables.

The following table presents the calibration result of WAF for New York network using fixed sensor traffic data.

Table 5-3. Calibration result of WAF

Parameter	β_0	β_1	β_2	β_3	β_4	β_5	R^2
q_{max}	0.9874	0.0015	-0.3753	-3.3884	-0.0243	-0.1267	0.6397
v_f	0.9570	0.0044	-0.0738	-1.8262	-0.0294	-0.1302	0.6987
k_b	1.0894	-0.0081	0.3924	-3.5266	0.1371	0.1888	0.2572
u_f	0.9303	0.0068	-0.1044	-1.1713	-0.0733	-0.1662	0.8466

Source: Mahmassani, et al., 2012

5.2.2 Validation of Weather Effect on Speed

Different from loop detector data, mobile data does not explicitly give density data; so direct calibration of traffic flow model using the same method cannot be accomplished. Instead, some initial validation for the existing models can be conducted.

The weather profile of the TomTom mobile data study period (2010/05/01 – 2010/05/17) is shown in Figure 5-6. The y-axis of the graph represents the rain intensity level, with 0 for clear weather, 1 for light rain, 2 for moderate rain, and 3 for heavy rain. It is observed that during that two-week time, there are two major periods when there was significant amount of rain precipitation, which are 2010/05/03 00:00 – 2010/05/03 10:00 and 2010/05/11 23:00 – 2010/05/12 14:30.

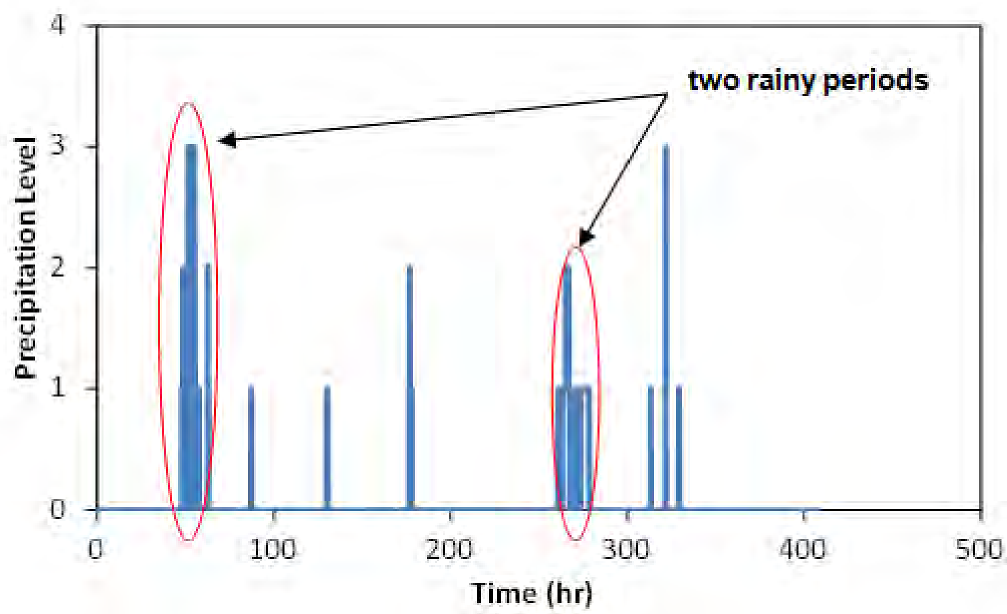

Figure 5-6. Weather Profile of NYC from 2010/05/01 00:00 to 2010/05/17 23:55 (0: no precipitation; 1: light rain; 2: moderate rain; 3: heavy rain) (Source: Northwestern University, May 2012)

To calibrate the weather effects on traffic, several time periods (listed in Table 5-4), for both clear and rainy weather, are identified within the two-week period when TomTom mobile data is available. Two separate time periods within a day are chosen, 0:00-3:00am and 7:00-9:00am, to study the effect of weather under different traffic conditions. The first period is a mid-night period when density is low and traffic is in free flow regime, while the second period is a morning peak period when traffic density is high and roads become congested.

Table 5-4. Selected Study Periods for WRTM calibration

rainy periods	2010/05/03 (Monday) 0:00-3:00am and 7:00-9:00am
	2010/05/12 (Wednesday) 0:00-3:00am and 7:00-9:00am
clear periods	2010/05/10 (Monday) 0:00-3:00am and 7:00-9:00am
	2010/05/13 (Thursday) 0:00-3:00am and 7:00-9:00am

Source: Northwestern University, May 2012

To perform the validation, two highway segments are selected, with segment 1 on Grand Central Parkway, and segment 2 on I-278. Both two segments are of length around 1.2 miles. By extracting

trajectories recorded during those study periods, it is observed that the average speeds under rain condition drop significantly from clear weather condition. A summary of the observed statistics are presented in
Table 5-5. The reductions of speed are consistent in range with the results calibrated using fixed sensor data.

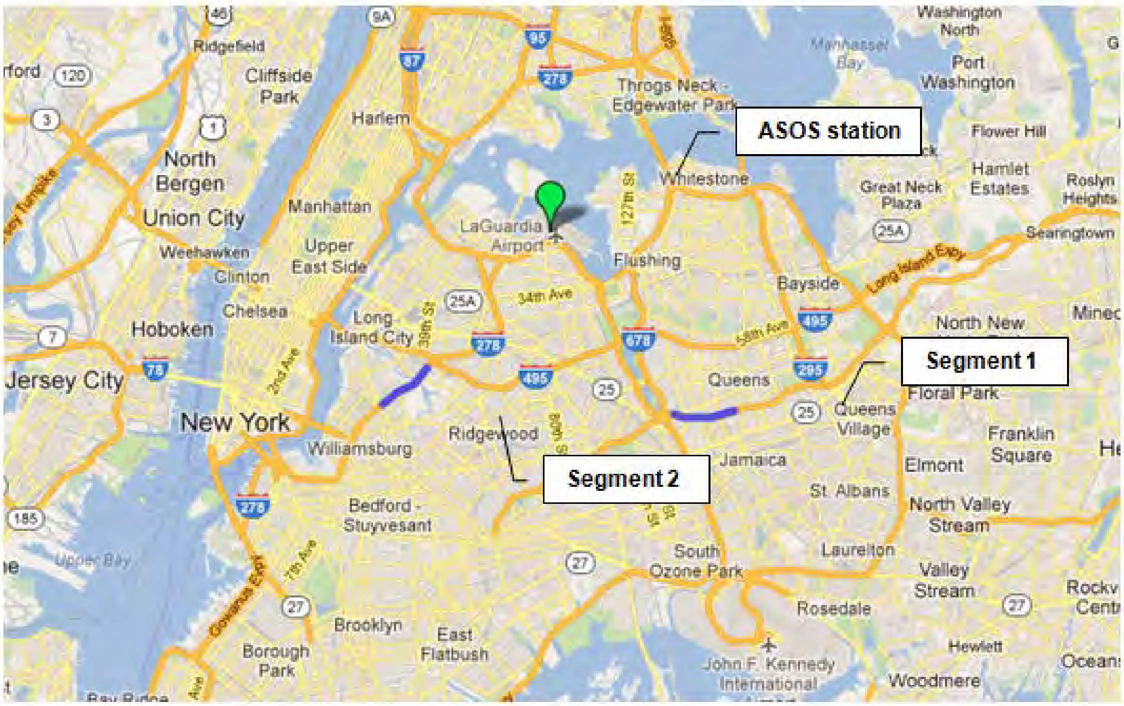

Figure 5-7. Selected highway segments for validating weather effect on travel time using mobile data (Source: Goole Maps, accessed July 2012)

Table 5-5. Observed average speed on two highway segments during selected periods

	0:00-3:00am		**7:00-0:00am**	
	clear	**rain**	**clear**	**rain**
segment 1	62.40 mph	57.09 mph	37.88 mph	26.19 mph
segment 2	50.80 mph	41.56 mph	31.36 mph	21.12 mph

Source: Northwestern University, July 2012

Figure 5-8 and Figure 5-9 show the variations of speed on the two highway segments with different departure times under different weather conditions. It shows that the rain effect on speed increases with precipitation intensity, as rainy day 1 (2010/05/03) has more speed drop than rainy day 2 (2010/05/12).

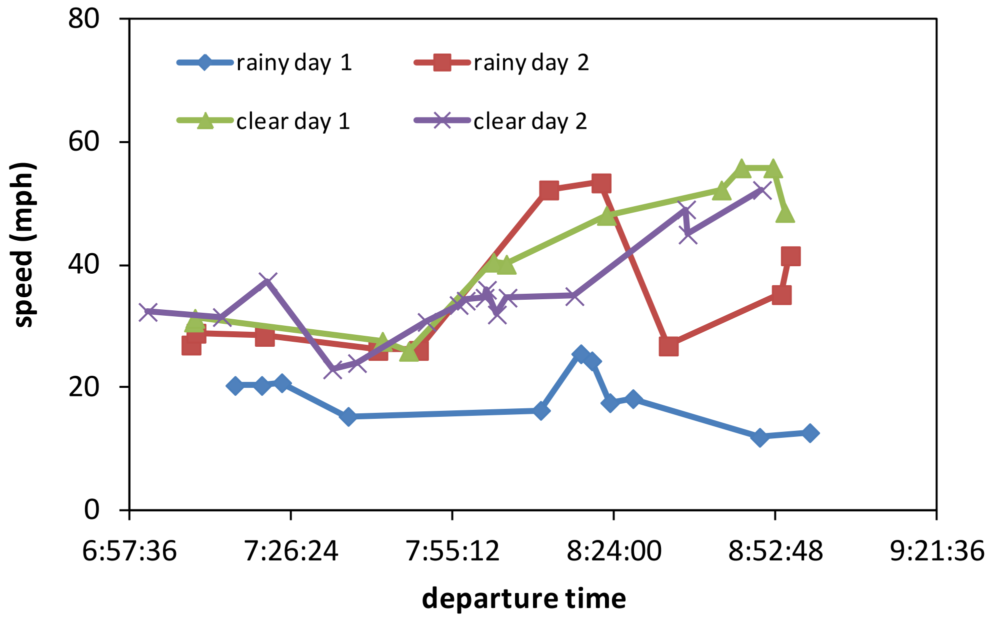

Figure 5-8. Observed speed on highway segment 1 under different weather conditions (Source: Northwestern University, July 2012)

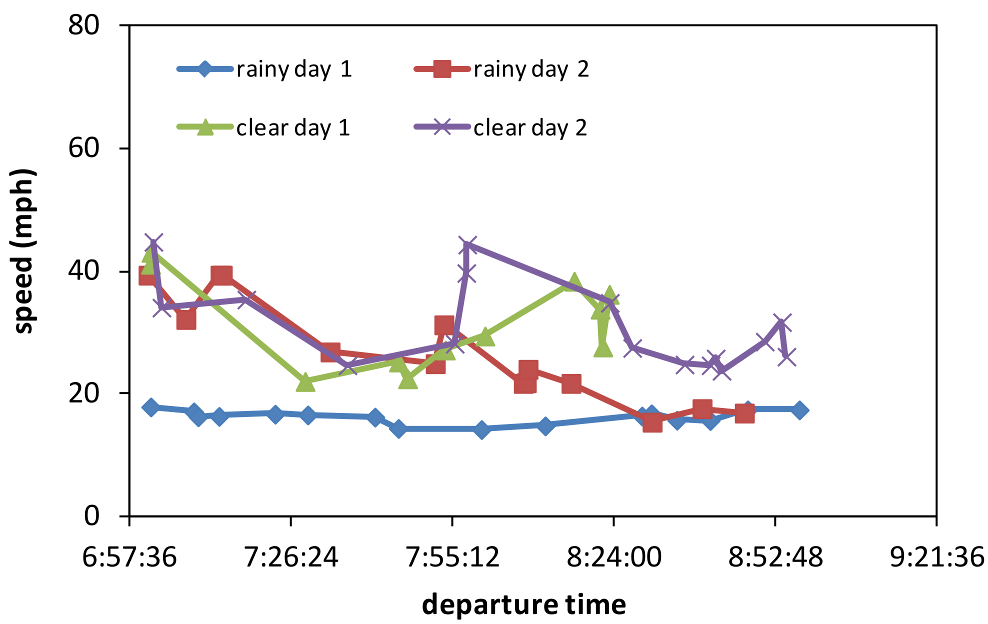

Figure 5-9. Observed speed on highway segment 2 under different weather conditions (Source: Northwestern University, July 2012)

5.2.3 Model Accuracy using Mobile Data

Update Traffic Flow Model Parameters by Bayesian Method using Mobile Data

Mobile data does not give density information directly; however, such information could be estimated using traffic flow theories. One of the simple approach to estimate traffic density is to apply the fundamental identity equation (Equation $q = k \cdot v$

(**5-2**) to speed and flow data under the assumption of stationary traffic.

$$q = k \cdot v \tag{5-2}$$

where q = traffic flow (veh/hr);
k = traffic density (veh/mile/lane);
v = space mean speed (mile/hr).

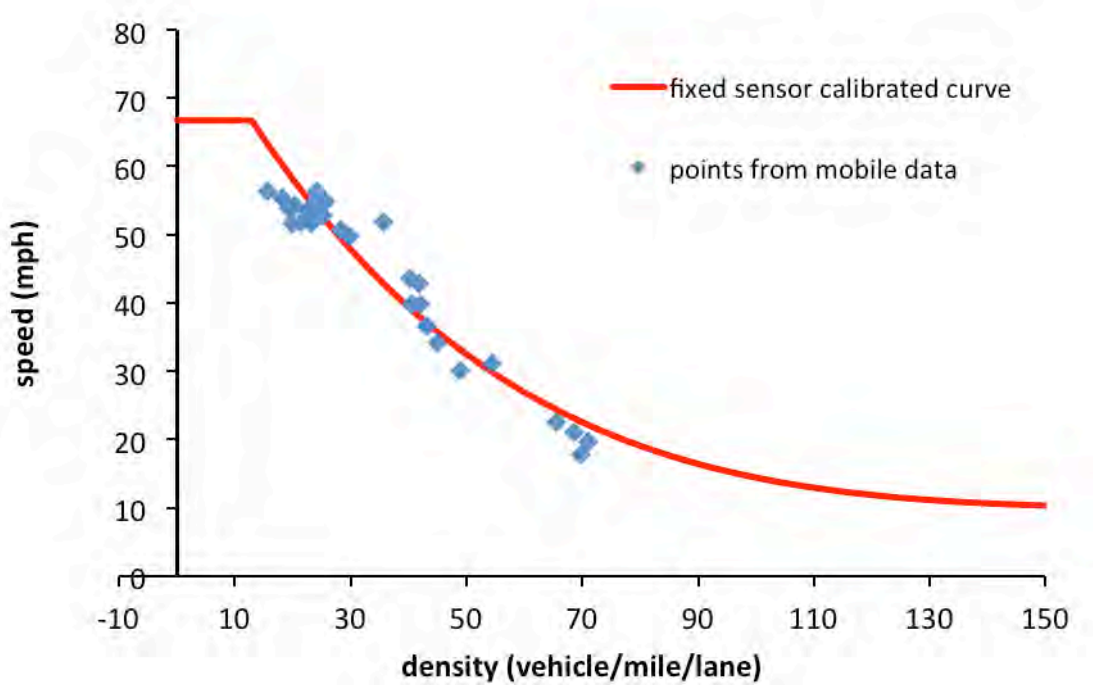

Figure 5-10. Fixed sensor calibrated traffic flow model with additional points from mobile data (Source: Northwestern University, August 2012)

Figure 5-10 shows a calibrated speed-density relation in New York network from fixed sensor data, together with some points obtained from mobile data. It is observed that the points from mobile data are scattered along the calibrated curve, and deviations between these two different sources of data exist. Although the mobile data alone is not as sufficient as fixed sensor data in calibrating traffic flow models directly, it could be used to improve the accuracy of the existing models, in conjunction with these inferred density data. The Bayesian statistical method rises naturally here, when some prior knowledge of the model parameters is known and new information is coming from mobile data. In the Bayesian inference context, a particular form of prior distribution of model parameter is assumed, then

$$P(\theta \mid D) = \frac{P(D \mid \theta)P(\theta)}{P(D)}$$

Bayes' rule (Equation

(**5-3**) is used to update the probability estimate with additional information, and the posterior distribution of model parameter is obtained as a result. The whole procedure could be repeated as long as new information is available.

$$P(\theta \mid D) = \frac{P(D \mid \theta)P(\theta)}{P(D)} \tag{5-3}$$

where

P(θ) = prior distribution of parameter θ;

P(*D*| θ) = likelihood of data *D* given model parameter θ;

P(θ |*D*) = posterior distribution of parameter θ.

$$P(\theta \mid D) = \frac{P(D \mid \theta)P(\theta)}{P(D)}$$

The denominator in Equation

(**5-3** is a normalization constant, which ensure that the posterior distribution on the left-hand side a valid probability density and integrates to one. Given these definitions, the posterior distribution of model parameters is actually proportional to the product of prior distribution and the likelihood of new data, i.e., $P(\theta \mid D) \propto P(D \mid \theta)P(\theta)$. It is known that if the prior distribution is Gaussian, the posterior is also Gaussian and the distribution parameters can be estimated analytically. In this study, for computational simplicity, we assume the prior distribution of model parameters is Gaussian. The detailed procedure of applying Bayesian method to traffic flow model calibration is described below.

1. Transform the second regime of modified Greenshields model into a linear form by taking the natural logarithm on both sides: $\ln(v - v_0) = \ln(v_f - v_0) + \alpha \ln(1 - \frac{k}{k_j})$, which is equivalent to linear model $Y = \theta_1 + \theta_2 X + \varepsilon$, where $X = \ln(1 - \frac{k}{k_j})$, $Y = \ln(v - v_0)$, $\theta_1 = \ln(v_f - v_0)$, and $\theta_2 = \alpha$, ε is random error.
2. Obtain prior distribution of speed-intercept (vf) and shape parameter (α) from existing traffic flow models calibrated using loop detector data, and covert them to prior distributions of θ_1 and θ_2, i.e., $P(\theta) = N(\theta_0, \Sigma_0)$
3. Convert speed and density data (v_i, k_i) obtained from mobile data to X_i, Y_i, where $X_i = \ln(1 - \frac{k_i}{k_j})$, $Y_i = \ln(v_i - v_0)$.
4. Find the posterior distributions of θ_1 and θ_2, i.e., $P(\theta \mid D) = N(\theta_N, \Sigma_N)$ where

$\theta_N = \Sigma_N(\Sigma_0^{-1}\theta_0 + \frac{1}{\sigma_\varepsilon^2}X^TY)$, $\Sigma_N = (\Sigma_0^{-1} + \frac{1}{\sigma_\varepsilon^2}X^TX)^{-1}$, and σ_ε is the standard deviation of the random error term which can be estimated from existing model.

Following the above listed steps, the speed intercept parameter (v_f) and shape factor (α) of modified Greenshields model from loop detector data are updated using Bayesian method. The other three parameters in the model, i.e., jam density (k_j), minimum speed (v_0), and breakpoint density (k_{bp}), are assumed unchanged. The estimation results are presented in Table 5-6. The comparisons of the prior and posterior distributions of the two parameters are shown in Figure 5-11. It is observed that there is little change in the mean value of model parameters after Bayesian treatment; however, the dispersions of the distributions get smaller, which indicates mobile data brings more confidence in the estimation process. Same methodology can be applied in updating weather adjustment factors (WAFs), as long as additional mobile data is available for different weather conditions.

Table 5-6. Traffic flow model parameter estimation results

model parameter		**before adding mobile data**		**after adding mobile data**	
		mean	**std dev**	**mean**	**std dev**
transformed parameter	θ_1	4.3293	0.0699	4.3158	0.0565
	θ_2	4.0811	0.7104	4.9528	0.3373
modified Greenshields model parameter	v_f	86.0787	5.3263	84.9958	4.2443
	α	4.0811	0.7104	4.9528	0.3373

Source: Northwestern University, July 2012

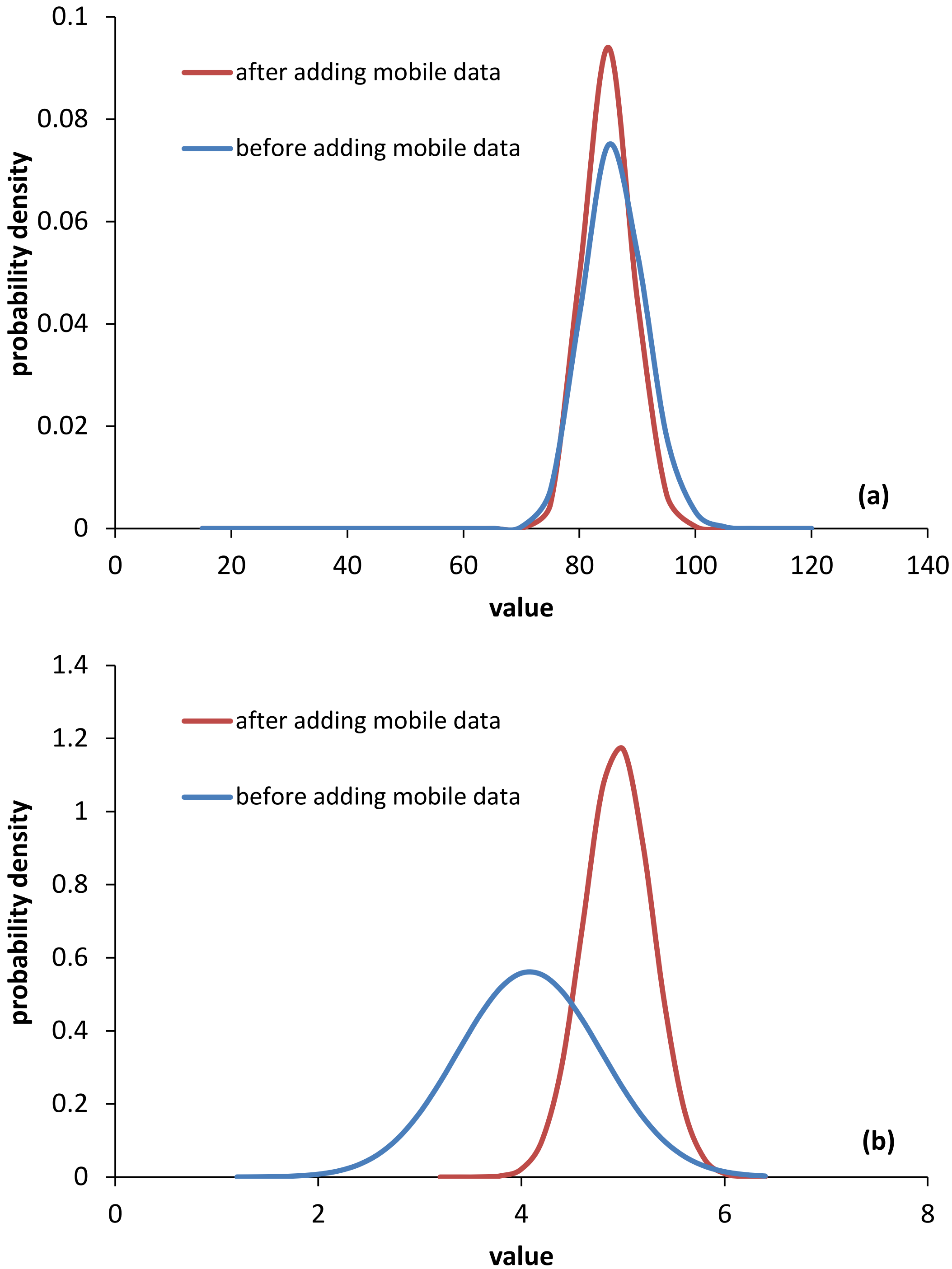

Figure 5-11. Comparison of prior and posterior distributions of (a) speed intercept parameter (b) shape factor (Source: Northwestern University, August 2012)

5.3 Demand-side Parameter Calibration

5.3.1 Estimation Methodology

Same as supply-side models, time-dependent (or dynamic) origin-destination (TDOD) matrices are of crucial importance as an input for dynamic traffic assignment (DTA) models. In the other FHWA funded WRTM-related TrEPS project, a bi-level optimization method that uses traffic counts data from loop detectors is adopted to estimate the time-dependent travel pattern (Verbas et al., 2011). In this study, an analogous method is used to accomodate new information extracted from mobile data. The method was originally developed using probe vehicles, in which automatic vehicle identification (AVI) counts serve as data sources (Zhou and Mahmassani, 2006). The approach is also proceeded in a bi-level framework. In the upper level of framework, in addition to minimize the sum of squared deviations of the simulated link flows from the corresponding observed values, it also seeks to minimize the deviation between simulated flow split fraction and observed flow split fraction at certain locations within the network; in the lower level a dynamic traffic assignment problem is solved. The process is iterated until convergence in the reduction of root mean square errors (RMSE) of the estimated link-flows is achieved.

The inputs to this framework are:

- Static/historical OD matrix for the planning time horizon,
- Time-dependent traffic counts on selected observation links.
- Time-dependent flow split fractions at certain locations.

The output is:

- Time-dependent OD matrices over the time horizon with a chosen time interval (usually 5 or 15 minutes).

The objective function is presented in the following equation. The first objective is to minimize the squared deviations between the simulated flows and observed flows on certain links. The second objective minimize the squared deviations between estimated dynamic OD pattern and historical static OD table. The third objective minimize the squared deviations between simulated and observed flow split fraction at selected locations.

$$\min\ w_1 \sum_{l \in L_{lc,t}} \left[c_{(l,t)} - \sum_{i,j,h} \hat{p}_{(l,t)(i,j,h)} \cdot d_{(i,j,h)} \right]^2 + w_2 \sum_{i,j} \left[g_{(i,j)} - \sum_{h} d_{(i,j,h)} \right]^2$$
$$+ w_3 \sum_{s_1 \in L_m, t} \sum_{s_2 \in L_m} \left[\frac{c^m_{(s_1,s_2,t)}}{c^m_{(s_1,t)}} - \frac{\sum_{i,j,\tau} \hat{p}_{(s_1,s_2,t)(i,j,h)} d_{(i,j,h)}}{\sum_{i,j,\tau} \hat{p}_{(s_1,t)(i,j,h)} d_{(i,j,h)}} \right]^2 \qquad (5\text{-}4)$$

$$subject\ to\ \hat{P} = assignment[D]\ from\ DTA$$
$$d_{(i,j,h)} \geq 0 \qquad \forall i, j, h$$

Where

L_{lc} : The set of links with link-count observations,
l : The index for observation links; $l \in L_{lc}$,
L_m : The set of links with flow split observations,
s_1 : The index for the first link within a link pair which has flow split observation; $s_1 \in L_m$,
s_2 : The index for the second link within a link pair which has flow split observation; $s_2 \in L_m$,
$c_{l,t}$: Observed link flow on link l at simulation/observation time t,
$c_{s1,t}^m$: Observed number of trajectories that traversed link s_1 at simulation/observation time t,
$c_{s1,s2,t}^m$:Observed number of trajectories that traversed link s_1 and s_2 at simulation/observation time t,
T : The set of simulation time intervals,
t : The index for simulation time intervals; $t \in T$,
h : The set of departure time intervals,
H : The index for departure time intervals; $h \in H$,
I : The set of origins,
i : The index for origins; $i \in I$,
J : The set of destinations,
j : The index for destinations; $j \in J$,
$d_{i,j,h}$: Time-dependent OD flow from origin $i \in I$ to destination $j \in J$ at the time interval $h \in H$
$g_{i,j}$: The static OD flow from origin $i \in I$ to destination $j \in J$
$p_{l,t,i,j,h}$: The proportion of demand for origin i, destination j, at departure time h, observed on link l, at simulation/observation time t.
$p_{s1,t,i,j,h}$: The proportion of demand for origin i, destination j, at departure time h, traversed link s_1, at simulation/observation time t.
$p_{s1,s2,t,i,j,h}$: The proportion of demand for origin i, destination j, at departure time h, traversed link s_1 and s_2, at simulation/observation time t.

w_1, w_2, and w_3 are positive weights associated with, respectively, the deviations with respect to link counts, historical static demand, and observed split fractions.

The proposed problem can be solved by the following iterative solution algorithm:

1. Select locations to obtain flow split fraction observations ($c_{s_1,t}^m$ and $c_{s_1,s_2,t}^m$) from mobile trajectory data.
2. (Initialization). Start from an initial guess of the demand matrix, obtain flow propositions ($p_{l,t,i,j,h}$, $p_{s_1,t,i,j,h}$ and $p_{s_1,s_2,t,i,j,h}$) from the DTA simulator.
3. (Optimization). Substitute simulated flow propositions into objective function to solve the upper level optimization problem.
4. (Simulation). Use estimated demand ($d_{i,j,h}$) to run DTA simulation so as to generate new flow propositions.
5. (Evaluation). Calculate the deviation between simulated link flows and observed link counts, the deviation between estimated demand and target demand, as well as the deviation between estimated flow split fractions and observed flow split fractions.
6. (Convergence test). If the convergence criterion is satisfied, stop; otherwise, go to Step 3.

The three stopping criteria used in this methodology are the root mean squared errors for demand, link count observations, and flow split fraction observations:

$$RMSE_{Demand} = \sqrt{\frac{\sum_{i=1}^{I}\sum_{j=1}^{J}\left[\left\{\sum_{h=1}^{H} d_{i,j,h}\right\} - g_{i,j}\right]^2}{IJH-1}} \tag{5-4}$$

$RMSE_{Demand}$ is the measure of error for the deviation between the new time-dependent demand matrix and the original static demand matrix.

$$RMSE_{Flows} = \sqrt{\frac{\sum_{l=1}^{L_{lc}}\sum_{t=1}^{T}\left[c_{l,t} - \sum_{i,j,h} \hat{p}_{l,t,i,j,h} \cdot d_{i,j,h}\right]^2}{L_{lc}T-1}} \tag{5-5}$$

$RMSE_{Flows}$ is the measure of error for the deviation between the simulated and the observed link flows.

$$RMSE_{Split} = \sqrt{\frac{\sum_{s1=1}^{L_m}\sum_{s2=1}^{L_m}\sum_{t=1}^{T}\left[\frac{c^m_{(s_1,s_2,t)}}{c^m_{(s_1,t)}} - \frac{\sum_{i,j,\tau} \hat{p}_{(s_1,s_2,t)(i,j,h)} d_{(i,j,h)}}{\sum_{i,j,\tau} \hat{p}_{(s_1,t)(i,j,h)} d_{(i,j,h)}}\right]^2}{L_m L_m T-1}} \tag{5-6}$$

$RMSE_{Split}$ is the measure of error for the deviation between the simulated and the observed flow split fractions.

5.3.2 Estimation Results

In this study, five locations in the New York network that have flow split observations from trajectory data are selected. They are all intersections for major highways, as shown in Figure 5-12, (a) split between I-95 and I-87; (b) split between I-495 and Grand Central Parkway; (c) split between I-278 and Brooklyn Battery Tunnel; (d) split between I-678 and Belt Parkway; (e) split between Brooklyn Queens Expressway W and Brooklyn Queens Expressway E. The iterative estimation procedure discussed in the previous section is then followed.

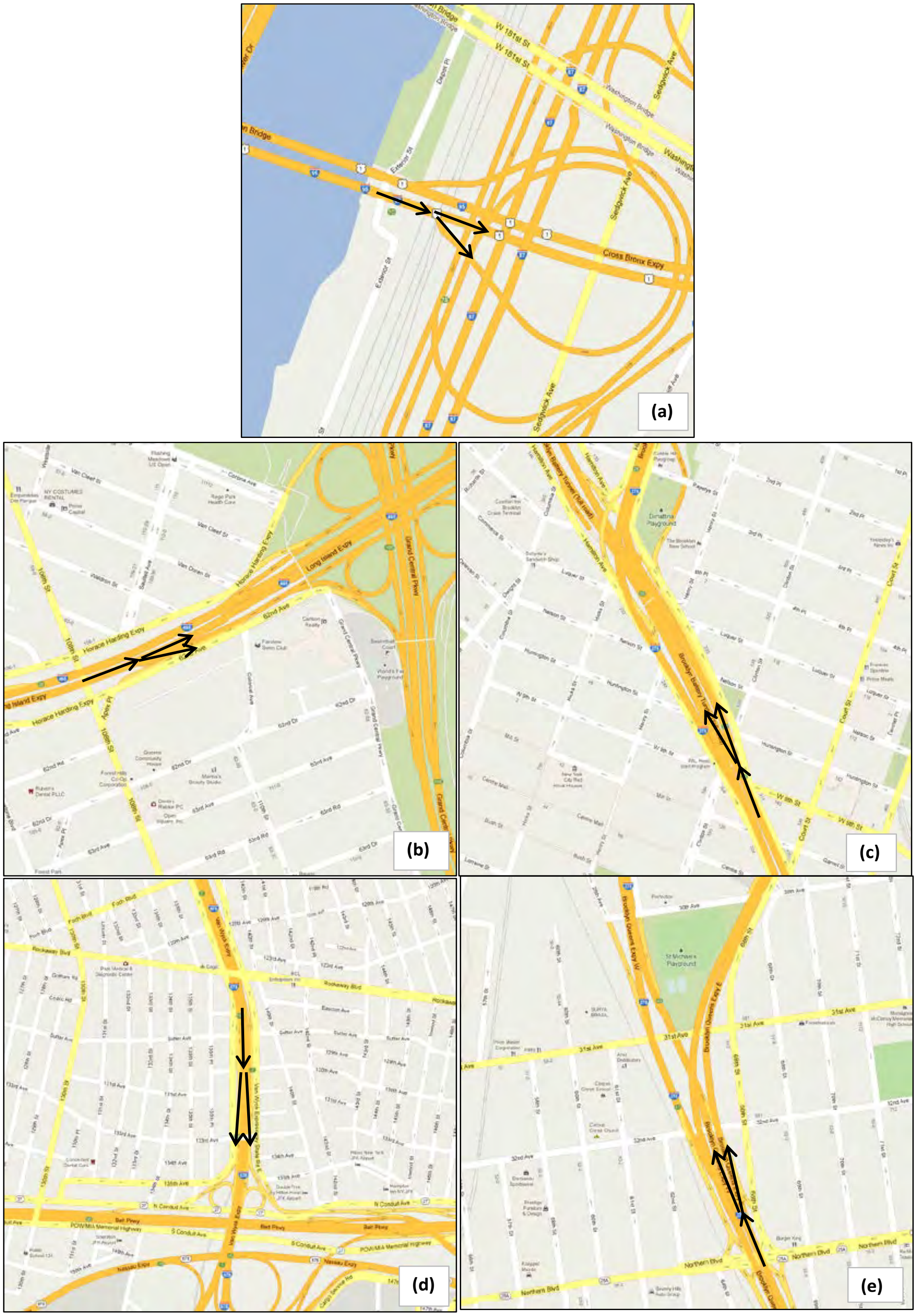

Figure 5-12. Selected locations with flow split
(Source: Google Maps, accessed August 2012)

The remaining materials in this section discuss the estimation results for the time-dependent OD matrix. Here we present the convergence pattern of the optimization process for obtaining the final OD matrix and the resulting time-dependent demand profile. For validation purposes, we compare the simulated link flows obtained from the estimated OD matrix to the observed link count data for selected links.

Table 5-7 shows the estimation results for the New York City network. The first two columns represent the number of single and high-occupancy passenger car trips after each iteration. The last three columns show the RMSE values that are discussed in the previous section (i.e., $RMSE_{Demand}$, $RMSE_{Flows}$ and $RMSE_{Split}$). In the first row, the results associated with the historical OD matrix is also presented for comparison. After the first iteration, $RMSE_{Demand}$ increases from zero because the new time-dependent OD matrix (in the second row), which is created based on the historical OD matrix, is the result of the optimization process that is not only minimizing $RMSE_{Demand}$ but also minimizing $RMSE_{Flows}$ and $RMSE_{Split}$. However, after iteration 2, the error does not increase dramatically and always stays below 0.55. $RMSE_{Flows}$ has decreased 21% after the first iteration and has been trending downward for the remaining iterations. Also, $RMSE_{Split}$ continues to decrease from initial value of 0.36, although some fluctuation exists. The rate of decrease is decreasing, which implies convergence. This means that the real-world link count and flow split observations are matched better with the simulation results produced by the new time-dependent OD matrix than with the historical OD matrix.

As a link-level validation, the simulated and observed link counts are compared for several selected links. Simulated results based on the estimated time-dependent OD matrix are compared with the actual observations, which are collected during the time period (6am – 10 am) that corresponds to the demand horizon used for the OD matrix estimation. Figure 5-13 displays the cumulative number of vehicle counts (left column) and the 15-minute aggregated vehicle counts (right column) for two selected links, respectively. Overall, link-level comparisons show good agreements. As a network-wide validation, the overall OD demand pattern is also compared. Figure 5-14 presents the temporal distributions of SOV trips of the historical OD matrix (denoted by “Old SOVs”) and the most up-to-date time-dependent OD matrix (denoted by “New SOVs”). Similarly, Figure 5-15 shows the temporal distributions of HOV trips for the historical OD matrix (denoted by “Old HOVs”) and the most up-to-date time-dependent OD matrix (denoted by “New HOVs”).

Table 5-7. RMSE Values for the New York Network

	Number of Trips		RMSE Values		
	SOV*	HOV*	$RMSE_{Demand}$	$RMSE_{Flows}$	$RMSE_{Split}$
Original Static OD matrix	1,561,111	634,848	0**	999.322	0.360
New time-dependent OD matrix after **Iteration 1**	1,545,857	627,533	0.626	785.802	0.341
New time-dependent OD matrix after **Iteration 2**	1,552,380	629,948	0.537	806.652	0.344
New time-dependent OD matrix after **Iteration3**	1,548,736	628,438	0.551	767.011	0.336
New time-dependent OD matrix after **Iteration4**	1,550,906	629,097	0.527	789.119	0.338
New time-dependent OD matrix after **Iteration5**	1,548,597	628,155	0.544	760.560	0.327
New time-dependent OD matrix after **Iteration6**	1,550,794	628,843	0.525	780.140	0.336
New time-dependent OD matrix after **Iteration7**	1,548,419	628,002	0.542	756.528	0.324
New time-dependent OD matrix after **Iteration 8**	1,550,007	628,414	0.525	774.139	0.337
New time-dependent OD matrix after **Iteration 9**	1,548,129	627,908	0.541	755.223	0.323
New time-dependent OD matrix after **Iteration 10**	1,549,531	628,465	0.527	772.799	0.337
New time-dependent OD matrix after **Iteration 11**	1,549,175	628,171	0.544	752.768	0.323

* *SOV: Single-occupancy vehicle, HOV: High-occupancy vehicle*

** *Deviation is zero because $RMSE_{Demand}$ in this case represents the deviation between the static OD matrix and itself.*
Source: Northwestern University, September 2012

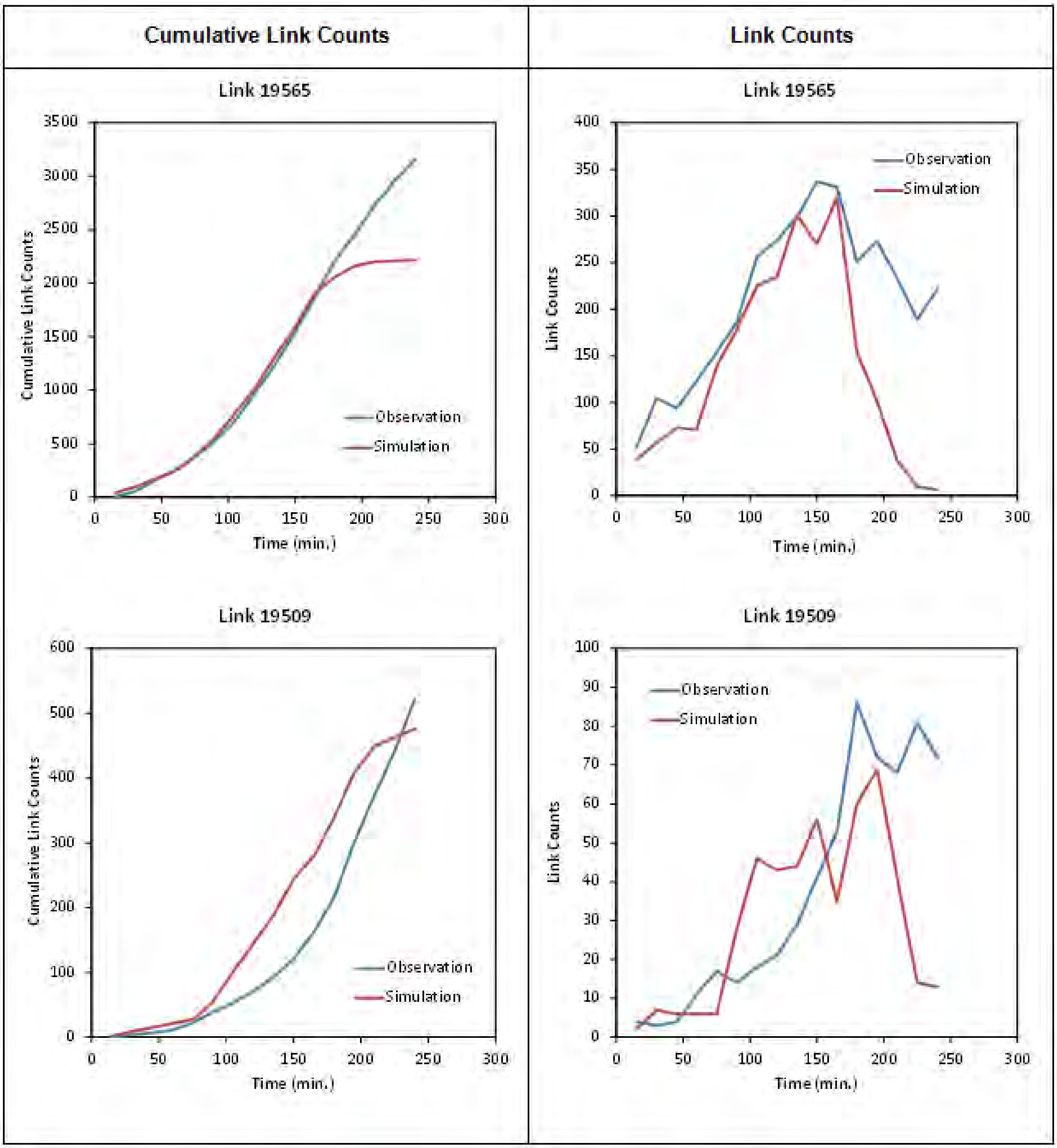

Figure 5-13. Observed and Simulated Counts on Selected Links
(Source: Northwestern University, September 2012)

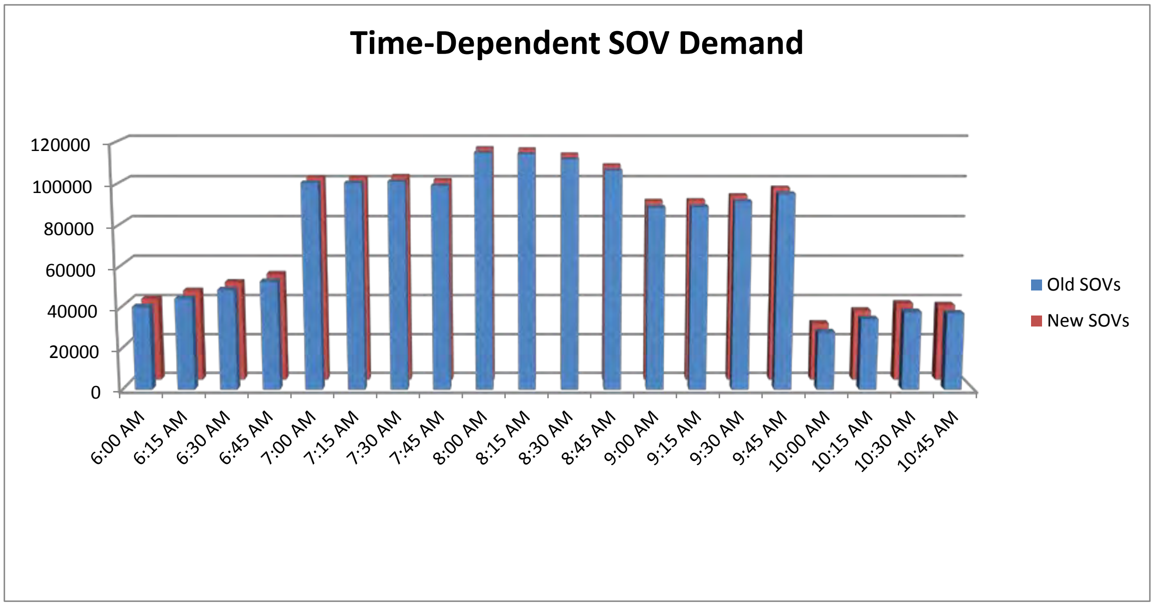

Figure 5-14. Temporal Distribution of SOV trips for the New York Sub-network (Source: Northwestern University, September 2012)

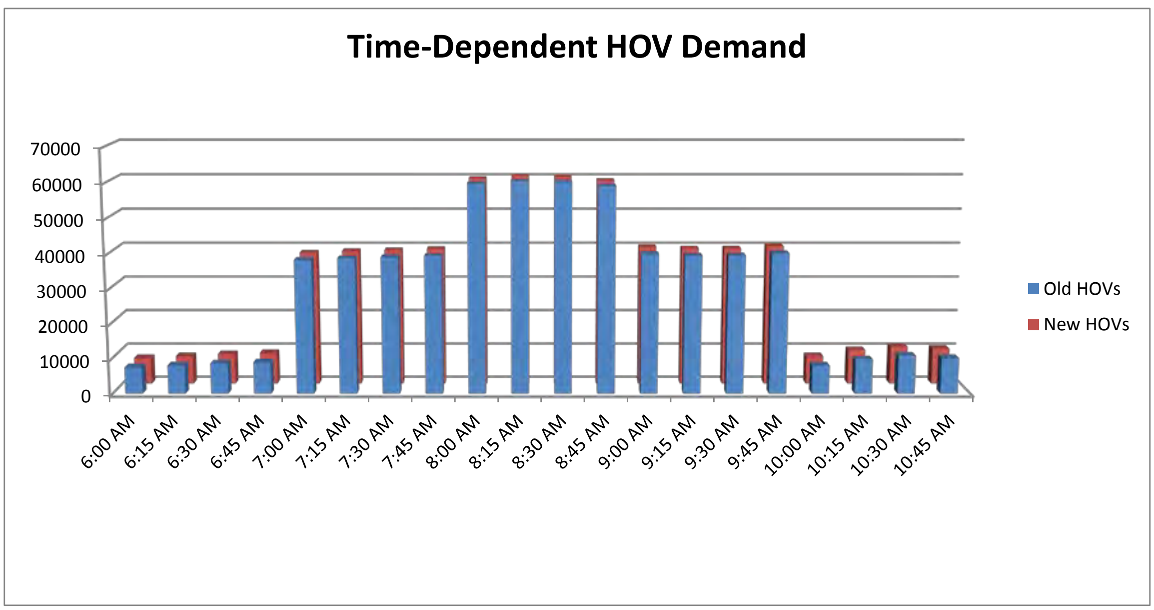

Figure 5-15. Temporal Distribution of HOV trips for the New York Sub-network (Source: Northwestern University, September 2012)

5.4 Model Validation

After the supply-side and demand-side parameters are obtained, the capability of capturing weather effects on the traffic flows is tested by performing simulations with specific weather scenarios. For the selected test network (New York), days with rain or snow events during the morning peak hours (between 6AM and 11AM) are identified and the traffic observations are collected for each identified day. The corresponding weather conditions are specified in the DYNASMART weather.dat input files. Each weather scenario is simulated with the calibrated OD matrix with and without using weather adjustment factors (WAF) in DYNASMART. Then the simulated results are compared with the actual observations under the weather condition the weather.dat input file is representing. The main focus is to see whether the mobile data calibrated TrEPS model produces realistic traffic states, that is, resemble real-traffic conditions under different weather conditions.

Traditionally, with fixed sensor traffic data, TrEPS models are validated by comparing simulated speed and flow data with observations from detectors at link level. By incorporating mobile data, the model validation work can be enhanced in the following ways:

- Validation can be extended from link level to path level as observations along different paths are available from trajectory data;
- The variable to be validated will not be limited to traffic flow and speed, but can also be travel time, which is an important property obtained from mobile data;
- Validation will not be restricted on highway segments where loop detector data are available, but will be extended to arterials as mobile data provides a much broader geographic coverage than fixed sensor data.

Two sets of validations are conducted, with one using link-level speed information and the other using path-level travel time information, both of which are extracted from mobile data.

5.4.1 Validation by Speed

For a link-level comparison, Figure 5-16 presents simulated speeds under clear and rainy conditions on a selected link. Figure 5-17 presents the speed values extracted from mobile data on the corresponding road segment. In the link-level comparisons, it is observed that both simulated data and mobile data give lower speed values under rainy condition than clear weather condition. The fluctuation of speed from mobile data is much greater than that of simulated data, probably due to a much smaller sample size.

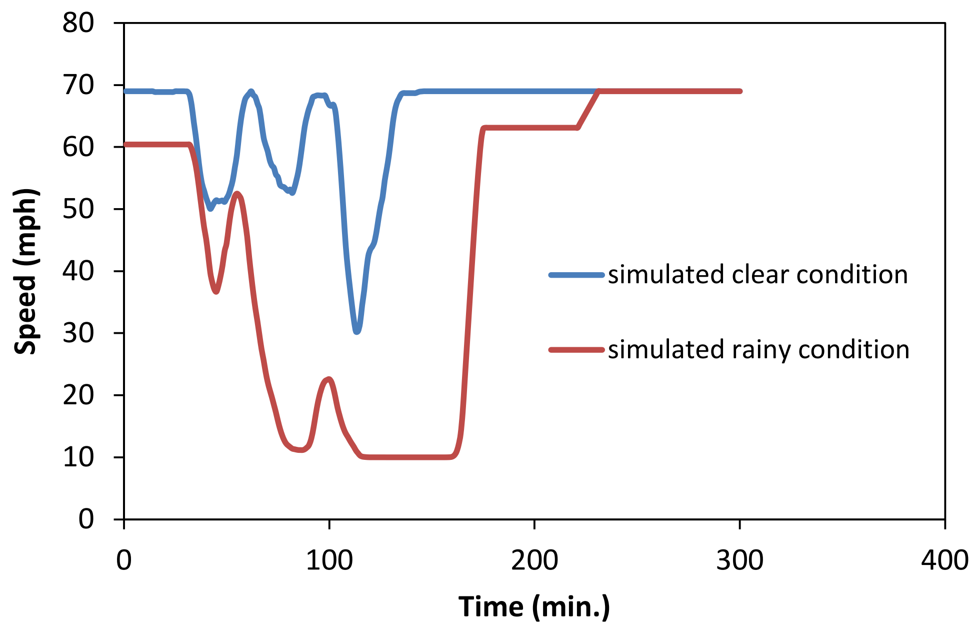

Figure 5-16. Comparison of simulated speeds on a selected link under clear and rainy conditions (Source: Northwestern University, September 2012)

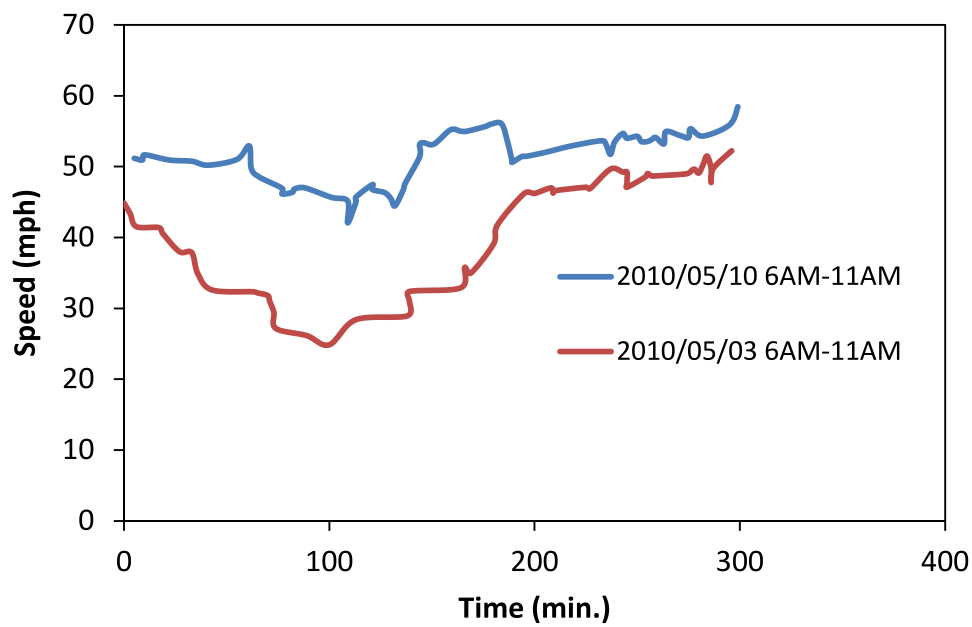

Figure 5-17. Comparison of mobile data inferred speeds on a selected link under clear and rainy conditions (Source: Northwestern University, September 2012)

5.4.2 Validation by Travel Time

Besides speed data, vehicle trajectory data also can be used to generate travel time information, and thus be used to validate simulated path travel times. To illustrate this, a road segment in New York network (I-495/ Long Island Expressway, Figure 5-18) is selected where trajectory data are available. The travel time that a vehicle spent traversing this segment is then extracted from vehicle trajectory data. Figure 5-19 shows the comparison of travel time histograms obtained from the mobile trajectory data and simulated trajectory data. It is observed that the mean travel time of that path obtained from simulated data is a bit smaller than that from TomTom trajectory data. Moreover, the cumulative distributions of travel times are compared in Figure 5-20, and similarities exist between observed and simulated travel time distributions.

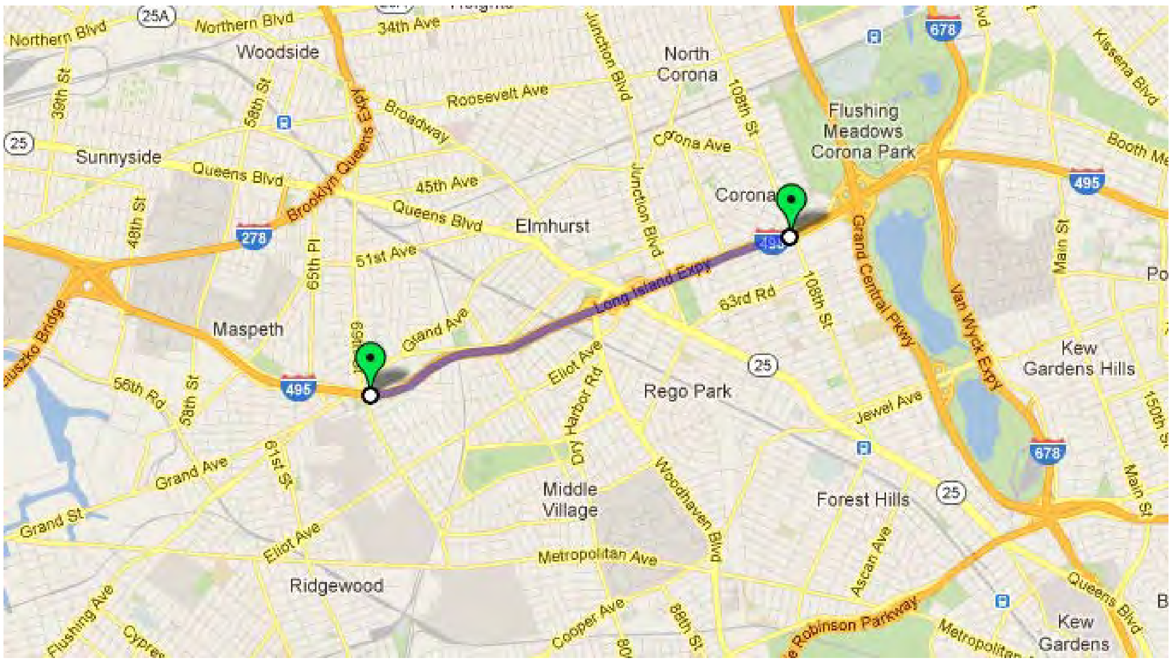

Figure 5-18. A selected path in New York network for travel time validation (Source: Google Maps, August 2012)

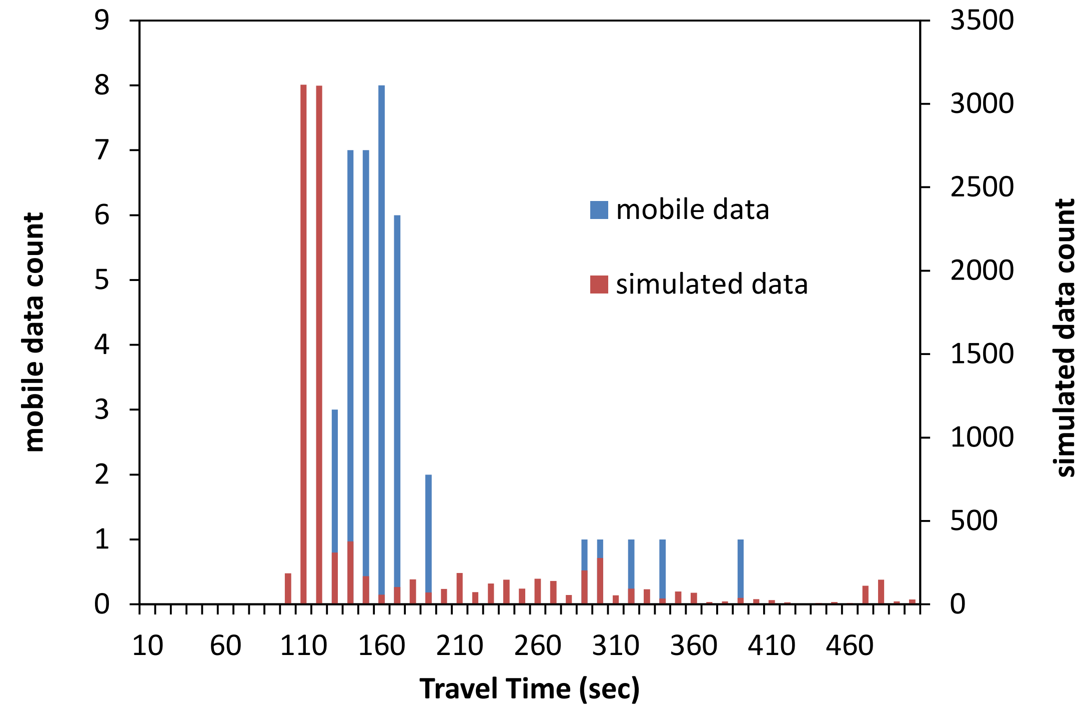

Figure 5-19. Comparison of travel time histograms from mobile data and simulated data (Source: Northwestern University, September 2012)

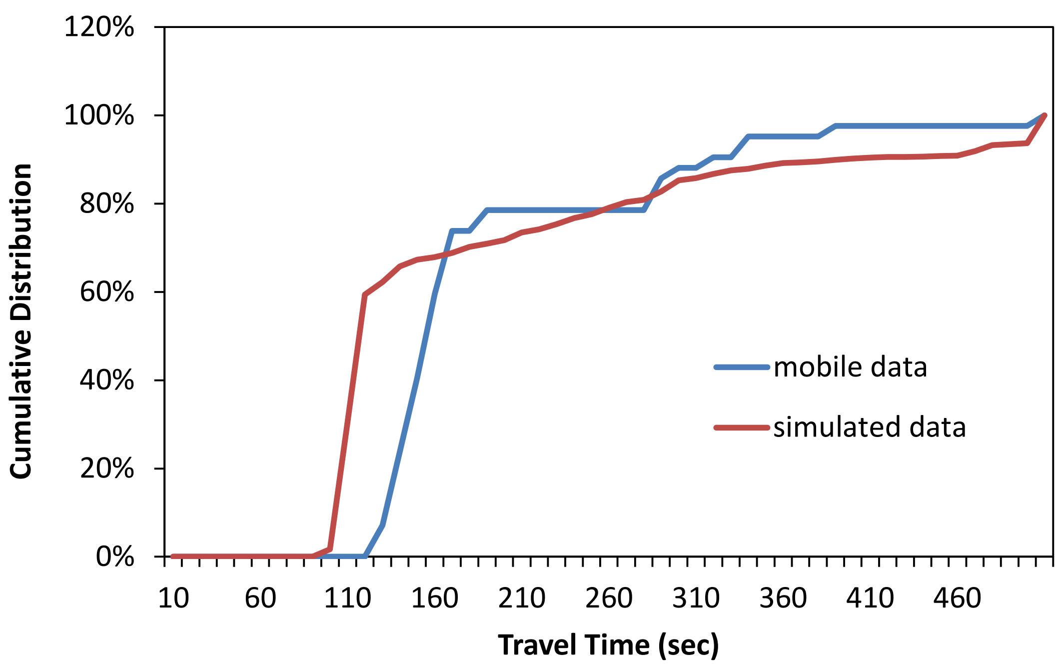

Figure 5-20. Comparison of travel time cumulative distribution from mobile data and simulated data (Source: Northwestern University, September 2012)

Chapter 6. Conclusions and Recommendations

The study has provided a systematic review and assessment of how mobile data, such as that available from GPS-equipped vehicles, can improve the performance of Weather-Responsive Traffic Management (WRTM) Traffic Estimation and Prediction (TrEPS) models. Focusing on the suite of models that have been developed in previous FHWA funded projects, the study has identified a set components within the WRTM framework to which new sources of traffic data, from mobile vehicle sources, could be incorporated.

The components identified in the study fall within both the supply and demand sides of the model system. On the supply side, mobile data can contribute to the calibration of the various relations of interest, particularly those that govern link propagation and flows through nodes. On the demand side, the most immediate application is the estimation of time-dependent origin-destination trip information. Mobile data can also be used to improve the validation process of these models. The potential application of mobile data in on-line implementation of Traffic Estimation and Prediction System (TrEPS) is also discussed.

Different types of mobile data that could become available from different sources and from major potential vendors are identified and compared with each other. It is found that vehicle trajectory data provides the best opportunities for the purpose of improving WRTM models and their application. A framework for how to implement the integration of mobile data and WRTM models is developed, from data fusion, model calibration, to model validation.

The New York City network is selected as the test bed in which to demonstrate the implementation of the framework for incorporating mobile data. Vehicle trajectory data provided by TomTom is used as the mobile data source. The study used DYNASMART, modified for weather-responsiveness in the previous FHWA projects, as the TrEPS model to perform the demonstration work. The detailed procedures for calibrating supply-side and demand-side weather-sensitive TrEPS models using mobile data are developed. The results are validated by speed and travel time data extracted from mobile data source. The results demonstrate that mobile data could be successfully incorporated into those models and improve the model accuracy especially by providing broader geographic coverage and additional travel time information than traditional fixed sensor traffic data. Such uses are especially valuable when sensor information is lacking, providing a local source of information to complement a priori model parameter estimates that may have been based on data from other locations.

Methodologically, this study has developed a procedure for updating flow model parameters, and weather adjustment factors using mobile data as a complement to available sensor information, or in some cases as a substitute for such information when it is not locally available. The study has also devised a new approach to combine three sources of information, historical, fixed sensor and mobile in estimating the origin-destination trip patterns for a given network.

While the work accomplished as a result of this research project advances the state of practice in using mobile data for WRTM models, additional efforts are needed to study the application of mobile data in on-line TrEPS implementation. Essentially, to achieve the full benefit of using mobile data in the intelligent management of traffic systems under weather-related events, development of the real-time components of traffic estimation and prediction tools, and their interface with real-time data sources is required. Actual field testing, monitoring, and collection of real-time mobile data, can provide essential data to calibrate and refine these mechanisms.

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Appendix A. Mobile Data Products Offered by Different Vendors

Contents

Introduction and Summary

General Purpose

Weather events have a significant role in traffic operations, road safety and in travel time reliability. This project demonstrates how mobile data can enhance the flexibility and performance of traffic models that are used to evaluate weather-responsive traffic management (WRTM) strategies. A lot of research has already been completed in this area, so the goal of this project is not to add to that research, but rather to evaluate the available mobile data and its applicability to existing WRTM models.

This Appendix identifies and evaluates current sources of mobile data. This contains a summary of our findings, as well as an inventory of current mobile data sets and their key characteristics. The report contains an inventory of existing data and an analysis of each potential source of data. This evaluation includes a determination of possible sources of data that could be integrated with one or more WRTM models.

During our data collection for this task we have identified possible future sources of mobile data to pursue, including new technologies and data sources that are currently not available to the public or for research.

Private firms provide the best sources of mobile data (Inrix; NAVTEQ; TomTom; and AirSage are most active in the US[1]). Several of these firms met directly with FHWA staff or via a webinar.

We evaluated the database details the firms were willing to provide. All firms indicated an interest is supporting future commercial sales for transportation planning models in general and WRTM models in particular.

Summary and Initial Recommendations

At present, Inrix appears to have the largest base of mobile data in the US. A large portion of these data come from commercial vehicles (mostly large trucks) however, which raises questions about their suitability for WRTM models. TomTom and AirSage have nationwide data as well, but with a focus on data from passenger vehicles. Their geographic coverage appears comparable or even better than Inrix. NAVTEQ and TrafficCast also provide nationwide data, but mix mobile data with fixed sensor information.

Both TomTom and AirSage have systems capable of providing origin-destination information and individual vehicle traces, but both firms are at early stages in converting these data into commercial products; so, while the prospects of such offerings are very promising, their practicality is still under investigation. TomTom derive data from GPS devices, making their technology easier to understand

[1] Outside the US Intellione has a cell phone based mobile data system in operation in Canada with data provided by Rogers Telecom and ITIS Holdings (now owned by Inrix) has cell phone and GPS-based systems in Europe, Israel, Australia and elsewhere in Asia and Cellint has cell-based systems in Israel and places in Europe. To date, none of these firms have been successful in generating mobile data systems in the US.

and evaluate. AirSage depends on data provided by wireless carriers and some technical details remain unclear. TrafficCast can provide origin-destination data between Bluetooth sensors, but their installed base is scattered and focused on major roads. Information is only available between Bluetooth devices located at fixed points.

None of the firms can provide volume counts across their full network. NAVTEQ does provide volume data for locations that have their proprietary sensors – mostly for selected Interstate routes in about two dozen major metropolitan areas.

Evaluation results are scattered. Inrix, AirSage and NAVTEQ have received positive results, with I-95 Corridor Coalition providing a detailed, independent evaluation of Inrix. TomTom has yet to be evaluated in the US – evaluations in Europe have been positive, but the TomTom system in Europe is not exactly comparable to that in the US (more GPS units in Europe and supplemented by cell probe data). Several years ago AirSage received some very negative evaluations from Virginia and other states. Since then they have signed up a second wireless carrier (Verizon), modified some of their algorithms, and have carried out additional data validation using their own floating car studies. All of these evaluations, however, have focused on estimates of speed along a given link. None have examined the potential value of these data for WRTM or other planning models.

Types of Data Needed For WRTM Models

To date the main sources of data for modeling purposes have included travel and traffic surveys (O-D / travel patterns, traffic volumes, travel times, etc.) and fixed sensors (flows, speeds, traffic occupancy / density). But practitioners and researchers in the transportation modeling field have long sought more detailed and robust data sets than what is typically used in current modeling applications, whether for transportation planning or traffic operations purposes. The emergence of mobile data availability over the past few years opens these horizons with regard to geographic and temporal coverage, level of detail / resolution, and also new types and complexity of modeling.

The data types available from mobile data providers to date (travel time and speed by road section) have primarily been geared towards traffic / traveler information and navigation applications. As the understanding and importance of such data for other applications have risen over time amongst transportation agencies and professionals, we have seen significant efforts (much of it supported by FHWA) to incorporate mobile data into traffic operations and performance measurement.

A complementary piece of information typically used in operations and performance applications involves the knowledge of traffic volumes in the network to match (to the extent possible) the coverage and detail available for travel times and speeds derived from mobile data. This has led to further efforts in the mobile data industry to provide inferred or imputed volumes of traffic, as the mechanism / installations of mobile data collection do not lend themselves to direct measurement of traffic volumes. Yet, the generation of inferred / imputed traffic volumes from mobile data is still in its infancy and the industry is trying to develop appropriate techniques and algorithms to derive this type of data.

So far mobile data has found their way first into traffic simulation models focusing primarily on transportation / traffic supply modeling applications (whether microscopic or mesoscopic models). Moving beyond traffic supply modeling, mobile data hold significant promise in enhancing the demand side of modeling applications as well. The underlying premise of mobile data collection (i.e., gathering data from GPS or cell phone based probes within a transportation network) provides the opportunity to gather information about trip origins and destinations as well as the paths / trajectories that such probes followed in their trips. This provides much more powerful information about traffic / travel experience at individual trip level of detail and the associated decisions with regard to route choice, trip end patterns, etc. This type of data can consequently be applied to the full spectrum of traffic demand-supply models, enhancing modeling components that range from demand estimation to route / path choice and other trip making decisions and operational behaviors, and which may be captured at any level of modeling detail (i.e., from macroscopic / planning applications, through mesoscopic planning and operations, to detailed microscopic operations applications). A major concern with the origin-destination / trajectory type of data is the need to protect personal privacy.

For WRTM modeling purposes in general though, mobile data can assist in the development / calibration of such models as well as in both offline and online application of such models for analyzing, designing and evaluating the performance and deployment effectiveness of WRTM strategies. Table 1 outlines which types of data attributes would be beneficial to each model component by level of suitability.

Table A-1

	Model Components		Types of Mobile Data				
			Travel times	**Speeds**	**Inferred Volumes**	**Trip Origin-Destination**	**Vehicle Trajectories**
Off-line Calibration	Supply Parameters (Meso)	Traffic flow Model: speed-density relations	*	***	***	-	*
		Weather Adjustment Factors: traffic flow model parameters, maximum or service flow raters, speed limit margin etc.	*	***	***	-	*
	Behavior Parameters (Micro)	Car following Model	**	***	*	-	-
		Gap acceptance model	*	***	***	-	-
		Lane changing model	*	***	***	-	-
	Demand Parameters (Meso & Micro)	Time dependent O-D matrix	**	**	***	***	***
		Demand adjustment factors under different weather conditions	**	**	***	***	***
		Vehicle Class Composition	**	***	***	*	*
On-line Traffic State Measurement	Supply Side Consistency Checking	Minimize discrepancy between observed and simulated travel time	***	*	*	**	**
		Minimize discrepancy between observed and simulated link speeds	*	***	*	*	**
	Demand Side Consistency Checking	Minimize discrepancy between observed and simulated O-D demand	*	*	***	***	***
Evaluation of WRTM Strategies	Performance Measures	Link travel measures	**	***	***	*	***
		O-D or Path Travel times	***	***	***	***	***
		Vehicle diversion rates or compliance rates	***	***	***	**	***

Note: Number of stars reflects greater suitability of corresponding data type for particular model components.

Current Sources of Mobile Data

This section provides summary information on the five largest providers of mobile traffic data currently active in the United States that claim to have traffic data on a national scale: Inrix; TomTom; TrafficCast; AirSage and NAVTEQ. Despite considerable progress, many parts of this market are still at an early stage of development. This means that certain key variables (price, for example) are not standard and vary based on market conditions. This is particularly true regarding data key to traffic models. To date, most mobile data firms have focused on traffic information that supports navigation systems or 511 systems. Some (AirSage, for example) have only recently begun to support traffic models.

We have identified all current private sector players with deployments that extend beyond one local deployment, including instances where we can pinpoint a technology as readily applicable to nationwide availability. The providers were willing to provide varying degrees of detailed information.

Vendor Overview

Available Data Types

All vendors focus on travel times and speeds since that reflects the current marketplace. The only vendor that offered volume data was NAVTEQ. These data, however, appear to be provided by NAVTEQ's own sensors located on certain major roads in large cities.

Data Coverage

National coverage is provided by the following vendors:

- AirSage
- NAVTEQ
- Inrix
- TomTom

TrafficCast was the only sampled vendor that did not offer complete national coverage; although they do offer urban coverage in most metropolitan areas.
All vendors utilize Traffic Message Channels (TMC) codes within their respected coverage ranges. NAVTEQ and TomTom offer the ability to provide data for more detailed segments than possible with TMC codes and can cover the full roadway network.

Pricing

All vendors customize pricing based upon specific client-tailored solutions. This is particularly true for data needed for traffic and planning applications since this market is largely under developed. Each vendor uses a number of factors to determine cost, including but not limited to:

- Total Number of Discrete Attributes
- Total Sample Area
- Total Time Period
- Intended Client Data Usage
- Number of Intended Client Users (e.g. single-use, multiple-user internal, external use)

The only vendor who provided specific pricing information when requested was AirSage.

Vendor Specific Information

Inrix

Information

www.inrix.com
10210 NE Points Dr., Suite 300 Kirkland, WA 98033
Contact: Pete Costello pete@inrix.com 202-550-5795

Pricing

All solutions are custom tailored.

Data Validation

I-95 Corridor Coalition **-** http://www.i95coalition.org/i95/Default.aspx
The four month I-95 Corridor Coalition study analyzed traffic on 111 miles of highways across Delaware, Maryland, New Jersey and Virginia. Using Bluetooth reader technology, the study compared 19,000 observations of ground-truth vehicle speeds for over 1,500 hours on 54 road segments against real-time speed information for those road segments that INRIX provides as part of its contract to the Coalition. In October, the I-95 Corridor agreed to extend the Inrix contract – although actual purchases are up to individual states.
Inrix Traffic Quality Benchmarking PDF document is available with more details.

Real-time and Historical data available

Real-time –yes
Historical - yes

Sources used in generating data

Commercial GPS data (large trucks), DOT sensor data, and other proprietary data sources including automobile and light truck GPS from fleets. Data from large trucks still seems to be the largest single source of data.

TomTom

Information

http://www.tomtom.com/traffic_solutions
11 Lafayette St
Lebanon, NH 03766
Contact : Kenneth Clay Kenneth.clay@tomtom.com 800 331 7881 ext. 11337

Pricing

All solutions are custom tailored with multiple licensing options available.

Data Validation

None in the US to date

Real-time and Historical data available

Historical data – yes
Real-time data - yes

Sources used in generating data

- Data from connected TomTom devices (GPS)
- Data from smartphone applications
- Data purchased from other vendors
- Data from connected TomTom Work devices – trucks (GPS)

- Data from the Vodafone mobile phone network (GSM) – but not yet in the US
- Data from governments and traffic control centers
- Historical databases (validation only)

TrafficCast

Information

http://trafficcast.com/
2801 Coho Street, Suite 100
Madison, WI 53713, USA
Tel: +1-608-268-3946
Contact: Paul Misticawi, pmisticawi@trafficcast.com, tel. 678-575-0958

Pricing

All solutions are custom tailored with multiple licensing options available.

Data Validation

Not provided, but available for Bluetooth sensors

Real-time and Historical data available

Historical data – yes
Real-time data - yes

Sources used in generating data

- Information derived from GPS tracking data (purchased from fleets), public sensors and reports of accidents, road works and weather reports.
- Bluetooth devices are being deployed in quite a few states. These can provide local data on travel times between devices.

AirSage

Information

http://www.airsage.com
400 Embassy Row, Atlanta GA 30328
Contact: Bob Pauley rpauley@airsage.com 404-906-1740

Pricing:

AirSage provided a document with Pricing for their Data Products

Data Validation

Independent testing firm Geostats - See geostatsreport.pdf for study details
Most recent tests involve AirSage's own floating car studies in Maryland/Virginia/Washington DC for data validation purpose indicating 95% accuracy in travel time measurements – Report has not yet been received
Reports from previous years were quite negative.

Real-Time Historical Data Available

Real-time data – yes
Historical Data – yes

Attributes Collected

Date and timestamp, market, TMC code, actual speed and historical mode value.

Sources used in generating data

Wireless signaling data provided by Sprint and Verizon; cell phone GPS, and other carrier data.

NAVTEQ

Information

425 West Randolph Street
Chicago, Illinois 60606
Contact: Skip Parker skip.parker@navteq.com 972-467-6086
T 312 894 7000

Pricing

Licensing dependent upon multiple factors.
http://www.nn4d.com/site/global/market/licensing/p_navteqlicensing.jsp

Data Validation

Not provided

Real-time and Historical data available

Real-time - Yes
Historical - Yes

Attributes Collected

http://www.nn4d.com/site/global/learn/basics_of_map_data/attributes/p_attributes.jsp

Sources used in generating data

Proprietary roadway sensors; fleet GPS purchased; and public sector sensors

Data Formats Available

http://www.nn4d.com/site/global/learn/documentation/nt_map_data_formats/p_map_data_formats.jsp

Table A-2: Data Vendor Overview without Data Validation Column

Mobile Traffic Data Sources	Technology Used	Traffic Data Elements Collected	O-D / Trajectory Data and Point Data Availability	Real Time and Historical Data Availability	Location-Codes Used	Other information
Inrix	Commercial GPS data, DOT sensor data, and other proprietary data sources. GPS-enabled vehicles	Speed Travel Time	Point	R, H	TMC Codes	Data available for TMC road functional classes FC1, FC2, FC3, and some FC4; Flexibility in data format / levels of aggregation for up to latest 90 days
TomTom	TomTom devices (GPS) Data from the Vodafone mobile phone network (GSM) Data from governments and traffic control centers	Speed Travel Time	Point, Trajectory Origin-Destination	R, H	TMC Codes, Proprietary Segment Tables	
NAVTEQ	State of the art probe data processing including both point and route-based observations (Cellular) Data from NAVTEQ's proprietary sensor network	Speed Travel Time Volume from own sensors	Point	R, H	TMC Codes, Proprietary Segment Tables	
AirSage	Wireless signaling data, Cell phone GPS, Other Carrier Data	Date and timestamp, Mode, Speed, Travel Time, Location ID, Alert	Point, Origin-Destination	R, H	TMC Codes	Data available for TMC FC1-FC4; O-D data available in blocks as small as 1,000 sq. [fast becoming their most popular product, latest application an O-D study for LA-Las Vegas hi speed rail];

Mobile Traffic Data Sources	Technology Used	Traffic Data Elements Collected	O-D / Trajectory Data and Point Data Availability	Real Time and Historical Data Availability	Location-Codes Used	Other information
TrafficCast	Information derived from GPS tracking data, public sensors and reports of accidents, road works and weather reports. Bluetooth Travel-time Origination and Destination devices.	Speed Travel Time	Point, Limited trajectory data depending on Bluetooth deployment configuration Origin-Destination	R, H	TMC Codes	

Table A-3: Public Agency Consumers of Private Sector Data

	Wisconsin DOT	HGAC	Michigan DOT	Texas DOT(d)	Phoenix MPO (MAG)
Status	Request for Information	Purchased	Purchased	Purchased	Purchased
Service Purchased (a)	H	H	H	H	H
Aggregation Level	Hourly day-of-week averages	15 min	5 min	Hourly day-of-week averages	Weekday
Data Purchased(b)	S/TT, PM	S/TT	S/TT	S/TT, PM	PM
Applications(c)	PM, TM	PM, TM, OD	PM	PM	PM
Coverage	All arterials	Houston region	MI Freeways	Statewide TMC network	Region
Timeframe	1-2 years	1 year	5 years	2009	1 year
Validation Criteria	Not yet established	Not yet established	Avail >99.5% Act less than +/- 10mph	None	Not yet established
Validation techniques	N/A	N/A	Probe, fixed point , re-id	None	Probe, fixed point.

	Wisconsin DOT	HGAC	Michigan DOT	Texas DOT(d)	Phoenix MPO (MAG)
Pricing (in thousands)	$80,000 (Est.)	$77,000	$200,000 per year	$28,000	Negotiating
Licensing	Multiple Use	Multiple Use	Single Use	Single Use	Multiple Use
Multi-Agency	Yes				Yes

NOTES:
(a) Service Purchased: “H”=Historical, “RT”=Real-time
(b) Data Purchased: “S/TT”=Speed or Travel Time”, “PM”=Performance Measures
(c) Applications: “PM”-Performance or Congestion Monitoring, “TM”=Traffic Model Validation or Calibration, “OD”=Origin-Destination Studies
(d) See http://apps.dot.state.tx.us/apps/rider56/list.htm for published study results.

Source: http://ops.fhwa.dot.gov/publications/fhwahop11029/index.htm

FUTURE SOURCES OF MOBILE DATA

Mobile Data Generation

Technology has become ubiquitous with the advent of personal devices such as smart phones and mobile tablets (“iPod” like devices). Equally important is the advent of the “app” stores where specialized software applications can be quickly added to these personal devices enabling almost any function imaginable. So it would not be difficult to create and deploy an application for these devices to generate the mobile data desired by the transportation community. In fact, there is precedent with the tracking cookies used by web sites to track visitors on the internet. An open question is whether these smart devices need to communicate with the conveyance – automobile, truck, bus, commuter train, etc. Another question is whether the communications needs to be real-time, collected later or some combination thereof.

This technology perspective naturally leads to the cellular phone and personal computing vertical markets. Apple Computer is an excellent example where they provide these devices and created an “app” marketplace. Google, initially an internet company, is quickly expanding into Apple’s markets as a device and application provider. There are indications Google is working to combine their internet services to create new service offerings. Another approach is the embedding of such devices into the car or truck. Ford in Synch or GM OnStar are excellent examples where the personal smart devices and connectivity is being adapted to the car.

Mobile Data Collection

Collecting mobile data from these devices, both personal and embedded, while technically feasible, may have more to do with economic incentives and associated business models. The communications protocols such as Wi-Fi or Bluetooth communications are already present in these technology devices so localized data transfer would not be an issue. The mobile data “app” would provide the user the ability to authorize the data transfer to an entity in exchange for economic consideration. A real time mobile data model would require the use of existing commercial communications such as cellular or broadband. The individual would bear the upfront cost through their existing service plans. However, depending on who the data aggregator is, an economic incentive may also be viable to offset the consumer data transmission costs. There are examples of mobile data being collected today through standalone GPS device providers such as TomTom.

A localized, non-real time mobile data example would be gas stations providing per gallon discounts when the consumer downloads a finite quantity of mobile data while pumping gas. The gas station in turn could have service agreements with a data aggregator who would purchase the mobile data from them. In essence, a new business model utilizes technology and infrastructure already in place today. This business model could be extended to almost any public location frequented by the traveling public today – gas stations, food stores, coffee shops or even public transportation. The oil companies who either own or franchise the gas stations could enter this market as well. This could even be extended to social media sites such as Facebook or LinkedIn where a large network is already in place. In the extreme, a company such as Groupon could offer its services in exchange for the mobile data.

Mobile Data Aggregation

Mobile data volume and transmission would require a company with significant data warehousing and mining capabilities. Again internet-centric companies such as Google or Facebook have the requisite data centers, server farms and associated infrastructure to effectively aggregate, process and use such vast amounts of mobile data. More traditional information technology companies such as IBM and Cisco would be capable as well. Knowledgeable transportation focused companies such as Intelligent Transportation System (ITS), A&E or outsourced services firms may have the requisite subject matter expertise but lack the information technology scale. Mergers and acquisitions may yet provide a winning combination. The recent acquisition of ACS by Xerox is a good example of combining IT expertise and scale with subject matter expertise.

The military market has numerous companies, Lockheed Martin, Boeing, Northrup Grumman, BAE and others who have the requisite IT expertise and scale to be successful in mobile data aggregation. In fact these companies may bring disruptive technologies such as unmanned aerial vehicles (UAV) to address elements of the mobile data problem.

Specific Issues that Will Shape Future Mobile Data

Existing mobile devices, particularly the smartphone market, has connected over 82 million users in the United States to the internet. The overwhelming majority of these devices include one or more GPS services that support real-time location information between the device and the service provider. This penetration rate of nearly 25% provides for the capability to have robust traffic information for most of the country.

For example, mobile users of Google Maps with the GPS enabled currently feed anonymous data back to Google that provides a speed profile. Google combines that information with other users to produce the traffic layers on their maps.

Effectively, every GPS enabled device including handheld navigation systems, and vehicles themselves through services such as GM's On-Star and Ford's SYNC can all collect detailed speed and location data to support a variety of mobility applications.
Looking beyond standard GPS utilities, the Bluetooth travel time collection market has proven to be a very cost effective source of mobile data for DOTs in evaluating congestion and travel characteristics, often with relative small penetration rates, sometimes less than 5 percent.

Insurance companies like Progressive have implemented Pay As You Drive (PAYD) insurance plans with associated measuring devices to allow users to pay based on per mile activity.

There are two key constraints to accessing mobile data sets.

1. Privacy – Despite the fact that people are no longer truly moving anonymously through the streets, in stores, and at home.
2. Private Sector Market Data – Although users of mobile devices are often willing to opt-in and share their private data, the collectors often have a competitive reason to not sharing details that reveal information about the numbers of customers, location densities of the customer base, and on/off status type of data.

Just as importantly the true utility and applicability of the information can be cloudy with the ability to effectively characterize the answers to the following questions.

- Can the frequency of collected location, speed and other movement data be effectively defined per data source?
- Can any penetration rate or volume data be gathered from the sources?
- What is the native accuracy of the data collected?

- Is the collected data available in sufficient intervals to support Applications X, Y, Z?
- What is the cost move that data and who will bear that cost?
- What is the cost to aggregate and integrate the data into safety and mobility applications?

Independent of the technological considerations, the willingness of the users and the simplicity with which they share their information, be it on a smart phone, at a point-of-sale handoff at the gas station, intersection, or store via a debit/credit transaction, or download from the vehicle, will depend on the handoff being unobtrusive and with some value provided back to the users. That value could be in many forms ranging from cash back payments to discounted services and goods to free applications or services.

While the connected vehicle initiatives will bring a level of coordination and standardization to the data collection process for very specific transportation analysis data, the reality is the private sector market place will move forward without standards, particularly where the value in sharing the information may support more private business strategic analysis and marketing uses. For example, if a company can more effectively market goods and services, by better targeting consumers, then those companies may be willing to pay the bills that support the collection of location information. For example, with the prevalence of electronic billboards, particularly in urban environments, the near real-time understanding of the density of potential customers and even potentially demographic information may provide those advertisers with a better return in terms of where, when and how to utilize the billboards, and potentially how to modify and target other marketing methods.

Looking at an even more anonymous methods of obtaining traffic information, the potential for high resolution satellite imagery and high resolution video analytics at least has the potential to serve as a massive CCTV network without requiring any user buy-in. For example, scaling up the powers of video analytics systems such as those provided by Citilog, Abacus, and other video technologies may be feasible. The ability to pay for that type of deployment is unclear.

Mobile Data Summary

In the final analysis, it would be difficult for any one company to have the core competencies for providing an end-to-end solution with sufficient market share to generate the volume and geographic footprint needed. While the technology has been present, four key success factors are:

- Reaching the mass market with minimal infrastructure, time to deploy and cost
- Applying the technology in a new or different way
- Creating new and beneficial business model(s)
- Strategic partnership(s) combining disparate core competencies.

Appendix B. Calibration Results for Traffic Flow Model Using Fixed Sensor Data in Baltimore Area

Location	Weather Condition	qmax (veh/ 5-min)	vf (mph)	alpha	kbp (vpmpl)	uf (mph)	v0 (mph)	kj (vpmpl)	# of observations		RMSE	R2	WAF			
									regime 1	regime 2			F_qmax	F_vf	F_alpha	F_kbp
I-695 @ Joppa Rd	normal	584	84.70	3.12	12.18	71.51	2	225	383	3.89	0.94	0.94	1.00	1.00	1.00	1.00
	light rain	594	85.13	3.12	15.22	68.81	2	225	17	4.31	0.96	0.96	1.02	1.01	1.00	1.25
	moderate rain	514	81.41	3.12	16.07	65.01	2	225	8	5.17	0.93	0.93	0.88	0.96	1.00	1.32
	heavy rain	542	84.58	3.12	30.19	54.67	2	225	22	4.88	0.90	0.90	0.93	1.00	1.00	2.48
	light snow	356	63.98	3.12	3.52	61.00	2	225	140	8.08	0.17	0.17	0.61	0.76	1.00	0.29
	moderate snow	260	61.12	3.12	2.96	58.72	2	225	112	6.64	0.34	0.34	0.45	0.72	1.00	0.24
	heavy snow	258	60.08	3.12	0.00	60.08	2	225	2	5.40	0.29	0.29	0.44	0.71	1.00	0.00
I-695 @ Providence Rd	normal	550	85.15	3.46	19.04	65.34	10	225	462	4.47	0.79	0.79	1.00	1.00	1.00	1.00
	light rain	477	80.53	3.46	22.15	59.28	10	225	265	4.06	0.83	0.83	0.87	0.95	1.00	1.16
	moderate rain	429	79.78	3.46	24.66	56.70	10	225	87	4.39	0.08	0.08	0.78	0.94	1.00	1.29
	heavy rain	400	N/A	N/A	N/A	55.11	10	225	N/A	N/A	N/A	N/A	0.73	N/A	N/A	N/A
	light snow	557	74.95	3.46	17.20	59.33	10	225	807	7.37	0.36	0.36	1.01	0.88	1.00	0.90
	moderate snow	504	64.77	3.46	16.04	52.41	10	225	278	8.21	0.36	0.36	0.92	0.76	1.00	0.84
	heavy snow	332	50.77	3.46	2.31	49.34	10	225	22	6.06	0.72	0.72	0.60	0.60	1.00	0.12
I-695 @ Stevenson Rd	normal	676	85.34	4.81	12.84	66.80	10	225	743	5.52	0.58	0.58	1.00	1.00	1.00	1.00
	light rain	653	84.79	4.81	13.79	65.18	10	225	163	4.06	0.94	0.94	0.97	0.99	1.00	1.07
	moderate rain	559	81.20	4.81	15.54	60.47	10	225	21	3.37	0.93	0.93	0.83	0.95	1.00	1.21
	heavy rain	589	81.67	4.81	16.72	59.45	10	225	77	3.94	0.90	0.90	0.87	0.96	1.00	1.30
	light snow	608	82.86	4.81	15.16	62.10	10	225	209	5.54	0.57	0.57	0.90	0.97	1.00	1.18
	moderate snow	489	68.50	4.81	12.68	54.27	10	225	389	7.43	0.16	0.16	0.72	0.80	1.00	0.99
	heavy snow	425	65.96	4.81	13.43	51.63	10	225	125	6.22	0.27	0.27	0.63	0.77	1.00	1.05
I-695 between Stevenson Rd and Greenspring Ave	normal	609	79.11	3.73	10.65	67.68	10	225	423	5.20	0.66	0.66	1.00	1.00	1.00	1.00
	light rain	570	76.76	3.73	10.38	65.98	10	225	100	3.72	0.93	0.93	0.94	0.97	1.00	0.97
	moderate rain	526	74.93	3.73	10.30	64.51	10	225	16	3.01	0.94	0.94	0.86	0.95	1.00	0.97
	heavy rain	515	72.88	3.73	12.37	60.92	10	225	73	3.86	0.86	0.86	0.85	0.92	1.00	1.16
	light snow	369	65.90	3.73	6.06	60.49	10	225	72	5.38	0.10	0.10	0.61	0.83	1.00	0.57
	moderate snow	366	66.67	3.73	7.73	59.74	10	225	329	7.32	0.04	0.04	0.60	0.84	1.00	0.73
	heavy snow	394	66.66	3.73	10.87	57.11	10	225	133	8.94	0.04	0.04	0.65	0.84	1.00	1.02
I-695 @ US 1 Outer Loop	normal	471	88.22	3.92	15.36	67.34	2	225	269	3.52	0.86	0.86	1.00	1.00	1.00	1.00
	light rain	484	84.29	3.92	18.36	60.93	2	225	174	4.78	0.95	0.95	1.03	0.96	1.00	1.20
	moderate rain	379	71.71	3.92	7.61	62.91	2	225	7	5.01	0.95	0.95	0.80	0.81	1.00	0.50
	heavy rain	306	69.59	3.92	13.86	54.67	2	225	81	5.34	0.83	0.83	0.65	0.79	1.00	0.90
	light snow	393	81.59	3.92	15.22	62.48	2	225	122	7.68	0.83	0.83	0.83	0.92	1.00	0.99
	moderate snow	195	N/A	N/A	N/A	50.70	N/A	N/A	N/A	N/A	N/A	N/A	0.41	N/A	N/A	N/A
	heavy snow	279	N/A	N/A	N/A	49.72	N/A	N/A	N/A	N/A	N/A	N/A	0.59	N/A	N/A	N/A

Location	Weather Condition	qmax (veh/5-min)	vf (mph)	alpha	kbp (vpmpl)	uf (mph)	v0 (mph)	kj (vpmpl)	# of observations regime 1	# of observations regime 2	RMSE	R2	WAF F_qmax	WAF F_vf	WAF F_alpha	WAF F_kbp	WAF F_uf
I-695 @ I-70	normal	543	83.11	4.53	16.36	61.95	10	225	230	174	3.88	0.91	1.00	1.00	1.00	1.00	1.00
	light rain	585	84.27	4.53	21.29	57.36	10	225	350	244	3.31	0.95	1.08	1.01	1.00	1.30	0.93
	moderate rain	514	83.40	4.53	22.70	55.35	10	225	58	18	3.01	0.89	0.95	1.00	1.00	1.39	0.89
	heavy rain	488	81.87	4.53	22.26	54.85	10	225	88	12	3.92	0.79	0.90	0.99	1.00	1.36	0.89
	light snow	521	88.28	4.53	19.51	61.92	10	225	81	33	4.06	0.86	0.96	1.06	1.00	1.19	1.00
	moderate snow	494	81.75	4.53	26.31	50.87	10	225	163	5	7.22	0.04	0.91	0.98	1.00	1.61	0.82
	heavy snow	360	54.12	4.53	8.58	47.00	10	225	37	17	6.43	0.19	0.66	0.65	1.00	0.52	0.76
I-695 approaching US 40 W	normal	650	96.75	5.00	16.81	68.83	10	225	407	140	3.61	0.80	1.00	1.00	1.00	1.00	1.00
	light rain	617	90.57	5.00	19.18	61.61	10	225	72	344	3.69	0.95	0.95	0.94	1.00	1.14	0.90
	moderate rain	560	85.45	5.00	18.63	58.97	10	225	52	58	4.41	0.93	0.86	0.88	1.00	1.11	0.86
	heavy rain	578	82.88	5.00	20.59	55.10	10	225	70	30	3.15	0.96	0.89	0.86	1.00	1.23	0.80
	light snow	538	90.69	5.00	17.29	64.10	10	225	124	82	7.54	0.56	0.83	0.94	1.00	1.03	0.93
	moderate snow	402	89.70	5.00	23.02	56.46	10	225	222	22	6.77	0.40	0.62	0.93	1.00	1.37	0.82
	heavy snow	191	N/A	N/A	N/A	43.94	N/A	N/A	N/A	N/A	N/A	N/A	0.29	N/A	N/A	N/A	0.64

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