COMMERCIAL REMOTE SENSING & SPATIAL INFORMATION (CRS & SI) TECHNOLOGIES FOR RELIABLE TRANSPORTATION SYSTEMS
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Draft Synthesis Report on Literature Review

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COMMERCIAL REMOTE SENSING & SPATIAL INFORMATION (CRS & SI) TECHNOLOGIES FOR RELIABLE TRANSPORTATION SYSTEMS

The accuracy and validity of transportation system reliability depends on travel time data. While global positioning systems (GPS) has been used widely in the past, there is an increase in use of buses as probes, Bluetooth detectors and cell phone tracking devices in recent years. There exist many technical papers, reports, articles published in journals and conference proceedings, and newspaper articles (identified from library and Internet sources) that provide insights into commercial remote sensing and spatial information (CRS & SI) technologies, the use of GPS and Bluetooth detectors for travel time studies, transit buses as probes and reliability as a function of traffic congestion. The following four areas were identified as the topics of interest for a detailed review of past research and to generate this synthesis report.

1. CRS & SI for transportation planning (in particular, travel time studies)
2. Use of GPS and Bluetooth detectors for travel time / delay studies
3. Transit buses as probe vehicles
4. Reliability as a function of recurring and non-recurring congestion components

1. Commercial Remote Sensing and Spatial Information (CRS & SI) for Transportation Planning

Today's road systems are equipped with field-based equipment such as cameras installed at fixed locations or radar sensors. These technologies are used to capture traveling vehicles related information such as position, speed, and direction. The information captured is crucial for transportation planning, safety analysis, resource allocation, and security surveillance. However, these technologies and systems cannot be used to cover a large area due to resource constraints.

Recently, remote sensing technology has emerged as an alternate option to collect traffic information which can cover a wider range of area as well as information. Data can be collected without disrupting traffic or using much manpower in the field. Moreover, remote sensing technique eliminates the subjectivity involved in test car studies, increases the statistical validity of the travel time estimate and travel time variation (Angel et al., 2003). Literature review in this section will cover the studies conducted to estimate several traffic parameters and problems with connecting information using satellite imagery.

1.1 CRS & SI for Travel Time and Congestion Studies

High resolution satellites such as Ikonos, QuickBird (QB) and WorldView-2 were launched to collect satellite imagery and capture images with good spatial resolution and hence can extract road traffic information. The satellite images obtained are first processed which are then used to extract vehicle information. Accurate vehicle detection is a prerequisite for collecting information about vehicles.

Literature on vehicle detection using remote sensing data can be categorized as: model-based extraction and data-based extraction (Liu et al. 2010). Gerhardinger et al. (2005) used automated vehicle extraction approach based on inductive learning technique incorporating ArcGIS for vehicle extraction and identification. Zhao et al. (2003) used a Bayesian network, while a vehicle queue model was used by Leitloff et al. (2005) to achieve the same objective. Jin et al. (2007) used a morphological shared-weight neural network while Li (2008) used a segmentation algorithm based on a fuzzy c-partition to segment color unmanned aerial vehicle (UAV) imagery. Sharma et al. (2006) investigated three methods: Principal Component Analysis (PCA), Bayesian Background Transformation (BBT), and gradient based method to separate vehicles from road pavement in a 1-m resolution satellite and airborne imagery. Stilla et al. (2004) described possibility to extract vehicles from data of three frequency domains, namely (i) visual, (ii) thermal IR and (iii) radar.

Road network is often characterized by its traffic flow for planning and traffic management purposes. Traffic flow is the product of speed and density. Not much work has been done on density estimation using remote sensing. However, several studies have been conducted based on airborne imagery or remote sensing. Toth et al. (2004) measured velocity of vehicles from the motion artifact in Light Detection And Ranging (LiDAR) data and the relative velocity of the sensor and the moving targets. The major drawbacks of this study are: 1) size of the true vehicle was unknown, and, 2) class mean or median data provided poor velocity estimates. To overcome these problems, Toth et al. (2005) determined the actual length of the vehicles by using scale information from imagery collected simultaneously with the LiDAR. Results showed that combining LiDAR with complementary sensor data provided a better base for velocity estimation. It allows for more reliable traffic flow parameter determination.

Etaya et al. (2004) determined vehicle position and speed using time lag of approximately 0.2 s between the panchromatic (PAN) image and corresponding multispectral (MS) image acquired by the QB satellite. Xiong and Zhang (2008) developed a methodology to determine vehicle's ground position, speed and direction using QB Pan and MS images. They presented an algorithm which could calculate vehicle's ground position directly from the images as difference of resolution and short time lag caused problem to compute vehicle position accurately. The limitation of this proposed approach is that vehicles' central positions are required to select manually from images which was later solved by automatic vehicle extraction procedure.

Leitloff et al. (2010) described an approach to automatically estimate movements of vehicles using optical satellite PAN and MS image. Vehicles were detected by robust least square fitting in combination with a shape-based matching algorithm. Velocity was calculated using time gap of PAN and MS images. Position and movement was estimated using sub-pixel matching approach relying on gradient directions followed by least-squares fitting of Gaussian kernels. The limitation of the study is that it used manual object selection (not automated and involves subjectivity).

Liu et al. (2010) developed a methodology to extract automatically moving vehicles and their speeds from QB satellite (PAN and MS images). To extract the vehicle position, an object based approach was incorporated with PAN image (0.6 m resolution) and area correlation method with MS (2.4 m resolution). The speed was computed using time lag of 0.2 s. However due to the limitation of extracting vehicles from a MS image, highly accurate speed determination was not possible.

Mishra et al. (2012) proposed a methodology to extract moving vehicle`s information (position, speed and direction) both automatically and more accurately from WorldView-2 satellite images (MS-1: BGRN1, Pan, and MS-2:CYREN2). A PCA-based technique and adaptive boosting (AdaBoost) algorithm was incorporated with MS image (2 m resolution) to detect position of moving vehicles accurately (which ensured accurate speed calculation). The speed was computed using time lag of 0.22 s of MS images. A vehicle detection rate over 95% has been achieved and vehicles' speed calculations were reliable. However, this study had some limitations pertaining to road extraction, velocity estimation from PAN images and vehicles image coordination.

Remote sensing and airborne image can be used to extract traffic congestion information for a large network, which is not possible from detectors or video cameras used on the road network. The National Cooperative Highway Research Program (NCHRP) study, Quantifying Congestion, concluded that travel time is the base measure of severity of congestion (Lomax and et al. 1997). Several studies have been conducted on travel time estimation using remote sensing or airborne imagery in the past. Mishalani et al. (2002) presented a method to collect travel time and turning fraction to estimate real-time origin-destination (O-D) flow. Travel time was estimated from the vehicle trajectory observed at exit and entry point of a link, which was identified from the digitized video images collected using video cameras located on a high-rise building. O-D flows were measured using the developed algorithm, which semi-automatically matched individual vehicles. However, the research did not provide any details about the configuration of video camera. Also, the study area consisted of only three intersections.

Angel et al. (2003) provided configuration of video camera and also described a method to collect aerial images and estimate travel times for a platoon of vehicles. Helicopter follows the platoon through the entire corridor to capture the travel time using video camera and still camera for one signal cycle. Airborne data was compared with data obtained from ground camera and test car. The comparison showed that the travel time from aerial image is closer to real field travel time obtained from ground video camera than test car. However, vehicle number was counted manually and automatic travel time estimation was not possible using this method.

Digital aerial image can also provide information about drivers' behavior during congestion. Hoogendorn et al. (2003) described a new data collection system prototype for determining individual vehicle trajectories from sequences of digital aerial images. This system first detects and tracks vehicles from image sequences. Besides the longitudinal and lateral positions as a function of time, the system can also determine the vehicle lengths and widths. The software was tested on data collected from a helicopter, using a digital camera gathering high resolution monochrome images, covering 280 m of a Dutch motorway. Test results showed that 98% of the vehicles could be detected and tracked automatically when conditions were reasonable; this number lowered to 90% if the weather condition is poor.

Kurz et al. (2007) presented a method for automatic estimation of travel times using optical wide angle frame sensor system (3K = “3-Kopf”), which consists of three non-metric off-the-shelf cameras (Canon EOS 1Ds Mark II, 16 MPixel). Road edges were detected by Deriche filters and combined with the road database. Vehicles were tracked based on positions and the movement direction. Vehicle velocities were calculated from its covered distance in two consecutive geocoded images.

Images captured from high rise buildings or satellite images can provide information about congestion which a road side detector cannot normally provide. Knoop et al. (2009) proposed a method to process video data to obtain vehicle trajectory which is more robust than identification of a single vehicle. In this method, the vehicle was not detected in each picture of the video separately. Instead, the video data were transformed so that the trajectories of the vehicles became visible in a single image. Results showed that this method detected 95% of the trajectories correctly and, more important, the segments of each trajectory were much longer compared to the existing method. Moreover, total processing time was much lower than any other method**.**

However, using satellites for travel time data collection have some drawbacks because of its transitory nature which makes it difficult to obtain the right imagery to address continuous problems. Further, traffic tracking cloud cover does not give good image quality on days with bad weather. Therefore, Puri et al. (2010) suggested using UAV which could be employed for a wide range of transportation operations and planning applications. The advantages of UAVs are that they can move at higher speeds than ground vehicles and most of the functions and operations can be implemented at a much lower cost, faster and safer. These UAVs are generally equipped with a variety of multiple and interchangeable imaging devices and sensors.

1.2 Other Applications of Remote Sensing Imagery Data

1.2.1 Identification of Road Geometry

Chi et al. (2009) developed a method to determine the operating conditions of roadways from satellite images. This method described a procedure to delineate automatically the traffic lanes, to detect the presence of debris and the blockage of roads as well as vehicle flows from satellite images. Traffic lane locations and the color tones of vehicles were combined with pixel intensity to improve vehicle detection rate. This lane detection method was able to eliminate the noises from dark vehicles and shadows and achieve very good results (100% accuracy) for the tested asphalt roadway sections and good results (81% accuracy) for tested concrete pavements.

1.2.2 *Identification and Categorizing of Vehicles*

Detection of small vehicles can cause problem compared to large vehicles and sometimes predefined dimension is necessary to be known. Klein et al. (2008) developed a method that focused on tracking motion rather than vehicle objects. As a result, the actual shape and size of the objects become less of a concern. This method detects the objects at an earlier stage as cameras are placed at higher vantage points or in oblique views that provides images in which vehicles in the near parts of the image can be detected by their shape or features, whereas vehicles in the far view cannot. This ability to detect vehicles earlier and to cover longer road sections is useful in providing longer vehicle trajectories for traffic models development and for improved traffic control algorithms.

Vehicle classification and traffic composition is another important area for operational analysis. However, existing automatic vehicle classification systems have deficiencies which include low accuracy, special requirements, fixed orientation, or additional hardware and devices. Cheng et al. (2005) defined vehicle detection and classification systems using model-based fuzzy logic approaches. No special orientation of the camera is required using this system while no additional devices are needed and high classification accuracy can possibly be achieved. Experimental results showed that the performance of the proposed system exceeded that of the existing video-based vehicle classification systems and the overall accuracy was 98.87% for 265 images.

1.2.3 *Traffic Safety*

Remote sensing images can also be used for intersection surveillance. Alexandar et al. (2006) reported that Minnesota Department of Transportation conducted a study on all rural intersection crashes. Investigation showed that poor gap selection was the predominant causal factor in these crashes. They developed an intersection decision support (IDS) surveillance system which consisted of sensors, processors, and a communication system to determine the intersection “state,” including location, speed, acceleration, lane of travel, and vehicle classification of each vehicle in the surveillance zone. This surveillance system information could help drivers to make correct decisions concerning the available gap.

Moreover, incidents on roadway cause large delays and reduce the capacity at the incident location. Knoop et al. (2008) reported that high-quality videos of the traffic flow around two crashes recorded was captured from a helicopter and then traffic volume was counted which showed that (outflow) capacity of the remaining lanes is about 50% lower than the (free flow) capacity of the same number of lanes.

1.2.4 Transportation Planning

Remote sensing data can be used to measure the usage of road network which is essential for transportation planning. Coifman et al. (2004) reported that high-resolution remote sensing images are an attractive alternative that can potentially augment the existing traffic monitoring programs with a spatially rich data set whereas an individual sensor has lack of spatial coverage limits and application. Using these images alongside populations, travel, and land cover information land use-transport models are developed. Wang et al. (2006) derived mixed-logit framework to study land cover evolution in Austin, TX. Satellite images were used to gather land cover information. Results indicated that neighborhood characteristics have strong effects on land cover evolution; clustering is significant over time, but high residential densities can impede future development.

2 Use of GPS and Bluetooth Detectors for Travel Time / Delay Studies

The review of past research on the use of Global Positioning Systems (GPS) and Bluetooth detectors for travel time studies is divided into two sub-sections: 1) GPS for travel time studies, and, 2) Bluetooth detectors for travel time studies. They are presented next.

2.1 GPS for Travel Time Studies

2.1.1 Introduction

Travel time studies are conducted to estimate delay and severity of congestion on roadways. The Department of Defense (DOD) monitors and maintains GPS closely and can disable the system anytime (Texas Transportation Institute, 1998). Quiroga and Bullock (1999) conducted a study on arterials to obtain travel time using GPS and dynamic sequestration technique. They used a general data model that includes a spatial model, a geographic location database, and GPS data transfer procedure using dynamic segmentation tools. Accuracy in measuring travel time and speed using this technique improves more than those using traditional techniques.

According to a study by Mauricio (2003) for collecting and utilizing travel time data through GPS and GIS on arterials in Philippines, the GPS units should be exposed to at least three satellites for tracing the location. The duration can range from 5 minutes to 30 minutes depending on the GPS unit position regarding the satellite. Day of survey, time of survey, and route information should be recorded while performing the run.

Less staff requirements, less human error, detailed data collection opportunity, good accuracy, and automatic geo-coding procedures are some of the many benefits of using GPS based system for travel time data collection. Signal loss, retrieving the base map, necessary and updated equipment identification, limited sample, high cost per unit of data, etc. are some of the drawbacks of that system (Texas Transportation Institute, 1998; Koprowski, 2012).

2.1.2 Feasibility

Bel-O-Mar Regional Council (2007) conducted a travel time study using GPS on US-250 and SR-331 in Belmont County and portions of US-250 and WV-2 in Ohio and Marshall Counties in West Virginia. They used the float vehicle technique (a vehicle mounted with a GPS antenna) to obtain average travel time and speed. The GPS datalogger recorded the coordinates of the position every two seconds. They concluded that GPS can be used as an efficient and in an advantageous way to collect travel time data.

Wilbur Smith Associates (2007) used GPS units to record the spatial coordinates and time of the test vehicle at every 0.03 mile (158 feet) for analyzing travel time and delay on major local and arterial roadways in Jonesboro, Arkansas. From that the average travel speed was calculated. The data formed the baseline for future assessment of the impacts of development and population increase on mobility.

2.1.3 Implementation Strategies

For calibration and analysis of data collected by GPS, various methods and software's were used in the past. Radford University's GPS website can be used to obtain differential correction data to identify precise location information (RVAMPO, 2000). Trimble's Pathfinder Office Software was used in one of the studies to transfer the GPS file from the TDC-1 collection unit (RVAMPO, 2000). In general, the raw data of GPS system should contain the time stamp, latitude, longitude, speed, Horizontal Dilution of Precision (HDOP), and number of satellites (Hunter et al., 2006). The information on altitude, heading, vertical dilution of precision (VDOP), and positional dilution of precision (PDOP) may also be collected from GPS receiver.

Faghri et al. (2010) quantified travel time and delay data using a Trimble GPS unit and a laptop computer with Trimble TerraSync and GPS Pathfinder Office software installed for the identification of the severity of congestion. They conducted the study on all major routes surrounding large population centers in Delaware and identified total peak delay and percent time in delay.

Tracy (2012) conducted a study along US-40 heading east from NJ-54 into Atlantic City in New Jersey to collect passenger travel time. The author identified that the GPS antenna is capable of recording the latitude and longitude, and speed of the test vehicle every second. ArcMap and PC Travel software were used as the analysis tools. The data provided direct measure of level of service (LOS) on that road during the run.

2.2. Bluetooth Detectors for Travel Time Studies

2.2.1 Introduction

Travel time data using Bluetooth detection technology captures travelers Bluetooth-enabled devices that broadcast unique identifiers known as Media Access Control (MAC) addresses. By recording the MAC addresses upstream and downstream, the travel time can be obtained (Wasson et. al., 2008). Bluetooth detectors use radio signals over short distances ranging from 3 feet (minimum) for Class 3 radios to more than 330 feet for Class 1 radios used for industrial purposes (Bluetooth, 2010). Class 2 radios found in mobile phones must provide a 33 feet range. These devices operate at a very lower power. For example, class 2 radios operate at 2.5 mW or 4 dBm. However, the low power negatively impacts the rate of data transfer, which ranges from 1 Mbit/s to 24 Mbit/s.

2.2.2 Instruments

Several researchers have used Bluetooth detectors to collect travel time in the last few years. A travel time study conducted in Indianapolis, Indiana by Wasson et al. (2008) showed that matching MAC addresses can be used to report travel time effectively. The initial study was performed along South Main Street in Houston, Texas. They also identified several key components of Bluetooth detectors, such as a Bluetooth MAC address detector and processor, a radio capable of reading the MAC address, and a Central Processing Unit (CPU) system to forward data to a central location.

The Smart Transportation Applications and Research (STAR) Lab devices Bluetooth detectors that contains a constant scanning Bluetooth chipset, a processing module to record MACs, and a communication module to transmit data in near real time (Malinovskiy, 2011). It takes 10.24 seconds at a minimum to discover all Bluetooth devices within range. During the process in which a Bluetooth device is discovered (inquiring process), the device hops on 32 channels consisting of 16 channel subsets (trains). It takes 0.01 seconds to scan each train. Each scan is repeated 256 times for providing necessary time to collect inquiry responses from other Bluetooth devices. In addition, two iterations of each train occurs due to the specification of at least three train switching, which overall results in 10.24 seconds to identify a Bluetooth device within range (Woodings et al., 2002).

2.2.3 Issues and Challenges

Bluetooth detection technology can allow up to eight devices to be connected at the same moment by using the adaptive frequency hopping (AFH) and frequency hopping synchronization (FHS) (Franklin and Layton, 2000). The probability of interference between any two devices is reduced down by FHS as it is highly unlikely for these two devices using the same transmitting frequency at the same time. Bluetooth detectors communicate over a personal area network (PAN) or piconet after connecting automatically. Physical obstacles that obstruct the line of sight between two Bluetooth detectors influence the signal attenuation of a Bluetooth device and reduce down the likelihood of getting connected (Logitech, Inc., 2005). However, Bluetooth signals can travel through glass and propagate off of other reflective surfaces.

However, high implementation cost, multiple readings from a single vehicle, and inclusion of bypass trips are some of the issues associated with using Bluetooth detectors for travel time data collection (Koprowski, 2012). Signal delay and non-uniform traffic flow can cause errors in Bluetooth travel time measurements in case of arterials (Nelson, 2010; Van Boxel et al., 2011). As it takes 10.24 seconds to detect a Bluetooth device, it can be a source of error in travel times though the inaccuracy decreases as the spacing between Bluetooth station increases (Malinovskiy et al., 2010; Puckett and Vickich, 2010). Wang et al. (2011) observed 2.4 to 11.4 seconds (4% to 13%) of average errors while performing the travel time data collection along the 0.98-mile-long arterial study corridor in Washington. They identified that absolute errors are dependent on sensor configurations and surrounding conditions, and independent of length of the study corridor. They concluded that longer corridors tend to allow a better performance for this technology based data collection process. A negligible amount of signal degradation occurs when the devices are more than 2 meters apart transmitting wirelessly (Logitech, Inc., 2005).

According to Fredman (2002), the operation of Bluetooth detectors can be inversely affected by other higher power devices (802.11b (Wi-Fi), cordless phones, two-way radios, and microwave ovens) while using the unlicensed 2.4 to 2.483 GHz industrial, scientific and medical (ISM) spectrum. Frequency dynamic noise occurs due to the interference of established Bluetooth piconets with the test Bluetooth piconet. When two or more Bluetooth detectors try to use same transmitting frequency channel, the signal degradation occurs, such as 5%, 11%, and 21% efficiency loss due to the presence of 4, 10, and 20 piconets, respectively. The transmission failure can also result from frequency collision of two overlapping piconets using the same transmitting frequency at the same time (Lynch Jr., 2002).

The outliers are another source of errors. For freeway data collection, the following situations should be filtered: (1) vehicles exiting and returning to the freeway between two stations, (2) vehicles that stop on the shoulder temporarily, (3) vehicles traveling slowly due to repair requirements, and (4) vehicles recorded at the upstream station but missed at the following station, detected at the second station traveling in the opposite direction later on in the day (Martchouk et al., 2011). Nelson (2010) preformed a travel time data collection comparison study on local and arterial roads, intersections, and interchanges in Washington, DC. The author recommended using minimum and maximum travel time filters to identify outliers. However, this procedure is not suitable for the roadways with high variability in travel times throughout the day. Roth (2010) developed a travel time data cleaning methodology collected by Bluetooth detectors based on a time series approach. The study compared the number of outliers detected by modified Z-Test, Grubbs' Test, and Chauvenet's Criterion, and identified that modified Z-Test detected the most outliers. The author recommended a modified Z-test to identify and remove outliers in an inexpensive way, which require only a single iteration.

Malinovskiy et al. (2010) and Puckett and Vickich (2010) have addressed the issue of MAC address groups that are produced by the data collection units (DCUs) by utilizing the time stamp for the first MAC address in a group as a solution to that problem. Quayle et al. (2010) performed an arterial performance measurement study on Tualatin-Sherwood Road in Portland, Oregon. They also acknowledged that multiple detection of Bluetooth devices is possible while passing by a DCU. They identified that MAC address group sizes depend on the DCU to road distance and time duration of the device within DCU range. Haghani et al. (2010) suggested using appropriate DCU spacing for the minimization of redundant detections for freeways. An average of the detection time can be used in case of multiple detections. According to Wasson et al. (2008), the travel time sample errors are negligible for the distances between DCUs that they examined (2-3 miles) on arterials.

Though, Bluetooth detection technology has been found to have acceptable accuracy to estimate the travel time under homogeneous traffic conditions, there are a few limitations. Pedestrians and bicyclists with detectable devices and buses with multiple Bluetooth devices onboard are other sources of outliers (Malinovskiy et al., 2010). The data collected from arterial highways showed a significantly larger variance compared to data from motorways due to traffic signals and vehicle diversion to side roads (Wasson et. al., 2008).

Malinovskiy et al. (2010) investigated Bluetooth MAC address-based travel-time detectors with Automated License Plate Recognition (ALPR) sensors indicating that Bluetooth detectors tended to be biased towards slower vehicles. So the calculated travel time can be slightly overestimated. A methodology is needed to be identified for the correction of the inaccurate travel times due to Bluetooth biasness (Wang et al., 2011).

Extraneous delay sources, such as traffic signals and nearby bus-stops, should be considered for avoiding such undesirable factors while conducting the travel time analysis on arterial roads (Wang et al., 2011). Length of the corridor can significantly affect the performance of the Bluetooth-based travel time collection system. A short corridor is more prone to errors and inaccurate results for arterials (Wang et al., 2011).

2.2.4 Feasibility

Low cost per unit of data, continuous data collection, and no disruption of traffic are some of the benefits of using Bluetooth detectors as travel time data collection technology. According to a travel time study by Tarnoff et al. (2009), Bluetooth-based method is found to be one of the most cost-effective approaches for the travel time data collection procedure. The Bluetooth detectors are found to be hundred times cheaper than equivalent floating car runs on both arterials and freeways. Phil Tarnoff, CEO of Traffax Inc., stated in 2010, that the estimated cost per travel-time data point of the Bluetooth detector data was just 1/300th of the cost of comparable floating car data (Bradley, 2010). The Center for Advanced Transportation Technology (2008) performed a travel time data collection and analysis study along I-95 between Baltimore, Maryland and Washington, DC. They estimated the Bluetooth detector based process is 500 to 2,500 times cost effective than floating car data collection based on the data points produced.

Blogg et al. (2010), from an O-D study, conducted on Centenary Motorway in southwest Brisbane and an arterial street network in north Brisbane between Stafford and Strathpine in Australia, found that the MAC data collection by Bluetooth detector technology is a cost effective way to collect vehicle O-D in small and controlled networks. However, for extensive networks, the MAC O-D data can be used as supplement to the traditional methods as a cost effective measure.

Puckett and Vickich (2010) found out from a study to identify real time travel time data for freeways and arterials that utilization of Bluetooth detectors on arterial streets is feasible. The accuracy of measuring travel times using Bluetooth detector is an important factor for the decision making processes. Malinovskiy et al. (2010), in their study to measure the travel time on SR-522 in Washington using Bluetooth detectors, found that the devices were representative of the ground truth travel time data obtained by the Automated License Plate Recognitions (ALPRs).

Haghani et al. (2010) aimed to use Bluetooth detectors as a new and effective mean of freeway ground truth travel time data collection by comparing the Bluetooth detector based data with floating car data. They conducted their study on I-95 between Washington, DC, and Baltimore, Maryland and found out that ground-truth provided by the new Bluetooth detectors and the actual travel times are not significantly different. KMJ Consulting, Inc. (2010) conducted a study to evaluate the ability of Bluetooth detector to collect and report travel times along I-76 at locations coincident with EZPasstag readers. The study found out that travel times measured by the Bluetooth detector technology were comparable to those obtained by EZPass tag readers.

Haseman et al. (2010) collected 1.4 million travel time records over a 12-week period for the evaluation and quantification of travel mobility for a rural Interstate work zone along I-65 in Northwestern Indiana. They used Bluetooth detectors to identify travel time delay in work zones. The Bluetooth detectors can be used to estimate O-D pairs. The system can also be used for route choice (Hainen et al., 2011).

2.2.5 Implementation Strategies

Kim et al. (2010) performed a study to evaluate the accuracy of estimated travel time using various technologies, such as TRANSMIT (RFID) readers, Bluetooth detectors, and INRIX (a traffic information system that reports real-time data). They concluded that Bluetooth detectors provided accurate results compared to TRANSMIT readers and INRIX system. Martchouk et al. (2011) conducted a travel-time variability study along two segments of I-69 in Indianapolis, Indiana to analyze inter-vehicle and inter-period variability. They combined speed and volume data collected by using side fire microwave detectors with the Bluetooth travel time data. They also developed duration models of travel time to identify when the traffic breakdown occurs.

According to a travel time estimation study by Araghi et al. (2012) on a selected road link in Sauersvej, Denmark, the Bluetooth detector technology has been found to have acceptable accuracy to estimate the travel time under homogeneous traffic conditions. The MAC address can provide the information of type of Bluetooth-enabled device (mobile phone or laptop) referred to as Class of Device (CoD) and can also be used to identify the type of vehicle carrying that Bluetooth device as a way to separate out motorized and non-motorized traffic.

Haghani et al. (2010) found that the accuracy of the travel speeds in freeways generated from the collected MAC addresses increases with the increase of distance between Bluetooth detectors and the decrease of vehicle speed. Malinovskiy et al. (2010) recommended the detection area on the road should be large enough for the detection of nearly all vehicles with Bluetooth-enabled devices traveling at different speeds. Schneider IV et al. (2010) compared Bluetooth to floating car methods on Interstates, urban arterial roads, and state highways. They found that arterial tests had much lower number of matches than the interstate tests. They suggested one to two miles spacing between Bluetooth stations for increasing the number of matches. Large detection zones, such as Class 1 radios, can be a source of error in short corridors as any Bluetooth device within the detection range may be detected by the Bluetooth detectors

(Vo, 2011). However, according to Malinovskiy et al. (2010), in spite of loss in accuracy in travel time measurements, larger detection zones provide higher matching rate. This improves the sample size and reduces random error rates for both freeways and arterials.

The sample size of data is another important aspect in providing accurate and up-to-date travel times. The study by Wasson et al. (2008) produced 0.7 to 1.2% match rates. Match rate is the percentage of Bluetooth devices detected at two or more Bluetooth detector locations out of the total traffic volume in the corridor. According to Neal Campbell, CEO of TrafficCast, BlueTOAD system can achieve match rates of 3 to 6% of the traffic stream (Bradley, 2010); which is found to be 4% by another study on arterials (KMJ Consulting, Inc., 2010).

Haghani and Young (2010) conducted a study to monitor traffic on I-95 in Maryland using Bluetooth detectors and obtained 2 to 5.5% match rates during a validation test in six eastern states. Wang et al. (2010) obtained 2.2% match rates on arterials in their study. According to the study by KMJ Consulting, Inc. (2010), these match rates are sufficient enough to identify travel times accurately. They suggested that, for roadways with 36,000 average annual daily traffic (AADT), 9, 36, and 864 matched pairs per 15-minutes, hour, and day (2% match rate), respectively can provide accurate travel time estimation. However, the percentage requirement increases with the decrease in AADT.

Detection rates are comparable to the traffic volume obtained from another method, which can be used as a baseline for that particular location (Nelson, 2010). Schneider IV et al. (2010) also identified that match rates are proportional to the traffic volume on arterial roads. They found that the proportion of Bluetooth devices per vehicle does not depend on the time-of-day (ToD).

Although it is difficult to identify Bluetooth penetration rate (percentage of vehicles containing discoverable Bluetooth devices), Asudegi (2009) conducted a research to identify optimal number and location of the Bluetooth detectors in a network for travel time data collection with a high reliability. The study assumed Bluetooth penetration rate to be 3 to 5% of normal traffic streams of freeways and arterials. Haghani and Young (2010) obtained the Bluetooth penetration rate as approximately 5% for freeways in United States. Hainen et al. (2011) performed a route choice and travel time reliability study on arterials in Indiana. They estimated 7 to 10% of passing vehicles have detectable Bluetooth devices for arterials. Brennan Jr. et al. (2010) performed a study on I-65 in Indianapolis to assess the influence of vertical placement of Bluetooth detectors on data collection quality. They assumed 5 to 10% of the vehicle population on the freeways has MAC addresses that can be discovered.

Porter et al. (2010) conducted a study to assess the suitability of different antennas to support a Bluetooth based travel time data collection system on Oregon Route 221 (Wallace Road NW) in Salem, Oregon. They found that vertically polarized antennas with gains between 9 and 12 dBi are good for Bluetooth based travel time analysis. According to Malinovskiy et al. (2010), two omni-directional antennas placed at the same location on opposite sides of the road provide the best detection rate. Multiple readers at one site may increase the number of detections. Combinations of sensors in tandem increase the accuracy of the detection and matching rates and reduce error in most cases on arterials (Wang et al., 2011). The height of the Bluetooth detector has an important role in detection rate. Brennan Jr. et al. (2010) conducted a study by placing five Bluetooth detectors at different heights ranging from 0 to 10 feet along I-65 in Indianapolis to identify the sensitivity of sample size to sensor placement. They concluded that 7.5 feet and 10 feet produced similar results while the others performed poorly. However, further research is necessary if optimal height depends on site characteristics.

3 Transit Buses as Probe Vehicles

3.1 Introduction

Travel time information is considered as one of the most important tools to manage arterial flow. This travel time information helps many travelers make their decisions on trip start time, mode choice, and, route choice, among others. In addition, transportation operators can easily evaluate developed traffic control methods and transportation policies using the estimated travel time. The results of several studies are quite acceptable in the case of freeway travel time estimation and prediction. For arterial travel time, however, the estimation work is more complicated due to traffic signals and interruption from side traffic. Therefore, the estimation of arterial travel time requires more accurate traffic measurement and more detailed estimation approaches (Ping et al., 2012).

Probe vehicles are moving sensors responding to changes in traffic flow as they traverse various links on the network and transmit location and travel time data to a traffic information center at a frequent time interval. Probes provide a great potential for improving the estimation accuracy of traffic conditions, especially where no traffic detectors are installed (Bertini & Tantiyanugulchai, 2003; Tantiyanugulchai, 2004).

Use of buses as probe vehicles adds little or no financial burden to a transit agency because most buses are equipped with GPS for tracking and predicting bus arrival times. Also, bus drivers generally observe traffic rules and speed limits. Further, a large number of buses run on the most used arterials and generally have higher frequencies during peak periods (Chakroborty & Kikuchi, 2004). The primary advantage of using buses as probes is because they are a closed and controllable group of vehicles. Consistent maintenance is relatively easy to ensure, and bus drivers can be instructed on how to use the system (Hall & Vyas, 2000).

As probe vehicles for the purpose of measuring arterial performance, Bus Rapid Transit (BRT) buses have prominent advantages over local buses. First of all, the BRT bus runs more like other traffic than the local bus does. The advanced BRT vehicle allows them to accelerate rapidly and cruise with higher speed. The other reason is that BRT typically runs headway-based service, so it does not need to adapt their cruising speed and dwelling time to meet the schedule (Ping et al., 2012). However, typical BRT buses with headway shorter than 15 min cannot provide enough probe samples (Ping et al., 2012).

The primary disadvantage is that bus speeds do not entirely represent general traffic speeds. Buses must stop to pick up and drop off passengers, must follow a schedule, and have different acceleration and deceleration profiles (Hall & Vyas, 2000). On the other hand, automobiles have disadvantages as probes. Ordinary drivers may stop and wait at unpredictable locations for unpredictable amounts of time. Any probe algorithm must be able to distinguish ordinary stopping from congestion. This makes verifying a congestion alarm with a second or third vehicle desirable; if probe vehicle density is insufficient, it may then be possible to verify the congestion (Hall & Vyas, 2000). Figure 1 depicts trajectories of test vehicles, local buses and BRTs.

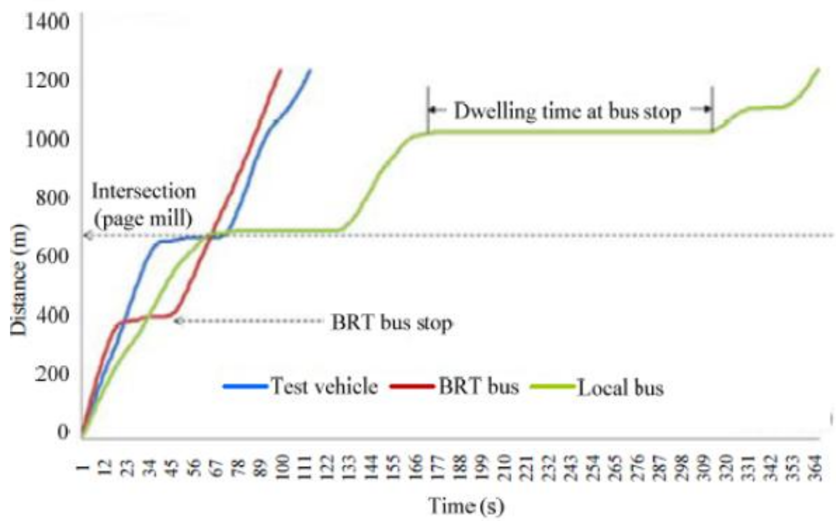

Figure 1. Trajectories of Test Vehicles, Local Buses and BRTs (Ping et al., 2012)

The difference between bus travel time and average travel time arises primarily because of the following (Chakroborty & Kikuchi, 2004):

- the stopping time of the bus at the bus-stops;
- the time lost by the bus because of repeated accelerations and decelerations from and to a stop;
- the basic difference between the operating abilities of the bus and the automobile;
- adherence (by the bus and the automobile) to the posted speed limits; and
- the tendency of the bus to use the right lane.

Also, it is important to recognize that the difference between bus travel time and average traffic travel time is a random variable even for the same section of a corridor. This is because buses stop at bus-stops, leave and join the traffic stream many times during their travel, incur additional time for merging and diverging as well as deceleration and acceleration to and from a stop, and idle at bus-stops to collect and discharge passengers for a certain amount of time. Since the number of times that a bus-stops and the duration of stop vary randomly, this difference is a random variable (Chakroborty & Kikuchi, 2004).

3.2 Data Collection

The data related to the probe vehicles is collected using Automatic Vehicle Location (AVL) systems. AVL is a means for automatically determining the geographic location of a vehicle and transmitting the information to a requester. Most commonly, the location is determined using GPS, and the transmission mechanism is SMS, GPRS, a satellite or terrestrial radio from the vehicle to a radio receiver. GSM and EVDO are the most common services applied because of the low data rate needed for AVL and the low cost and near-ubiquitous nature of these public networks. It is a powerful concept for managing fleets of vehicles such as service vehicles, emergency vehicles, precious construction equipment, and especially public transport vehicles.

AVL systems comprise three elements (Zygowicz, Beimborn, Peng, & Octania, 1998). The first element is locating hardware which is the component necessary to identify the position of a vehicle on the earth's surface. The next is the communication package which takes the positional data and relays it back to the central office. The final element is the computer display system which reveals the location of the vehicle as it travels in real time.

To track and locate vehicles along fixed routes, a technology called signpost transmitters is employed. This is used on transit routes and rail lines where the vehicles to be tracked continually operate on the same linear route. A transponder or RFID chip along the vehicle route would be polled as the train or bus traverses its route. As each transponder was passed, the moving vehicle would query and receive an acknowledgement or handshake from the signpost transmitter. A transmitter on the mobile would report passing the signpost to a system controller. This allows supervision, a call center or a dispatch center to monitor the progress of the vehicle and assess whether or not the vehicle was on schedule. These systems are an alternative inside tunnels or other conveyances where GPS signals are blocked by terrain.

GPS signals are impervious to most electrical noise sources and do not require the user to install an entire system. Usually only a receiver to collect signals from the satellite segment is installed in each vehicle and radio or GSM to communicate the collected location data with a dispatch point. AVL systems send data from GPS receivers in vehicles to a dispatch center. Location data is periodically polled from each vehicle in a fleet by a central controller or computer. In the simplest systems, data from the GPS receiver is displayed on a map allowing us to determine the location of each vehicle.

The most commonly used AVL system to collect data from transit/buses is Bus Dispatch System (BDS). The BDS system comprises three main components (Figure 2): the GPS satellite system, the real time information system and the data archive system. The GPS satellite system provides vehicle location information feeding into the AVL system in order to monitor vehicle locations in real time. Vehicle location is determined by the on-board computer and transmitted using a real time communication system to the transit dispatch center. The real time component also supports voice and data communication using a mobile radio system. Information is transmitted from the vehicle to the dispatch center either at a regular interval or in response to specific operator initiated events such as route detour, accident or vehicle breakdown. This system is used to ensure that the bus dispatch center is updated with at least the minimum amount of information for tracking and reporting purposes and to provide assistance to bus operators. Finally, the most important part of the BDS is the archived element. Information regarding bus operational characteristics such as distance traveled, passenger activities, vehicle location (GPS coordinates) and maximum speed achieved on every link traveled are recorded into storage (a PCMIA memory card) while the bus is in service. The archived data are downloaded to the control system at the garage at the end of day. Such information is extremely valuable and records detailed operating and travel characteristics for every bus which is useful for revealing traffic movements on the arterial system (Bertini & Tantiyanugulchai, 2003; Tantiyanugulchai, 2004).

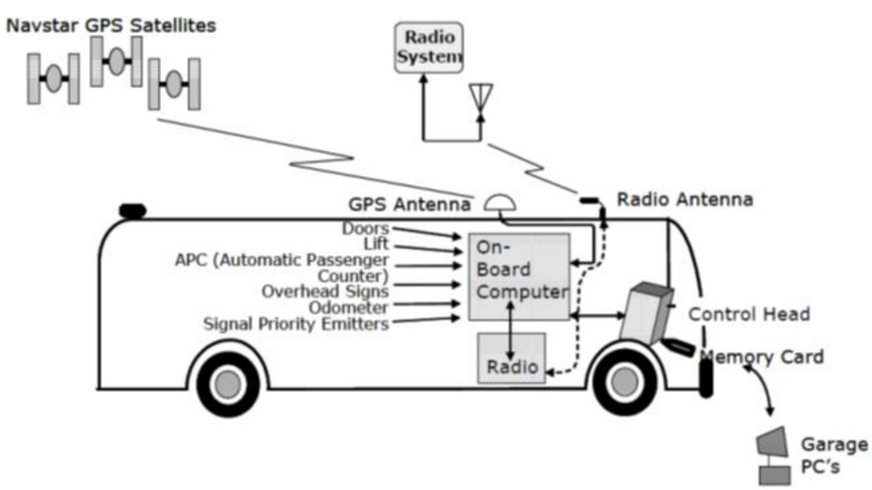

Figure 2. Components of BDS (Tantiyanugulchai, 2004)

For each bus trip and for each geo-coded stop, the BDS records arrival time, departure time, number of boardings and alightings, and location (in NAD83 state plane X-Y coordinates). In addition, the system stores the maximum instantaneous speed achieved between stops. The position of the GPS equipped buses is calculated every second, with a spatial accuracy in positioning of plus or minus 10 meters (33 feet). If the bus does not stop at stop i, the BDS records the time that the bus is within 30 meters (100 feet) of an accurate location of the next bus-stop that is stored on the data card with the schedule as "arrive time." The BDS then records "leave time" when the bus is no longer within 30 meters (100 feet) of the bus-stop location. If the bus-stops at stop j, then the BDS records the time that the door opens as the "arrive time," records the "dwell time" (the difference between door open time and door close time) and records the "leave time" as the time the bus is no longer within 30 meters (100 feet) of the bus-stop location. Also, at each stop where passengers are served, the BDS records the number of boardings and alightings through both doors using automatic passenger counters (APCs), a pair of infrared beams situated across the front and rear doors of the bus. Figure 3 shows the stop circle where the BDS records times and locations (Bertini & Tantiyanugulchai, 2003; Tantiyanugulchai, 2004).

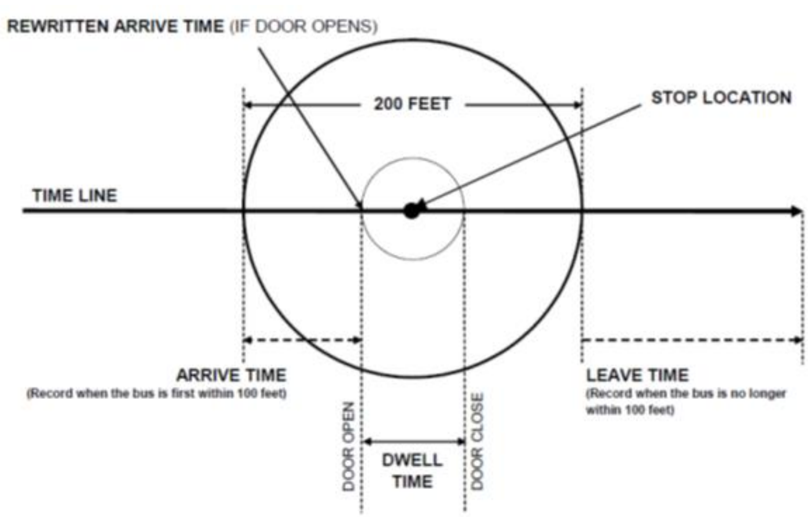

Figure 3. Stop Circle where the BDS Records Times and Locations (Bertini & Tantiyanugulchai, 2003; Tantiyanugulchai, 2004; Tantiyanugulchai & Bertini, 2003a, 2003b)

Bus trip information includes: service date, vehicle number (unique identification number), train number (grouped / scheduled trips for a single vehicle), badge number (operator identification number), direction (0 for outbound and 1 for the inbound direction), travel time information, departure time, arrival time, stop time (bus scheduled departure time at a given location), maximum speed recorded between stops, location information, pattern distance (linear scheduled distance measured from the beginning of the route), X-Y Coordinates (geo-coded location of the bus), stop location, passenger activity information, dwell time, door open indication, lift used indication and numbers of passengers boarding and alighting (Bertini & Tantiyanugulchai, 2003; Tantiyanugulchai, 2004).

3.3 Forecasting Actual Traffic Condition Using Buses as Probes

Bertini and Tantiyanugulchai (Bertini & Tantiyanugulchai, 2003; Tantiyanugulchai, 2004; Tantiyanugulchai & Bertini, 2003a, 2003b) have suggested that it is important to focus on the management of traffic on arterial facilities in addition to the current heavy focus on freeways. The authors designed an experiment to determine the statistical relationships between bus travel time and speed and actual traffic conditions, examining a system for applying AVL data to characterize the performance of an arterial. Table 1 represents their experimental designs features. First, data were extracted from the bus BDS of the Tri-County Metropolitan Transit District (TriMet), the transit provider for Portland, Oregon. Each bus is equipped with a BDS which includes AVL, comprised of differential GPS, automatic passenger counters on most vehicles, wireless communications, and stop-level data archiving capabilities. Then, the performance characteristics as described by bus travel on an arterial were compared with ground truth data collected by probe vehicles equipped with GPS traveling with normal (non-transit) traffic on the same arterial on the same days.

To further explore the relationship between bus travel time and general traffic travel time, hypothetical and pseudo bus analyses were also conducted. For these studies, hypothetical buses are defined as the buses traveling non-stop and pseudo buses are buses traveling at the maximum speed recorded for each link. The statistical analysis confirmed the existence of a relationship between test vehicle speed and pseudo bus speed and conversely the relationship between their travel times. This study found that the test vehicle speeds for all four study days, during both morning peak and midday off-peak periods, were between 0.78 and 0.81 times the maximum instantaneous speed achieved by the buses (pseudo bus speed). Conversely, it was shown that the test vehicle travel times ranged between 1.24 and 1.29 times the pseudo bus travel time.

Table 1. Bertini and Tantiyanugulchai's Experimental Features (Tantiyanugulchai, 2004)

Features	Experiment
Question	Can buses accurately report actual traffic conditions?
Hypothesis	There are relationships between bus behavior and traffic movements
Requirement	Bus data: Bus AVL data Traffic condition data: Test vehicle travel time data Level of consistency: Same location Approximately same distance traveled Same date Same time Variety of traffic conditions (peak and off-peak hours)
Comparison	Key performance measures: Travel time; Speed

Ping et al. (2012) developed a series of data processing methods to estimate arterial travel time and LOS based on real-time BRT bus data and signal timing data. The authors mentioned three main factors that cause the travel time difference between BRT buses and general traffic; cruise speed difference, bus-stop effects, and traffic signal effects and signal coordination. First, the average cruise speed for the test vehicle and the BRT bus are 17.5 and 17.6 meters/second, respectively, while their standard deviations are 1.37 and 1.24 meters/second, respectively. Furthermore, the result of statistical test shows that there is no difference between both modes' free-flow speed at a 95% significant level. Therefore, it is not necessary to estimate the cruise speed relationship between two modes when estimating the arterial travel time. Second, the major difference between bus travel time and other traffic travel time is the delay caused by the dwelling time at the bus-stops. The delay consists of three elements: stop time, deceleration delay, and acceleration delay. To calculate these delays, it is a prerequisite to detect whether a bus halts at a bus-stop. Buses sometimes skip bus-stops if there is no passenger to board and alight at bus-stops. Finally, traffic signal delay is the most important component of arterial travel time because most variations of the travel time come from traffic signal control and the resulting queues. Moreover, the dwelling time at bus-stops keep buses from flowing with other traffic within the green band of traffic coordination. Therefore, the signal delay experienced by buses might not be representative for general traffic.

Many BRT buses are able to receive transit signal priority at intersections. Under the prioritized treatment, BRT buses can typically reduce about 10% of the intersection delay. Traffic signals along most major arterials are under semi-actuated control. As a result, the traffic signal timing in each signal cycle might vary a lot demanding on the volume of side-street and left-turn traffic. In summary, the queuing delay is a more direct measurement of arterial congestion level than total traffic signal delay and total travel time. Therefore, Ping et al. (2012) used the bus queuing delay to be an indicator of LOS on arterials. They concluded that traffic intersection delay and queuing delay can be estimated by using bus probe data directly.

El Esawey and Sayed (2010) proposed a new method to estimate travel times, on segments without travel time information, using bus travel time data of nearby (neighbor) links. Unlike other probe vehicles such as taxis, routes and schedules of transit vehicles are known. Their main hypothesis was that travel times of nearby links have strong correlation as these links are subject to similar traffic conditions. A general methodology was presented for travel time estimation using historical travel time data of the link itself and real-time bus data from neighbor links. Indeed bus travel times of neighbor links were used instead of a sample of passenger vehicle probes. Firstly, bus travel times of neighboring links were used to estimate average automobile travel times on these neighbors. Subsequently, the estimated neighbor travel times were used to compute real-time average travel time on link. According to their results, for links with no bus-stops, the correlation was estimated directly between the average bus and automobile travel times. For other links with one or more bus-stops, the correlation was obtained between average automobile travel time and the bus travel time after subtraction of the average dwelling time multiplied by the number of bus-stops on the segment. The correlation of average bus and automobile travel times for both groups was high and statistically significant. This indicates a strong relationship between the average travel times of buses and autos and facilitates developing auto transit travel time models. As a result, bus travel times can be used not only to estimate auto travel times of their travel links but also for neighboring links.

Another issue of interest concerns over what distances one should predict travel time. It is thought that for travel time predictions to be useful, the distance over which travel time is predicted should be long enough so that predicted time is meaningful to the average driver. Chakroborty and Kikuchi (2004) have suggested the following equation to predict the average travel time according to bus travel time and length of the link.

$$\text{ATT} = \frac{\text{length of the section}}{\text{free flow speed}} + \text{b} \times (\text{BTT} - \text{TST})$$

where, ATT is the average travel time of the automobile, BTT is the observed travel time of the bus, and TST is the total time bus spends stopping at all bus-stops.

Hall and Vyas (2000) evaluated the congestion probe feature by comparing automobile and bus trajectories and examining alternative means for detecting congestion. Congestion classifications were based on estimated bus speeds on roadway segments, after adjusting for bus-stop time. The speed was compared to a nominal free-flow speed (estimated to approximate speed limits). Depending on the ratio, congestion was classified as none, light, moderate, or heavy. The estimated speed was calculated using the following equation:

$$\text{Estimated Speed} = \frac{\text{N}_1 \times \text{SL}}{\text{ST} - \text{SDT} - \text{N}_2}$$

where, SL is physical length of segment, ST is measured time to traverse the segment, SDT is station dwell time (including acceleration and deceleration loss time), and N1 and N2 are empirical coefficients to compensate for performance differences between automobiles and buses.

According to Hall and Vyas (2000), bus and automobile speeds and delays differ greatly; however, they do show a correlation during major incidents. Automobiles travel at greatly reduced speeds (less than 4 mph) for 4 minutes or longer during these incidents. Buses also have major delay, which is logical because automobile delays typically occur at an oversaturated intersection when automobiles and buses have similar travel times. The data therefore indicated that automobile probes could be useful for predicting delays on transit lines. Unfortunately, using bus probe data to predict major automobile delays is more difficult than the reverse prediction. Results provide that major bus incidents do not result in major automobile incidents.

Pu et al. (2009) studied the usability of bus travel information to infer general vehicle traffic conditions. In their research, the usability can be proven if two conditions are met:

condition (a) there are quantifiable relationships between bus travel and automobile travel; condition (b) infrequent bus travel observations (constrained by the scheduled bus headway and AVL polling frequency) are sufficiently sensitive to infer real-time general vehicle traffic conditions (probably by means of the relationships identified in condition 1). A large amount of historic data can be used to identify possible bus–automobile relationships. Historical relationships, however, do not guarantee the real-time sensitivity of bus probes to traffic conditions, as bus observations could be too sparse to draw a reliable conclusion in a short time. Thus, condition 2 needs to be satisfied.

Traffic speed is a better traffic parameter than travel time to be directly used in modeling bus–automobile relationships (Pu, Lin, & Long, 2009). This could be due to intrinsic measurement errors in measuring bus travel time in the interval-based real-time AVL polling scheme, and lack of availability of bus-stop dwell time (the most significant noise to be filtered when relating bus travel time to automobile travel time). It is found that bus–automobile speed relationships were location specific; at mid-blocks, buses and automobiles exhibit similar speed patterns with or without constant differences; at bus-stop only locations (where no control is imposed on non-transit vehicles), bus and automobile speeds could differ greatly as buses have to respond to passengers' demands while automobiles can travel freely if not disturbed by buses; and at controlled intersections (with or without bus-stops), buses and automobiles are subjected to the same control strategies (assuming no transit priority strategy presents) but buses tend to have slower start-up and slow-down times (i.e., longer acceleration and deceleration distances) than automobiles.

Historic bus-automobile speed relationships were quantified using classic multiple linear regressions, in which the dependent variable was the difference between bus mean speed and automobile mean speed of a link (automobile speed minus bus speed) and the final independent variables were two locational dummies (Pu et al., 2009). Bus-stop only (short link that includes only a posted bus-stop and general vehicles can travel freely if not disturbed by buses) and signal (signalized intersection exists) are the independent variables. It was observed that automobile speed on average is much faster than bus speed across all types of locations on the study segments.

Hall et al. (1999) conducted a field operational test of AVL systems. The potential of using bus data to estimate automobile speeds and travel times was studied. The authors suggested that bus tracking systems provide many potential benefits: helping drivers stay on schedule, dispatchers respond to problems, schedulers determine how much time to allocate between schedule check points, and general public know when buses will arrive. Conclusions from their study include the following.

- Missing and undetected data result from inoperable or failed units, lack of complete coverage on routes, and inability to immediately update data at schedule changes.
- Little correlation between transit speeds and automobile speeds in normal traffic conditions.
- Strong correlation between bus delays and automobile delays when major incidents occurred.

Dailey and Elango (2000) used transit vehicles as probes to develop a framework for modeling the time series and estimate speed as a function of time and space. They suggested an optimal solution using the Kalman filter containing the variables speed and position. This solution requires developing a model for the process; a relationship between time and location of vehicles and creation of a measurement model to account for measurement errors. Further, the use of this procedure depends upon the assumption that the deviation of the data from the model is normally distributed.

Cathey and Dailey (2001) presented new algorithms that use transit vehicles as probes for determining traffic speeds and travel times along freeways and other primary arterials using AVL data from the King County Metro Transit system. They developed process models of a Kalman filter/smoother that estimates vehicle state (position, speed, and acceleration) from AVL sensor reports. The results showed that the smoothed speed estimates were similar to those obtained from loop detectors in terms of variability along the day.

Sarvi et al. (2003) developed a general methodology to identify traffic condition utilizing Internet Protocol probe cars (IPCar) in Yokohama and Nagoya cities. Although the Yokohama IPCar project was using 179 vehicles consisting of 140 taxis and 39 buses, the authors studied just 47 taxis. Employing this method to cleanse the IPCar data and search for trip ends, they combined it with vehicles trajectories to classify different traffic condition patterns into five discrete patterns namely A1, A2, B1, B2 and C.

Berkow et al. (2008) studied arterial performance measures using both traffic signal system detectors and information from buses as probe vehicles, and generated an algorithm for identifying congestion intervals. This research demonstrated the potential for using bus AVL data to construct the shape of the congested regime on arterials, using source of archived data from two sources, graphical tools and statistically valid algorithms. It proved that it is possible to compare the evolution of bus trajectories over an arterial segment with hypothetical trajectories generated from loop detector data.

Uno et al. (2006; 2009) proposed a methodology for evaluating the road network from the viewpoint of travel time stability and reliability using bus probe data, and an approach to evaluate the LOS of road networks based on the concept of travel time reliability. To obtain an accurate travel speed and time estimate, they used a correction method composed of three steps: detection of stops at bus-stops, detection of deceleration (or acceleration) before (or after) stopping at bus-stops, and eliminating increases in travel time due to stopping at bus-stops. As the observed travel time distribution conformed to the lognormal distribution in seven sections among the twelve analytical sections, they assumed that travel time distribution conforms to a lognormal distribution.

Among the various factors that affect the LOS of the road network, research has focused on both the efficiency and stability of the road transport conditions (Uno, et al., 2006; 2009). In that sense, the ideal road transport condition is defined as that under which travelers can reach their destinations in rapid and reliable manner. The average travel time for 1-kilometer was used to evaluate the efficiency of the network, and the coefficient of variation (COV) of the travel time was used to evaluate the reliability of the network.

El-Geneidy and Bertini (2004) used a combination of loop detector and AVL data from a bus fleet to find the optimal spatial resolution for loop detector placement and the optimal temporal resolution for detector data reporting. Speed reported by AVL data at several spatial and temporal resolutions were compared to speeds reported by inductive loop detectors. The integration of AVL and loop detector data facilitated a reduction in the measurement error associated with aggregation and extrapolation. Based on the results, the speed reported by loop detectors every 20 seconds when displayed on a freeway map could be misleading when extrapolated over a long inhomogeneous segment. Of the several cases examined, the five minute median speed appeared to be the most representative of measured speed along a segment. The five minute average was also in the accepted range for reporting speed.

Pu and Lin (2008) used real-time bus tracking data for urban signalized street travel time estimation developing a multivariate time series state-space modeling technique. The authors found a significant interrelation between bus and automobile speeds. In particular, stronger influence of automobile operations (in terms of speed) was found on bus operations in the traffic stream than buses on automobiles. These findings indicate that AVL buses are plausible probes for urban street Advanced Traveler Information System (ATIS). In particular, automobile speeds are found to be unaffected by bus speeds in light traffic even though significant influence is found in reverse, probably due to the prevalent presence of automobiles in the traffic stream. Therefore, the case study concluded that buses can be probes for travel information on signalized urban streets, especially under medium to heavy traffic conditions.

Coifman and Kim (2009) used transit AVL data to measure travel time and average speed over the freeway and thereby quantify conditions on the facility. By comparing results against measurements from loop detectors, the results were validated. As the study corridors typically had fewer than 50 observations per day per kilometer per direction, the presented procedure selects those segments with at least one observation per hour. These low density observations were aggregated to show the recurring congestion patterns, and non-recurring events were also evident with longer detection times. After filtering errors in both data sets, they found that trip-based travel speeds from transit data are generally consistent with the concurrent estimates from loop detector data, and link-based speeds capture the general trend of the traffic state. The presented methodology is also effective to rapidly identifying nonrecurring congestion for observations with higher frequency.

Vanajakshi et al. (2009) used GPS data collected from public transportation buses plying on urban roadways in the city of Chennai, India to predict travel times under heterogeneous traffic conditions using an algorithm based on the Kalman filtering technique. This algorithm was based on a model discretized over space compared with existing algorithms which used models discretized over time. The results showed that the proposed algorithm is a viable applicable option in heterogeneous traffic conditions.

4 Reliability as a Function of Recurring and Non-recurring Congestion Components

4.1 Introduction

Reliability is defined as the probability that a component or system will perform a required function (without failure) for a given period of time when used under stated operating conditions (Ebeling 1997). Therefore, reliability of a link, corridor or the transportation road network, in general, could be defined as the ability to provide an acceptable LOS to the traveler under stated environmental and operational conditions during a given period.

Literature documents use of several terms such as connectivity reliability, travel time reliability, network reliability, capacity reliability and system reliability. The definition of network reliability has its roots in providing good network connectivity. The probabilities of link existence between an origin and a destination are used to define connectivity reliability (Iida and Wakabayashi 1989; Iida 1999; Asakura 1999).

4.2 Reliability Based on Travel Times

Practitioners and researchers in recent years have been using travel time reliability as it better quantifies the benefits of traffic management and operation activities than simple averages. Asakura (1999) and Bell (1999) define travel time reliability as the probability that a trip between a given O-D pair can be made successfully within a given time interval and a specified LOS.

Zehen-Ping et al. (1996) proposed a model to improve system reliability and to identify critical components for a simple network. The practical measures of reliability are also described along with the algorithms for solving the reliability model. This model could get exact solutions only for very small or regular networks. The best approach described to estimate the system reliability is approximate solution and recursive algorithm which shows how the component reliabilities, system reliability are connected, and also demonstrating the recursive algorithm which converges quickly to the correct value.

Noland (1997) developed a model to determine optimal home departure times with a supply-side congestion model of a highway facility and got the results which suggested that costs of commuting can be reduced by polices suggested by author to reduce travel time variance and not just travel time. The analyses showed the behavioral adjustments that commuters make before entering traffic in response to given levels of uncertainty. These results are applicable to some very common situations as the route choice problem or interactions in a network and mode choice are not considered during analysis.

Chen et al. (2000) proposed capacity reliability index which includes connectivity reliability and gives travel time reliability. A structure was developed which included network equilibrium models, sensitivity analysis and reliability, uncertainty analysis, which are used to obtain numerical results to demonstrate feasibility of reliability evaluation procedure. Five topics were suggested which require further research to get significant and practical results.

Sanchez et al. (2005) proposed a model to optimize the allocation of resources based on the operational reliability of transport network systems. This model provides a very useful structure for optimizing the assignment of resources to enhance the reliability of any transport network system. To compute transportation system reliability of a network, the authors adopted a method which is based on probabilistic view. In this method, the state of the infrastructure and the behavior of the network users were considered as two main elements. The first element infrastructure is based on the state of the network i.e., the relationship between the failure and repair rates of every link of the network and these rates are directly related to physical characteristics of the road such as condition of the road, or frequency and size of landslides. The second element behavior of road users is known by modeling the decision making process of the individual to take a route between any two nodes.

Lint et al. (2005) stated that mean and variance of travel times on a route in a particular ToD and day-of-week (DoW) tend to obscure important aspects of the travel time distributions under specific conditions. Instead, the authors proposed two reliability metrics - width and skew based on three characteristic percentiles: 10th, 50th and 90th percentile for a given route and ToD-DoW period. The authors have not only been able to identify the unreliability of travel times for a given ToD-DoW period, but also identified periods in which congestion is most likely to occur. Later, depending on the weight given to each metric, unreliability maps could be generated.

Lui et al. (2005) examined time-dependent effects on traveler's route choice decisions by assuming that travelers' tastes toward the travel time and its reliability vary with time. The authors have adopted a mixed-logit formulation of route choice behavior as a function of travel time, reliability, and cost. The authors have compared time-dependent traffic volume data from loop detectors with route choice model to identify the coefficients using genetic algorithms. The results indicate that travel-time savings may be more important than uncertain travel time when departure time is close to such time constraints as work-start time under the time-dependent formulation.

The prevailing traffic information that depicts the current network conditions is generally provided to trip makers to avoid recurrent and non-recurrent congestion. Dong Jing et al. (2006) state that route guidance based on prevailing trip times could be counterproductive. Anticipatory information is derived from forecasts of network sites in order to consider the social and temporal changes in traffic conditions. The authors examined these values with predictive travel time calculated using both analytical and simulation based approaches and concluded that predictive travel time is more reliable.

Pulugurtha et al. (2007) estimated travel time using the Bureau of Public Roads (BPR) equation and travel delays due to crashes on each link. The travel times and travel delays due to crashes were combined to evaluate the reliability of the link. The reliability was calculated in two different ways. The first one is reliability based on percent variation in travel time, and, the second one is reliability score based on percent variation in travel time and the impact of crashes on travel times.

Bertini et al. (2007) used archived ITS data to examine the use of measured travel time reliability indices to improve the real-time transportation management and traveler information. Many reliability measures were tested to find out the ways to improve the communication about reliability to the users, so that, the travelers can make the most appropriate usage of the system for their purposes. There by, it improves the health of the whole transportation system. The paper provided ways to explore and analyze the existing field data to know the ways of reporting field data. It also analyzed the changes in travel time reliability with respect to time.

Wasson et al. (2008) used Bluetooth detectors to collect MAC addresses in order to evaluate travel-times through address matching. The study was conducted on arterials and freeways in Indianapolis to estimate travel times. The authors indicate that, due to the impacts of traffic signals and the noise that is introduced when motorists divert from the network, data from arterial highways showed a significantly larger variance compared to data from the freeways.

Travis et al. (2009) proposed a system-optimum design network model with probabilistic guarantees on travel times. In the model developed, the authors have considered the uncertainty in the link performance. Upon testing the model on a small test network it was observed that different solutions were obtained when compared with conventional network design models.

Chang (2010) gave two different definitions for reliability and punctuality of travel time; here reliability of travel time deals only with variations of in-vehicle times. After research on reliability of travel time, the author identified seven factors which cause unreliable travel time and used two evaluation requirements (measurements and valuations) to estimate travel time reliability. Korean data of road and rail usage was taken to calculate unit values for the requirements. The travel time values were estimated using logit-based choice model and very useful results were obtained, which are practical and can be used for transport appraisal.

Uniman et al. (2010) explored the potential of using automated fare card data to quantify the reliability of service as experienced by passengers of rail transit systems. A set of service reliability measures were developed using the distribution of passenger journey times from fare card data to evaluate transit service. The authors indicate that a large proportion of the unreliability experienced by passengers can be attributed to incident related disruptions and sizable improvements in overall transit service quality can be attained through reliability improvements.

Haseman et al (2010) evaluated travel time delays at work zones using Bluetooth probe tracking. The study involved collection of 1.4 million travel time records over a 12 week period for a rural interstate highway work zone along I-65 in northwestern Indiana and compared with traditionally measured travel time profiles in both incident and non-incident conditions. Results indicate that 30% of observed probes took alternate routes upon implementation when compared to negligible percent of probes taking alternate route through self-guidance. The authors concluded that real-time data acquisition could help 1) improve trip planning, both before and during their trip, 2) evaluate alternative maintenance of traffic techniques and identify best practices, 3) improve work zone queue forecasts, 4) assess the relationship between crashes and work zone queuing, and 5) enable future contracts to include innovative travel time reliability clauses. However, additional studies are warranted to formally test the hypothesis, especially for roadway segments not subject to special event traffic.

Hainen et al. (2011) proposed a Bluetooth MAC address sampling technique to assess route choice and travel time. The proposed technique was to evaluate the impacts of a bridge closure in Indiana on four possible alternate routes. The authors indicate that the route choice behavior was consistent with the observed travel time estimates. The authors also indicate that the proposed technique is not only cost-effective to deploy but also the direct measurement of travel times and route choice is useful for public agencies to assess mobility and travel time reliability.

Kwon et al. (2011) proposed an empirical, corridor-level method to divide the travel time unreliability or variability over a freeway section into various component such as incidents, weather, work zones, special events, and inadequate base capacity or bottlenecks. Results from applying the methodology to a 30.5 mile corridor in San Francisco, California indicate that traffic accidents contributed 15.1% during the morning and 25.5% during the afternoon, among others, and most of the remaining reliability came from recurrent bottlenecks**.**

Figliozzi et al. (2011) produced informative performance measures and segments using GPS truck data. The authors proposed a methodology by processing and aggregation of GPS data to identify distinct segments and characteristics of travel time reliability in freight corridors.

Pu (2011) analytically examined a number of reliability measures and explored their mathematical relationships and interdependencies with an assumption that travel time follows a log-normal distribution using percent point function, which is a subset of reliability measure expressed in relation to the scale/shape parameter of the lognormal distribution or to both. Instead of standard deviation, the authors found coefficient of variation to be a good proxy for several other reliability measures. However, when travel times are heavily skewed, the author recommended median-based buffer index or failure rate as use of the average-based buffer index or average-based failure rate is not always appropriate.

Edwards et al. (2012) investigated travel time reliability using probe vehicle-based travel time data for 2010 acquired from private sector by Virginia Department of Transportation. The authors quantified travel time reliability at 15 work zones with 95th percentile travel time, a buffer index and a planning time index using the data obtained to examine the effects of travel time reliability at work zones. Results from the analysis indicate that work zone mean buffer index, planning time index, and 95th percentile travel time rates were higher by 48%, 18%, and 16%, respectively. Also, lane closures occurred during off-peak periods. Work zones that involved lane closures experienced increases in their mean buffer index, planning time index, and 95th percentile travel time with rates of 67%, 23%, and 22%, respectively. The authors concluded that annual average daily traffic per lane and the number of access points per mile were found to have the most obvious relationships with declines in reliability at work zones.

4.3 Effects of Incidents on Travel Time & Reliability

About half of traffic delays/congestion is caused by incidents that take away part of the roadway from use. The effect of an incident on travel time varies based on the type and severity of incident.

Liu et al. (2005) developed a statistical model using stepwise regression analysis for estimating incident duration. The results show that 85% of variations in incident duration can be forecasted using the developed regression model. Whereas, Nam et al. (2007) and Chung (2010) developed hazard-based statistical models to predict traffic incident duration.

Ozbay et al. (2006) applied Bayesian networks approach to develop a model that can automatically learn emerging patterns in data in to predict incident clearance times. This study shows that the proposed methodology is fully capable of representing the stochastic nature of incidents, but should be improved in detail.

Wie et al. (2007) forecasted incident duration using Artificial Neural Network models considering incident characteristics, traffic data, time gap, space gap, and geometric characteristics as model inputs. When an incident is reported, the estimated incident duration can be calculated by using the relevant traffic data. Similarly, Guan et al. (2010) developed Artificial Neural Network Models to predict traffic incident durations.

Zeng et al. (2010) adopted empirical method in estimating traffic incident recovery time. The authors used both incident and travel time data to estimate traffic recovery time using difference-in-travel-time method. The authors indicate that the proposed method helps represent incident impacts without any assumptions and calibrations, and can be incorporated to support the calculation of various measures to monitor the performance of freeway and incident management programs.

Xia et al. (2010) proposed a framework for prediction of freeway corridor travel time under incident conditions. Traffic measurements from field detectors and incident data were used to develop various models such as speed estimation, traffic prediction, incident duration prediction, incident impact identification, and corridor travel time prediction models. The results obtained indicate that considering the impacts of incidents in prediction of corridor travel time are more accurate when compared with those methods that do not consider the impact of incidents.

5 Limitations

Travel times used to calibrate regional transportation planning models currently are based on generalized BPR equation established by the federal government, as well as by surveys or sample data collected in the study areas. The data from surveys or field data are not collected regularly or even annually due to financial constraints. They do not account for hourly and day-to-day variations, and are often too simplistic, leading to inaccuracies. Consulted state and regional transportation planners indicated a need for novel and/or improved techniques to generate meaningful travel time estimates, preferably for all the links along major roads in the transportation network.

Different methods or sources of travel time data are currently available to compute travel time and reliability of links in the network. They include data from sources such as Inrix, from AVL units on transit buses, or Bluetooth detectors (apart from GPS units in test vehicles). However, the literature documents limited research comparing and validating the accuracy of the data from these sources.

5.1 Limitations on Technologies for Travel Time Studies

The major problems faced during the usage of satellite images are: vehicle identification, road extraction and manual data extraction. Accurate vehicle detection is a prerequisite for collecting information about vehicles. Several techniques such as inductive learning technique, Bayesian network, vehicle queue model, morphological shared-weight neural network, segmentation algorithm, Principal component analysis, and gradient based method were used to identify vehicles in the past. Methods such as fuzzy method and Deriche filter method were used to extract road details. These techniques and methods need to be analyzed to estimate the efficiency of estimating travel time or velocity alongside vehicle detection.

Several researchers have used Bluetooth detectors to collect travel time in the last few years. However, while collecting data with Bluetooth detectors, pedestrians and bicyclists with detectable devices and buses with multiple Bluetooth devices onboard could be other sources of outliers. The data collected from arterial highways showed a significantly larger variance, probably due to the presence of traffic signals and vehicle diversion to side roads. Further, results tended to be biased towards slower vehicles. So the calculated travel time can be slightly overestimated. Improved processes are needed for the correction of the inaccurate travel times due to Bluetooth biasness.

The length of the corridor can significantly affect the performance of the Bluetooth-based travel time collection system. A short corridor could be more prone to errors and lead to inaccurate results.

Using buses are probes also have some limitations. The signal delay experienced by buses might not be representative of general traffic. The method to define corridors and appropriate distance of road section, acceleration and deceleration at bus-stops, layover time and inadequate sample size could result in incorrect or inaccurate estimates, for which a particular model developed should be applied

5.2 Limitations on Reliability

There is a paradigm shift in focus from intersection-level to corridor-level analysis and performance measures. Travel time reliability (or index or variability) is considered the most viable performance measure though agencies currently use volume-to-capacity ratio for ranking and prioritization of projects. The possibility of capturing dynamic travel time data from sources such as Inrix opens many pragmatic avenues and would be an added asset. However, none of the past research has proved the accuracy of such data for various road classifications in the network. Moreover, reliability calculated as a function of recurring and non-recurring congestion components in the past is solely based on travel times and delays.

Not many researchers have incorporated safety as a component in evaluating reliability. Also, one needs to consider spatial dependency and the effect of congestion on links within the proximity (based on distance - decay effect) to compute travel time variability or reliability and better understand the cause of congestion. Such effects were not given much attention in the past while evaluating reliability.

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