Project Title: Developing a Real-Time Incident Decision Support System (IDDS) for the Freight Industry

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LITERATURE REVIEW

Freight Performance Measures

The trucking industry represents the largest portion of domestic freight movement in the United States. According to the ATA U.S. Freight Transportation Forecast for 2021, the trucking industry's share is about 68% of total tonnage; trucks move more than 80% of freight revenue. Safe and efficient trucking services are essential, not only to provide door-to-door freight transportation, but also to ensure the effective operation of other freight modes and facilities.

Trucks usually occupy more than twice the space of passenger vehicles on the roadway and they carry a higher value of goods. Truck delay due to traffic congestion or other environmental factors have a more significant impact on our nation's economy than automobile delay. The Federal Highway Administration (FHWA) has developed a national congestion monitoring program that uses archived traffic detector data for measuring traffic congestion and travel reliability (Turner et al., 2004; Pu, 2011;). NCHRP Synthesis Report 384 (Kuzmyak, 2008) identified the challenges that many metropolitan planning organizations (MPOs) are facing in forecasting and modeling freight transportation. Many MPOs model heavy trucks as a surrogate for modeling freight activity because trucks account for more than 80% of freight movement in most metropolitan areas. The FHWA and the American Transportation Research Institute (ATRI) recently released findings on the level of truck congestion at 250 freight significant highway locations. Five highway interchange locations in the Twin Cities Metropolitan Area (TCMA) were included in this study (ATRI, 2011).

Schofield and Harrison (2007) reported the status of freight performance measures used in DOTs nationally and suggested a set of relatively broad performance measures including mobility, reliability, economic, safety/environment, and infrastructure for emerging users. Varmar (2008) compiled, organized, and analyzed freight data by mode, performance measure and indicator categories. The report suggested that there is a need to: (1) determine what performance measures or indicators are relevant and most important for freight planning support, and (2) identify freight significant strategic corridors and nodes.

The Minnesota Department of Transportation (MnDOT) Office of Freight and Commercial Vehicle Operations (OFCVO) has identified and included travel time by mode as one of its four performance indicators (MnDOT's Statewide Freight Plan, 2005). MnDOT has also deployed Automatic Traffic Recorders (ATR) and Weigh-In-Motion (WIM) systems statewide for measuring truck weight and classifications with varying axle configurations at highway speeds. Existing ATR and WIM sensors collect truck volume and speed information at selected locations statewide, but they do not provide truck travel time information. On-board GPS systems that collect truck location at a constant polling rate, present an excellent data source for monitoring travel time and reliability. In the past, GPS-based truck trip data was not available and was difficult to collect due to the proprietary nature of the data.

Probe Vehicle Based Performance Measures

With the prevalence of GPS receivers on vehicles and portable navigation devices, probe vehicle based data collection has been increasingly attractive to the transportation community. The GPS based vehicle location data has been used to estimate traffic states and derive travel time information for traffic monitoring (Lund and Pack, 2010; Guo et al., 2008; Smith, 2006; Nanthawichit et al., 2003). Probe vehicle data, when fused with loop detector data and other data sources, can provide more complete and continuous coverage of traffic monitoring. Turner et al. (2011) outlined the primary data requirements for congestion-related performance measures and introduced core data elements and various metadata to ensure data consistency among data providers. They also examined legal and institutional issues related to privacy and Freedom of Information (FOIA) with regard to implementation.

Travel time reliability is one of the key measures of freight performance along interstates or interregional corridors in the nation (Lomax et al., 2003; TTI, 2006). Pu (2011) examined several reliability measures and recommended a median-based buffer index (a measure which compares the 95th percentile of travel time to the median travel time) or a percent on-time rate as more appropriate to handle heavily skewed travel time distributions.

Since 2002, FHWA has established a partnership with the American Transportation Research Institute (ATRI) to measure average truck travel speed on major freight-significant corridors (Jones et al., 2005). A spatial data processing methodology was evaluated and refined by Liao (2008) to improve the effectiveness of freight performance measures. Analyzing truck speed, volume and travel time by location can also help identify network impediments and variations of seasonal flow changes (Liao, 2009). Derived vehicle speed and travel time from the GPS and terrestrial wireless system used by the trucking industry provides potential opportunities to support freight planning and operation on the surface transportation system.

A majority of commercial vehicles are equipped with on-board Automatic Vehicle Location (AVL) systems that collect truck locations at a fixed polling rate. The continuous trajectory information presents an excellent data source for monitoring travel time and reliability. However, GPS-based truck trip data usually are not available and are more difficult to collect due to the proprietary nature of the data. Commercially available travel time information (for example, from INRIX) provides some coverage using aggregated general traffic speed data from loop detectors and other probe vehicle based data sources. However, heavy commercial vehicles are considerably underrepresented in this type of data source.

McCormack and Hallenbeck (2006) used 25 portable GPS data collection units with 1-second polling rate to gather truck positioning data for measuring freight movements along freight significant corridors in Washington State. The study concluded that GPS data can be collected cost effectively and can provide an indication of roadway performance. Based on processed truck speed data, a route model including analyses of truck travel time, delay and reliability can be developed to better understand current freight network performance, freight origin to destination flows, and to study possible solutions to future freight demand growth (Short & Jones, 2008).

In its initial phase, the FHWA FPM initiative measured average travel rates on five freight-significant corridors (Jones et al., 2005). ATRI analyzed the severity of 30 key freight bottlenecks in the U.S. interstate system (Short et al., 2009). Freight bottlenecks occurring at highway interchanges were analyzed using a freight congestion index. Possible causes for the bottlenecks may include roadway geometry (e.g., grade, curvature, and sight distance), capacity (number of lanes), toll booths, speed limit, weather, truck volume vs. general traffic volume, and available lanes of travel for trucks.

MnDOT completed a study on truck parking analysis. The goal was to develop the information necessary to support decisions regarding future approaches to the truck parking problem in Minnesota (Maze et al., 2010). Short and Murray (2008) demonstrated the capability of utilizing FPM data for truck parking analysis. Another application is to utilize the FPM data to evaluate the travel time and delay at border crossings. FHWA conducted a study to address the need to reduce the hours of delay for commercial motor vehicles passing through ports-of-entry (FHWA, 2002). However, manual truck data collection at border crossing plaza is labor intensive and expensive.

Recently, FHWA has led an effort to assess and validate the appropriateness of using GPS data from commercial vehicles to derive mobility and reliability performance measures and to support congestion monitoring on the highway system. Four key factors, including average daily traffic (ADT) per lane, percent of heavy vehicle, grade, and congestion level, were investigated. The preliminary findings indicated that (1) estimates of speed from FPM data are sufficiently accurate for performance measurement on most roadways in the United States, (2) FPM speed estimates show a consistent negative bias due to differences in operating characteristics of trucks and autos, and (3) grade and congestion have the greatest effect on FPM data accuracy among the four key factors evaluated (FHWA, 2012).

National Corridors Analysis & Speed Tool (N-CAST)

ATRI in coordination with the FHWA recently announced (10/22/2012) a beta release of a Freight Performance Measures (FPM) tool that expands on the scope and functionality of the original FHWA-sponsored “FPMWeb” application (www.freightperformance.org/). The National Corridors Analysis & Speed Tool (N-CAST, www.atri-online.org/n-cast) provides key roadway performance and truck mobility information for the U.S. Interstate Highway System. The N-CAST database includes the average speed and a proportion of total GPS data points for each one-mile segment during each AM peak (6-10AM), mid-day (10AM-3PM), PM peak (3PM-7PM), and off peak (7PM-6AM) periods. The N-CAST tool has the potential to be integrated with existing truck data sources to generate critical performance measures (such as delay and reliability) to provide technical guidance to stakeholders in the freight industry.

Incident Detection

Rapid incident detection can reduce the impact of traffic congestion and the risks associated with secondary incidents. It is also critical for improving freight mobility, just-in-time deliveries, reducing unnecessary idling, and improving safety. An incident delay estimation model will be developed to estimate the potential delay when an incident is identified. Estimated delay information provides a key decision support element for freight dynamic route guidance which gives the freight driver or the dispatcher real-time route-specific information allowing them to make the best decision about whether to wait out the incident or take an alternative route.

Ozbay & Kachroo (1999) raised three basic issues (surveillance, algorithm, and verification issues) concerning incident detection. New sensors using different technologies have been adopted by DOTs. Sensor reliability, performance under different environmental condition, accuracy, real-time performance, and cost play pivotal roles in the selection of a detection system. Two types of algorithms are commonly used for incident detection and delay estimation on freeways: point-based and spatial-based algorithms.

A number of incident detection algorithms have been described in the literature. However, these algorithms were based on roadway point data, for example, loop detectors or fixed traffic detectors. The point-based approach uses comparative or pattern recognition, statistics, traffic modeling, and artificial intelligence based algorithms for incident detection. As such, these systems do not adequately generate continuous roadway/traffic conditions in the real world since they are neither ubiquitous nor free from malfunction and error.

The spatial measurement based approach uses video camera or probe vehicles which are becoming more available for traffic engineering applications. In recent years, probe vehicle based approaches have been applied in limited instances, with most probe based incident detection algorithms having only been tested in a simulation environment (Baykal-Gursoy et al., 2006; Li et al., 2006; Zeng & Songchitruksa, 2010) and/or limited to metropolitan areas (Giuliano 1989; Yu et al, 2007).

Martin et al. (2000) evaluated a range of incident detection technologies for use in the Utah Department of Transportation's (UDOT) Advanced Traffic Management System (ATMS). Based on the research findings, the research recommended that cellular telephone technology be used as the primary form of incident detection.

<u>Incident Duration and Delay</u>

An incident is defined as any occurrence of events that affects roadway capacity (Giuliano, 1989). Incident duration is the time taken to remove an incident and recover the road capacity. It varies significantly depending on numerous factors, including incident type, location, response time, and clearance time. It is almost impossible to predict incident duration with acceptable accuracy even when a great deal of historical data is available.

Predicting traffic incident delay is a challenging task in Advanced Traffic Incident Management (ATIM). The duration of an incident delay consists of the incident time period (detection, response, and clearance time periods) and the recovery time. In the recovery period, all obstacles are removed from the roadway and the traffic queue begins to resolve until the traffic is restored back to the normal condition. Although traffic recovery time is crucial to determining incident induced delay, relatively few studies have focused on modeling post-incident traffic recovery time (Saka et al., 2008; Zeng & Songchitruksa, 2010).

The most widely used technique to estimate incident delay is the use of deterministic queuing based delay estimation technique proposed by Morales (1989) who used a simple deterministic queuing model as an analytical procedure for estimating delay under a specific incident scenario. Traditionally, incident duration and delay have been typically modeled in the form of lognormal distributions (Golob et al., 1987 and Sullivan, 1997), the log-logistic hazard-based model (Jones et al., 1991; Nam & Manning, 2000), and the truncated regression model (Khattak et al., 1995). Giuliano (1989) included incident type and occurrence time of day in an incident time estimation model based on statistical distributions. Khattak et al. (1995) formulated a clearance time prediction model using incident type and severity as the most significant impact factors.

Fu (2004) developed a fuzzy queuing model to predict possible delay of a vehicle near an incident location based on real-time information, traffic demand, queuing condition and lane closure. Fu (2004) demonstrated through simulation that incident delay prediction from a deterministic model is highly sensitive to the uncertainty of traffic conditions. Boyles & Waller (2007) took incident duration distribution from a Bayesian classification and lognormal distribution to account for uncertainty in incident duration prediction. An analytical formula for total incident delay was developed and tested in simulation using four different traffic demand profiles. They concluded that failing to properly account for uncertainty will possible result in underestimating incident delays by up to a factor of two.

Skabardonis et al. (1996 & 1997) developed a methodology for estimating incident delay using data collected along a segment of highway I-880 in the San Francisco Bay Area. In addition, Skabardonis et al. (1999) studied the incident patterns on I-10 in Los Angeles, identified major factors affecting incident frequency, and compared the results with previous analyses on I-880. They concluded that the resulting development and analyses could help improve incident management and support the development and calibration of incident detection algorithm in simulation models.

Ji et al. (2011) developed incident recovery and delay models based on a macroscopic cell transmission model (CTM) to reproduce the traffic behavioral phenomena. They found that the recovery time increases significantly with the increase of traffic demand, which has a more significant influence over incident time than recovery delay.

<u>Incident Detection Performance Measures</u>

The following parameters have commonly been used to measure the performance of incident detection algorithms. The parameters are detection rate (DR), false alarm rate (FAR), and mean time to detect (MTTD).

1. Detection Rate (DR):

$$DR = \frac{Number\ of\ detected\ incidents}{Total\ number\ of\ recorded\ incidents} \times 100\%$$

2. False Alarm Rate (FAR):

$$FAR = \frac{Number\ of\ detected\ incidents\ that\ are\ NOT\ incidents}{Total\ number\ of\ actual\ incidents} \times 100\%$$

3. Mean Time to Detect (MTTD):

$$MTTD = \frac{1}{N}\sum_{i=1}^{N}(t_{id} - t_{io})$$

Where,

t_{io} is the time incident actually occurred,
t_{id} is the time incident was detected by the algorithm, and
N is the number of incidents.

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