A GUIDEBOOK FOR FREIGHT TRANSPORTATION PLANNING USING TRUCK GPS DATA

DRAFT FINAL REPORT

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EXECUTIVE SUMMARY

Freight transportation plays a very important role for the United States (U.S.) economy. According to the U.S. Department of Transportation (US DOT, 2009), the value of international merchandise trade, transported through the national freight gateways, increased by 9% from 2008 to 2009 and reached $3.4 trillion (in 2009 dollars). It is crucial to understand freight movements in order to improve performance of freight transportation corridors and freight facilities. Trucks remain an important link of todays' supply chains as the majority of goods in the U.S. and around the world are delivered to their final destination by trucks. Taking into consideration increasing roadway network congestion, it is crucial to obtain detailed truck trip data to assist with freight transportation planning and operations. With recent advances of Global Positioning System (GPS) devices, various public and private transportation agencies have the opportunity to obtain more precise information regarding truck travel patterns.

The main objectives of this study include: 1) review of current practices using truck GPS records to evaluate traffic conditions at freight corridors, 2) analysis of existing procedures to process truck GPS records, and identification of freight performance measures (FPMs) commonly used by researches and practitioners, 3) development of algorithms that can be used by Tennessee Department of Transportation (TDOT) to process truck GPS data and estimate link FPMs for the Tennessee (TN) Freight Transportation Network, 4) development of freight facility performance indicators, 5) analysis of inter- and intra-city truck trips within the State of TN.

Contributions of the conducted research can be summarized as follows: 1) an up-to-date overview of current practices and methods for processing truck GPS data, 2) development of the methodology to compute link FPMs for the TN Freight Transportation Network, 3) assessment of performance of selected freight facilities, located in the Greater Memphis Area (TN), 4) design and application of algorithms for identifying truck trips, and 5) development of an integrated ArcGIS application for estimating link FPMs. The proposed methodologies, developed algorithms, and the new tool can be used by TDOT in identification of bottlenecks, freight transportation planning, resource allocation between highway segments that require improvements, development of strategies for enhancing performance of freight facilities, identification of peak hours at freight transportation corridors and freight facilities, highway segment reliability assessment, etc.

1. INTRODUCTION

One of the challenges in freight transportation planning is obtaining accurate truck trip data. Several databases exist (e.g., Commodity Flow Survey, Freight Analysis Framework, TRANSEARCH, etc.) that provide detailed information regarding freight movements between different states, counties, and metropolitan areas by all transportation modes (Barker & Chen, 2008; Battelle, 2011). However, aggregate commodity flows, moved by trucks, should be split into truck trips. The subject is important, especially in the U.S, since trucks cause increasing traffic congestion and are the primary mode of freight transportation (either by choice or necessity - e.g., last mile deliveries). Based on recent statistics, published by Forbes (2014), Los Angeles, CA (U.S.) is the third congested city in the world after Brussels (Belgium) and Antwerp (Belgium). According to 24/7 Wall St. (2014), "*at peak hours, traffic on Interstate 405 in Los Angeles moved at just 14 miles per hour, adding 26 minutes to what should be an eight minute drive*".

In the last twenty years various technological advances from the passenger industry have been adopted by the trucking industry (with the latest endeavor being autonomous trucks[1,2]). At the end of 20th century private and public agencies began utilizing GPS devices to analyze truck travel patterns and to estimate freight performance measures (FPMs). Nowadays, GPS technologies are very advanced and capable to detect even minor truck movements. For example, Cheaters CoPilot Real-Time GPS Tracker locates and tracks a vehicle anywhere in the world (Cheaters Spy Shop, 2014). In general, data provided by GPS devices includes spatial information (X and Y coordinates), time stamp, heading, spot speed, and a unique truck identifier. Depending on the device, additional information can also be available such as engine on/off, stop duration, weather conditions, distance, etc.

Truck GPS data processing remains a challenging task as will be discussed in more detail in the next section. The American Transportation Research Institute (ATRI) in collaboration with the Federal Highway Administration (FHWA) developed the Freight Performance Measures Web-Based (FPMweb) Tool in 2011. The FPMweb Tool estimates operating speeds of highway segments based on truck GPS observations for 25 interstate corridors (FHWA, 2011). Average speed values can be retrieved for a given state, corridor, year, month, day, and time of the day. Along with numerous advantages, FPMweb developers highlighted several drawbacks of the tool (FHWA, 2011): a) lack of commodity and origin-destination data; b) inability to forecast future truck volumes and speeds for given interstate segments; c) analysis of average and not individual truck speeds. Along with the FPMweb tool, a number of researchers developed various approaches for analyzing raw truck GPS data and estimating network and freight facility FPMs, which also have certain limitations (e.g., device

[1] The future begins today: Technology that will revolutionize trucking is already here. Commercial Carrier Journal - Fleet Management Magazine, Accessed July 10th, 2014, http://www.ccjdigital.com/

[2] 'Driverless' trucks become reality: Daimler unveils prototype, dubbed Highway Pilot. Commercial Carrier Journal - Fleet Management Magazine, Accessed July 10th, 2014, http://www.ccjdigital.com/

spatial errors, associating the observation with a link, identifying genuine stops and trip ends, data collection, effect of non-recurring congestion).

The main objectives of this project are:

- Review the existing practices of using truck GPS data to evaluate performance of busy freight corridors;
- Develop algorithms to process GPS truck data and estimate FPMs;
- Evaluate TN freight corridors with a particular focus on travel time and flow;
- Provide performance indicators for freight facilities in TN;
- Analyze inter- and intra-city truck traveling patterns;
- Provide data to support development, calibration, and validation of TN State and MPO travel demand models.

The rest of the report is organized as follows. The next section presents an up-to-date literature review on freight transportation network analysis using truck GPS data. The third section describes the data available and the methodology for data processing. The fourth section presents FPMs, estimated for TN freight transportation network, while the fifth section focuses on developing performance indicators for freight facilities in the Greater Memphis Area (TN). The sixth section analyzes inter- and intra-city truck traveling patterns, while the seventh section presents the developed ArcGIS tool for estimating FPMs within the ArcGIS domain. The last section concludes the report and proposes the scope of the future research.

2. LITERATURE REVIEW

The main objectives of the literature review were to: 1) analyze studies that used GPS data to evaluate traffic conditions at freight corridors, and the procedures employed to process the data, 2) identify freight performance measures (FPMs), commonly used by researches and practitioners, 3) determine drawbacks and possible errors that can be caused by GPS devices, and 4) survey methodologies that can detect truck stops for delivery, refueling, rest, etc. (not due to congestion, a.k.a. outliers). All collected studies were classified into 3 categories, depending on how the average travel time (TT) was estimated: A) link TT (LTT) – travel time is computed for a link; B) trip TT (TTT) – travel time is calculated for a trip (in some cases also for a tour, i.e. tour duration); C) miscellaneous – different from A and B. TT estimation was chosen as a classification criterion, because as a result of conducted literature review it was found that the most of FPMs could be determined based on the average TT values. The majority of studies (53%) used GPS data to estimate LTT, and roughly 34% of studies analyzed vehicle trip patterns (e.g., average trip speed, average trip time, trip length, etc.) and tour characteristics (e.g., generation of tours by traffic assignment zone, number of stops, stop duration, stop purpose, stops by time of the day, etc.). Several studies did not present any data analysis results and focused on development of various methodologies and frameworks that could be implemented to process GPS data and produce FPMs (Fisher et al., 2005; NCHRP Report 818, 2008; Dong & Mahmassani, 2009; Memphis Urban Area MPO, 2013). Next we present a detailed description of the studies reviewed by class.

2.1 LTT Focus

Quiroga & Bullock (1998) proposed a methodology to perform studies for estimating TT of roadway segments using GPS and Geographic Information System (GIS) technologies. GPS data were collected from three metropolitan areas in Louisiana, LA (i.e., Baton Rouge, Shreveport, and New Orleans). Average TT and travel speed (TS) values were computed for all highway segments. A length of segment comprised 0.2-0.5 miles. GIS was utilized to process queries, produce reports and colored-theme maps, depicting TT by link. Results showed that shorter GPS sampling periods (1 to 2 seconds) decreased errors in TS estimation. The authors underlined that median speed was a more accurate measure of the central tendency than mean speed as the latter was affected by incidents occurred during peak hours. Quiroga (2000) conducted a similar study for the LA transportation network (Baton Rouge). Highways were separated into segments, and LTT was calculated for each segment. The author also provided a procedure for estimating several other performance measures (acceptable TT, segment TS, travel rate, delay, total delay, delay rate, and relative delay rate) that could be used for quantifying congestion.

Storey & Holtom (2003) used GPS data to compute link TS (LTS) and LTT at West Midlands highways in the UK. The GPS device provided information every 60 seconds, while a vehicle ignition was being on. Around 20% of the data were discarded, as they provided coordinates (latitude and longitude) that didn’t belong to the road network. Links of the considered highways were separated into 50 m segments, and the average TS was calculated for each segment. It was assumed that segments between two GPS data points had the same average speeds. The journey times at the link level, estimated using GPS data, were calibrated, and results demonstrated an acceptable accuracy of the proposed approach. The analysis of journey speeds indicated the existence of congestion issues at major junctions of links, leading to the city center.

Jones et al. (2005) presented a methodology that could be applied to measure performance of busy freight corridors. The procedure was separated in 4 steps: 1) identification of freight corridors, 2) review of data collection technologies, 3) System Alpha Test, and 4) System Beta Test. Top ten US cities with the highest truck volumes were identified using American Transportation Research Institute (ATRI) satellite position reports. The busiest freight corridors were determined for each of those cities based on the data, provided by Cambridge Systematics. Different methods of data collection were described: satellite-based systems, terrestrial wireless systems, hybrid systems, on-board systems, and fixed site systems. GPS was found to be efficient for the analysis. The Alpha Test was performed to associate a vehicle ID with a highway segment geo-position, to calculate the average vehicle TS, and to remove outliers that could affect the accuracy of speed estimation. The main purpose of the Beta Test was to process TT and TS at each segment and to transfer the data to the visualization tool. As a result of the conducted study, the authors created a map, depicting the average TS at the busiest US corridors.

Ando & Taniguchi (2006) developed a model for the vehicle routing problem with time windows (VRPTW), minimizing the total cost of LTT uncertainty and penalties due to early arrival/delayed arrival to customers, requesting a particular time window. The information on LTT was collected using sensors, radio beacons, and GPS devices. Truck arrival times were assumed to follow a normal distribution. Statistical TT distributions were obtained for each link and were approximated to triangular distributions. An additional linear regression analysis was performed to quantify relationship between LTT and link distance. The traffic flow simulation was used to estimate TT distribution for each route and determine the optimal visiting order of customers. Results indicated that the proposed approach reduced the total cost by 4.1%, the total cost standard deviation by 75.1%, and mitigated environmental impacts, caused by trucks.

Schofield & Harrison (2007) underlined the importance of FPMs for the US Department of Transportation (DOT), State DOTs, and various transportation agencies. Practices for assessing performance of freight corridors, employed in different states, were described in the report. The study focused on developing appropriate FPMs in the Texas (TX) area. The busiest state highways were identified. GPS records were provided by ATRI for the entire year of 2005. The authors indicated that the location error for each observation could reach up to ¼ mile. The segment length comprised 50 miles. TT, TS, and TT index (TTI) were estimated for each segment. Changes in travel pattern were noticed when the Hurricane Rita notification was announced. The report provided distribution of hourly truck traffic. Future research directions included comparison of the actual speed with the free-flow speed for each segment, estimating FPMs for highway corridors in case of non-recurring congestion, calculating of truck wait time at boarders, consideration of other FPMs, etc.

Liao (2008) compared two ATRI FPM database systems: the GIS – based system and the Structured Query Language (SQL) – based system. The second system was able to process truck GPS data without the GIS software. The GIS-based system allowed separation of a highway into segments with minimum size of 10 miles. The minimum segment size for the SQL-based system was 3-miles. It was found that smaller segments improved accuracy of average speed estimation. The author underlined the importance of trip filtering parameters and projection algorithms. The GIS-based system employed a ¼ mile radius search method, while the SQL-based system used more complex snapping algorithm. Several deficiencies of the SQL-based system were mentioned (e.g., duplication of data in tables). According to the report, the ideal FPM system should include the SQL-server, capable to process data from external applications and visualize performance measures using a GIS - based software.

Liao (2009) evaluated performance of I-94/I-90 freight corridor between St. Paul, Minnesota (MN), and Chicago, Illinois (IL). GPS data for 12 months (May 2008-April 2009) were provided by ATRI. The raw data were processed in ArcGIS software, GPS points were snapped to the nearest route, and then the average TS was computed for each 3-mile segment. The analysis was performed for the key corridor locations (i.e., St. Paul, O'Hare Airport, I-90 toll highway), including truck speed, volume, TT reliability, truck stops, truck stop duration, etc. Results indicated that average speeds declined in areas approaching Chicago from 55 mph to 40 mph and lower. The westbound traffic between St. Paul and Madison had higher speed standard deviation than the eastbound traffic. A significant speed standard deviation and the average speed drop were observed on I-90 toll highway, leading to Chicago.

McCormack (2009) described how GPS data were used to improve performance of the Washington State (WA) freight network. LTT and its reliability were chosen as performance measures. The data were collected from various vendors. GPS records were received with frequencies, varying from vendor to vendor (every 30 seconds, every half-mile, every 15 min, etc.). ATRI and FWHA developed a program, focusing on performance of interstate corridors. A specific algorithm was developed to define origin and destination of each trip, using stop time, travel distance, GPS signal quality, and location of travel. It was highlighted that some GPS points were removed as they provided erroneous data. In some cases truck information was known only every 15 min. The author concluded that truck GPS data could be very useful for public agencies to evaluate conditions of busy freight corridors and to identify bottlenecks.

The Washington Department of Transportation (WSDOT) outlined the main features of the Truck Performance Measure Program at the Washington State Transportation Commission (2011). The WSDOT initiated this program in 2007. GPS data process and analysis are similar to the ones, described by McCormack (2009). LTT and its reliability were selected as performance measures. The main objective of the program was to identify and rank bottlenecks at the WA State highways. Four criteria were developed for prioritizing highway segments for further improvements: 1) Truck speed below the congestion threshold (60% of posted speed limit); 2) Average speed; 3) Speed distribution; 4) Truck volume. The authors underlined that the program was efficient, and its future success would be highly dependent on the access to the data, owned by trucking companies. McCormack et al. (2011) and McCormack & Zhao (2011) conducted a similar study, using the same FPMs as McCormack (2009). The authors described the process of bottleneck identification and prioritization in WA. The overall procedure was subdivided into 5 parts: a) Segment the roadway; b) Add attribute information to the segments; c) Geo-locate the truck; d) Locate the bottlenecks; e) Rank the bottlenecks.

Chien et al. (2011) estimated link and path TT, variability of TT by departure time of the day and days of the week for 18 New Jersey highway corridors. The data were collected from GPS enabled devices, installed into different vehicles, traveling along considered highways between October 8, 2007 and April 21, 2008 from 6.15 am to 8.15 am during weekdays. The buffer index (BI) and 95th TT percentile were calculated for each route. Results indicated that TT on the most of roads followed a shifted log-normal distribution. The lowest mean TS was found for a segment NJ 208 & NJ 4 (28.3 mph), while the highest one was determined for a segment NJ 24 & I-78 (59.9 mph). The highest TT coefficient of variation (TTCV) was calculated for a segment US 46 & NJ 3 during A.M. peak hour (TTCV=0.4). The lowest TTCV was estimated for US 1 (TTCV=0.09). The scope of research didn’t include assessment of incident impacts on link/path TT due to data limitations.

Cortes et al. (2011) used GPS data to evaluate performance of a bus transportation system in Santiago, Chile. Data were collected for 6,178 buses operating over a one week. The authors applied a path rectification procedure to determine paths for each route. The path rectification identified line segments that were located close to GPS points with an acceptable error. Rectified paths were separated for grid elements. An average bus TS was calculated for each grid element. The report presented speed diagrams illustrating bus speeds for each route segment during a given time of day. The proposed methodology was found to be efficient for problem identification in bus operations (e.g., low speeds at certain segments, congestion issues, improper traffic light times, etc.).

The Federal Highway Administration (FHWA) Office of Freight Management and Operations (2011) developed a Freight Performance Measures (FPM) web Tool to evaluate performance of the US freight corridors using truck GPS data. The FPMweb Tool estimates the operating speed of a given segment by averaging over the total number of speed observations. The segment length was assumed to be 3 miles. The tool can process data by time and date for 25 interstate corridors. Several drawbacks of the tool were mentioned: 1) it doesn’t provide commodity and origin-destination data; 2) it is not capable to forecast future truck volumes and speeds; 3) it is useful for analysis of average and not individual truck TS.

Figliozzi et al. (2011) developed an algorithm for assessing TT reliability of the I-5 interstate in Oregon (OR). GPS data were provided by ATRI. The corridor was separated into particular segments. Traffic flows were estimated for every mile and direction of each segment. Smoothing was performed by averaging counts for 20-miles segments. Volumes were also determined for different seasons of the year. Segments were analyzed based on two factors: a) time of the year and corresponding weather conditions, and b) truck density pattern along the segment. The designed algorithm was able to estimate 95%, 80%, and 50% percentile TT for each segment (if traffic counts were sufficient at considered segment) using GPS data. Minimum and maximum TS limits (10 mph and 80 mph) were set to remove outliers. Results indicated that differences between three types of TT (i.e., 95%, 80%, and 50% percentile TT) were significant for urban areas and relatively small for rural areas. TT costs per mile were calculated and presented in the paper.

Wheeler & Figliozzi (2011) assessed effects of recurring and non- recurring congestion on freight movement characteristics (LTS, LTT, and TT reliability) at the Oregon I-5 Interstate (the same freeway as studied by Figliozzi et al., 2011). Along with GPS data, the authors used corridor TT loop data and incident data (provided by the Oregon DOT). A specific methodology was developed to identify through trucks (that don't make any stops and provide at least two GPS readings in the beginning and in the end of the corridor). Results of a recurring congestion analysis indicated that the highest TT and TTCV were observed during evening peak. As for non-recurring congestion, it was found that incidents significantly affected truck TS in the incident area throughout the day. Congestion cost estimates indicated that daily delay costs for freight vehicles were 19% higher that free-flow costs without variability consideration (and 22%-31% higher with variability consideration). GPS data were found to be more accurate in estimating TT than the loop sensor data.

Blazquez (2012) addressed the problem of snapping GPS points to roadways segments. Various techniques, resolving spatial ambiguities, were listed (e.g., semi-deterministic map-matching, probabilistic map-matching, fuzzy logic map-matching, Kalman filter approach, etc.). The author developed a topological map-matching algorithm for snapping GPS points. The algorithm was able to identify a feasibility of the path between two snapped points (by comparing a speed along the path and the average vehicle speed). Numerical experiments were conducted using the data, collected by winter maintenance vehicles in Wisconsin (WI) and Iowa (IA). Preliminary calculations were performed to determine the buffer size. Results demonstrated the efficiency of the presented methodology. It was found that the GPS spatial error decreased the percentage of solved cases on average by 30%. Frequent sampling intervals provided more accurate results. An increasing number of consecutive GPS points improved performance of the algorithm.

Liao (2014) used GPS data, provided from ATRI for twelve months in 2012, to estimate FPMs, such as truck mobility, delay, and reliability index, and to identify bottlenecks for 38 key freight corridors in the Twin Cities metropolitan area (TCMA). To validate the methodology the computed average truck speeds and hourly volume percentage at certain locations were compared with the data from weight-in-motion (WIM) sensors and automatic traffic recorders (ATR). Truck bottlenecks were identified and ranked based on hours of delay and number of hours with TS less than the target speeds, set by Minnesota DOT during A.M. and P.M. peak hours. Also the truck congestion cost was estimated for TCMA to be $212 and $286 million annually based on ATRI's truck operation cost and Texas Transportation Institute's (TTI) truck congestion cost respectively. As another part of the study, one month data from FHWA's National Performance Management Research Data Set (NPMRDS) was used to compute freight mobility and speed variations along Minnesota's National Highway System.

Wang et al. (2014) suggested naïve and mapping methods to estimate LTT using GPS data. The naïve method computed the average TS and its variability on each link individually. The variability was measured by a standard deviation. The authors presented a mathematical formulation for a mapping method with an objective, minimizing the total difference between the recorded trip times and the estimated trip times for all trips. Both methodologies were tested on the San Antonio corridor (TX) and the Milwaukee highway corridor (WI). The mapping method was found to be more efficient, since it was able to analyze truck trips with large road intervals covering multiple links.

2.2 TTT Focus

McCormack & Hallenbeck (2005) suggested two data collection methodologies to evaluate truck movements along particular roadway corridors in WA and to measure performance of freight mobility improvement projects against benchmarks. The first approach was based on implementation of Commercial Vehicle Information System and Networks (CVISN) electronic truck transponders, which were installed on the windshields of approximately 20,000 trucks. A specific program was designed to estimate TTT using the data, provided by transponders. Another technology employed GPS devices that transmitted truck movement records every 5 seconds. The information, collected using CVISN and GPS, was processed to identify congested segments, TTT, and TT reliability. It was highlighted that both techniques might be efficient for analysis of truck trip patterns. However, selection of a methodology should depend on the data required for a particular benchmark project.

Greaves & Figliozzi (2008) processed passive GPS data from 30 trucks to identify characteristics of freight movements in the Greater Melbourne region, Australia. The authors underlined difficulties of getting GPS data from trucking companies. The GPS device was installed into each truck and provided second-by-second information. The trip identification algorithm was developed to determine trip ends. Around 5% of records were inaccurate due to loss of satellite signal and were excluded. The final output of the processed data included a summary for all truck trips and tours. The average number of stops per tour was found to be 12.2 stops. The lowest average TS were observed for morning and evening peak hours. A trip length distribution was presented in the paper. It was mentioned that GPS data didn't provide additional information about driver behavioral features (respond to weather, empty/loaded vehicle, type of commodity, etc.) that might be useful for the analysis.

NCHRP Report 008 (2010) highlighted the importance of truck GPS data for evaluation of freight corridors performance. The study was conducted for the following metropolitan areas: Los Angeles (California CA), Chicago (IL), Phoenix (Arizona AZ), and Baltimore (Maryland MD). GPS records were used to identify the number of stops during the trip, distance between stops, stop purpose, stop location, TT between stops, etc. It was found that likelihood of making trip in the tour depended both on the truck trip purpose in the current and subsequent stops. Besides, the information about trip origin, origin land use, and trip destination could be used to predict the destination land use. The highest percent of stops in industrial land use (27%) was observed in Chicago. Retail and commercial land use stops were more common in Los Angeles (31%). The most of residential land use stops occurred in Phoenix (31%).

Bassok et al. (2011) demonstrated how truck GPS data, collected from the device vendors, could be used for the analysis of freight movements in the WA area. The authors developed an algorithm for identifying trip ends. Truck stops for refueling, rest and delivery were filtered out (dwell time threshold comprised 180 sec, which is a common standard in WA). A threshold speed limit of 5 mph was set to determine trip ends. The analysis was performed for 91 days in the Puget Sound region (WA), when 2,400 trucks made 22,000 tours and 215,000 individual trips. Results indicated that each truck made on average 9 tours and 10 trips per tour. Besides, around 2 truck trips at each tour were made to grocery stores. Areas with higher population density produced more truck trips.

Golias et al. (2012) used truck GPS data to analyze freight movements within the Greater Memphis area in TN. Available data provided information about truck trips from September 1, 2011 to October 30, 2011. The highest truck volumes on I-40 were observed during evening peak hour between 4 pm and 5 pm. Trip durations were increasing for a period since 10 pm until 8 am. This was explained by the fact that most of truck drivers stopped for rest during that time interval. Truck turn times were considered for 4 types of facilities: public warehouses, private warehouses, distribution centers, and intermodal facilities. The authors developed regression models predicting facility turn times depending on the truck volume per time interval and facility type. The overall fit of proposed models was found to be low due to small sample size. Intermodal facilities and private warehouses demonstrated the best fit. The scope of research included truck stop and rest stop demand analysis. All truck stops with duration from eight to twelve hours were considered. The authors provided frequency of truck stops based on the time of the day for major TN rest stop areas.

Pinjari et al. (2012a, 2012b & 2013) investigated how GPS data, provided by ATRI, could be used for assessing performance of freight corridors and transportation planning in Florida (FL). The study was directed to identify FPMs for state highways, build a truck-trip database to understand truck travel patterns, and derive truck trip O-D tables for the Florida Statewide Model. Several FPMs were suggested, such as average trip TS (TTS), reliability measures (TTI and Planning Time Index PTI), analysis of chokepoints, truck flow analysis, etc. Truck flows were estimated by month of the year and by day of the week. It was found that seasonal variations of truck speeds were not significant. However, travel patterns during weekdays were different as compared to weekend travel patterns. Trip Origin Destination Identification algorithm was designed to define O-Ds. The procedure was validated based on comparison with Google Earth and discussions with ATRI and FDOT. Trip length and trip duration distributions were provided in the report.

You (2012) studied tour-based models for drayage trucks at San Pedro Bay Ports in Southern California area. The main objective was to develop a methodology, which could help to alleviate congestion of trucks at the gates, reduce truck turn times at the ports, and mitigate environmental impacts. A tour-based approach was found to be more efficient for modeling behavior of drayage trucks than a single trip-based approach. GPS data for 545 drayage trucks was provided by the ports of Los Angeles and Long Beach. The collected data were processed to identify closed and open tours. It was observed that each truck made on average 1.7 tours and 6.2 stops per day. A typical tour TT lied between 3 and 9 hours. The author suggested two approaches to analyze trip-chaining behavior of drayage truck movements: 1) A disaggregate level tour-based model based on Sequential Selective Vehicle Routing Problem (SSVRP); 2) An aggregate level tour-based model based on Entropy Maximization Algorithm (EMA). It was underlined that the SSVRP was more realistic approach for modeling drayage truck tours.

Bierlaire et al. (2013) used GPS data, generated by smartphone Nokia N95, for route choice modeling in the Lausanne area, Switzerland. The authors listed advantages (short warm-up time, full track of trips) and disadvantages (weak signals, not accurate data points in some cases, high energy consumption) of GPS capable phones. A probabilistic map matching method was developed to estimate the likelihood of choosing a particular path based on the smartphone GPS data. A path with a higher log-likelihood was more preferable among all alternative paths. Speed distributions were generated from the observed speed data. Data points with speeds less than 8 km/h were filtered out. Results obtained by the suggested approach were close to the ones, provided by the Mobility Meter (dedicated GPS device, carried by the person along with smartphone).

Carrion & Levinson (2013) assessed the effect of converting I-394 (between Minneapolis and St. Paul, MN) High Occupancy Vehicle (HOV) lanes to High Occupancy Toll (HOT) lanes. The main objective was to determine a traveler's respond to increasing TT reliability on HOT lanes. The GPS devices were installed in 54 vehicles to collect the detailed trip information. A 20-meter buffer was used for all roads. GPS points, located outside the buffer area were excluded. The authors developed an algorithm to identify the commute trips (from origin to home location, from destination to work location and vice versa). The preference of travelers for choosing tolled or non-tolled routes was analyzed using discrete choice models. The utility function included TT measures, travel cost, and socio-demographic factors. TT reliability was measured by standard deviation, shortened right range, and interquartile range. Results of study indicated that the desire of travelers to pay tolls for reliable routes was dependent on how they perceived reliability savings.

Golias & Mishra (2013) used truck GPS data, provided by ATRI for the months of September and October 2011, to evaluate the impact of the new Hours of Service (HOS) rule for Commercial Motor Vehicles (CMV) drivers on traffic conditions using as case study a part of I-40 network between Memphis and Nashville, TN. Existing truck TTT and volume by time of day on a daily and weekly basis were computed by statistically analyzing the provided data, while future conditions were estimated for the shifted truck trips which had to be identified based on the new working hours. The Level of Service (LOS) for both cases was calculated based on the methodology suggested in Highway Capacity Manual with some adjustments because of the low percentage of data used. By comparing LOS in both cases it was found that the new HOS would worsen LOS, as truck volumes would increase at certain routes after each rest period, which might cause delays.

Kuppam et al. (2014) demonstrated how truck GPS data could be used for Tour-Based Truck Travel Demand Modeling. The study was conducted based on GPS data for 22,657 trucks and 58,637 tours, purchased from ATRI. The number of tours for each truck was determined using the information about truck coordinates, changes in TT and TS. The accuracy of vehicle stops was checked using highway maps and Google Earth. The following Tour-Based Truck Models were developed for the Phoenix region (AZ): tour generation, stop generation, tour completion, stop purpose, stop location, stop time of day choice. It was found that construction tours had lower tendency to making stops, while government-related tours were dedicated to making more stops. An increasing number of stops caused incompletion of tours for the majority of trucks. The purpose of the previous stop influenced duration of the next stop.

2.3 Miscellaneous

Fisher et al. (2005) proposed a modeling framework to evaluate the Los-Angeles County (CA) freight transportation network performance. The framework combined characteristics of logistics chain and tour-based models. Logistics chain models were found to be useful for cases, when particular types of goods were transported from the production points to the assigned destinations. Those models combined information from three layers: economic, logistics, and transport. Tour-based models were efficient to determine vehicle tours and trips without focusing on commodity type. Those models provided the following information: generation of tours by zone, number of stops during the tour, stop purpose, stop time, stop location, number of trips during the tour, etc. The suggested integrated framework was found to be promising for analysis of freight movements.

Cambridge Systematics (2007) indicated that GPS devices could be effectively employed along with travel diary surveys for data collection and understanding truck traveling patterns in urban areas. Several disadvantages of using diaries were mentioned: 1) process of data depends on willingness of drivers to complete the form, 2) lack of the contact information, 3) some vehicles may not be registered in the study area, 4) low response rates due to confidentiality issues, etc. GPS devices, installed into trucks, might be utilized to validate the data, collected from driver diaries (e.g., trip origin, trip destination, routing, speeds at particular road segments). However, GPS data don't provide any information regarding commodity hauled, size of shipment, and type of carrier operation (e.g., truckload, LTL, private). Besides, high cost of GPS devices was found as a major implementation issue.

NCHRP Report 818 (2008) suggested a set of performance measures that can be used to evaluate highway conditions. Performance measures were classified into two categories: individual measures (related to an individual traveler) and area measures (related to the area, region or corridor). Delay per traveler, TT, TTI, BI, and PTI were referred to individual measures. Area measures included total delay, congested travel, percentage of congested travel, congested roadway, and accessibility. The report also distinguished between the performance measures as primary and secondary depending on the analysis area.

Dong & Mahmassani (2009) developed a methodology for estimating TT reliability. TT reliability was associated with traffic flow breakdowns and delays. A probability distribution function for pre-breakdown flow rate was calibrated using field data, from I-405 Irvine freeway in CA. The normal distribution was the most suitable for the Jeffrey section of the freeway, while the Weibull distribution provided the best fit for the Red Hill section. The authors assumed a linear relationship between breakdown and pre-breakdown flow rates. The delay was estimated based on TTI and flow rate values. Numerical experiments were performed for I-405, and results indicated that the proposed concept was efficient for relieving congestion and TT delays.

The Memphis Urban Area MPO (2013) conducted a Freight Peer to Peer Program meeting to exchange the best practices between regional freight industry stakeholders from public and private sectors, and also various transportation agencies. Establishment of performance measures for freight transport was found to be a very important aspect in prioritizing highway improvement projects. It was underlined that performance measures should be set at state level with assistance of regional agencies if necessary. Performance measures should take into consideration interests of both private and public sectors.

2.4 Summary

The main features of reviewed studies are presented in Table 1. The table includes information about vehicle types considered by researchers (trucks and/or cars and/or buses), FPMs (LTT, LTS, TTT, TTS, TT reliability, TT variability, etc.), tested networks, and difficulties encountered during the analysis. It can be observed that the majority of authors (64% of papers) investigated truck traveling patterns. A few papers evaluated bus transportation systems (Storey & Holtom, 2003 and Cortes et al., 2011). Several researches didn't report vehicle type in the study area (roughly 21% of papers).

TABLE 1 Overview of Collected Studies

Authors (Year)	Vehicle Composition	Performance Measures	Tested Network	Difficulties/Notes
Quiroga & Bullock (1998)	Vehicles (not categorized)	LTT, LTS, TT reliability	LA metropolitan area	2-5 m GPS spatial error; small GPS sampling rates could generate erroneous data; decreasing speeds due to incidents
Quiroga (2000)	Vehicles (not categorized)	LTT, LTS, TT reliability	Baton Rouge (LA)	2-5 m GPS spatial error; small GPS sampling rates could generate erroneous data; decreasing speeds due to incidents
Storey & Holtom (2003)	Private cars, light goods vans, heavy goods vans, buses	LTT, LTS, TT reliability	West Midlands county (UK)	Around 20% of the data points were discarded, because they didn't belong to the road network
Fisher et al. (2005)	Vehicles (not categorized)	TTT, TTS, number of tours, tour duration	Los-Angeles County (CA)	The authors proposed the freight modeling framework, which integrated logistics chain and tour-based models
Jones et al. (2005)	Trucks (not categorized)	LTT, LTS, TT reliability	US freight network	Existence of outliers*
McCormack & Hallenbeck (2005)	Trucks (not categorized)	TTT, TTS, TT reliability	WA metropolitan area	Lack of observations at certain road segments; existence of outliers*
Ando & Taniguchi (2006)	Trucks (not categorized)	LTT, TT reliability	South Osaka area (Japan)	The data were available only for 50%-70% of all major urban roads; GPS and detectors provided different TT distributions
Cambridge Systematics (2007)	Trucks (not categorized)	-	US freight network	Data collection using travel diaries and GPS devices
Schofield & Harrison (2007)	Trucks (not categorized)	LTT, LTS, TT reliability	TX metropolitan area	GPS spatial error; existence of outliers*; low speeds caused by non-recurring delay; errors caused by snapping
Greaves & Figliozzi (2008)	Australian Class 3 and Class 4 trucks	TTT, TTS, number of tours, tour duration, trip length	Greater Melbourne region (Australia)	Loss of the data in the beginning of the trip; satellite signal loss (around 5% of points); data points with no movements were discarded; trip end identification
Liao (2008)	Trucks (not categorized)	LTT, LTS	Portland (OR) – Sacramento (CA) corridor	Spatial mismatches between GPS coordinates and road network; existence of outliers*
NCHRP Report 818 (2008)	Vehicles (not categorized)	Individual and area performance measures	-	-
Dong & Mahmassani (2009)	Vehicles (not categorized)	TT reliability	I-405 Irvine freeway (CA)	-
Liao (2009)	Trucks (class 8 mostly)	LTT, LTS, TT reliability, number of stops	I-94/I-90 corridor between St. Paul (MN) and Chicago (IL)	Existence of outliers*; GPS points, not belonging to the network, were filtered out
McCormack (2009)	Trucks (not categorized)	LTT, TT reliability	WA metropolitan area	Some of GPS points were removed, because they provided erroneous data; in some cases the truck information was known only every 15 min

TABLE 1 Overview of Collected Studies (continued)

NCHRP Report 008 (2010)	Trucks (not categorized)	TTT, TTS, number of tours, tour duration, trip length	Los Angeles (CA), Chicago (IL), Phoenix (AZ), and Baltimore (MD)	GPS records, obtained during weekends and holidays were excluded
Bassok et al. (2011)	Trucks (not categorized)	TTT, TTS, number of tours, tour duration	WA metropolitan area	Spatial mismatches between GPS coordinates and road network; existence of outliers*; GPS signal loss due to overhead obstructions
Chien et al. (2011)	Vehicles (not categorized)	Link/path TT, link/path TS, buffer index, 95th TT percentile	18 New Jersey highway corridors	GPS records for weekends and holidays were discarded; excessive TT due to non-recurring congestion (e.g., incidents)
Cortes et al. (2011)	Buses	LTT, LTS	Santiago area (Chile)	GPS points, not belonging to the network, were filtered out; path rectification problems at junctions
FHWA (2011)	Trucks (not categorized)	LTS	25 US interstate corridors	-
Figliozzi et al. (2011)	Trucks (not categorized)	LTT, TT reliability, travel cost	I-5 Corridor (OR)	Existence of outliers*
McCormack et al. (2011)	Trucks (not categorized)	LTT, TT reliability	WA metropolitan area	GPS points, not belonging to the network, were filtered out
McCormack & Zhao (2011)	Trucks (not categorized)	LTT, TT reliability	WA metropolitan area	GPS points, not belonging to the network, were filtered out
Wheeler & Figliozzi (2011)	Trucks (not categorized)	LTS, LTT, TT reliability, emissions, cost of delay	I-5 Corridor (OR)	Existence of outliers*; bias at interstate junctions
WSDOT (2011)	Trucks (not categorized)	LTT, TT reliability	WA metropolitan area	-
Blazquez (2012)	Winter maintenance vehicles	LTT, LTS	WI and IA metropolitan areas	GPS points, not belonging to the mainline highway, were filtered out; 2-5 m GPS spatial error
Golias et al. (2012)	Trucks (not categorized)	TTT, TTS	Greater Memphis area (TN)	Trip duration increased in cases when truck drivers made rest stops
Pinjari et al. (2012a, 2012b & 2013)	Trucks (not categorized)	TTT, TTS, TT reliability	FL metropolitan area	Existence of outliers*
You (2012)	Drayage trucks	Tour TT, tour TS, number of stops, number of tours	San Pedro Bay Ports (CA)	Falsely detected GPS pointed were eliminated; existence of outliers*
Bierlaire et al. (2013)	Vehicles (not categorized)	Path TT, path TS, route choice modeling	Lausanne area (Switzerland)	High energy consumption by smartphones; some data points were not accurate; weakness of signal in some cases
Carrion & Levinson (2013)	Vehicles (not categorized)	TTT, TTS, TT reliability	Minneapolis (MN) – St. Paul (MN) metropolitan area	Inaccurate GPS records (outside the established buffer area) were excluded; trips during holidays were not analyzed

TABLE 1 Overview of Collected Studies (continued)

Golias & Mishra	Commercial Motor Vehicles (CMV)	TTT, TTS	I-40 corridor between Memphis (TN) and Nashville (TN)	Various adjustments were made in the methodology due to data limitations
Memphis Urban Area MPO (2013)	Trucks (not categorized)	-	-	Freight Peer to Peer Program meeting
Kuppam et al. (2014)	Trucks (not categorized)	TTT, TTS, number of tours, tour duration	Phoenix region (AZ)	Some of GPS points provided erroneous data; incidental movements of trucks within the same trip end
Liao (2014)	Trucks (class 8 mostly)	LTT, LTS, TT reliability	I-94/I-90 corridor between St. Paul (MN) and Chicago (IL)	Existence of outliers*
Wang et al. (2014)	Trucks (not categorized)	LTT, TTT, TT variability	San Antonio corridor (TX); Milwaukee corridor (WI)	Existence of outliers*; GPS points, not belonging to the mainline highway, were filtered out

Note: TT – travel time ; TS – travel speed; LTT – link travel time; LTS – link travel speed; TTT – trip travel time; TTS – trip travel speed; Outliers* - observations that represent truck stops, not caused by congestion (e.g., refueling, driver's rest, delivery, etc.)

The following FPMs were identified as a result of conducted literature review:

a) Link/path/trip/tour TT (min, hrs.)
b) Link/path/trip/tour TS (km/hr., mi/hr.)
c) Tour characteristics: tour generation, stop generation, stop duration, tour duration, tour completion, stop purpose, stop location, stop time of day choice, number of stops during the tour, number of trips during the tour
d) TT reliability/variability
1. 90th and 95th percentile travel time ($tp_{90\%}$ and $tp_{95\%}$)
2. Buffer index $BI = \frac{tp_{95\%} - \bar{x}}{\bar{x}}$
where $\bar{x} = \frac{1}{N}\sum_{i=1}^{N} x_i$ - mean travel time; x_i - travel time for the observation *i*; N – number of observations
3. Buffer travel time $BTT = tp_{95\%} - \bar{x}$ (minutes, hours)
4. Planning travel time $PTT = tp_{95\%}$ (minutes, hours)
5. Planning travel time index $PTTI = \frac{tp_{95\%}}{x_{FFS}}$
where x_{FFS} – free flow speed travel time
6. Travel time index $TTI = \frac{x}{x_{FFS}}$
7. Travel time standard deviation $\sigma = \sqrt{\frac{(\sum_{i=1}^{N} x_i - \bar{x})^2}{N-1}}$
8. Travel time coefficient of variation $CV = \frac{\sigma}{\bar{x}}$
9. Travel time range $Range = x_{max} - x_{min}$
10. Ratio of mean travel time to median travel time $r = \frac{\bar{x}}{\hat{x}}$
where $\hat{x}$ - median travel time
e) Total segment delay $TSD = (tp_{95\%} - x_{FFS}) \times V$ (vehicles-minutes)
where V – volume of vehicles at the segment

f) Congested travel $CT = \sum ConLength \times V$ (vehicles-miles)
where $ConLength$ – congested segment length
g) Congested roadway $CR = \sum ConLength$ (miles)

A few studies computed the average travel cost along with FPMs for considered highway corridors. Ando & Taniguchi (2006) estimated the total cost of link TT uncertainty and penalties due to early arrival/delayed arrival to customers, requesting a particular time window. Wheeler & Figliozzi (2011) and Figliozzi et al. (2011) included TT, cost of traveling, and TT variability into the cost function. Several researches also assessed environmental impacts and emissions, produced by vehicles. Emissions were estimated based on the vehicle travel distance and the vehicle TS (see Ando & Taniguchi, 2006; Wheeler & Figliozzi, 2011).

2.5 Conclusions

Various difficulties of using and processing GPS data were discovered from the literature. One of the common issues found is the difficulty in obtaining GPS data from the trucking companies (Greaves & Figliozzi, 2008; McCormack et al., 2011; McCormack & Zhao, 2011). Although a significant number of trucking companies have GPS devices installed in their trucks to receive necessary information about current location, speed, required stops for rest, etc., the majority of them are not willing to share any data regarding their vehicles and type of commodity transported due to security and privacy issues. Several studies were performed using GPS data from vendors (Bassok et al., 2011; McCormack et al., 2011; McCormack & Zhao, 2011 and others). Bassok et al. (2011) mentioned several advantages of obtaining the data from vendors (e.g., professional analysis, not voluntary participation; dedicated technical staff for producing necessary reports). However, GPS data, provided by device vendors, may be quite expensive. Another type of difficulties is related to processing of the data, which contain erroneous information for some vehicles during particular time periods at specific locations due to various reasons. Errors, revealed during the analysis of GPS data and reported by researchers, can be classified into the following groups:

1) Errors caused by device (e.g., 2-5 m GPS spatial error; existence of data points not belonging to the road network; signal loss due to spatial obstructions)
2) Errors caused by outliers (e.g., in some cases it is difficult to determine if a vehicle stopped for refueling, delivery, driver's rest, etc.)
3) Errors caused by snapping (e.g., buffer radius of the data point covers more than one segments and it is necessary to relate the point to a segment)
4) Errors caused by data collection (e.g., GPS points collected during weekends and holidays should be disregarded, since vehicle traveling patterns may change during those days)
5) Errors caused by non-recurring congestion (e.g., an incident will substantially affect speed of vehicles at the given roadway segment)

Several papers, dealing with vehicle trips, highlighted the difficulty of defining a trip end (Greaves & Figliozzi, 2008; Bassok et al., 2011; Kuppam et al., 2014). In some cases vehicles were not static even when the trip ended (e.g., trucks moving within a distribution facility). Different approaches were used to identify trip ends (e.g., threshold on the minimum allowable speed, changing vehicle coordinates, check if a trip is genuine, ensure that there is no signal loss, etc.).

From the available literature it can be concluded that GPS data are widely used to evaluate performance of corridors, estimate trip generation rates at intermodal and transmodal terminals, determine congested segments of highways, identity areas of future improvement needs, mitigate possible environmental issues caused by vehicles, and develop FPMs for different types of facilities (highway corridors, distribution centers, intermodal terminals, public and private warehouses, etc.). FPMs, estimated using GPS data, can assist public and private stakeholders along with various transportation agencies to prioritize congested roadway segments and efficiently allocate available monetary resource to enhance travel conditions at those segments. However, the process of GPS data may become a difficult task due to erroneous data, inaccurate analysis approach, and inability of tracking driver's behavior.

3. DATA DESCRIPTION AND PROCESSING

This section provides a description of the data available and a methodology for processing GPS records and estimating FPMs. Additional procedures will be developed to evaluate performance of freight facilities and to analyze individual truck trip traveling patters (see sections 5 and 6 of the report).

3.1 Data Description

3.1.1 General Statistics

The GPS records used in this study were provided by ATRI and include trucks, traveling within the State of TN in 2012 (January-December). A total of 104,232,699 observations were provided for 60,962 unique trucks. The given data for the whole year was embedded in a PostgreSQL database used to process the data, retrieve GPS records for specific days, assign a unique identifier to each observation, and conduct a statistical analysis. All observations were roughly equally distributed among the four quarters of the year: 22.27% of the observations were for the first quarter (January-March), 24.86% were for the second quarter (April-June), 26.2% were for the third quarter (July-September), and 26.67% were for the fourth quarter (October-December). Figure 1 demonstrates the average percentage of observations for each day of the week. It can be noticed that the majority of GPS records (52.4%) were obtained between Tuesday and Thursday, while only 17.17% of observations were received during weekends.

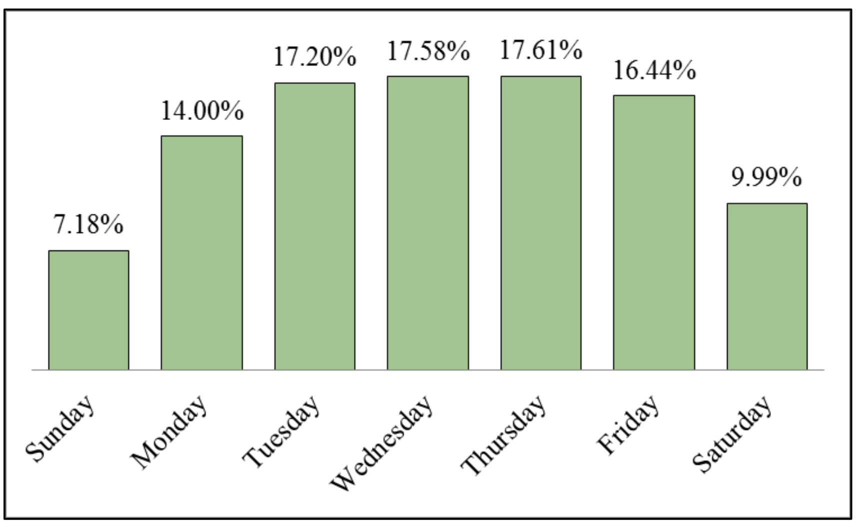

FIGURE 1 Distribution of Observations per Day of the Week

The total number of observations per truck varied as the provided dataset was a random sample, accounting approximately for 3%-5% of the whole population. The maximum number of GPS records for a single truck in a day was 1501. However, the majority of trucks had less than 80 observations in a day (see Figure 2). The frequency of GPS signal was not fixed, and a significant percentage (29%-39%) of these observations included stopped trucks. A truck was considered as stopped in this study, if its spot speed was less than 5 mph, which is a common speed threshold established by researchers[3]. On an hourly basis approximately 95% of the trucks had up to 20 observations (see Figure 3), which translates to one observation per 3 minutes (stopped trucks included), while 50% had less than 10 observations (i.e., one every six minutes). Non-unique truck observations in a 15 minute interval ranged from 266 to 7931, while stopped trucks observations for the same interval ranged from 62 to 3411.

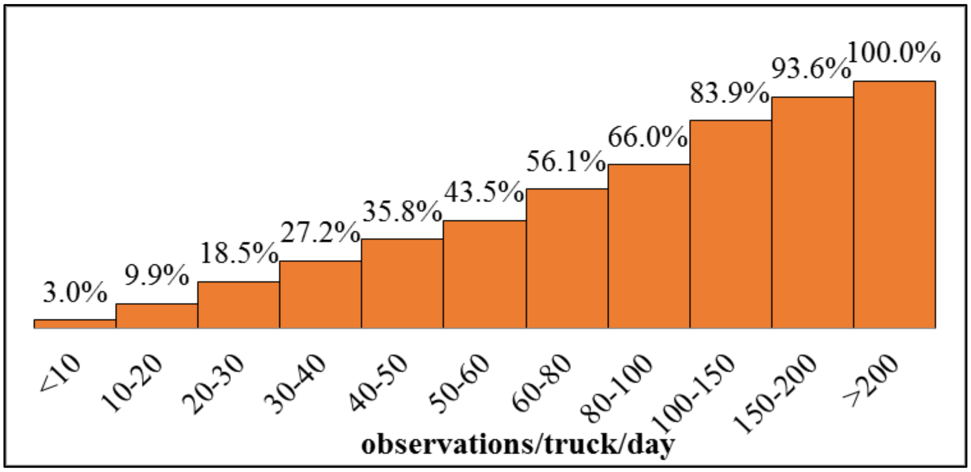

FIGURE 2 Number of Daily Observations for a Single Truck

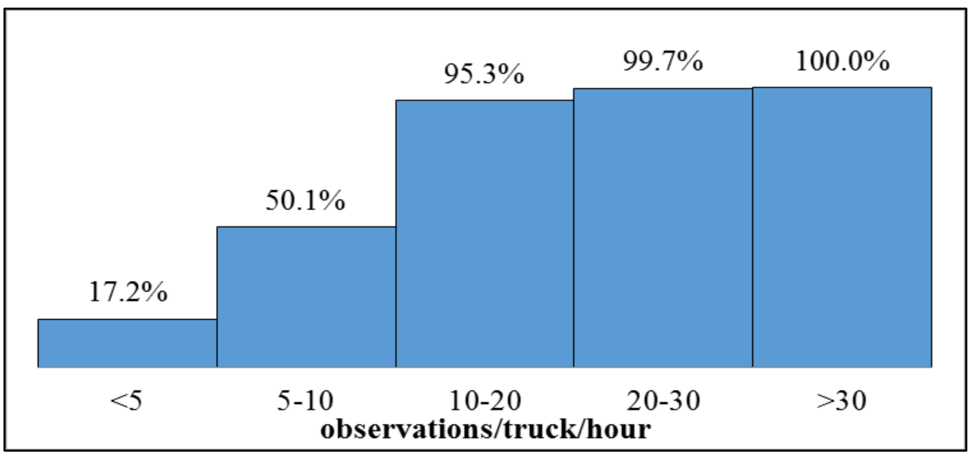

FIGURE 3 Number of Hourly Observations for a Single Truck

The data provided were analyzed for four time periods: i) AM Peak: 6am – 9am, ii) Midday Peak (MD): 9am – 2pm, iii) PM Peak: 2pm – 6pm, and iv) Off-peak (OP): 6pm – 6am. Truck distributions by day of the week and time of the day are presented in Figure 4. The majority of observations were obtained for the OP time period. The smallest amount of GPS records (on average 10% during weekdays, except Saturdays with 15%) were transmitted during the AM peak hours, as this time period covers only 3 hours of the day. Approximately 14-15% of observations were obtained for the PM peak

[3] McCormack & Hallenbeck, 2005; Wheeler & Figliozzi, 2011; Golias et al., 2012, etc.

period. Figure 5 shows the percentage of stopped trucks during each of the four time periods. The largest percentage of stopped trucks was observed during the PM and MD time periods (35.02% and 35.01% respectively), while during AM and OP time periods this percentage was slightly lower (31.96% and 31.09% respectively). However, the largest amount of trucks was identified during the OP time period for each weekday (see Figure 6). Percentage of stopped trucks comprised on average 16% during the PM peak hour during weekdays. Substantial percentage of stopped trucks was noticed during the MD time period for Saturdays (≈19.5%).

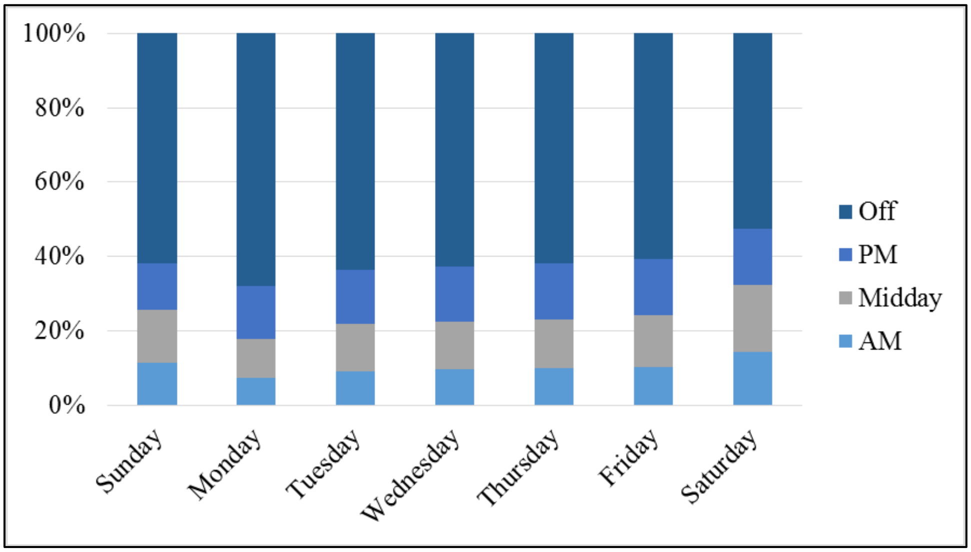

FIGURE 4 Truck Distribution by Day of the Week and Time of the Day

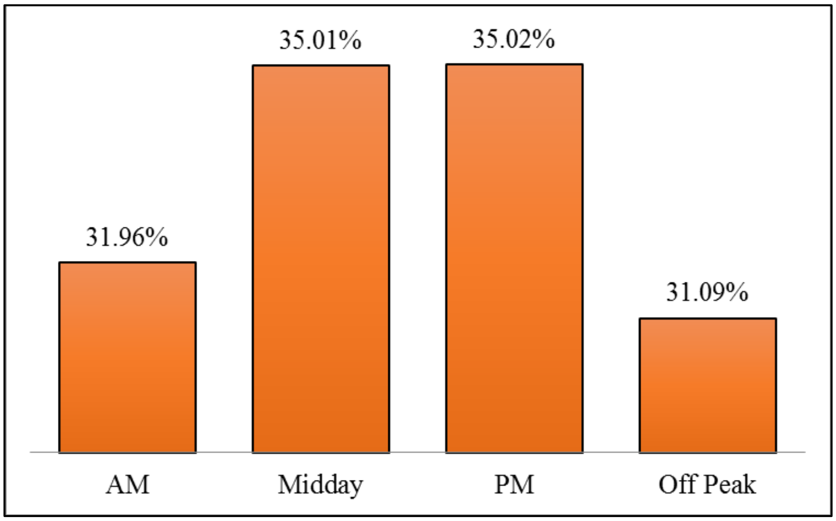

FIGURE 5 Percentage of Stopped Trucks per Time of the Day

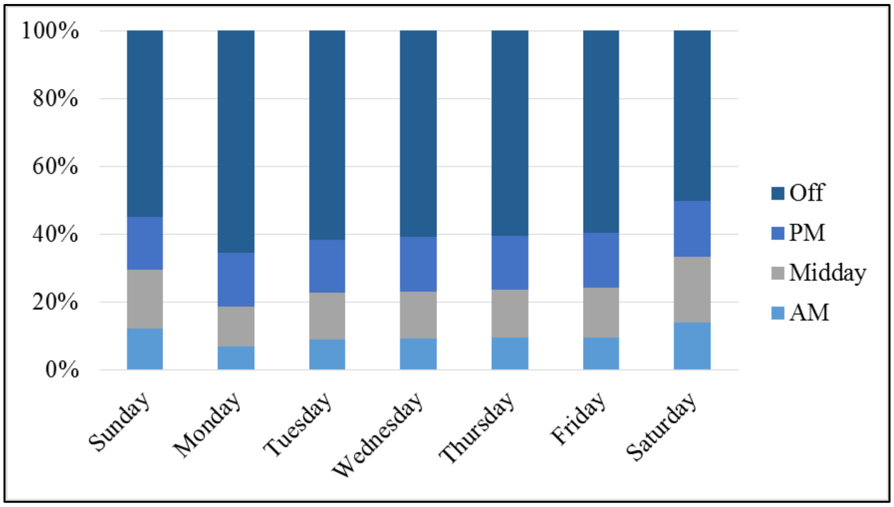

FIGURE 6 Stopped Truck Distribution by Day of the Week and Time of the Day

3.1.2 Dataset Description

A GPS data sample, obtained for a random day in the year of 2012, is presented in Figure 7 and used to describe the available data. The following information was provided for each GPS record:

- GPS waypoint (X and Y coordinates)
- Time stamp
- Heading
- Spot speed
- Truck Identifier

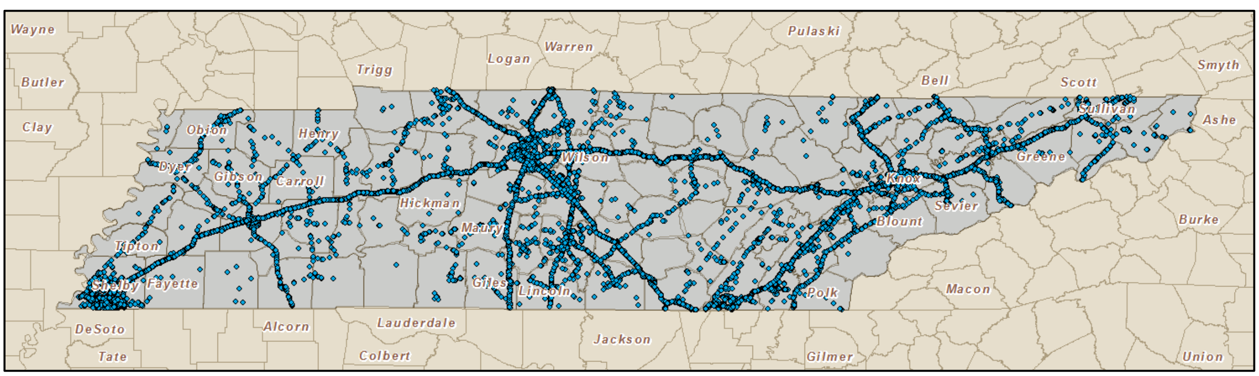

FIGURE 7 Random Day GPS Data Display

Time stamps were given for Coordinated Universal Time (UTC) zone. The State of TN lies in two time zones: Central Daylight Time (CDT) zone and Eastern Daylight Time (EDT) zone. The local time should be estimated for each GPS point in order to conduct the analysis for specific time periods. The Extract Analysis Toolbox, of ESRI ArcGIS 10.0[4], was used to assign a time zone to each observation based on its spatial

[4] www.esri.com

disposition (see Figure 8). Once a time zone was determined for a GPS record, a local time was computed based on the difference between the given time zone and UTC zone. A daylight saving time for the year 2012 was considered as well. EDT zone was 4 hours behind UTC, while CDT zone was 5 hours behind UTC between March 11, 2012 and November 4, 2012[5]. For the rest of the year EDT zone was 5 hours behind UTC, while CDT zone was 6 hours behind UTC.

FIGURE 8 CDT and EDT Zones in TN

One of eight possible headings was recorded for each observation: E, W, N, NE, NW, SE, and SW. A unique identifier was assigned to each truck as most trucking companies are not willing to share any information regarding their vehicles and type of commodity transported (Greaves & Figliozzi, 2008; McCormack et al., 2011; McCormack & Zhao, 2011).

3.2 Data Processing

3.2.1 Associating GPS Records with the Network

In order to associate (or snap) GPS points on the network, the Proximity Analysis Toolbox, of ESRI ArcGIS 10.0, was used. In this study the Freight Analysis Framework (FAF) transportation network for the State of TN was evaluated. The FAF network includes 3,393 road segments with average link length of 2.66 miles. Since truck GPS data did not include any information on the accuracy of the GPS devices, the worst case scenario of a quarter mile (as reported in the literature, see Jones et al., 2005; Schofield & Harrison, 2007), was assumed. In theory, the search radius for snapping observations should be equal to sum of the device spatial error and the positional error of the used network. In FAF network this can be up to ±260 feet (FHWA, 2014). GPS records lying outside the search radius were discarded.

3.2.2 Direction and Outlier Identification (DOI) Algorithm

DOI algorithm was developed to address the issue of multiple directions of GPS truck records, associated with the same link. Figure 9A illustrates this issue with 17 observations, snapped to link, having a total of six unique headings: E, N, NE, SW, SE, and W. These GPS records should be separated in two groups: 1) trucks moving from the link start point (with coordinates [x_{st}, y_{st}]) to the link end point (with coordinates [x_{end}, y_{end}]), and 2) trucks moving from the link end point to the link start point. Based on the

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[5] http://www.timeanddate.com/time/dst/2012.html

link's geometry those groups should be either NE or SW directions respectively. The major steps of DOI are as follows:

DOI Steps

Step 1: Load GPS data for a given day/time period

Step 2: Associate each GPS record with a link (based on a predefined radius around each record)

Step 3: Remove outliers[6] based on speed (if speed threshold is known)

Step 4: For each link

Step 4.1: Identify the number of unique truck headings

Step 4.2: Separate observations in two groups based on the link spatial disposition (see Figure 9)

Step 4.3: Remove additional outliers based on the Chauvenet's criterion (optional)

Next we present a small example to showcase how DOI is implemented.

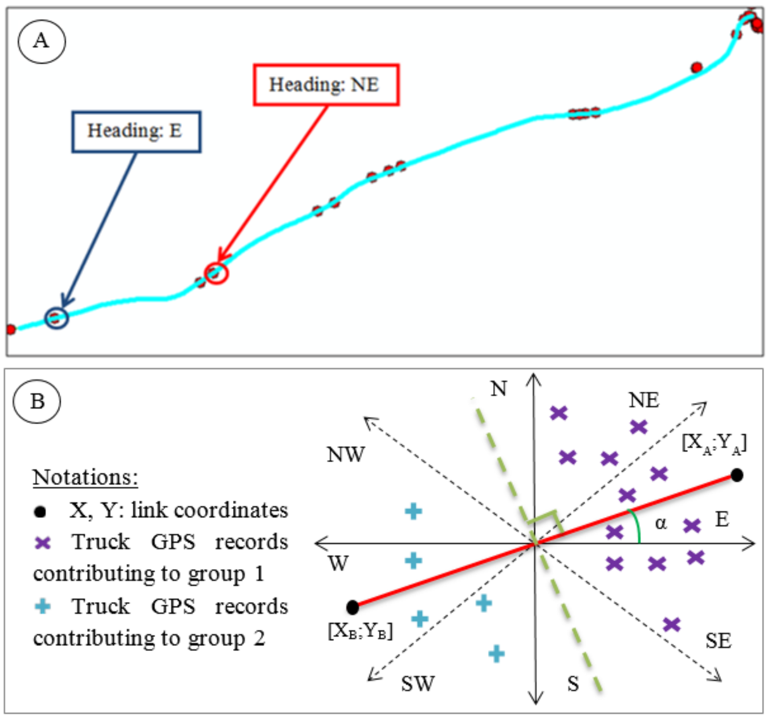


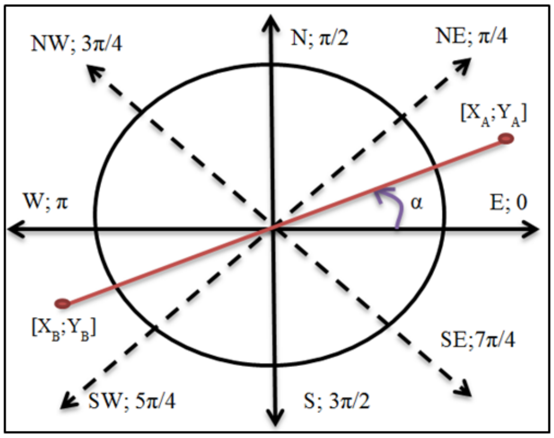
FIGURE 9 DOI for Resolving the Problem with Headings

3.2.3 DOI Example

Figure 9B provides an example of step 4.2. for a fictitious link. First, the start and end point coordinates for the given link are calculated. The link is then approximated by a straight line, connecting the start and end points. The next step calculates the angle (α),

[6] Observations with spot speeds less than 5 mph are considered as outliers.

between the E-W axis and the straight line representing the link. The value of *α* can be estimated using line coordinates and trigonometric functions (e.g., arccosine, arcsine, arctangent, etc.). In the given example (see Figure 9B) angle *α* lies between 0 and π/4, hence trucks with headings E, N, NE or SE will be assigned to the direction from B to A (BA) and trucks with headings W, S, SW or NW to the direction from A to B (AB). Groups of headings, contributing to BA and AB directions, for every possible angle *α* are presented in Figure 10.



Angle, α	Headings assigned by DOI	
	BA	AB
0<α<π/4	E, NE, N, SE	W, SW, S, NW
π/4<α<π/2	E, NE, N, NW	W, SW, S, SE
π/2<α<3π/4	N, NW, W, NE	S, SE, E, SW
3π/4<α<π	N, NW, W, SW	S, SE, E, NE
π<α<5π/4	S, SW, W, NW	N, NE, E, SE
5π/4<α<3π/2	S, SW, W, SE	N, NE, E, NW
3π/2<α<7π/4	S, SE, E, SW	N, NW, W, NE
7π/4<α<2π	S, SE, E, NE	N, NW, W, SW

FIGURE 10 DOI Heading Assignment

3.2.4 Outlier Detection: Chauvenet's Criterion

Detection and removal of outlier GPS truck records is a crucial component of the analysis if accurate FPMs are to be calculated. Removal of outliers based on predetermined thresholds (e.g., 10 mph) may result in high misclassification of records during different time periods of the day (e.g., 10 mph may not be an outlier for peak periods). To escape the use of predetermined speed thresholds the Chauvenet's criterion was adopted (Chauvenet, 1960). The criterion assumes that speeds follow a Normal Distribution, and observations are considered as outliers, if the probability of obtaining their deviation from the mean is less than $1/(2N)$, where N is the number of observations.

3.2.5 FPM Calculation

Once GPS records are associated with links, direction of truck movement has been assigned, and outliers have been detected and removed, preferred FPMs can be calculated using DOI. The list of FPMs, calculated in this study, includes TS (in each direction), TT, and TT reliability measures (90th percentile TT, 95th percentile TT, buffer TT or BTT, BTT index or BI, TT standard deviation or TTSD, TTCV, TT range, mean to median TT ratio). Average TS were computed based on spot speeds available from GPS truck data. This approach was chosen as most of consecutive GPS points for a given truck belong (for the majority of the trucks) to different links (i.e., link length and the mean time interval between observations cannot be used to calculate average TS). Once FPMs are calculated for all links, it will be possible to identify areas, where bottlenecks occur for a given time period.

3.2.6 DOI Validation

DOI was validated on the FAF network with LTS obtained from the FPMweb Tool. Data for the I-40 section in TN was retrieved from the FPMweb Tool for 36 days (3 consecutive weekdays for each month of 2012). Average LTS over 3 days of each month were computed for four time periods (see section 3.1.1). Then average LTS were estimated using DOI for the same links and time periods. Results of a comparative analysis indicated that the differences between LTS, provided by the FPMweb Tool, with the ones, calculated by DOI, were not significant (less than 5% on average). Differences were mostly observed on short links (< 3 mi) and could be possibly caused by snapping errors. Note that DOI can be applied to any network (not only FAF), and its accuracy will depend on length and shape of each roadway segment.

3.2.7 Iterative DOI (IDOI)

Another issue that was discovered during the study was that no more than 450,000 observations could be processed at a time (≈2-3 days depending on the number observations/day). Obviously, this number can vary based on CPU capabilities[7]. The problem was addressed by considering truck GPS data for one day at the time. The algorithm, developed to estimate FPMs for multiple days, was named IDOI.

[7] For this research a Dell T1500 Intel(T) Core™ with i5 CPU and 2.00 GB of RAM was used

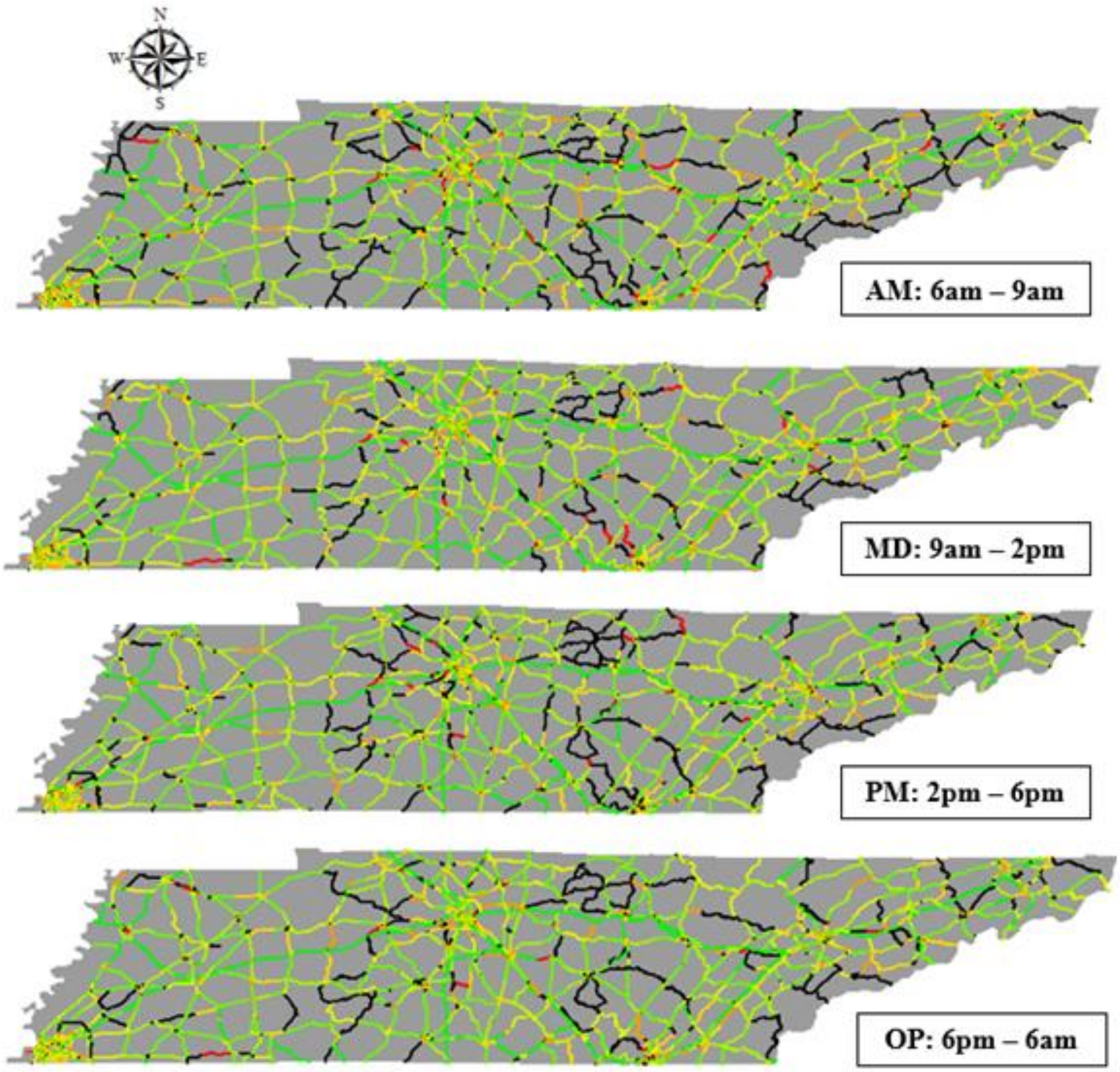
4. LINK PERFORMANCE INDICATORS

The proposed methodology was applied to the FAF network in the State of TN using truck GPS data (provided by ATRI) for selected weekdays of each month over the whole year of 2012. In this section we present the analysis of GPS records, obtained for January 3rd-5th, 2012. A total of 832,532 observations were available for a total of 11,852 unique trucks. Approximately, 20% of trucks during that time period had only one GPS record available and were only used for LTS estimation. Note that the Chauvenet's criterion was used to exclude any outliers. As a result of the snapping procedure, observations were associated with 3,127 unique links. Around 29.1% of GPS points had spot speeds less than 5 mph. The total number of not snapped observations was 196,978 (23.7%), while the total number of filtered GPS records (snapped & spot speed more than 5 mph) was 507,690 records (61.0%). The remaining GPS records had spot speeds less than 5 mph and/or were not located near the FAF network links within the search radius.

4.1 Average LTS and Total Truck Volumes Estimation

Average TS were estimated using the DOI for four time periods of the day defined in section 3.1.1. Results of the analysis are presented in Figure 11 were mean speeds of the FAF network links are reported. It can be noticed that fewer filtered records were obtained for the AM peak period (only 114,693 GPS points), while the maximum number of records were obtained for the OP period (293,238 GPS points), which may be explained from AM being the shortest peak period. The maximum number of links was analyzed during the MD time period (85.7%), while the minimum number of links was analyzed during the AM time period (77.3%). On average bi-directional speeds were calculated for 80.6% links of the FAF network in TN. In general, most of the vehicles traveling along major freight corridors (I-40, I-24, I-65, I-75, and I-81) had TS over 51 mph. Average speeds significantly decreased at links in the vicinity (or beltways / ring roads) of large metropolitan areas (i.e., Memphis, Nashville, Knoxville, and Chattanooga, TN).

Along with average LTS, total truck volumes (in both directions of traveling) were computed for the same weekdays and four time periods and results are shown in Figures 12 and 13. It was found that less than 500 trucks were observed on major freight corridors for the AM peak period between January 3rd and January 5th, while greater volumes (> 500) were noticed for the remaining time periods. Similar analysis can be conducted for any day of the year or for multiple days (e.g., average weekday or monthly TS for the same time periods) using DOI. The computational time for calculating TS and other FPMs will depend on the computer specifications (RAM, number of cores, etc.). Analysis of truck GPS data with DOI presented herein required 4.5 hours on a Dell T1500 Intel(T) Core™ with i5 CPU and 2.00 GB of RAM. Average TS and total truck volumes for selected weekdays of each month (except January) of the year 2012 are presented in Appendices A and B respectively.



Features\period	AM	MD	PM	OP
Total # of observations	114693	248093	176508	293238
# of links with observations	2622	2906	2689	2725
# of observations with speed < 5mph	37435	71890	47178	85802
# of observations not snapped	29362	61383	40364	65869
# of observations filtered (>5mph, snapped)	65445	148617	111403	182225

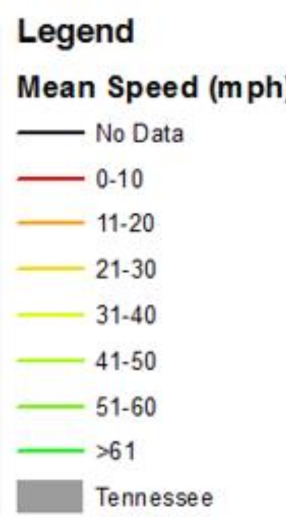


FIGURE 11 Mean Speeds, January 3rd-5th

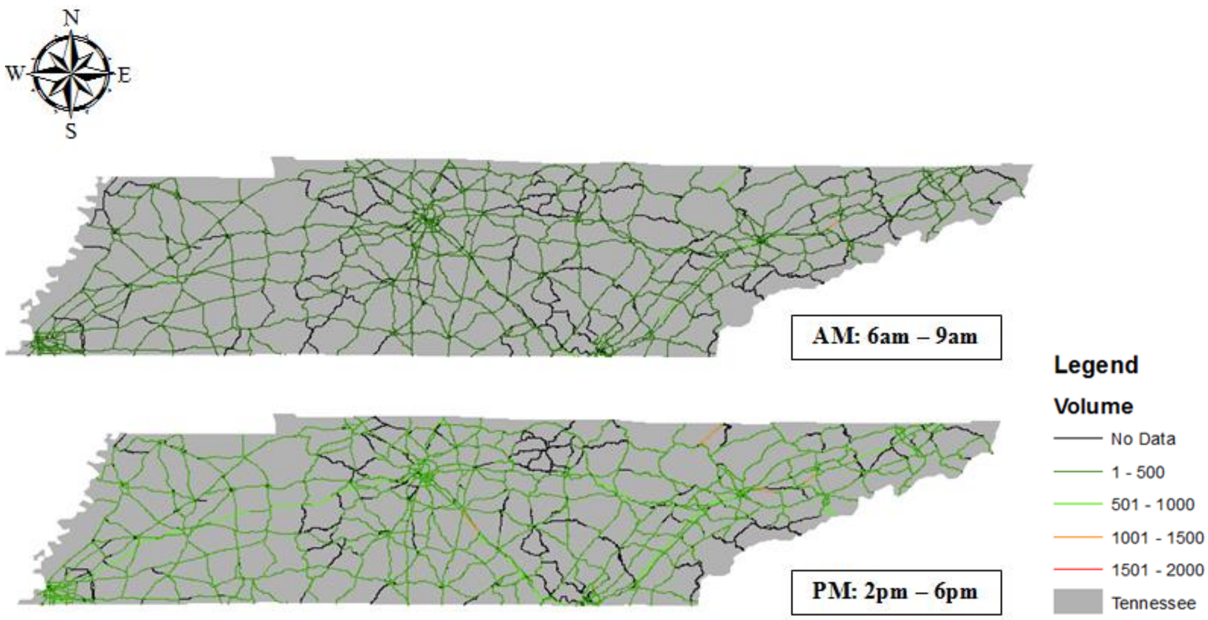


FIGURE 12 Total Truck Volumes, January 3rd-5th, AM & PM Periods

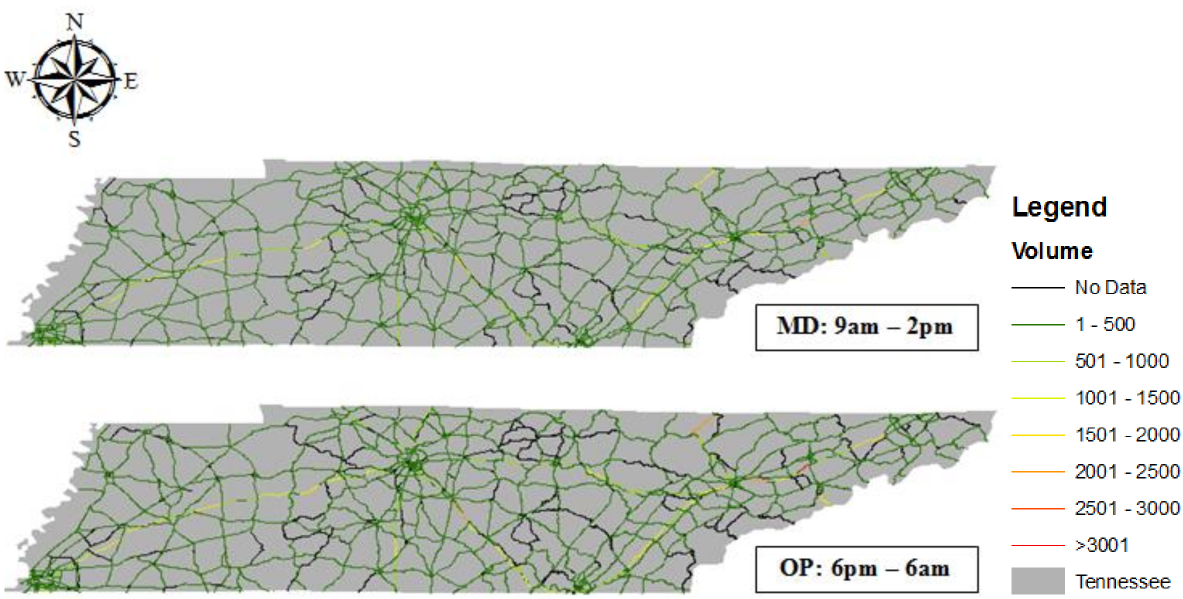
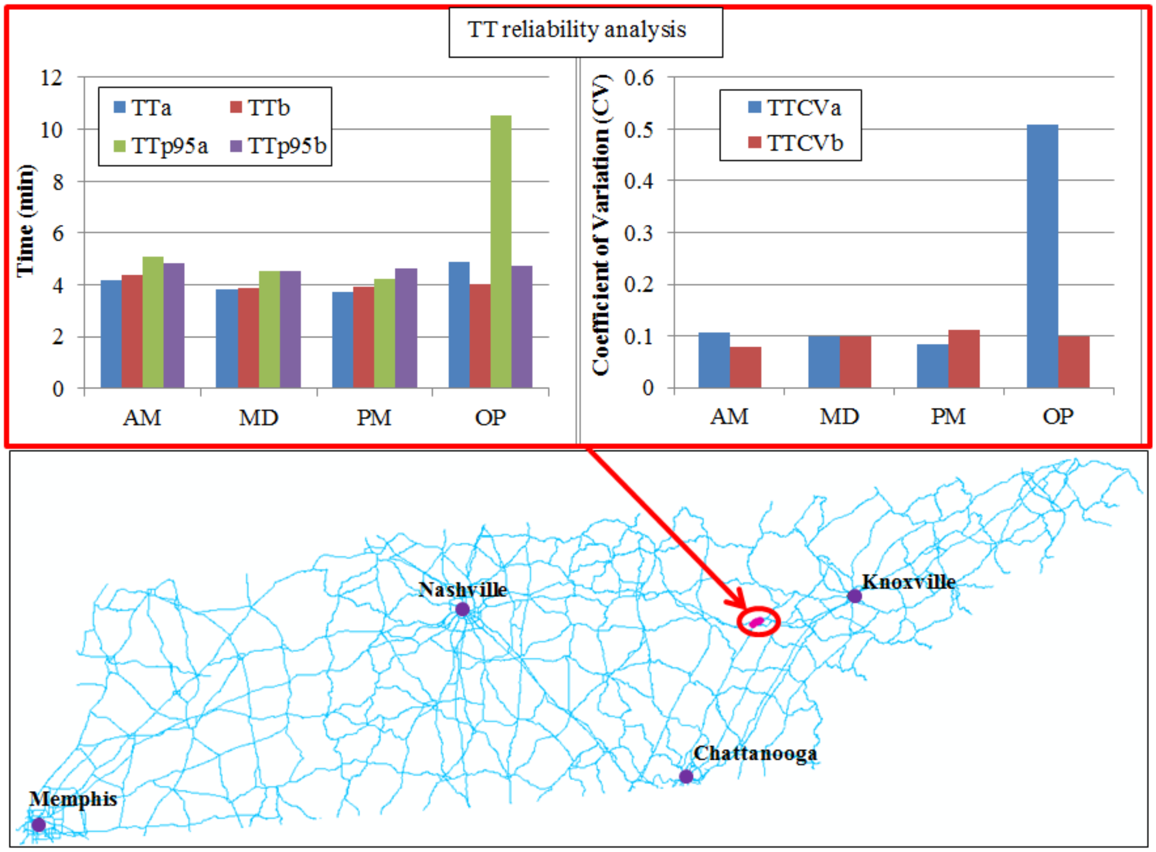


FIGURE 13 Total Truck Volumes, January 3rd-5th, MD & OP Periods

4.2 Travel Time Reliability Estimation

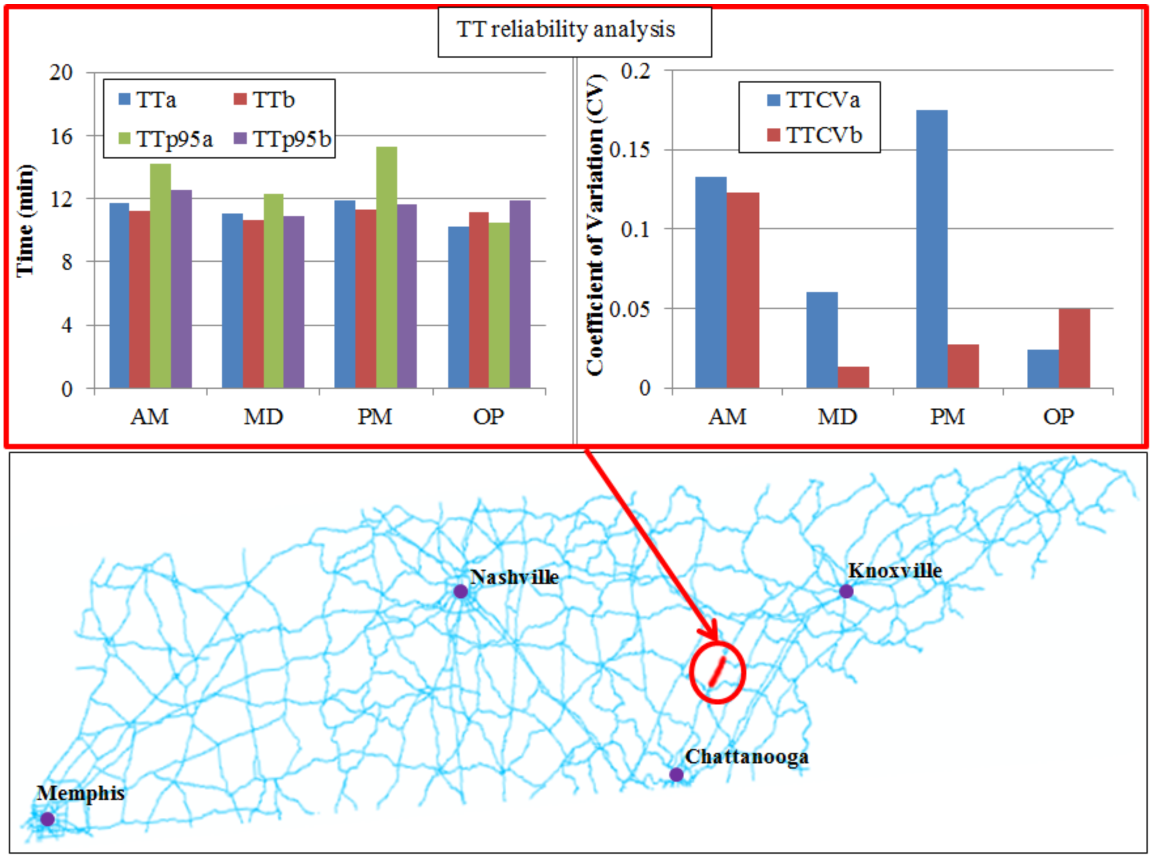
DOI output can also be used to estimate TT reliability measures on the transportation network. Results from an example of TT reliability analysis are presented in Figure 14 for a random link of the FAF network. The link is part of I-40 (East-West) connecting Nashville, TN and Knoxville, TN. Average TT on the selected link did not exceed 5 min for all time periods. However, the 95th percentile TT was substantially greater during the OP time period in the East direction (approximately 10.5 min), while TTCV comprised 0.50. Low speeds (< 30 mph) were observed between 00:29 AM and 02:32 AM and could be explained by the fact that truck drivers were accelerating on I-40 after making rest/refueling stops in Rockwood, TN, which is located close to the link.



Note: TTa – travel time in East direction; TTb – travel time in West direction; TTp95a – 95th percentile travel time in East direction; TTp95b – 95th percentile travel time in West direction; TTCVa – travel time coefficient of variation in East direction; TTCVb – travel time coefficient of variation in West direction;

FIGURE 14 TT Reliability Measures for Random Link #1

Another TT reliability analysis was conducted for a second random link of the FAF network. The second link is a part of US-27, heading to Chattanooga, TN. Average TT of the selected link comprises approximately 11.5 min for all time periods. However, it can be noticed that the 95th percentile TT substantially increased during the PM peak hour in the North East direction (approximately 15.0 min), while TTCV was 0.18 (see Figure 15). This can be explained by the fact that vehicles, leaving Chattanooga, faced traffic congestion during the PM peak hour. Besides, significant coefficient of variation (TTCV ≈ 0.13) was observed during the AM peak hour in both North East and South West direction. As for MD and OP time periods, the 95th percentile TT was close to the average TT, while TTCV did not exceed 0.6 in both directions of traveling.



Note: TTa – travel time in North East direction; TTb – travel time in South West direction; TTp95a – 95th percentile travel time in North East direction; TTp95b – 95th percentile travel time in South West direction; TTCVa – travel time coefficient of variation in North East direction; TTCVb – travel time coefficient of variation in South West direction;

FIGURE 15 TT Reliability Measures for Random Link #2

4.3 Conclusions

This section demonstrated how DOI can be used to compute average TS, calculate total truck volumes, assess reliability of various highway segments, and estimate other FPMs for freight transportation corridors of the TN transportation network. The algorithm may be applied in freight transportation planning, identification of bottlenecks, calculating various FPMs, prioritizing busy freight transportation corridors for improvement projects (based on total truck volumes, average TT, and TT reliability).

5. FREIGHT FACILITY PERFORMANCE INDICATORS

This section focuses on estimating performance indicators for freight transportation facilities. Different types of facilities will be analyzed using truck GPS data, obtained for selected days of the year 2012.

5.1 Introduction

Freight transportation plays a crucial role in the economic development of the country. According to the U.S. Department of Transportation (US DOT, 2009), the value of international merchandise trade, transported through the national freight gateways, increased by 9% from 2008 to 2009 and reached $3.4 trillion (in 2009 dollars). It is important to understand freight movements in order to improve performance of freight transportation networks and facilities. Section 4 demonstrated how truck GPS data could be used to estimate FPMs for busy freight corridors. This section evaluates performance of different freight facilities in the Greater Memphis Area, TN (see Figure 16). Note that similar analysis can be also conducted for freight facilities at any given metropolitan area, if GPS records are available.

Source: Google Maps

FIGURE 16 Study Area

5.2 Facilities of Interest

Three types of freight facilities were considered: a) intermodal terminals (road-rail), b) distribution centers, and c) warehouses. Each facility was assigned a unique identifier (ID) for privacy purpose. A total of twenty facilities were analyzed: 1) 5 intermodal terminals (I1 – I5), 2) 6 distribution centers (D1 – D6), and 3) 9 warehouses (W1 – W9).

5.3 Data Description and Processing

Performance of freight facilities was analyzed using GPS data, obtained for the month of January (total of 7,317,754 observations). ESRI ArcGIS 10.0 was used to associate the daily truck GPS data with each facility. A total of 20 polygons were geocoded for all considered freight facilities. Once the polygon shapefiles were imported to ArcGIS environment, the Extract Analysis Toolbox was applied to identify observations, transmitted from a given facility. An example of associating GPS data with facility W2 is depicted in Figure 17. Only 254,123 GPS records were received from 20 freight facilities, which comprise approximately 3.5% of the total observations, obtained for the State of TN during the month of January. Such a low percentage can be explained by the fact that only a selected group of freight facilities, located in the Greater Memphis

Area, was evaluated. Distribution of observations by facility is presented in Figure 18. Most of GPS records were received from intermodal terminals (126,955 or 49.9% of the total). Approximately 46.1% of GPS points were obtained from warehouses. Only 9,971 observations (≈4%) were available for distribution centers. The largest amount of GPS records among all facilities was received from warehouse W6 (85,671 observations). Next we present facility performance indicators that were estimated using available GPS data.

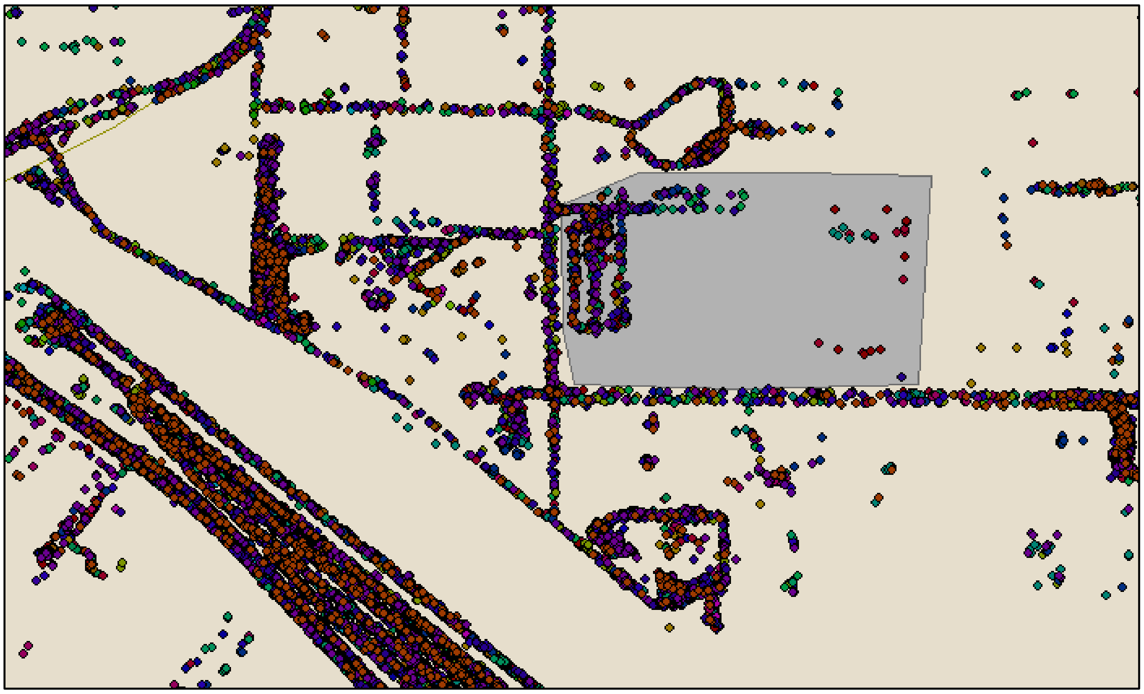


FIGURE 17 GPS Data for Facility W2

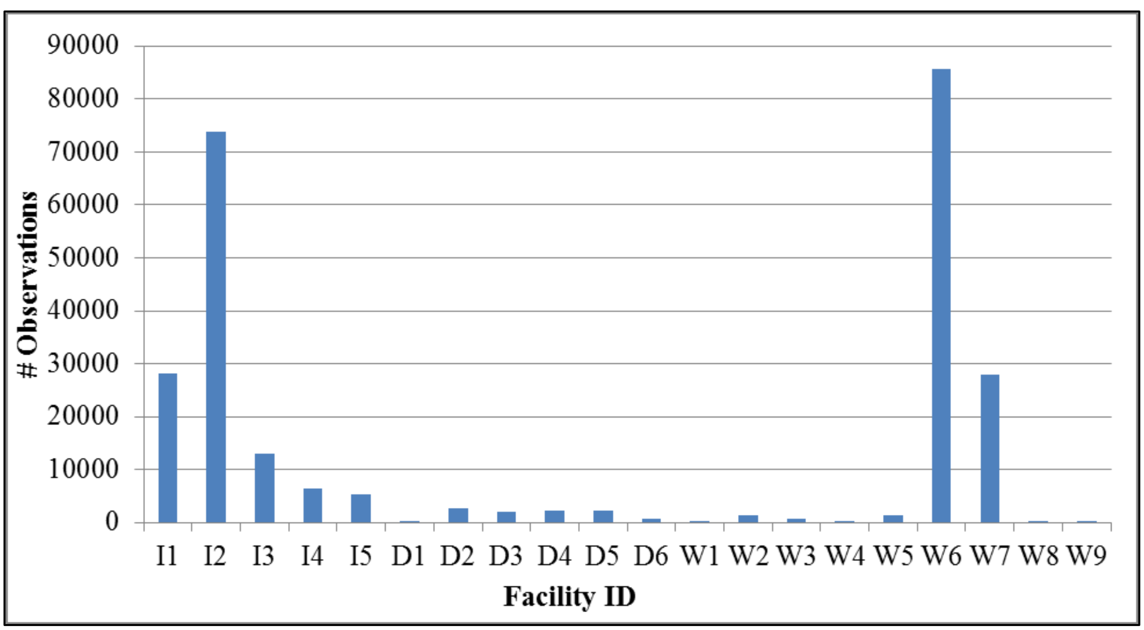


FIGURE 18 Distribution of Observations by Facility

5.4 Facility Turn Times

According to Huynh and Walton (2005), truck turn time is considered as one of the key performance indicators for intermodal terminals. Turn time is the total time, which takes the given truck to enter the facility, pick up/drop off the cargo, and exit the facility. Increasing turn times may cause congestion at the facility, cargo delays, increasing inventory costs. Various strategies can be applied to reduce truck turn times (depending on the facility type). For example, the most common methods for decreasing truck turn times at marine container terminals (see Huynh and Walton, 2005) are: a) adding yard cranes to provide faster service of drayage trucks, and b) introduction of an appointment system. A gate appointment strategy allows negotiating a specific transaction time between the terminal and drayage operators (Maguire et al., 2009). Along with the gate appointment system, there exists an extended gate hours strategy, which consists in extending hours of gate operations.

Estimating accurate truck turn times at freight facilities remains a challenging task (Golias et al., 2012). In this study a turn time for each truck at the given facility was computed based on the available GPS data. The procedure for calculating truck turn times is outlined next.

Truck Turn Time Estimation

Step 0: Identify GPS records that were transmitted from a given facility for a specific time period (e.g., one month)
Step 1: Estimate the number of days with available observations
Step 2: Remove trucks with only one available observation
Step 3: Select a day *d*
Step 4: Define the number of unique trucks with available observations for day *d*
Step 5.0: For truck *t* of a given day *d*

Step 5.1: Determine the earliest GPS record (with time stamp TS_E)
Step 5.2: Determine the latest GPS record (with time stamp TS_L)
Step 5.3: Compute turn time as $TS_L - TS_E$
Step 5.4: Is truck *t* the last
If YES – go to Step 6
Else go to Step 5.0 and set *t=t+1*

Step 6: Is day *d* the last
If YES – go to Step 7
Else go to Step 3 and set *d=d+1*
Step 7: Retrieve truck turn times

Table 2 presents truck turn time statistics by facility type. Large mean turn time, turn time standard deviation (SD) and coefficient of variation (CV) were observed at most of the facilities. This can be explained by the fact that many GPS records were obtained from trucks staying within the facility after unloading the cargo. It was noticed that some trucks stayed inside the facility for more than one day. The majority of trucks were observed within intermodal facilities and two warehouses (W6 and W7). Turn time histograms were created for each facility individually and are presented in Appendix C.

TABLE 2 Turn Time Statistics by Facility Type

Facility Type	Facility ID	Total Trucks	Avg. Turn Time (min)	Turn Time SD	Turn Time CV
Intermodal	I1	2078	158	252	1.59
	I2	3643	689	509	0.74
	I3	1102	116	171	1.47
	I4	664	81	131	1.62
	I5	782	73	134	1.84
Distribution	D1	70	35	39	1.11
	D2	163	902	459	0.51
	D3	272	89	157	1.76
	D4	357	66	159	2.41
	D5	155	526	503	0.96
	D6	65	129	153	1.19
Warehouse	W1	26	47	74	1.57
	W2	185	454	490	1.08
	W3	62	209	225	1.08
	W4	3	237	328	1.38
	W5	176	85	96	1.13
	W6	3972	569	474	0.83
	W7	1510	550	404	0.73
	W8	30	48	27	0.56
	W9	5	8	8	1.00

5.5 Development of Facility Turn Time Models

Linear and non-linear regression models were developed for predicting turn times (response variable) based on percentage of truck entries (predictor or regressor variable) in preceding 1 hour interval. Both types of models are presented next.

5.5.1 Linear Regression Model

$$Y = a + b \times X$$

where

Y – average turn time (in min) of vehicles, entering the facility within 15 min interval
a – intercept
b – predictor coefficient
X – % of daily entry volume in preceding 1 hour interval

5.5.2 Non-Linear Regression Model

$$Y = a + b \times exp(X)^8$$

where
Y – average turn time (in min) of vehicles, entering the facility within 15 min interval
a – intercept
b – predictor coefficient
X – % of daily entry volume in preceding 1 hour interval

An example of a time diagram, which can be used for estimating response and predictor variables, is depicted in Figure 19. Assume that a given truck enters facility at 2:04 PM and its turn time is 12 min. The first step is to compute the number of trucks, which entered the facility in the past 60 min, i.e. between 1 PM and 2 PM (=5 trucks). If the total daily volume of entering trucks is 100, then the predictor variable will be $X = \left(\frac{5}{100}\right) = 0.05$ or 5%. Next, it is necessary to identify trucks, entered the facility between 2 PM and 2:15 PM. It can be noticed that along with a considered truck, another GPS record was obtained from a different truck around 2:11 PM (assume that turn time for that truck was 16 min). Now the response variable can be computed as $Y = \frac{12+16}{2} = 14$ min.

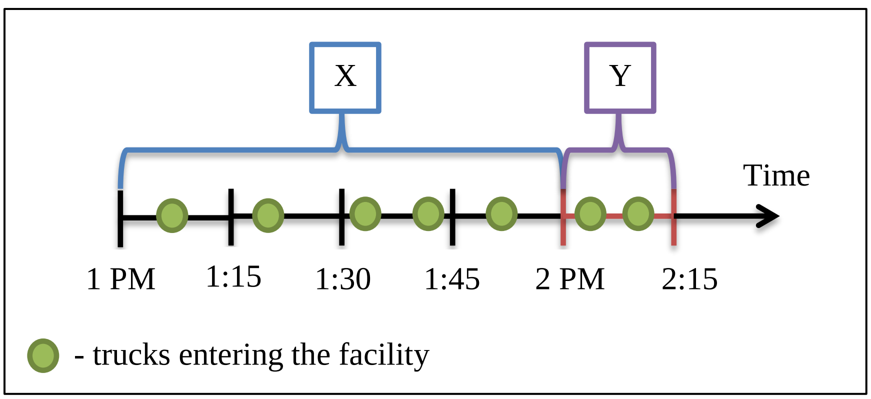


FIGURE 19 Example of a Time Diagram for Regression Models

Trucks with large turn times were removed from the dataset to avoid potential bias in the analysis. In this study before trucks with turn times greater than 1 hour were excluded from the datasets used for the regression analysis.

[8] Note: another type of a non-linear regression function was tested: $Y = a + b \times X^c$, where c is a predictor's power coefficient. However, that function returned infinite response variables for a given array of predictors, constructed based on available GPS data, and was excluded from the analysis

5.5.3 Regression Analysis by Facility

The first regression analysis aimed to derive truck turn time models for 20 freight facilities. Results of the regression analysis for each facility are presented in Tables 3 and 4, including regression model, coefficient of determination (R^2), t-statistic (for intercept and predictor), and p-value (for intercept and predictor). The t-statistic is estimated as ratio between the coefficient of intercept/predictor to its standard error. The standard error represents the standard deviation of the coefficient, its variability for all considered instances. Thus, large t-statistic demonstrates that the intercept/predictor was computed accurately. The p-value shows the result of a statistical test with the null hypothesis, stating that the coefficient for a given intercept/predictor is equal to zero. A low p-value (e.g., <0.05 at 0.05 level of significance) leads to rejection of the null hypothesis, which means that the intercept/predictor significantly contributes to the response variable value. Predictors with high p-values may be discarded from the model, since they don't make any substantial affect at the response variable.

TABLE 3 Linear Regression Analysis by Facility

Facility ID	Linear Regression Model	R^2	t-statistic (a/X)	p-value (a/X)
I1	$Y = 24.14 + (-2.67) \times X$	$R^2 = 0.001$	21.198/-0.228	0.001/0.820
I2	$Y = 22.45 + (6.27) \times X$	$R^2 = 0.001$	20.705/0.458	0.001/0.647
I3	$Y = 28.19 + (-5.50) \times X$	$R^2 = 0.001$	23.532/-0.446	0.001/0.656
I4	$Y = 24.01 + (3.85) \times X$	$R^2 = 0.001$	15.654/0.289	0.001/0.773
I5	$Y = 16.69 + (12.31) \times X$	$R^2 = 0.008$	16.574/1.352	0.001/0.178
D1	$Y = 22.27 + (40.24) \times X$	$R^2 = 0.037$	7.024/1.053	0.001/0.301
D2	Not enough data			
D3	$Y = 14.94 + (8.44) \times X$	$R^2 = 0.006$	8.592/0.664	0.001/0.509
D4	$Y = 20.59 + (10.73) \times X$	$R^2 = 0.007$	16.434/1.071	0.001/0.286
D5	$Y = 26.69 + (11.63) \times X$	$R^2 = 0.010$	8.715/0.548	0.001/0.588
D6	Not enough data			
W1	Not enough data			
W2	$Y = 22.83 + (-3.39) \times X$	$R^2 = 0.001$	12.683/-0.216	0.001/0.829
W3	Not enough data			
W4	Not enough data			
W5	$Y = 36.20 + (-20.47) \times X$	$R^2 = 0.026$	14.303/-1.250	0.001/0.216
W6	$Y = 38.49 + (6.80) \times X$	$R^2 = 0.001$	43.770/0.539	0.001/0.590
W7	$Y = 22.47 + (-6.47) \times X$	$R^2 = 0.002$	14.721/-0.464	0.001/0.644
W8	Not enough data			
W9	Not enough data			

It can be noticed that for all facilities R^2, which represents goodness of fit, of both linear and non-linear regression models did not exceed 0.04. Such poor goodness of fit can be explained by limited data. GPS records were provided only for a random small size sample of trucks, approximately accounting for 3-5% of the whole population. It was observed that array of predictors (X) had many zero values for all facilities, which negatively affected accuracy of regression models (low t-statistic and high p-value for predictors). Some of regression models have negative volume coefficients (e.g., I1, I3, W2), which contradicts the known fact that truck turn time increases with volume. For certain facilities regression analysis was impossible after eliminating trucks with turn times greater than 1 hour. Those facilities were labeled as "*Not enough data*" in Tables

3 and 4. More accurate regression models can be designed, if larger data sample is provided.

TABLE 4 Non-Linear Regression Analysis by Facility

Facility ID	Non-Linear Regression Model	R^2	t-statistic (a/X)	p-value (a/X)
I1	$Y = 27.75 + (-3.54) \times exp(X)$	$R^2 = 0.001$	2.526/-0.344	0.012/0.731
I2	$Y = 19.20 + (3.36) \times exp(X)$	$R^2 = 0.001$	1.545/0.283	0.124/0.778
I3	$Y = 31.98 + (-3.86) \times exp(X)$	$R^2 = 0.001$	2.808/-0.361	0.005/0.718
I4	$Y = 20.41 + (3.58) \times exp(X)$	$R^2 = 0.001$	1.612/0.305	0.109/0.761
I5	$Y = 5.52 + (11.18) \times exp(X)$	$R^2 = 0.008$	0.637/1.395	0.525/0.164
D1	$Y = -12.19 + (34.47) \times exp(X)$	$R^2 = 0.036$	-0.358/1.045	0.723/0.305
D2	Not enough data			
D3	$Y = 8.67 + (6.35) \times exp(X)$	$R^2 = 0.005$	0.752/0.599	0.454/0.551
D4	$Y = 11.80 + (8.84) \times exp(X)$	$R^2 = 0.007$	1.324/1.074	0.187/0.285
D5	$Y = 18.39 + (8.36) \times exp(X)$	$R^2 = 0.009$	1.045/0.511	0.305/0.614
D6	Not enough data			
W1	Not enough data			
W2	$Y = 26.24 + (-3.39) \times exp(X)$	$R^2 = 0.001$	1.809/-0.249	0.075/0.804
W3	Not enough data			
W4	Not enough data			
W5	$Y = 52.09 + (-15.99) \times exp(X)$	$R^2 = 0.024$	3.541/-1.191	0.001/0.239
W6	$Y = 31.99 + (6.49) \times exp(X)$	$R^2 = 0.001$	2.658/0.563	0.008/0.574
W7	$Y = 28.57 + (-6.08) \times exp(X)$	$R^2 = 0.002$	2.233/-0.507	0.027/0.613
W8	Not enough data			
W9	Not enough data			

5.5.4 Regression Analysis by Facility Type

The second regression analysis was directed to derive truck turn time models by facility type (i.e., intermodal – I, distribution – D, and warehouse – W). Results of the regression analysis by facility type are presented in Tables 5 and 6, including regression model, coefficient of determination (R^2), t-statistic (for intercept and predictor), and p-value (for intercept and predictor). Low coefficient of determination (R^2), low t-statistic and high p-value for predictors of linear and non-linear regression models were observed for all facility types. A negative volume coefficient was estimated for warehouse facilities. As mentioned previously, poor goodness of fit and erroneous outcomes are caused by limited data. If more GPS records are provided, it will be possible to design more accurate regression models, which can be further used to predict truck turn times for different freight facility types.

TABLE 5 Linear Regression Analysis by Facility Type

Facility ID	Linear Regression Model	R^2	t-statistic (a/X)	p-value (a/X)
I	$Y = 23.11 + (0.57) \times X$	$R^2 = 0.001$	43.083/0.105	0.001/0.917
D	$Y = 19.75 + (10.64) \times X$	$R^2 = 0.007$	20.973/1.422	0.001/0.156
W	$Y = 32.98 + (-11.98) \times X$	$R^2 = 0.004$	44.667/-1.609	0.001/0.108

TABLE 6 Non- Linear Regression Analysis by Facility Type

Facility ID	Non-Linear Regression Model	R^2	t-statistic (a/X)	p-value (a/X)
I	$Y = 22.84 + (0.28) \times exp(X)$	$R^2 = 0.001$	4.528/0.059	0.001/0.953
D	$Y = 11.21 + (8.59) \times exp(X)$	$R^2 = 0.006$	1.697/1.401	0.091/0.162
W	$Y = 43.77 + (-10.79) \times exp(X)$	$R^2 = 0.005$	6.550/-1.707	0.001/0.088

5.6 Facility Occupancy

Based on the available GPS data the average daily facility occupancy (i.e., number of trucks per day during a given time period) was estimated for each facility. Results of the analysis are presented in Figures 20-23 by facility type. The highest intermodal facility occupancy was observed at facility I2 during 11 AM – 2 PM time period (≈79 trucks). As for other intermodal facilities, the majority of GPS records were received between 12 PM and 4 PM. The highest distribution center occupancy was identified at facility D4 (≈19 trucks). For all analyzed distribution facilities the majority of observations were obtained between 12 PM and 4 PM. Warehouses were separated in two groups based on their occupancy: 1) Group A – high occupancy (W6 and W7), and 2) Group B – low occupancy (all warehouses except W6 and W7). The highest warehouse occupancy at facilities W6 and W7 was observed during 10 AM – 2 PM time period and comprised ≈71 and 33 trucks respectively (see Figure 22). As for other warehouses, the average occupancy did not exceed 3 trucks throughout the day (see Figure 23). The average occupancy substantially decreased after 7 PM for all considered types of facilities. Facility occupancy is an important performance indicator that can be used to determine peak periods for each facility, allocate workforce and equipment, negotiate service charges imposed to trucking companies, etc. Relative daily facility occupancy (measured as percentage of trucks) is presented in Appendix D for all facility types.

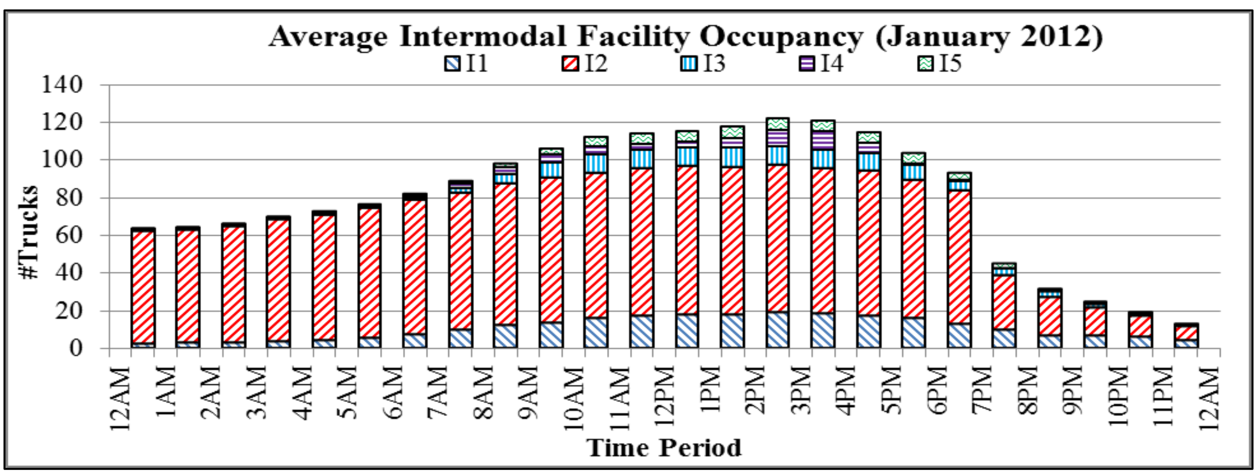


FIGURE 20 Daily Intermodal Facility Occupancy

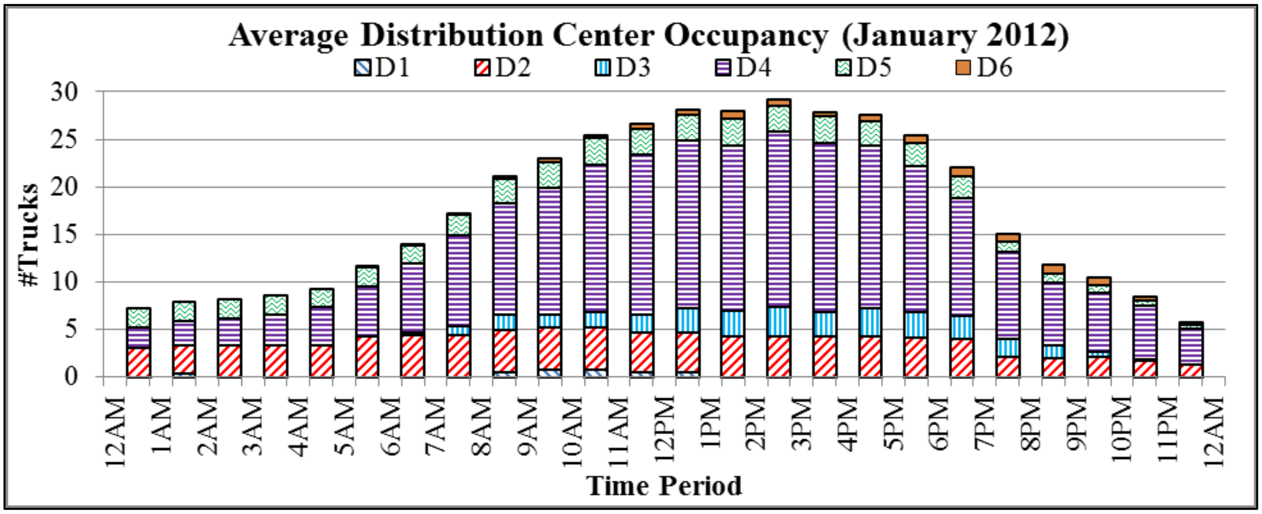


FIGURE 21 Daily Distribution Center Occupancy

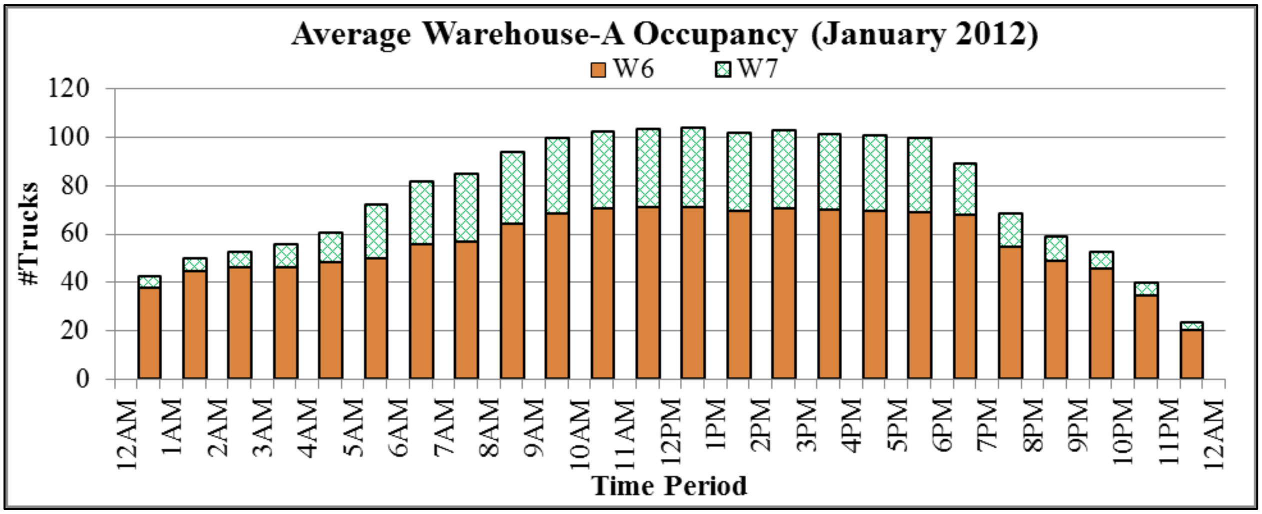


FIGURE 22 Daily Warehouse-A Occupancy

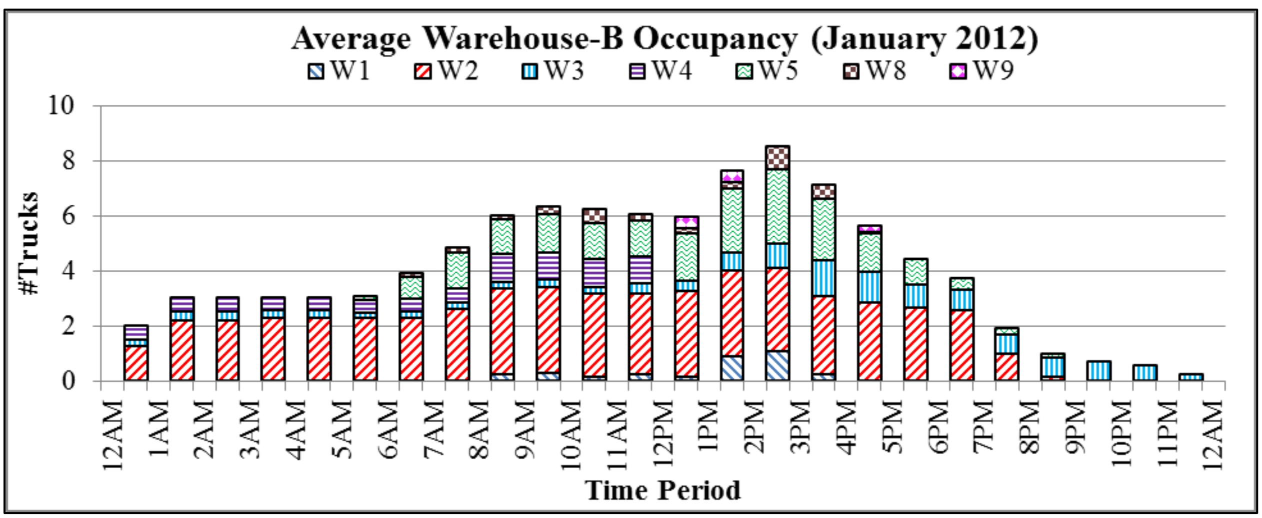


FIGURE 23 Daily Warehouse-B Occupancy

5.7 Entry/Exit Volumes

GPS data can be also used to estimate entry and exit truck volumes for a given freight facility during specific time periods. In this study average daily entry and exit volumes were computed for 1-hour time periods[9] for the month of January. Results are presented in Figures 24-31 by facility type. Note that actual truck volumes at each facility are expected to be greater than the ones presented herein, mainly due to the fact that GPS data provided represent a random small sample of trucks from the whole population (approximately 3% to 5%). The highest volumes of entering and exiting trucks were observed at the intermodal facilities. Two peak periods can be identified for all intermodal facilities based on entry volumes (see Figure 24): 1) 8AM – 11AM, and 2) 2PM – 5PM. The amount of exiting trucks substantially increased after 3 PM (see Figure 25). As for distribution centers, spikes in entry volumes were observed around 6AM for D2 and D3, which can be explained by the start of the work day. Entry volumes were increasing after 8AM for other distribution facilities. Exiting truck volumes significantly increased between 6PM and 7PM. Spikes in entry and exit volumes, occurred between 11PM and 1AM at facilities D2 and D4 (Figures 26 and 27), indicate that a substantial amount of trucks were staying inside those distribution centers overnight (such conclusion can be also made based on large mean truck turn times and turn time SD, estimated for D2 and D4, see Table 2).

Warehouses were divided in two groups based on their entry/exit volumes: 1) Group A – high entry/exit volumes (W6 and W7), and 2) Group B – low entry/exit volumes (all warehouses except W6 and W7). Spikes in entry and exit volumes, occurred between 9PM and 2AM at warehouses W6 and W7 (Figures 28 and 29), indicate that a substantial amount of trucks were staying inside those facilities overnight (this can be confirmed with large mean truck turn times, estimated for W6 and W7, see Table 2). It can be noticed that truck entry volume spikes occurred around 6AM for the majority of warehouses, which can be explained by the start of the work day. The amount of exiting trucks substantially increased after 5PM for group A warehouses, while multiple spikes in exiting volumes were observed for group B warehouses. Relative daily facility entry/exit volumes are presented in Appendix D for all facility types.

[9] Note that similar analysis can be conducted for various time periods (e.g., every 15-min; AM, MD, PM, OP time periods) and days of the week (e.g., weekdays vs. weekends)

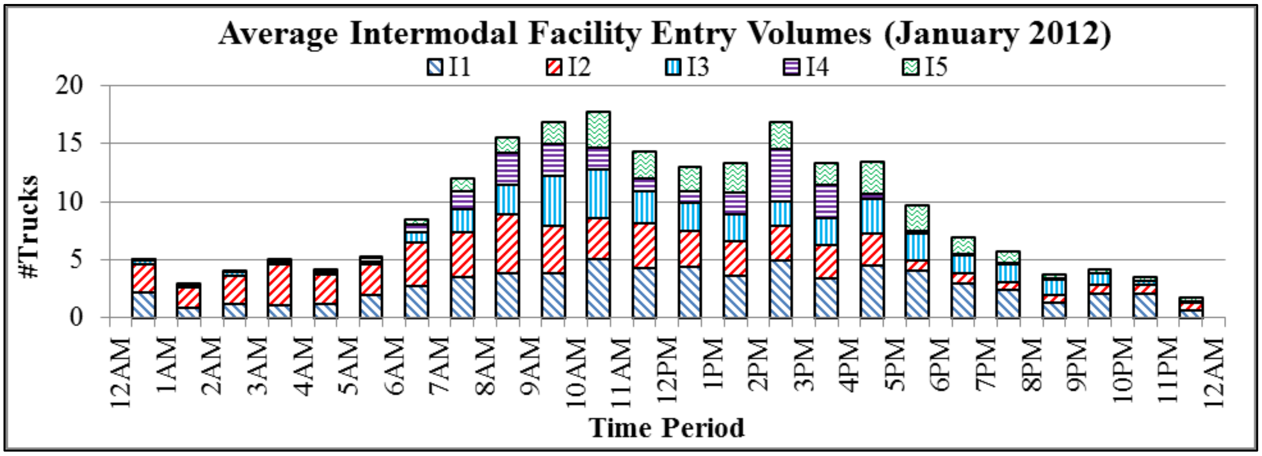


FIGURE 24 Daily Intermodal Facility Entry Volumes

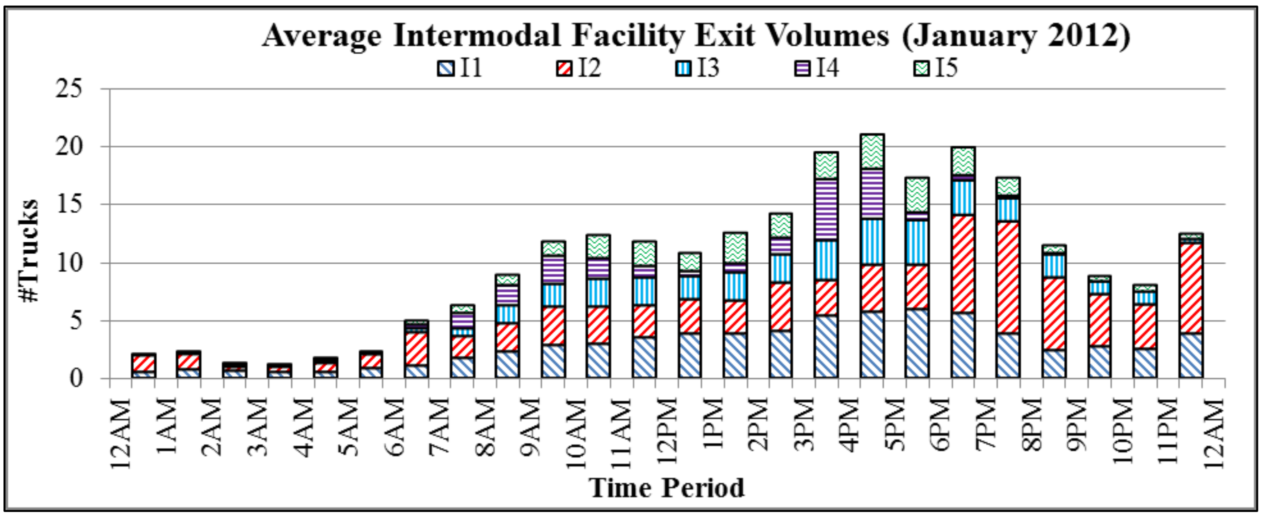


FIGURE 25 Daily Intermodal Facility Exit Volumes

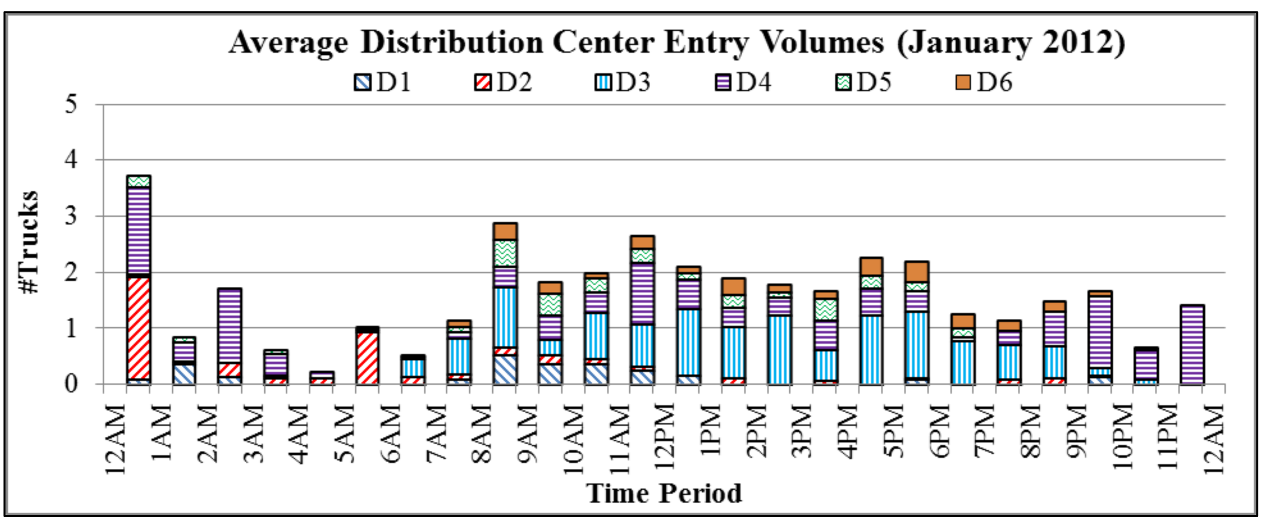


FIGURE 26 Daily Distribution Center Entry Volumes

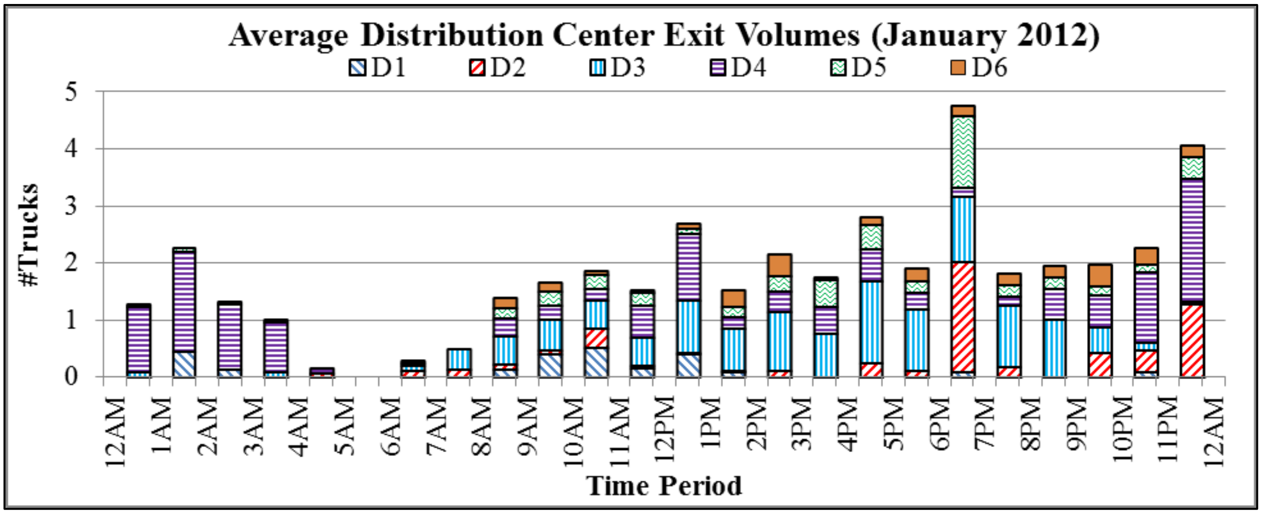


FIGURE 27 Daily Distribution Center Exit Volumes

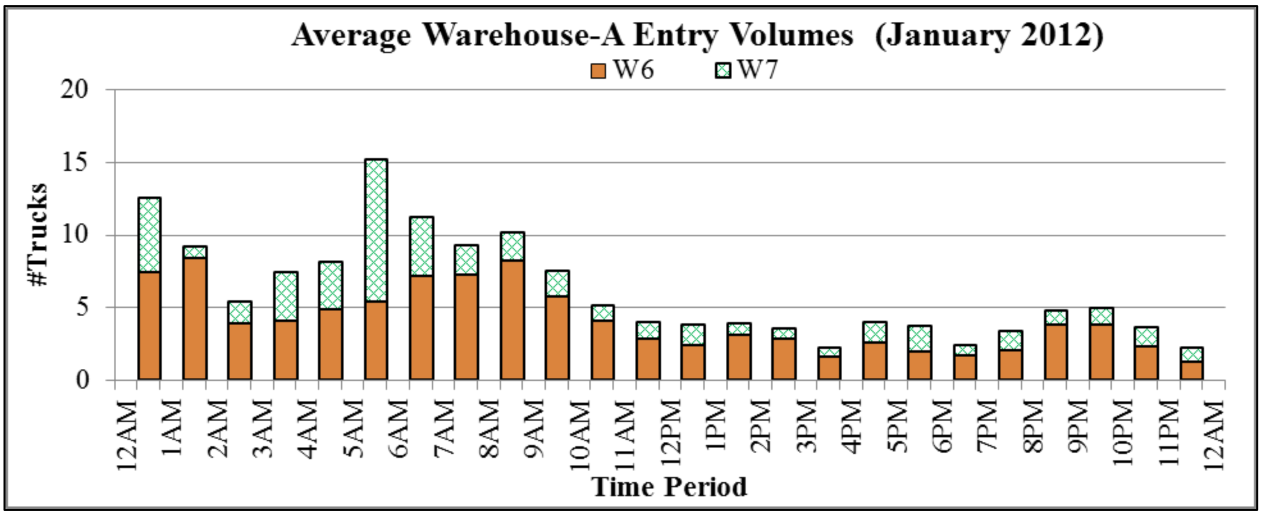


FIGURE 28 Daily Warehouse-A Entry Volumes

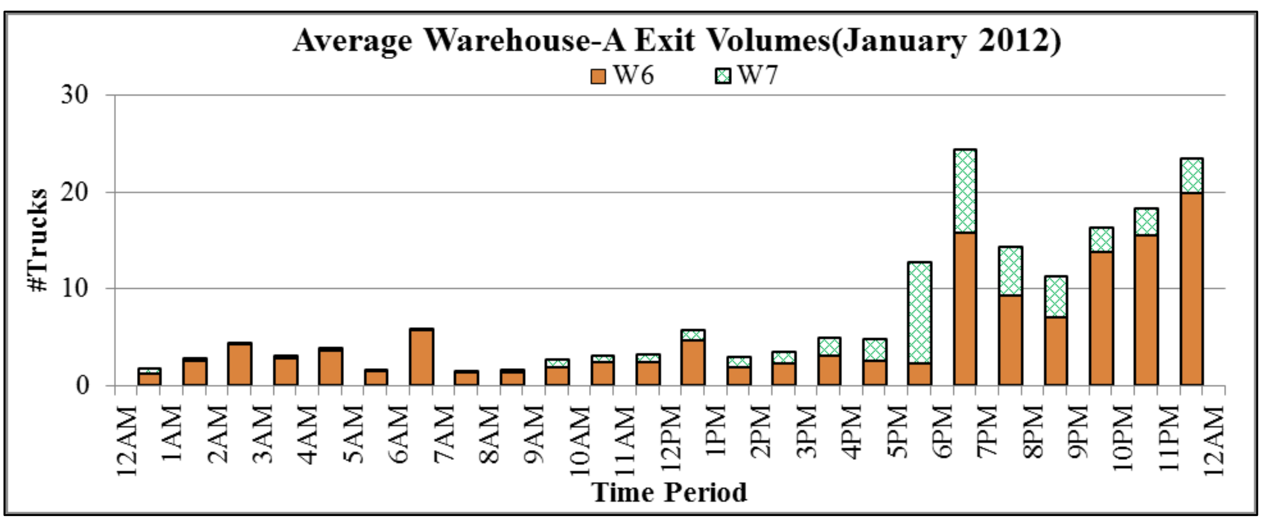


FIGURE 29 Daily Warehouse-A Exit Volumes

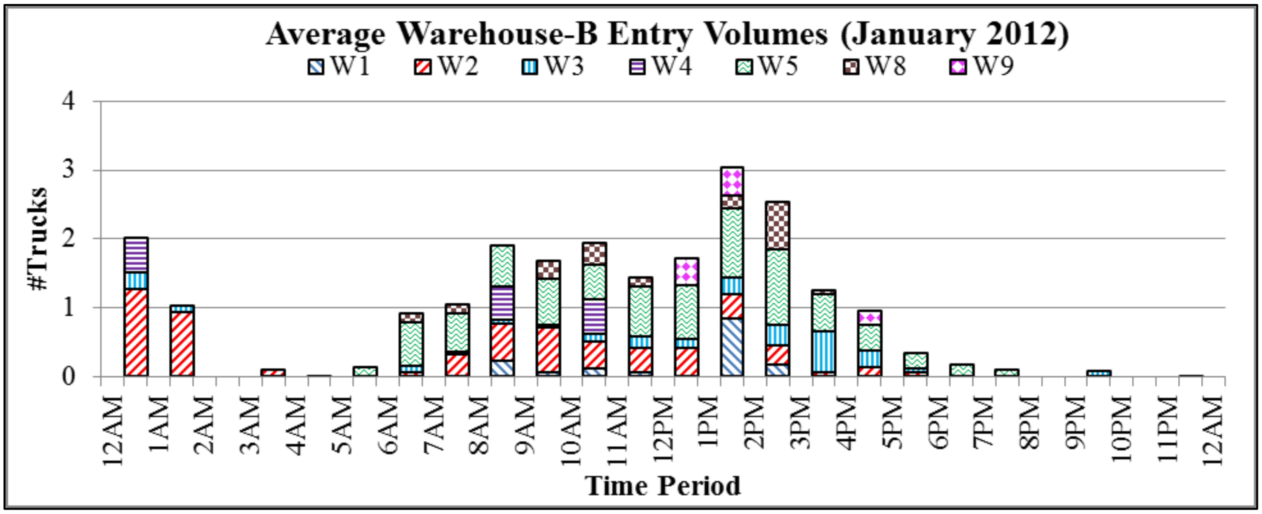


FIGURE 30 Daily Warehouse-B Entry Volumes

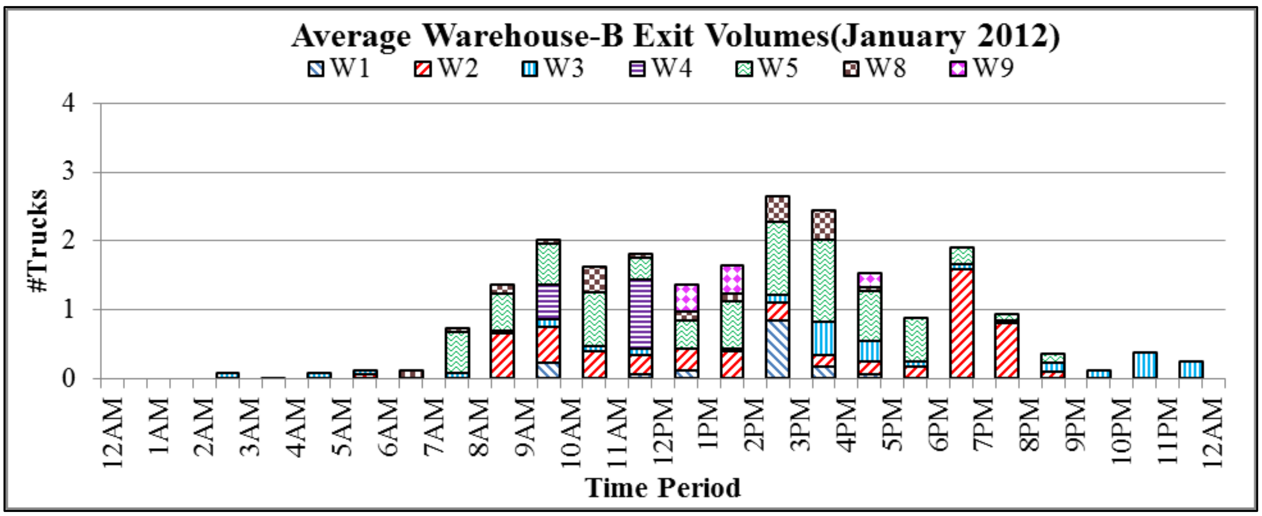


FIGURE 31 Daily Warehouse-B Exit Volumes

5.8 Freight Facility Trip Generation Models

Freight demand modeling remains a challenging task mainly due to the limited data. According to Ortuzar & Willumsen (2011), the factors, affecting freight movements, include the following: a) location factors (e.g., location of manufacturing plants and final markets), b) range of products (different types of commodities can be carried by a single truck), c) physical factors (special conditions have to be maintained for transport of certain goods, e.g. refrigerated cargo), d) operational factors (size of a freight facility, type of equipment used, available resources, inventory policies, etc.), e) geographical factors (geographic location may affect distribution of the products), f) dynamic factors (e.g., demand fluctuation during the year), g) pricing factors (prices are more flexible as compared to passenger demand), and others. Since the data, required for development of freight facility trip generation models, are not available at the moment, this step is left for the future research.

5.9 Conclusions

This section demonstrated how freight facility performance indicators (truck turn times, facility occupancy, entry/exit volumes) can be estimated using available truck GPS data. Computed facility performance measures can be used to determine peak periods for each facility, identify facilities that may require future improvements, allocate workforce and equipment, etc. Accuracy of truck turn time prediction models can be improved if more GPS records are provided. Development of freight facility trip generation models is left for the future research due to lack of the data.

6. INTER- AND INTRA-CITY TRUCK TRIP ANALYSIS

This section describes two algorithms that were developed for analysis of truck trips: Origin-Destination Identification Algorithm (ODIA) and Trip Detection Algorithm (TDA). ODIA was designed to identify inter-city truck trips[10], while TDA can be applied to analyze both inter- and intra-city truck trips and to estimate truck trip characteristics (e.g., dwell times at origin, destination, freight facilities, traffic light stops, etc.). Both algorithms and examples of their application are presented next.

6.1 Origin-Destination Identification Algorithm (ODIA)

OIDA was developed to estimate the number of truck trips between traffic analysis zones (TAZs) in the State of TN. Along with truck trips additional information can be retrieved (e.g., start trip time, end trip time, trip duration, etc.). Once GPS records are loaded, ODIA filters out observations with spot speeds greater than a set value (=5 mph), and leaves for analysis only those observations (with spot speeds ≤5 mph), which can be potentially either origins or destinations. Then the algorithm sorts all trucks by IDs and observations for each truck by their time stamps in the ascending order. Next OIDA starts an iterative process, which consists in checking TAZ for each observation of a given truck. If TAZ_p and TAZ_s[11] for two consecutive GPS records are the same, it is more likely that no trips were made by the truck. When two consecutive observations have different TAZ_p and TAZ_s, OIDA marks the preceding record as "ORIGIN", while for the succeeding record the algorithm checks if it is a genuine destination. If there is only one consecutive observation with TAZ_s, OIDA marks that observation as "DESTINATION". If there is a group of GPS records with the same TAZs as TAZ_s, the algorithm calculates the total travel distance between those observations. If the distance does not exceed ¼ mile (GPS spatial error), OIDA marks the earliest observation of this group as "DESTINATION". Otherwise (the distance >¼ mile), the truck was most probably still traveling (e.g., traffic light stop). Note that travel distance between two consecutive GPS points was computed based on their coordinates. The procedure continues until all observations for all trucks are analyzed. Final OIDA output also contains full Origin-Destination (OD) matrix. The main OIDA steps are outlined next.

OIDA Steps

Step 0: Initialize origin-destination matrix $OD = \emptyset$
Step 1: Load GPS data for a given day/time period
Step 2: Remove observations with spot speeds greater than a set value (=5 mph)
Step 3: Sort GPS data based on truck IDs and time stamps (in the ascending order)
Step 4.0: For each truck *t* set observation *i=0*

  Step 4.1: Select observation *i=i+1*
  Step 4.2: Does the next observation (i.e., *i+1*) have the same TAZ
  If YES - go to Step 4.1
  Else go to Step 4.3

[10] Note that OIDA can be also used not only for identifying inter-city truck trips, but also for estimating trips between specific areas (denoted by ZIP codes), State counties, particular metropolitan areas, etc.
[11] TAZ_p denotes TAZ for a preceding observation; TAZ_s denotes TAZ for a succeeding observation

Step 4.3: Flag observation *i* as “ORIGIN”, record trip start time
Step 4.4: Count the total number of observations *j≥i+1* with the same TAZ as *i+1* and denote it as *Q*
Step 4.5: Is *Q* greater than 1
If YES – go to Step 4.6
Else flag observation *i+1* as “DESTINATION”, record trip end time, count trip → $OD(TAZ_i, TAZ_{i+1}) = OD(TAZ_i, TAZ_{i+1}) + 1$ and go to Step 4.8
Step 4.6: Compute the total travel distance between consecutive observations *i+1, i+2,…,i+Q* and denote it as *D*
Step 4.7: Is *D* greater than a set value (=¼ mile)
If YES – go to Step 4.8
Else flag observation *i+1* as “DESTINATION”, record trip end time, count trip → $OD(TAZ_i, TAZ_{i+1}) = OD(TAZ_i, TAZ_{i+1}) + 1$ and go to Step 4.8
Step 4.8: Is *i+Q* the last observation for truck *t*
If YES – go to Step 4.9
Else go to Step 4.1
Step 4.9: It truck *t* the last
If YES – go to Step 5
Else go to Step 4.0 and set *t=t+1*

Step 5: Retrieve necessary truck trip data

6.1.1 OIDA Application

OIDA algorithm was implemented to identify truck trips between TAZs within the State of TN in January and February, 2012[12]. The State of TN is divided into 6,095 TAZs. The Extract Analysis Toolbox, of ESRI ArcGIS 10.0, was used to associate GPS records with each TAZ. Some of TAZs did not have any available observations (≈14.1% for January and ≈13.4% for February). Results of truck trip analysis are presented in Figures 32-35 and Table 7. It was found that approximately 1.0% of trucks had suspiciously large trip travel time, i.e. more than 10 hours, which is the travel time between two cities, located close to the opposite TN boarders (Memphis, West TN, and Johnson City, East TN). Manual inspection indicated that a large trip travel time was caused by loss of the GPS signal (i.e., a truck arrived to its destination earlier). Hence, all trips with travel times greater than 10 hours were discarded from the analysis to avoid erroneous outcomes.

TABLE 7 Truck Trip Descriptive Statistics

Month	January	February
Number of unique trucks	22,807	23,189
Total number of trips	648,486	666,469
Average trips/truck/month	28.4	28.7
Average trips/day	20,919	22,982
Mean trip travel time (min)	57.2	55.3
Median trip travel time (min)	21.0	21.9

[12] Note that OIDA can be used to estimate inter-state truck trips as well, if GPS records are available

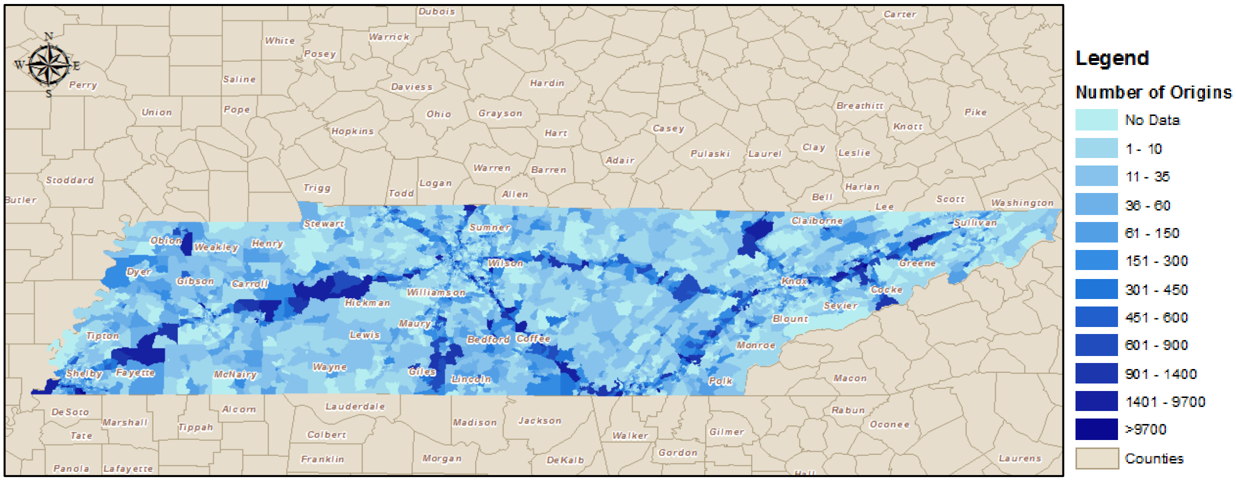


FIGURE 32 Number of Origins by TAZ for January 2012

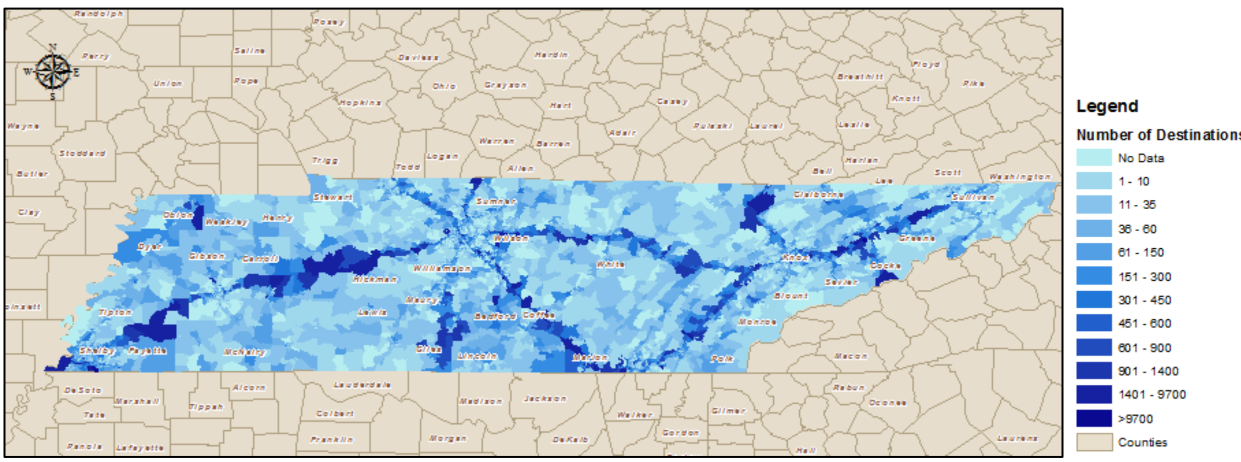


FIGURE 33 Number of Destinations by TAZ for January 2012

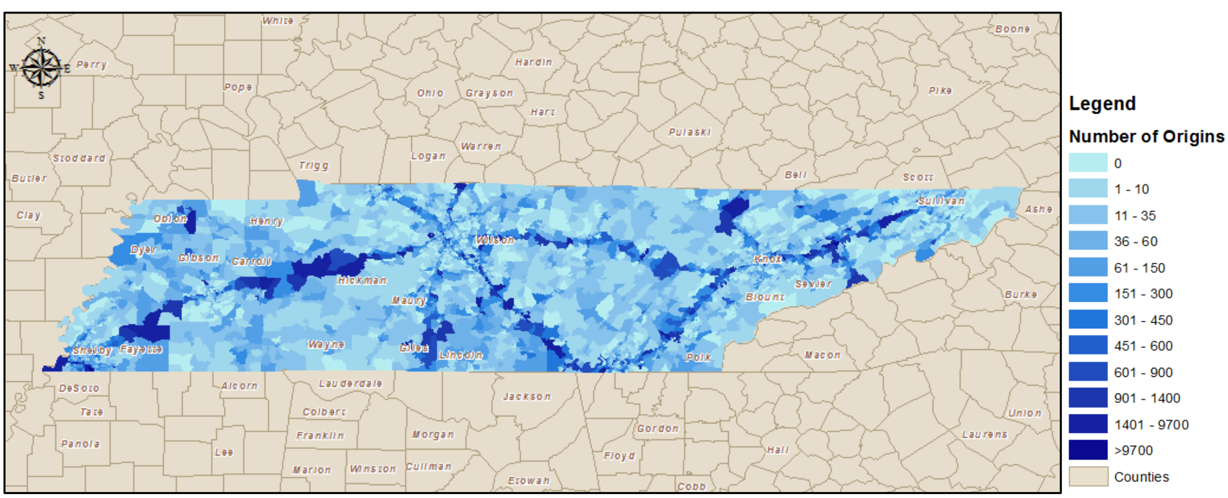


FIGURE 34 Number of Origins by TAZ for February 2012

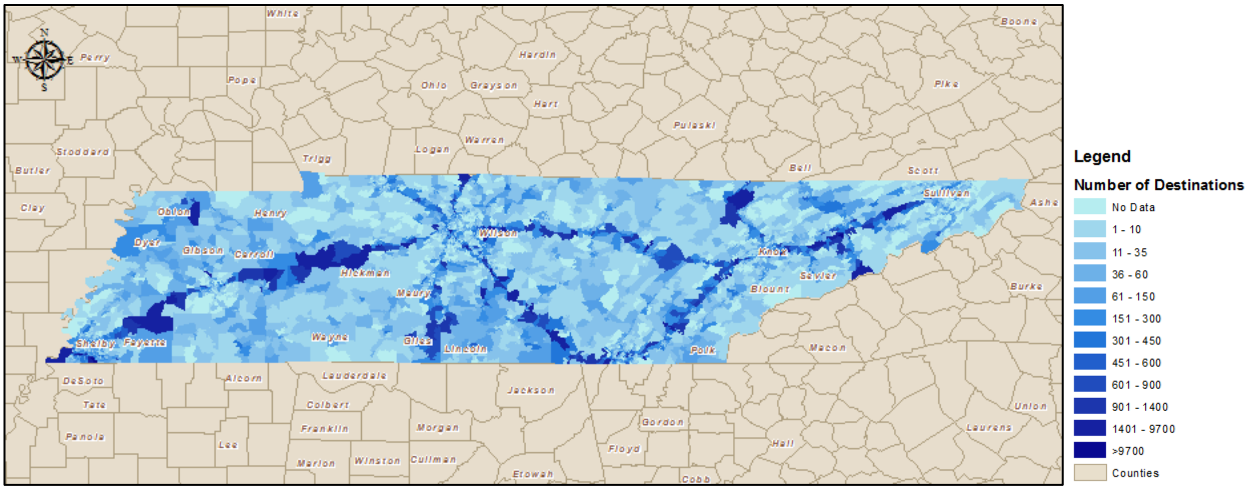


FIGURE 35 Number of Destinations by TAZ for February 2012

Generally, it can be noticed that distribution of origins/destinations was similar for January and February (see Figures 32 and 34 for origins and Figures 33 and 35 for destinations). This can be explained by the fact that most of trucks have a predetermined set of pick-up/drop-off locations, which have to be visited with a specific frequency (i.e., daily, weekly, bi-weekly, etc.). Besides, if was found that the majority of trips were originated/destined near large metropolitan areas (i.e., Memphis, Nashville, Knoxville, Chattanooga, etc.). A substantial number of origins and destinations were observed along the major freight corridors (I-40, I-24, I-65, I-75, and I-81). It is more likely that in the latter case truck drivers stopped for refueling, rest, or other activities, not involving commodity pick-up/drop-off. OIDA does not include logical tests for identifying those stops due to a number of reasons (i.e., high GPS signal frequency is required, locations of rest stops should be provided, lack of commodity data, etc.).

A higher number of unique trucks and truck trips were identified in February as compared to January (most probably due to the holiday season). On average, each truck averaged 28 trips per month (see Table 7). It can be noticed that the majority of trucks traveled between TAZs located close to each other, as the mean trip travel time did not exceed 1 hour for both months. The average number of detected trips was 20,919 and 22,982 for January and February respectively. OD matrices were estimated for each day of January and February, but are not presented in the report due to their size (i.e., trucks originated/destined in more than 5,000 TAZs). Note that similar analysis can be conducted for any month of the year or multiple months.

6.2 Trip Detection Algorithm (TDA)

TDA was designed to analyze individual truck trip (both inter- and intra-city) patterns for a given time period. The TDA steps are outlined next. Along with truck GPS data, TDA requires a GIS database, containing polygons of freight facilities. The major TDA steps are as follows:

TDA Steps

Step 1: Load GPS data for a given day/time period

Step 2: Sort GPS data based on truck IDs
Step 3: Sort observations for each truck based on time of the day
Step 4: For each truck
    Step 4.1: Determine trip ORIGIN (if any)
    Step 4.2: Identify truck stops (if any)
    Step 4.3: Define possible reasons for each stop
    Step 4.4: Determine trip DESTINATION (if any)
    Step 4.5: Obtain truck trip characteristics
Step 5: Retrieve necessary truck trip data

For each truck trip the following conditions are checked by TDA for each GPS record:

1. If spot speed for the earliest observation is less than a set value (=5 mph) and the truck is not at a facility, flag the observation as "ORIGIN", else "NO ORIGIN";
2. If there is a group of the earliest observations with spot speeds less than a set value (=5 mph) and the truck is not at a facility, flag the first observation as "ORIGIN" and the rest as "STAYS AT ORIGIN";
3. If spot speeds for all observations are equal to zero and the truck is not at a facility, flag them as "NO MOVEMENT";
4. If spot speed for the observation is less than a set value (=20 mph) and the truck is at facility, flag the observation as "AT FACILITY";
5. If spot speed for the observation is greater than a set value (=20 mph) and the truck is within the facility area, flag the observation as "PASSING FACILITY";
6. If a group of consecutive observations has a travel distance less than a set value (=5 mi), max spot speed less than a set value (=20 mph), and one of the observations was transmitted from a facility, flag them as "AT FACILITY";
7. If a group of consecutive observations has travel distance less than a set value (=10 mi), max speed less than a set value (=20 mph), travel time greater than a set value (=30 min), and none of them were transmitted from a facility or destination, flag them as "MOVING SLOWLY";
8. If spot speed for the observation is greater than a set value (=5 mph) and the truck is not at a facility or moving slowly, flag the observation as "MOVING";
9. If spot speed for the observation is less than a set value (=5 mph), and truck is not at a facility, destination or moving slowly, flag the observation as "STOPPED";
10. If a group of consecutive observations has spot speeds less than a set value 1 (=5 mph), travel time between the first and preceding one is less than a set value 2 (=3 min), travel time between the last and the proceeding one is less than a set value 3 (=3 min), and the total stop time is less than a set value 4 (=3 min), flag them as "STOP AT TR.L." or stopped at traffic light;
11. If the observation has spot speed less than a set value (=5 mph), the total stop time is greater than a lower bound (=3 min) but less than an upper bound (=15 min), and the truck is not at a facility, destination or moving slowly, flag the observation as "SDTUR" or stopped due to unknown reason;

12. If the truck was stopped for more than a set value (=15 min), and it is not at a facility, destination or moving slowly, flag the corresponding observation as "POT. NEW ORIGIN" or potential new origin;
13. If spot speed for the last observation is less than a set value (=5 mph) and the truck is not at facility flag the observation as "DESTINATION", else "NO DESTINATION";
14. If a group of latest observations has spot speeds less than a set value (=5 mph) and the truck is not at a facility, flag the first one as "DESTINATION" and the rest as "STAYS AT DESTINATION".

In this study threshold values for identifying a truck status were set based on travel patterns in the State of TN, data features (e.g., truck speeds within facilities, average time interval between consecutive observations), and current practices, revealed in the literature (common time and speed threshold values for stopped trucks, traffic light stops[13]), which can differ by metropolitan area). Along with truck GPS data, the authors had access to a GIS database, containing polygons of freight facilities, located in the Greater Memphis area (not all TN). Travel distance between consecutive observations was estimated using coordinates of GPS records. This method will be accurate for interstates, but approximate when approaching cities (due to high curvature of links or change of direction). GPS records, when a truck possibly made a pick-up/delivery stop at a freight facility, and for which facility the coordinates were not available, TDA marked the truck movement as "MOVING SLOWLY". In some cases a truck may stop for more than 3 and less than 15 minutes. Those observations were flagged as stopped due to unknown reason or SDTUR (fueling, rest stop, traffic incident, etc.). When observations are labeled as "MOVING SLOWLY" or "SDTUR" a supplementary inspection (e.g., Google maps or satellite images) is recommended to identify the stop purpose. If consecutive GPS points indicated that a truck has been stopped for longer than 15 min the algorithm will mark the corresponding GPS record as a potential new origin (PotNewOr). Next we present two examples of TDA application.

6.2.1 TDA Example 1

The first random truck #1, selected for analysis, was traveling in Memphis (TN) on January 3rd between 12:04 AM and 4:24 PM (see Figure 36). A total of 23 GPS records were available for truck #1.

TDA identified that the first seven records were transmitted, when the truck was at its trip origin. A manual inspection (based on satellite images) indicated that the truck originated at a commercial warehouse. The truck spent around 12.0 hours at that warehouse and then started its trip approximately at 2:42 pm. The algorithm determined the first truck stop at 2:57 pm. Based on coordinates of the stop location, it was established that the truck was at a freight facility. Nine observations, transmitted between 2:57 pm and 3:48 pm, were flagged as "AT FACILITY'. The next group of GPS records, received between 4:04 pm and 4:07 pm, indicated that the truck was moving.

[13] McCormack & Hallenbeck, 2005; Wheeler & Figliozzi, 2011; Golias et al., 2012, etc.

TDA marked those GPS points as “MOVING”. The second truck stop occurred at 4:09 pm near E Shelby Dr – Lamar Ave intersection. A manual inspection (based on satellite images) suggested that a truck driver stopped at Pilot Travel Center. The stop duration could not be established, since there was only one “STOPPED” observation available. The next GPS record was transmitted at 4:24 PM, when the truck started moving again. Since that observation was the last for a considered truck, it was marked as “NO DESTINATION” by TDA.

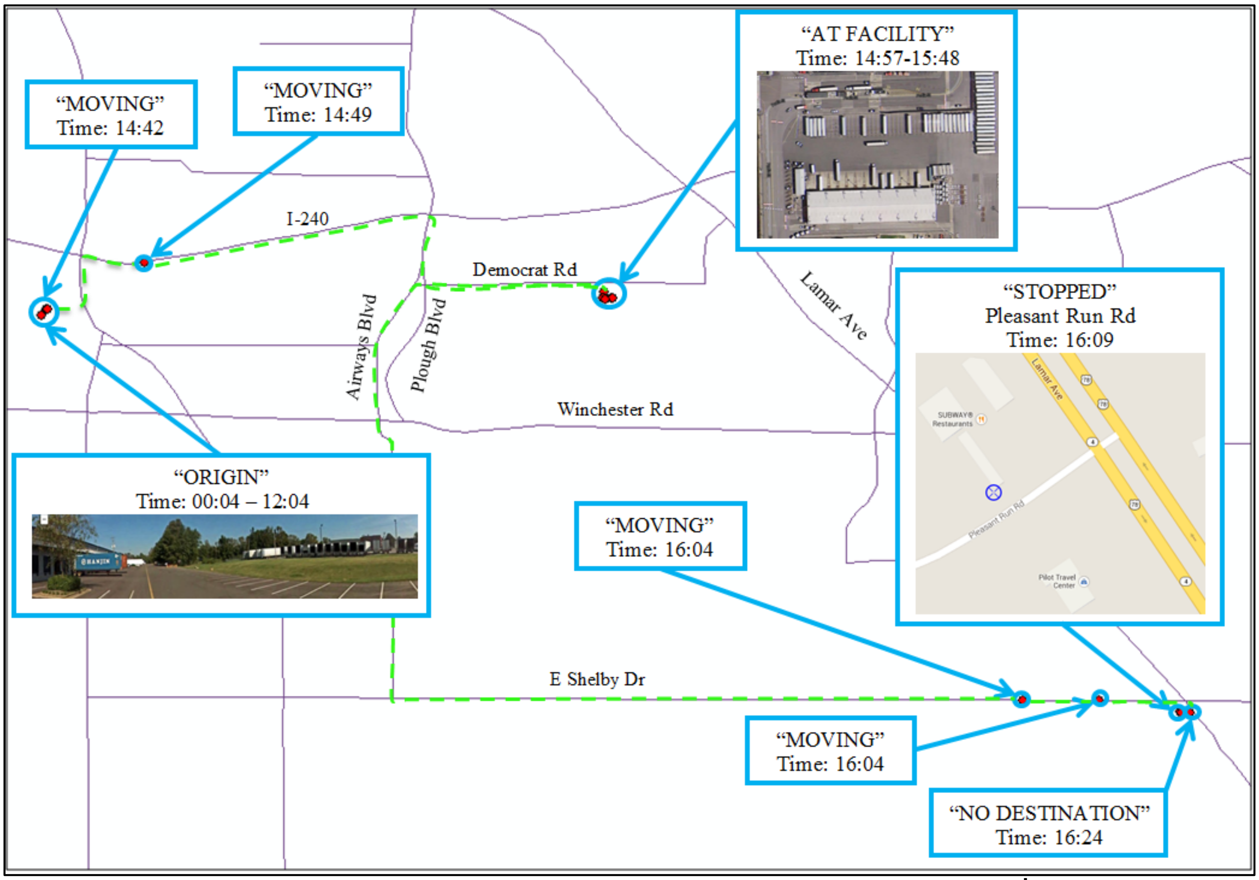


FIGURE 36 Trip of a Random Truck #1 on January 3rd

6.2.2 TDA Example 2

The second randomly selected truck #2 was also traveling within the Greater Memphis Area (TN). A total of 28 observations have been transmitted between 10:15 AM and 06:05 PM (see Figure 37).

TDA determined that the first two GPS points were received, when the truck was at its origin. Based on satellite images it was found that the truck origin located in the residential area near intersection Frayser Blvd – Madewell St. The truck started moving at 10:33 AM. The next ten observations were flagged as “MOVING” by TDA. A large time interval was noticed between 11th and 12th GPS records (i.e., between 11:00 AM and 03:50 PM). The truck could potentially make additional stops within that time period. The only truck stop was detected at 03:51 PM. Four consecutive observations were marked as “AT FACILITY” by TDA. A manual inspection indicated that the truck was at one of freight facilities, located near Lamar Ave – Tuggle Rd intersection. The total dwell time at facility was very small (i.e., ≈ 1 min). This fact indicates that there was a loss of GPS signal after 11:00 AM (or observations were not provided in the dataset), and it is more likely that the truck arrived to the freight facility before 03:51 PM (i.e., sometime between 11:00 AM and 03:50 PM). The next group of observations has been transmitted between 03:54 PM and 04:25 PM, when the truck was moving. The truck arrived to its destination between 04:25 PM and 04:28 PM. The destination location had coordinates close to the origin coordinates (i.e., the truck made a tour). The last observation was received at 06:05 PM. TDA indicated that at least 1 hour and 37 min the truck had been staying at its destination.

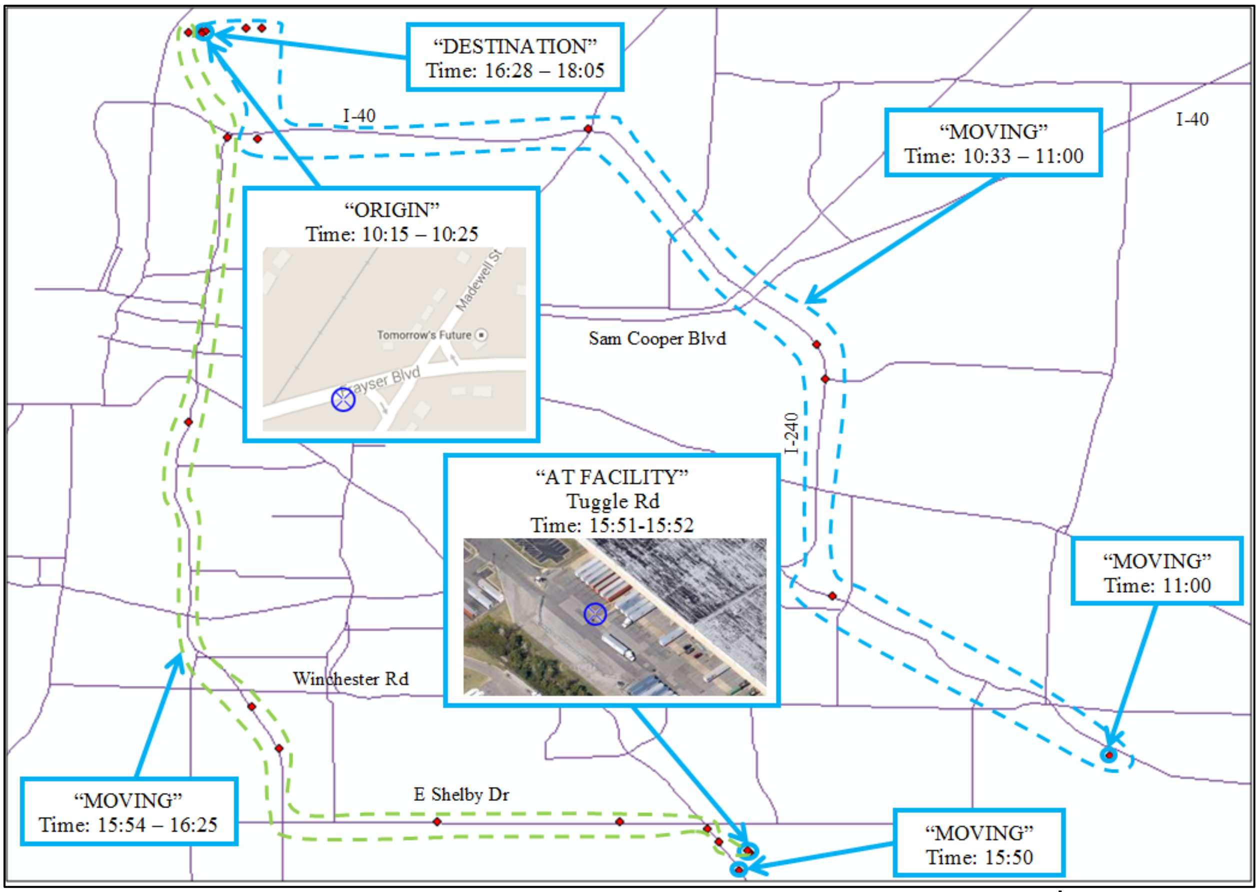


FIGURE 37 Trip of a Random Truck #2 Trip on January 3rd

6.2.3 Truck Trip Characteristics

Along with truck status TDA estimates additional trip characteristics (dwell times at origin, destination, freight facilities, traffic light stops, etc.), which are presented in Appendix E for both TDA examples. Producing similar output data for individual trucks can be time consuming if performed manually, especially if we consider some trucks may have more than 200 observations per day. Thus, use of TDA can significantly reduce the effort, required for individual truck trip analysis. Note that most likely TDA underestimates truck dwell TT due to GPS data quality. Dwell TT at stops is counted from the first observation available with speed ≤ 5 mph, but it is impossible to know with certainty if the truck stop was initiated at an earlier time (i.e., between GPS records with speed > 5 mph and speed ≤ 5 mph respectively). Dwell TT could be computed with higher accuracy if the GPS signal is provided more frequently (e.g., every 10 sec).

6.3 Conclusions

This section presented two algorithms for analysis of truck trips using GPS data. The first algorithm (OIDA) can be applied for estimating inter-city truck trips, while the second algorithm (TDA) was designed to identify both inter- and intra-city truck trips and compute truck trip characteristics. Applications of both algorithms were demonstrated using truck GPS records available for the State of TN. It was found that the majority of truck trips originated or destined near the major metropolitan areas and along the key freight transportation corridors. Accuracy of OIDA and TDA can be improved, if more frequent GPS signal is provided and additional information (i.e., location of freight facilities, rest stops, pick-up/drop-off business locations, commodity data, etc.) is available.

7. ARCGIS APPLICATION DEVELOPMENT

The developed procedures of associating GPS records with links of the transportation network and estimating link FPMs using DOI were automated and embedded into a ArcGIS add-on tool named "Link FPM Estimation". This section describes the developed application and provides guidelines for installation and use.

7.1 Introduction

As discussed earlier (see section 3 of the report) the Proximity Analysis Toolbox of ESRI ArcGIS 10.0 was used to snap GPS points with the network. After that the DOI algorithm was executed to estimate link FPMs for the given network. The main objective of the integrated ArcGIS application was to perform both tasks (i.e., snapping observations to links and calculating link FPMs) within the ArcGIS domain.

7.2 Tool Components

The folder with installation files (named as "Tool") includes 4 components:

1) DOI.exe – executable file, launching the DOI algorithm
2) FPM.py – python script, required for a new ArcGIS toolbox
3) MCR_R2014a_win32_installer.exe – executable file, enabling installation of MATLAB Compiler Runtime (MCR)
4) splash.png – image, which is used by DOI.exe

The DOI algorithm was coded in MATLAB 2014a on Dell T1500 Intel(T) Core™, i5 Processor with 1.96 GB of RAM, Windows 32-bit Operating System. A standalone executable application DOI.exe was created using the MATLAB code for the DOI algorithm and MATLAB Compiler. DOI.exe can launch DOI without installation of MATLAB on a given PC. However, DOI.exe requires installation of MCR, which is available at mathworks.com[14] (open source). The user does not have to download MCR, as it is included in the folder with installation files. Note that file splash.png should remain within the installation folder along with DOI.exe, as it is used by the latter application.

Python file FPM.py performs 4 major functions:

a) Loading the initial data (paths with GPS data and transportation network, and search radius) and associating GPS records with links of the transportation network
b) Creating temporary text files, which contain input for DOI.exe
c) Launching DOI.exe
d) Removing temporary text files

7.3 Installation Guideline

The installation process can be summarized as follows:

[14] Link: http://www.mathworks.com/products/compiler/mcr/

1) Create a new folder on the desktop of a given PC. Note that the folder's name should not contain blanks (underscore is accepted, e.g. "Integrated_Tool"). Blanks may cause errors, when reading paths of DOI.exe and input shapefiles. Move the folder with installation files "Tool" to that new folder "Integrated_Tool").

2) Create shapefiles for the transportation network and available GPS data and place them in a separate folder (can be named as "Shapefiles"). Then move the folder "Shapefiles" to the folder "Integrated_Tool". This version of the tool does not automatically generate shapefiles for available GPS records. Those shapefiles can be created using ArcGIS. Example shapefiles for GPS data and transportation network are provided along with tool installation files.

3) Run MCR_R2014a_win32_installer.exe application and complete MCR installation.

4) Open ArcMap of ESRI ArcGIS. Open ArcToolbox window. Right click on ArcToolbox window and select "Add Toolbox…" option. Then create or choose the folder, where a new toolbox should be placed. Create a new toolbox within a selected folder (Figure 38). Name a new toolbox (e.g., "Link FPM Estimation.tbx"). Click Open. A new toolbox will appear in ArcToolbox window.

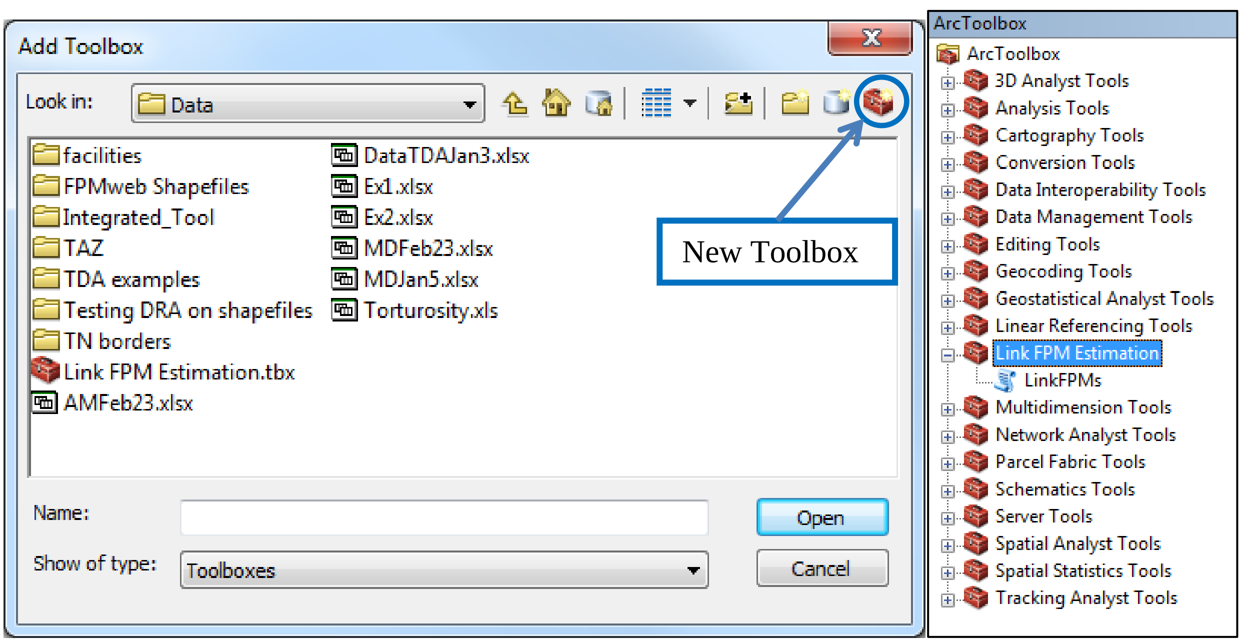


FIGURE 38 Adding New ArcGIS Toolbox

5) Right click on "Link FPM Estimation.tbx" and select "Add…Script…" option.

6) Declare name and label of the application (e.g., Link FPMs). No blanks in name/label of the script are allowed. Providing description is optional (see Figure 39 left). Click Next.

7) Load FPM.py file, located in the "Tool" folder (see Figure 39 right). Click Next.

8) Create fields for input variables, required for the tool (see Figure 40): a) "Data" – path to .dbf file with GPS data (e.g., C:\Users\UserName\Desktop\Intergrated_Tool \Shapefiles\GPSFileName.dbf); b) "Network" – path to .dbf file with Network data (e.g., C:\Users\UserName\Desktop\Intergrated_Tool\Shapefiles\NetworkFileName.dbf); c) "Radius" – search radius (possible to set a default value of 0.25 Miles); d) "PathDOI" – path to DOI.exe file (e.g., C:\Users\UserName\Desktop\Intergrated_Tool\Tool); e) "LinkFIDs" – link FIDs to be analyzed. Click Finish.

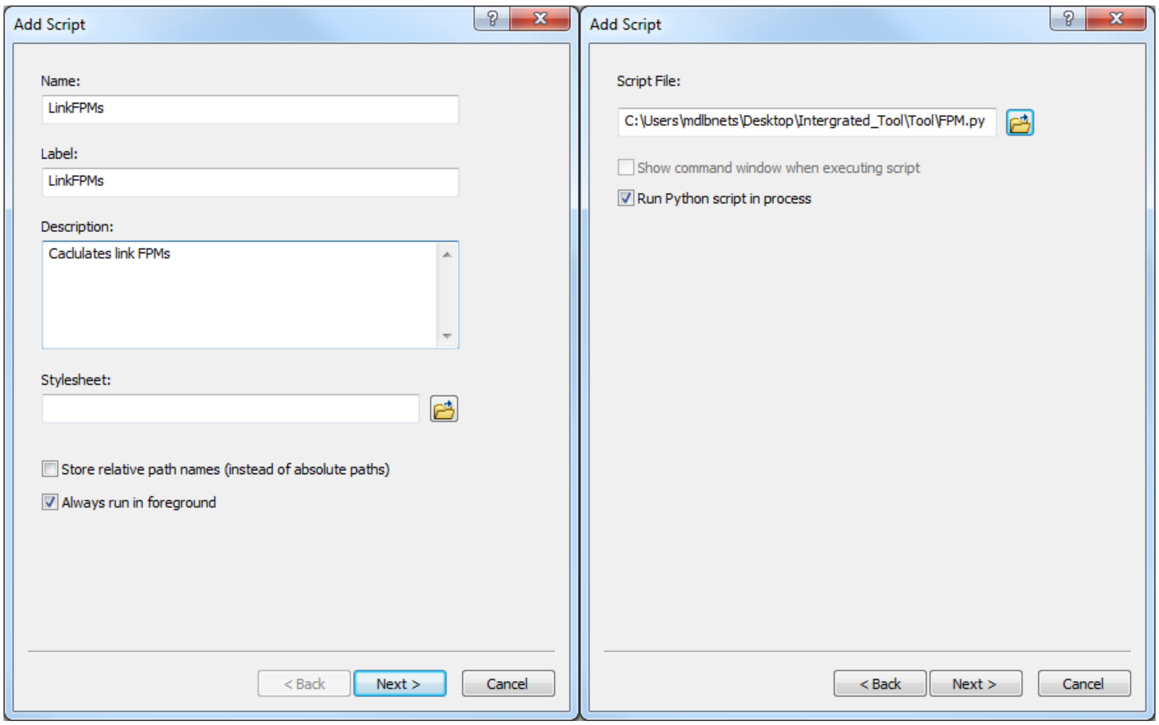


FIGURE 39 Adding New Script Window (1&2)

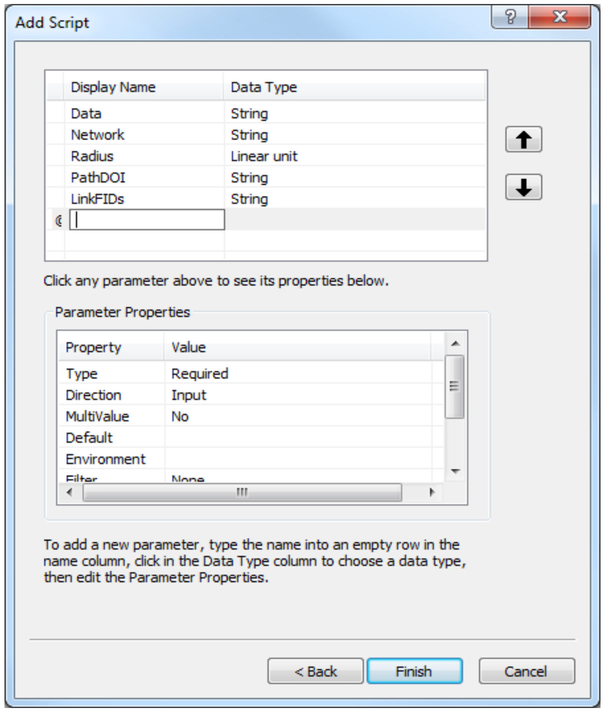


FIGURE 40 Adding New Script Window (3)

Now the tool is ready to be used. A window of the ArcGIS application is presented in Figure 41. An example of input data is demonstrated in Figure 42.

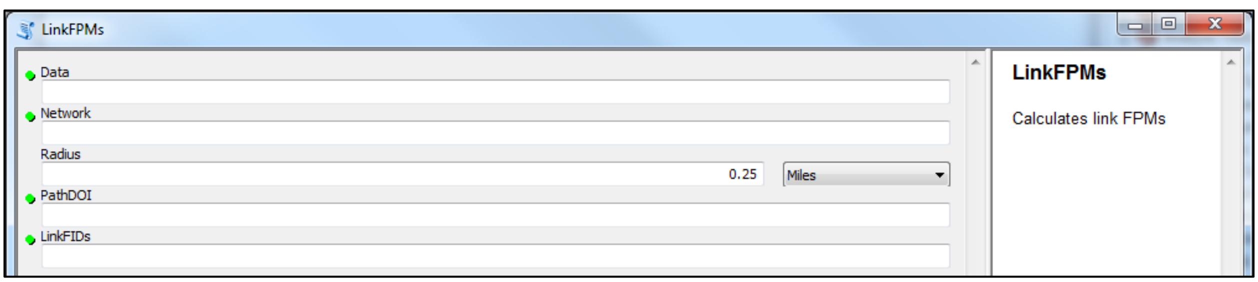


FIGURE 41 ArcGIS Application Window

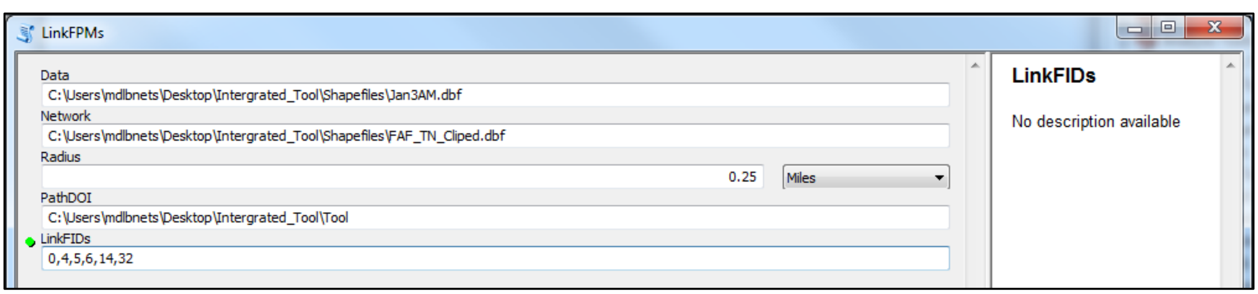


FIGURE 42 Input Data Example

Note that link FIDs to be analyzed should be listed using commas. If the user would like to estimate FPMs for all links of the transportation network, "all" statement should be typed in "LinkFIDs" field. If the user requests FPMs for links that do not exist or there are no GPS data for those links, the application will return an error message (see Figure 43: the user requested analysis for the link with FID = - 5, which does not exist).

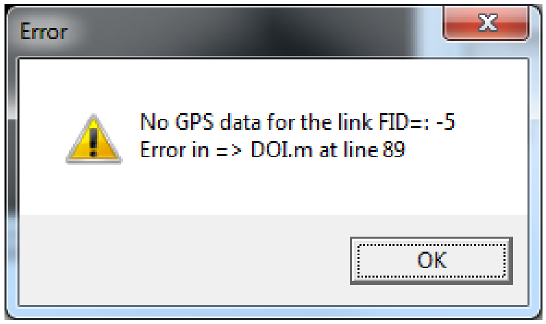


FIGURE 43 Error Message

If input data are assigned correctly, the application will start associating observations with links of a given transportation network. The application invokes a task completion window, which reports status of each task (see Figure 44). Once the first step is done, the tool creates a few temporary text files with input data for DOI.exe in the folder “Tool”. Next the DOI algorithm is executed via DOI.exe. An additional window will appear at this step (see Figure 45). Once FPMs are estimated for all requested links, DOI window disappears, the ArcGIS application removes all temporary files and reports completion of the last step (fourth step or phase).

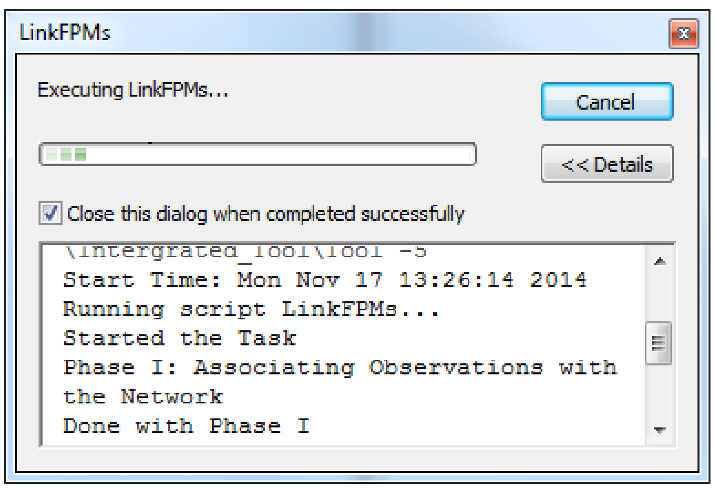


FIGURE 44 Task Completion Window

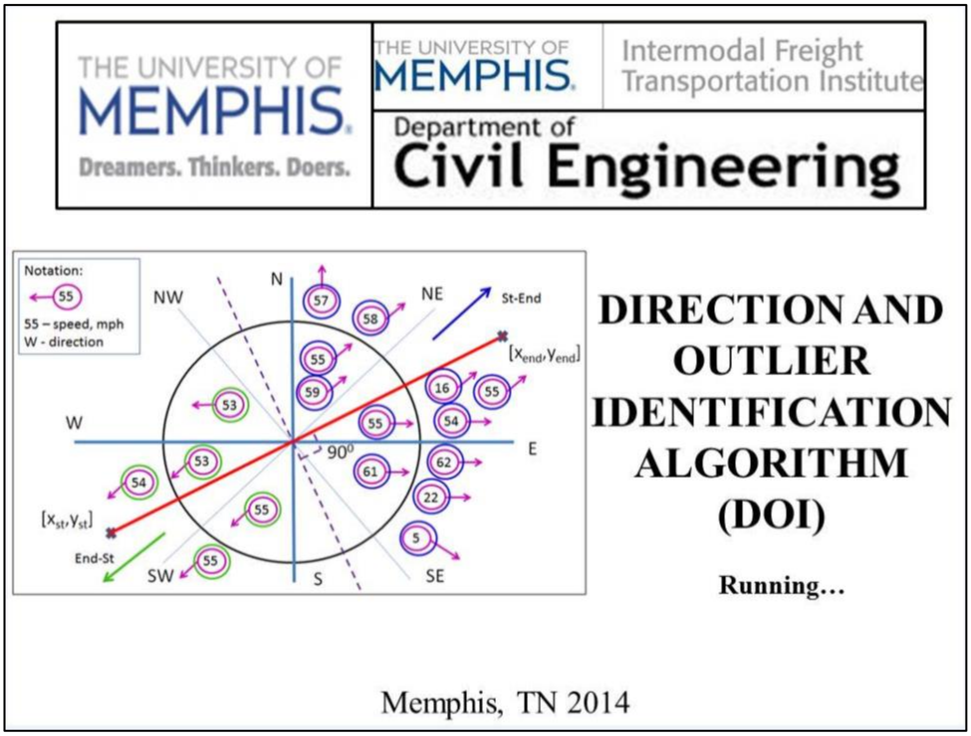


FIGURE 45 Executing the DOI Algorithm

The application generates a file (OUTPUT.xlsx) in the folder “Tool” at the end of its run. This file contains 4 sheets: a) “FPMs” – list of all FPMs, revealed in the literature (except the ones that require free slow speed), for each requested link, b) “Legend” – description of each field from the sheet “FPMs”, c) “Statistics” – descriptive statistics of the snapping procedure, and d) “HeadingDist” – distribution of headings for each requested link. Note that travel speed was measured in mph, while travel time was computed in hours. Descriptive statistics provides the following information: total number of observations, total number of links with snapped observations, number of outliers (observations with spot speeds ≤ 5 mph), number/percentage of not snapped observations, number/percentage of filtered observations (i.e., snapped and spot speed > 5mph). Once file OUTPUT.xlsx is generated, the user may load the “FPMs” sheet to AcrGIS and associate it with links of the given network using Spatial Join of ESRI ArcGIS (see Figures 46-47). The imported data should be joined to links of the network based on link FIDs.

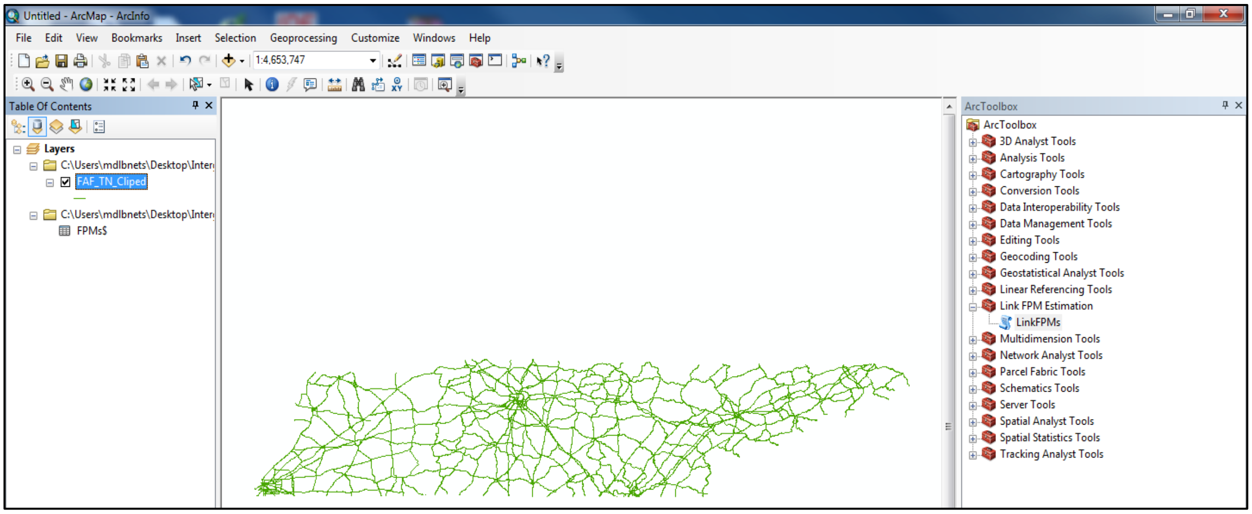


FIGURE 46 Loading FPMs to ArcGIS

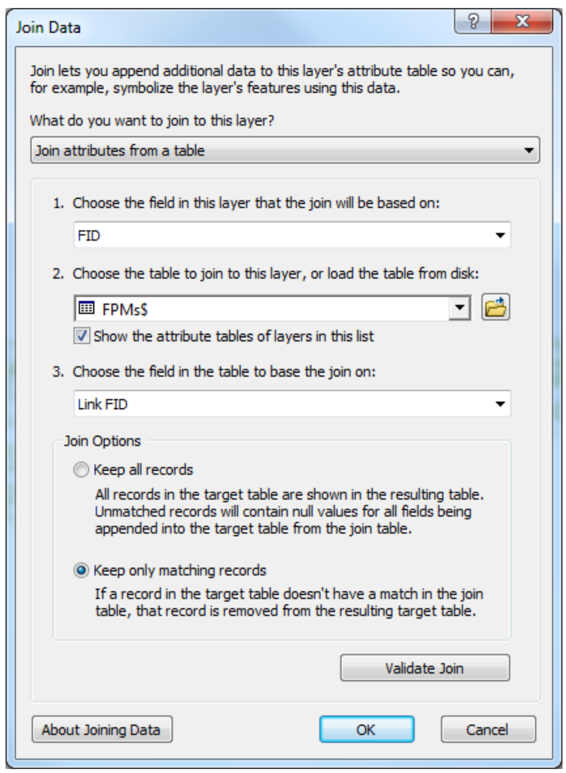


FIGURE 47 Associating FPMs with Links

OUTPUT.xlsx file should be deleted (or renamed) from the “Tool” folder before the application is executed again as it will be replaced by the newly developed file. If the user is interested in link speeds, all other FPMs can be removed from the OUTPUT.xlsx file before importing the “FPMs” sheet to ArcGIS to reduce the size of the file. The developed application will assist TDOT in computing FPMs for specific freight transportation corridors, identification of segments that require improvement projects, and improving travel time reliability. The user is not required to install any additional software (e.g., Python Shell, MATLAB), except ESRI ArcGIS.

8. CONCLUSIONS

One of the main challenges in freight transportation planning is the lack of truck trip data. This report demonstrated how truck GPS data can be used to estimate FPMs for transportation networks and freight transportation facilities, evaluate performance of freight corridors, identify inter- and intra-truck trips, and analyze individual truck trip patterns. A number of algorithms were developed to process truck GPS data and develop freight performance indicators. Validation of the algorithms was based on link travel speeds available through the FPMweb Tool, Google maps and satellite images. Generally, accuracy of developed algorithms can be improved if more GPS records are available and more frequent GPS signal is provided. Truck trip analysis also requires additional information (i.e., location of freight facilities, rest stops, pick-up/drop-off business locations, commodity data, etc.).

One of the main obstacles of using the available GPS dataset was the large size which prohibited processing of long time periods at a time (e.g. month). The following practical recommendations can be provided to TDOT for processing these large size GPS datasets:

1. Use more advanced CPU (i.e., recent processor, more RAM, multiple cores, etc.)
2. Partition the data in smaller portions based on:
    - time of the day: AM, MD, PM, and OP
    - specific areas of the region under study
    - special characteristics (e.g., freight corridors, major metropolitan areas, etc.)
3. Parallel machine processing – use all available CPUs for processing the given dataset. For example, if there are four CPUs available, each one can be assigned for processing AM, MD, PM, and OP periods of a given day respectively.

The scope of future research may focus on the following:

- Develop a new version of the ArcGIS tool with additional capabilities
- Test the DOI algorithm on various networks
- Geocode all freight transportation facilities in the Greater Memphis Area (which may be further extended for the whole TN)
- Derive trip generation models for freight transportation facilities
- Apply the developed algorithms to GPS dataset with more frequent observations

The proposed methodology and the developed GIS application can be efficient in supporting TDOT in achieving MAP-21 goals within their short and long range planning efforts by providing network performance measures. Outcomes of this research may be used in development, calibration, and validation of TN State and MPO travel demand models as well as support project selection.

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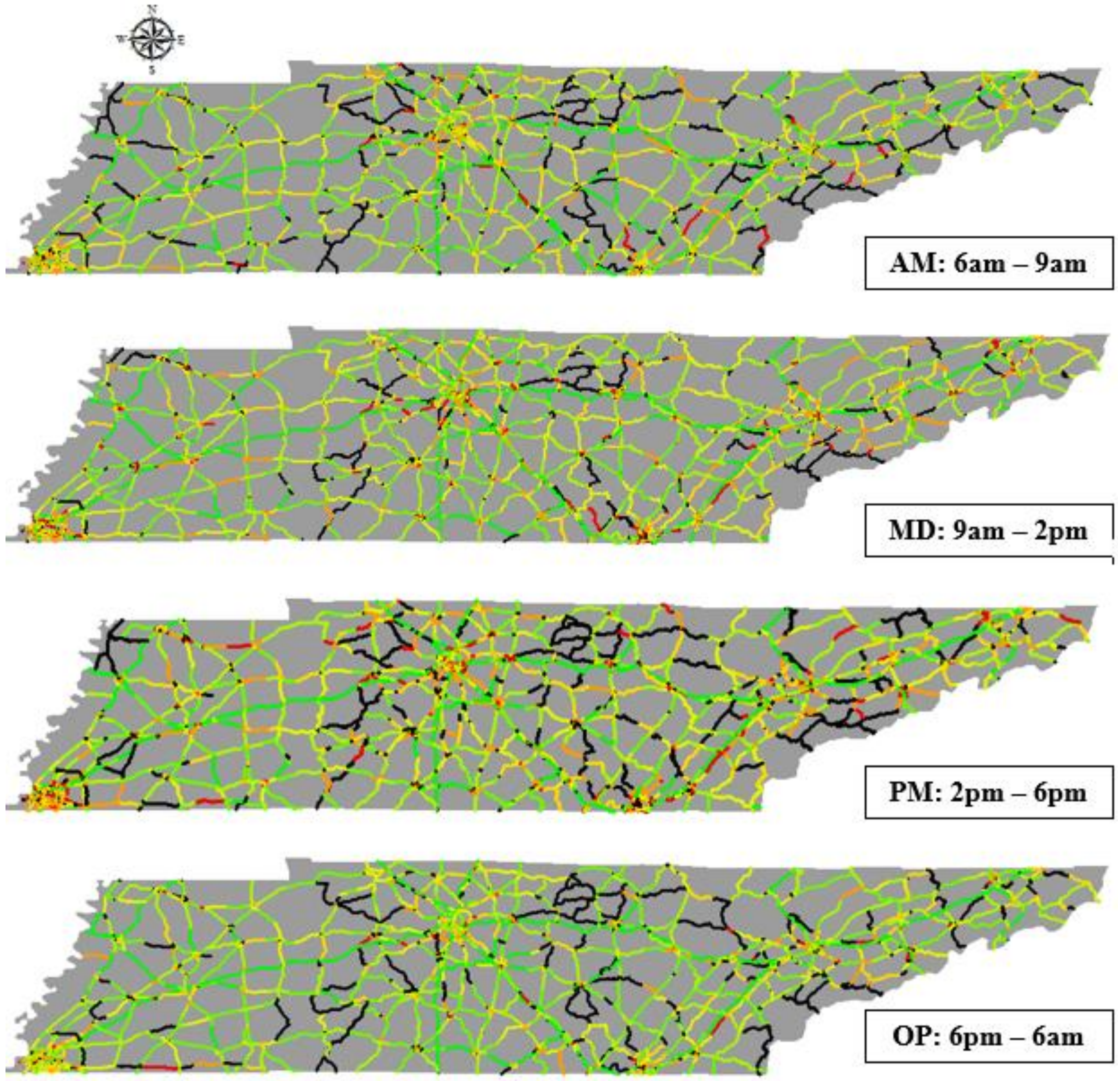
APPENDICES

APPENDIX A
AVERAGE MONTHLY TRAVEL SPEEDS FOR TN ROADWAYS



Features\period	AM	MD	PM	OP
Total # of observations	139301	284213	195964	344118
# of links with observations	2678	2953	2707	2755
# of observations with speed < 5mph	43670	79524	51658	101190
# of observations not snapped	33147	65252	43862	76001
# of observations filtered (>5mph, snapped)	82111	175944	124833	213505

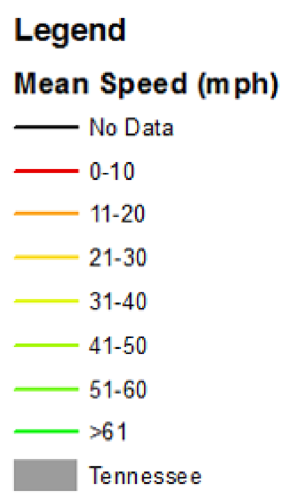
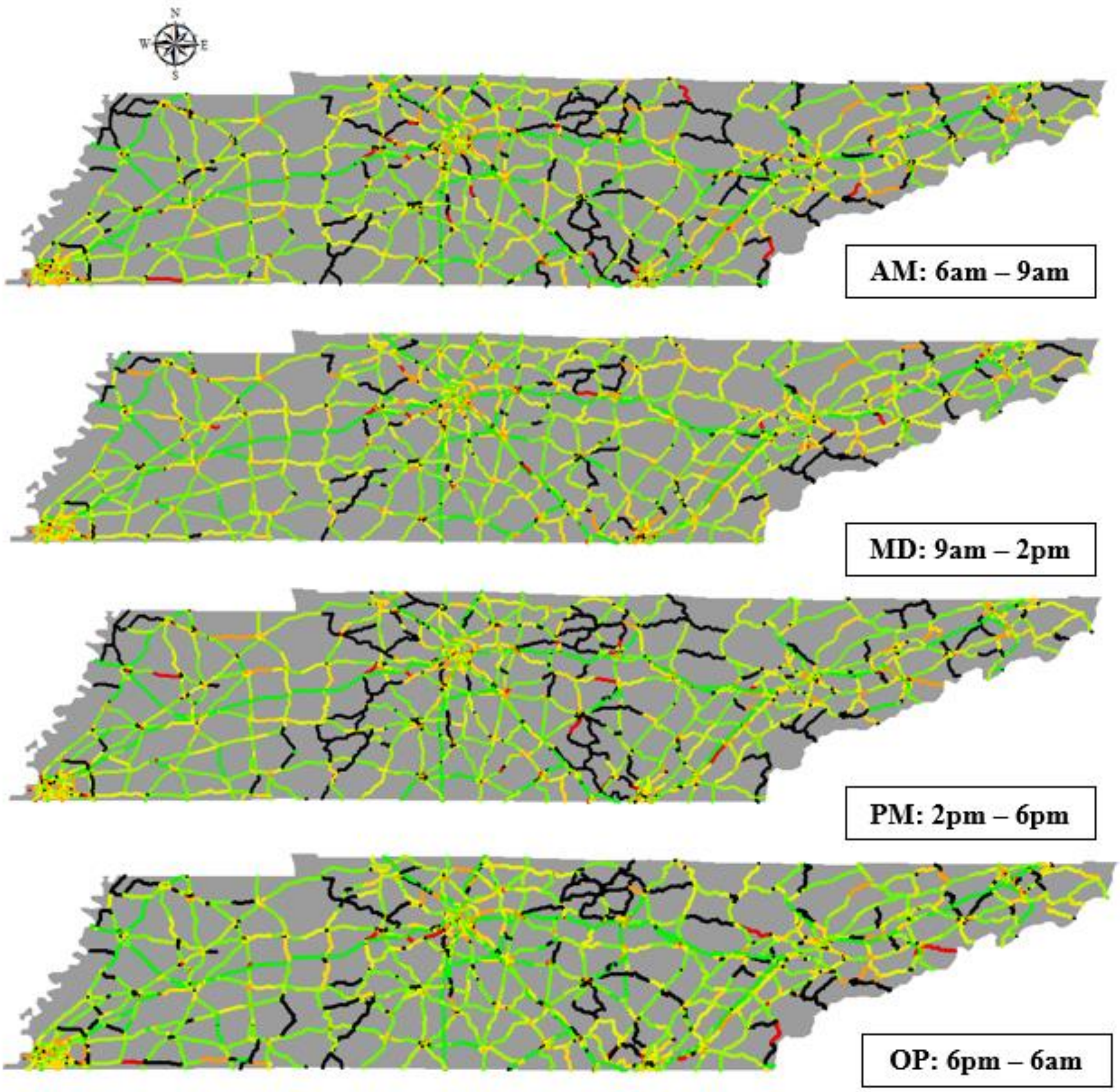
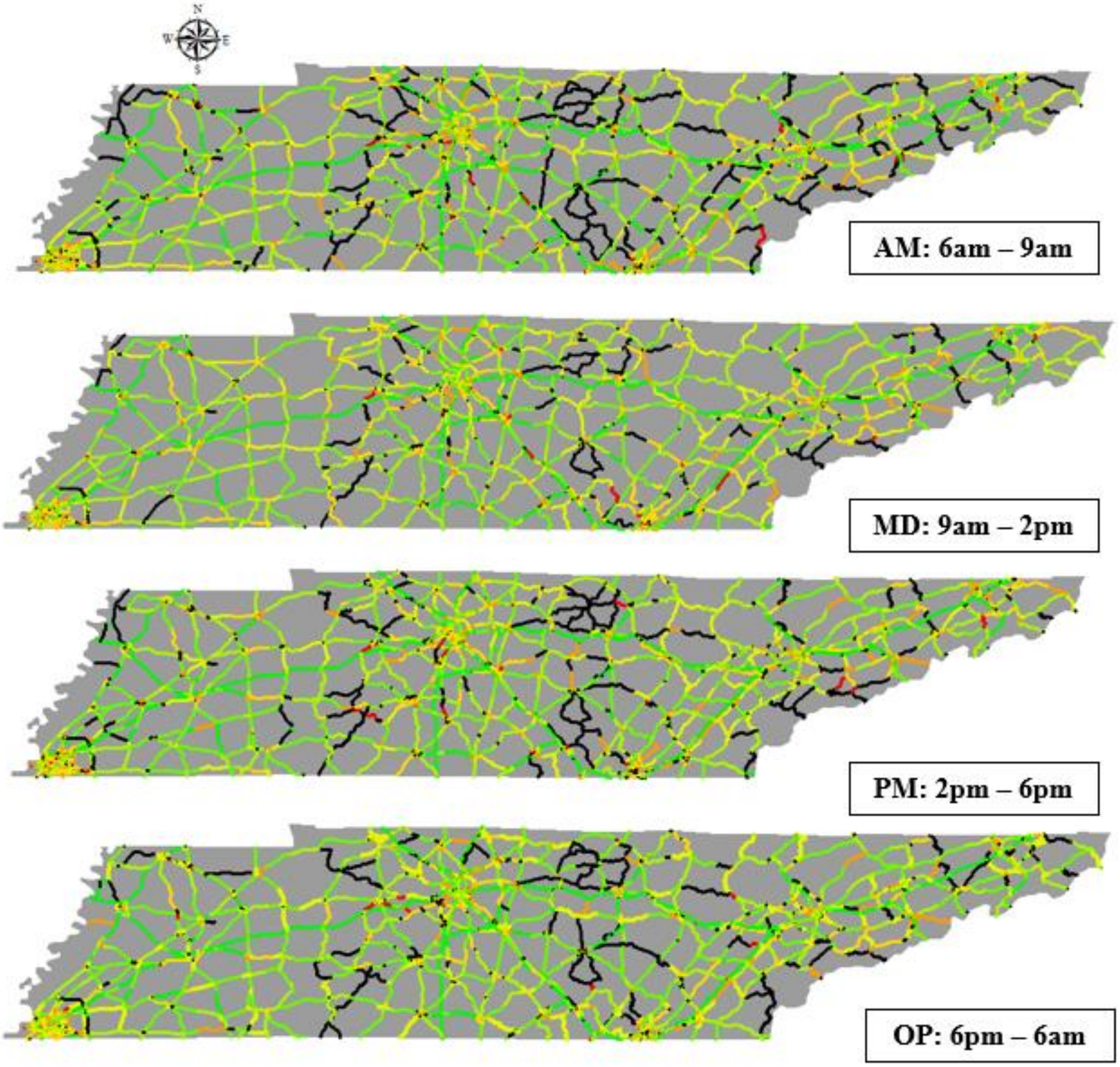


FIGURE A-1 Mean Speeds, February 21st – 23rd



Features\period	AM	MD	PM	OP
Total # of observations	142572	296138	204505	363657
# of links with observations	2685	2959	2716	2758
# of observations with speed < 5mph	46089	82975	54991	106980
# of observations not snapped	34243	68472	45132	79047
# of observations filtered (>5mph, snapped)	82738	182314	129246	226301

FIGURE A-2 Mean Speeds, March 20th – 22nd



Features\period	AM	MD	PM	OP
Total # of observations	150367	303771	211328	375844
# of links with observations	2672	2969	2765	2815
# of observations with speed < 5mph	47748	83129	56506	111317
# of observations not snapped	35796	68949	47050	82756
# of observations filtered (>5mph, snapped)	88077	189128	133648	232465

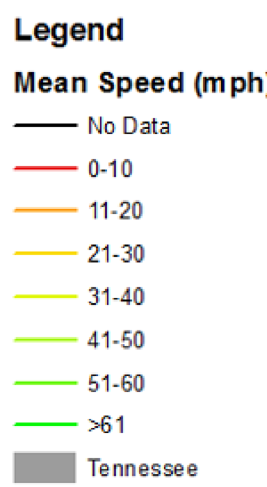
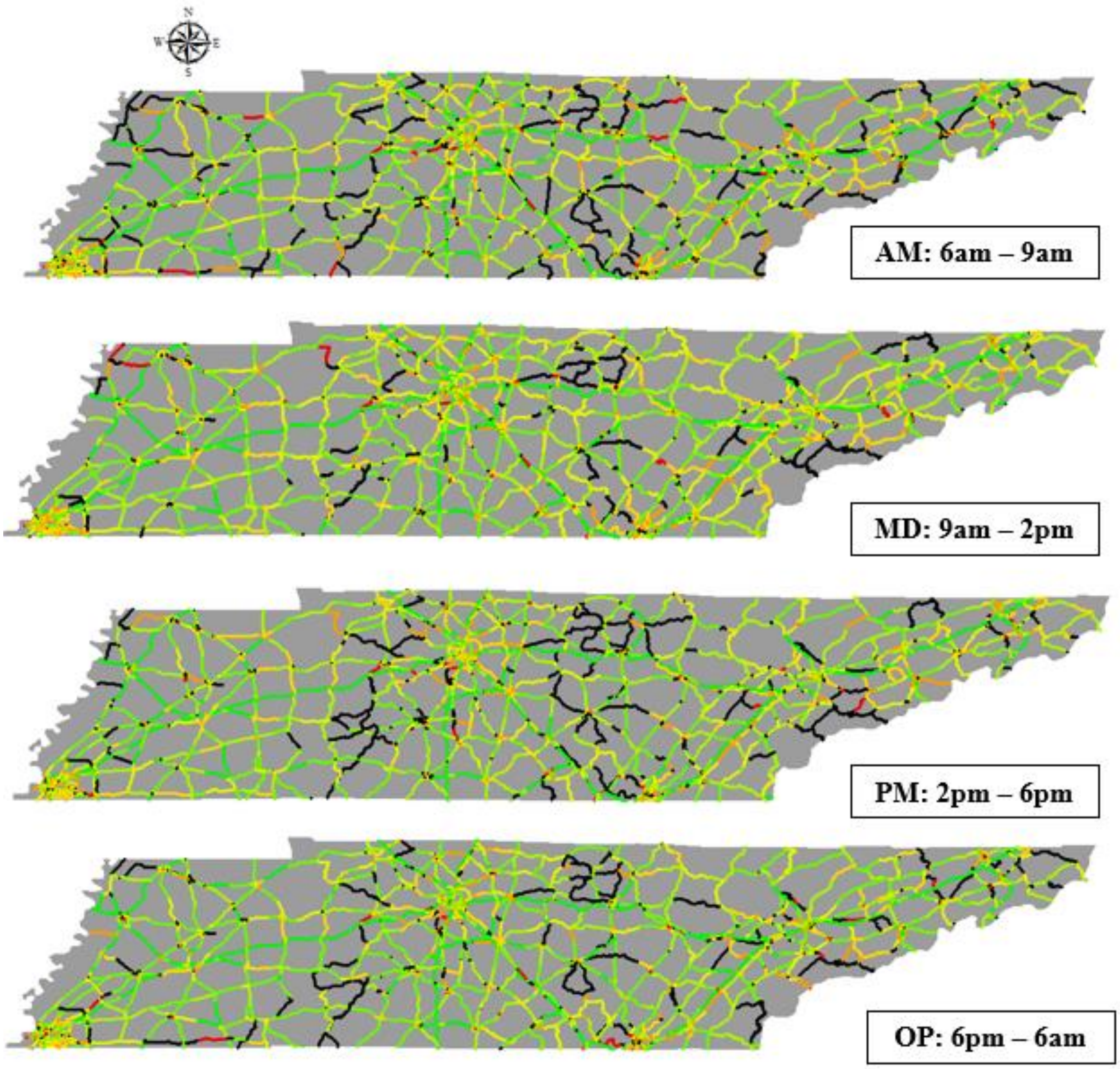


FIGURE A-3 Mean Speeds, April 17th – 19th



Features\period	AM	MD	PM	OP
Total # of observations	154961	306509	216217	385604
# of links with observations	2720	2991	2756	2834
# of observations with speed < 5mph	48600	83783	57132	114517
# of observations not snapped	37113	69956	48698	87846
# of observations filtered (>5mph, snapped)	91227	191644	137584	237418

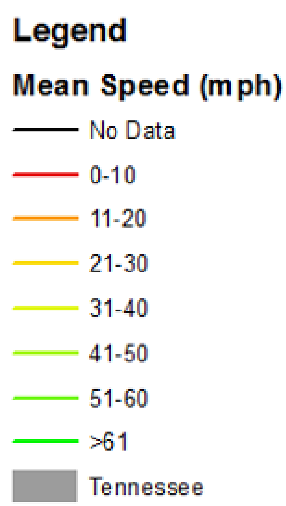
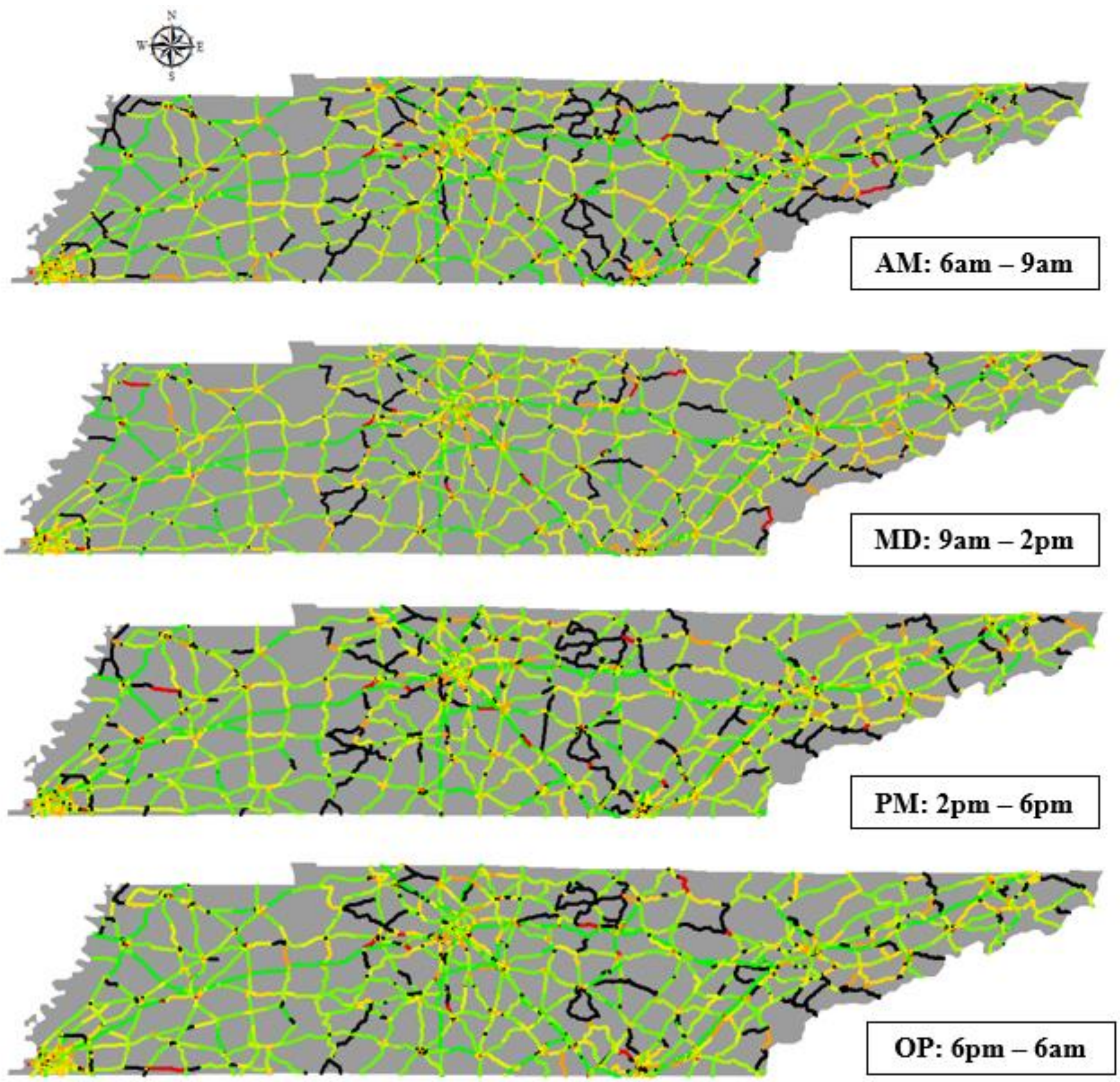


FIGURE A-4 Mean Speeds, May 15th – 17th



Features\period	AM	MD	PM	OP
Total # of observations	156153	312684	219397	399356
# of links with observations	2706	2986	2748	2813
# of observations with speed < 5mph	49799	86456	58635	117501
# of observations not snapped	36657	70627	49407	88360
# of observations filtered (>5mph, snapped)	91806	194612	138958	247526

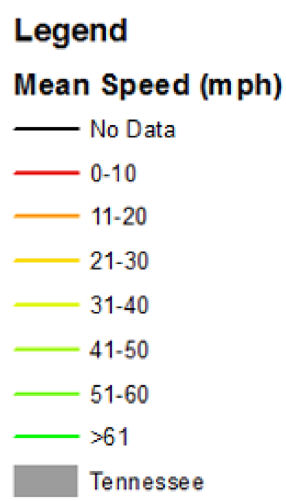
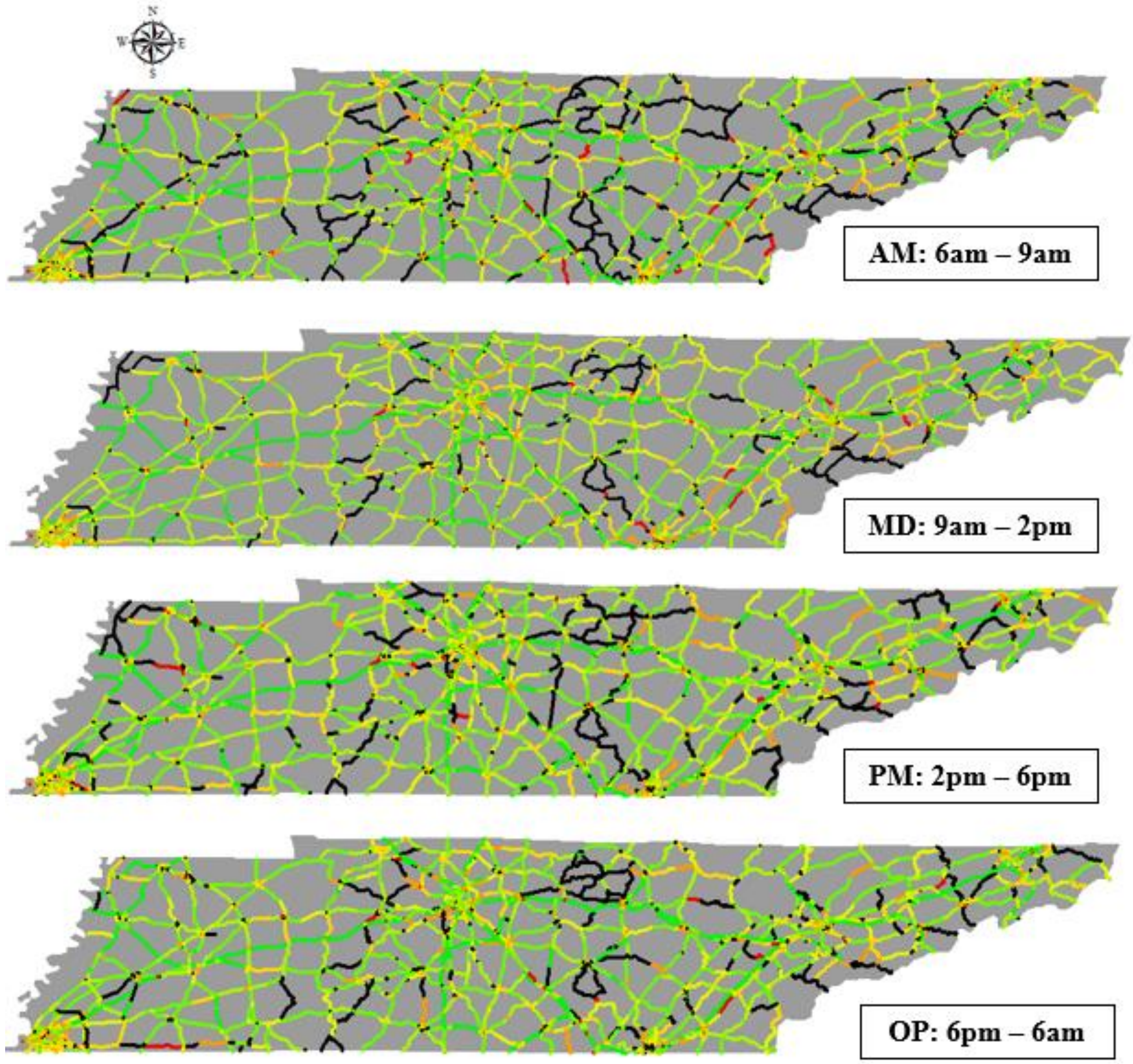


FIGURE A-5 Mean Speeds, June 12th – 14th



Features\period	AM	MD	PM	OP
Total # of observations	153985	314914	221889	398626
# of links with observations	2696	2963	2750	2794
# of observations with speed < 5mph	48568	87901	61388	120229
# of observations not snapped	36691	71641	51170	89507
# of observations filtered (>5mph, snapped)	90798	195582	138443	244725

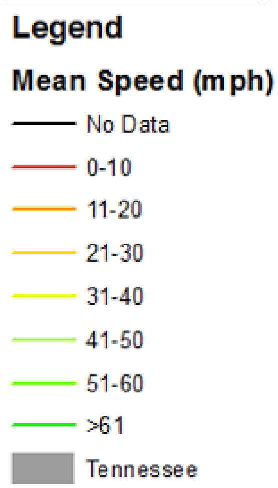
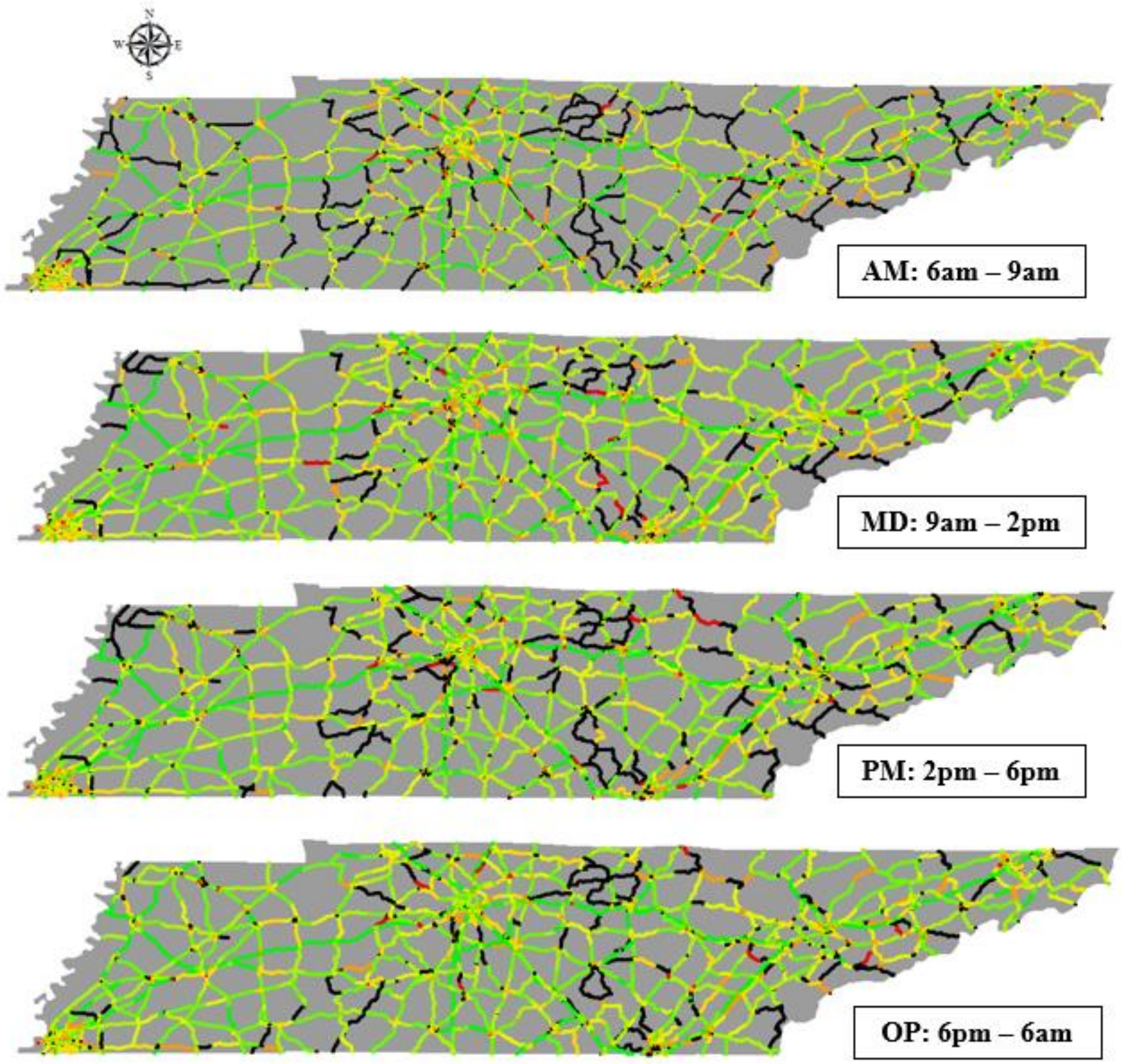
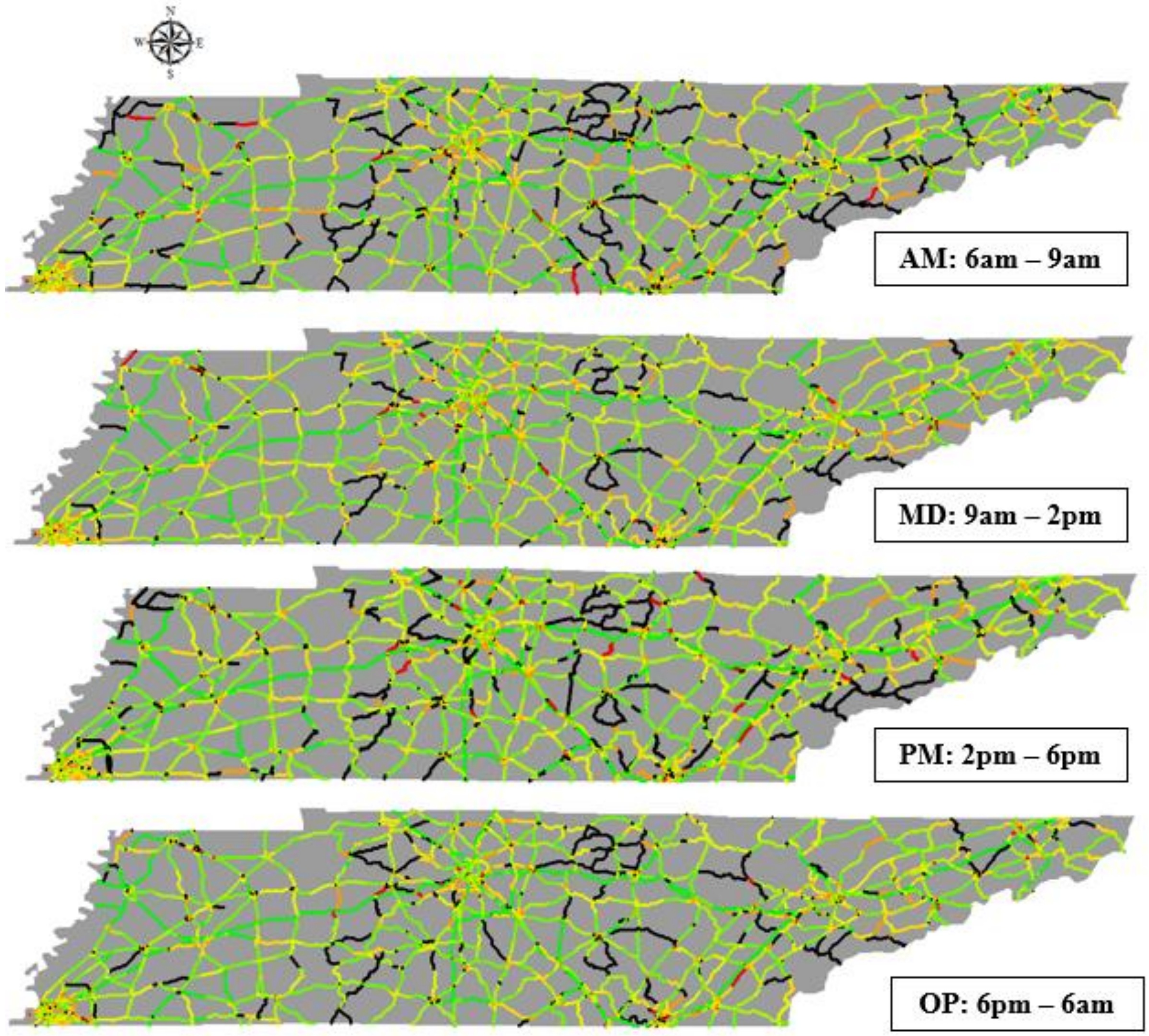


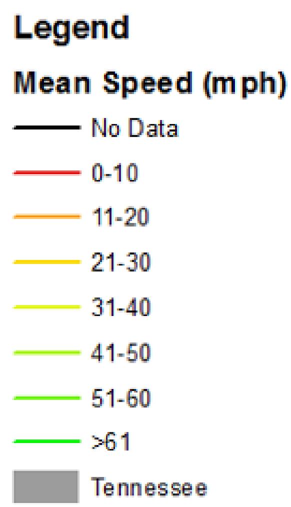
FIGURE A-6 Mean Speeds, July 17th – 19th



Features\period	AM	MD	PM	OP
Total # of observations	181302	295397	195596	329109
# of links with observations	2678	2963	2704	2814
# of observations with speed < 5mph	69629	91740	55405	99428
# of observations not snapped	47213	73132	46125	74242
# of observations filtered (>5mph, snapped)	96646	174883	120631	202648

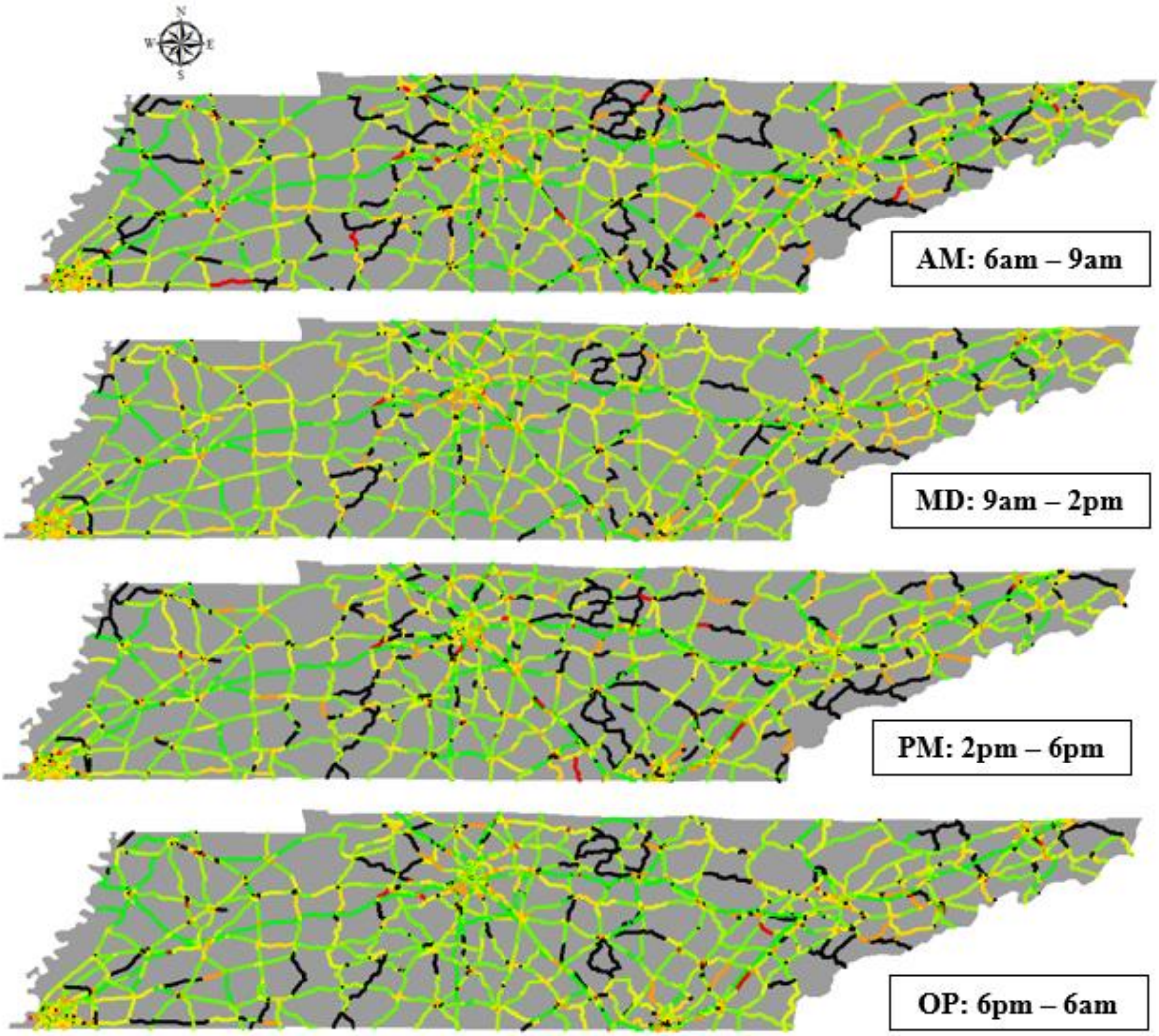
FIGURE A-7 Mean Speeds, August 14th – 16th





Features\period	AM	MD	PM	OP
Total # of observations	159364	320535	227882	406699
# of links with observations	2711	2995	2716	2847
# of observations with speed < 5mph	51268	90980	61692	123738
# of observations not snapped	37694	75167	52619	92274
# of observations filtered (>5mph, snapped)	93304	196502	143081	248244

FIGURE A-8 Mean Speeds, September 18th – 20th



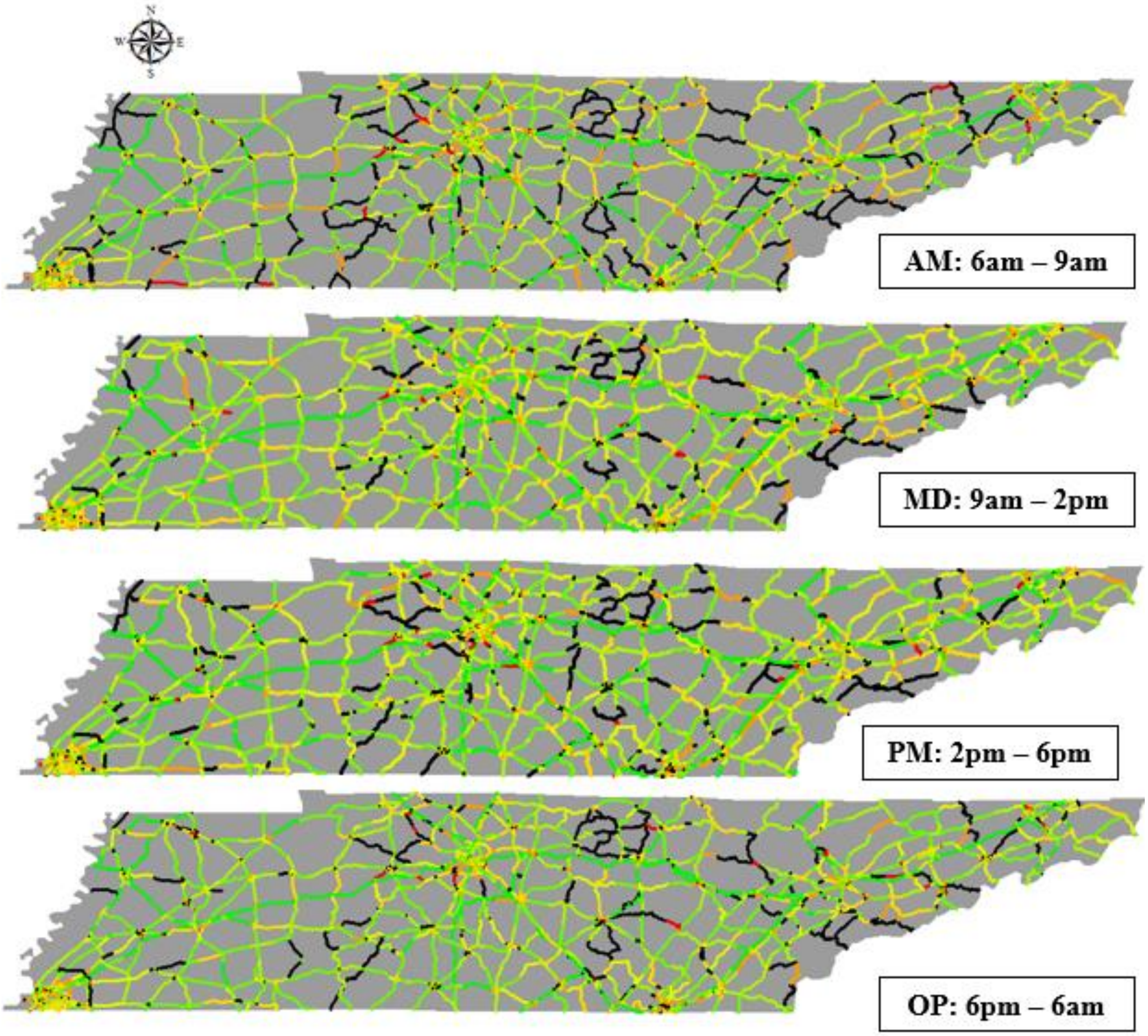
Features\period	AM	MD	PM	OP
Total # of observations	166743	342118	248299	440800
# of links with observations	2718	2992	2768	2846
# of observations with speed < 5mph	55161	99049	69799	143931
# of observations not snapped	40357	80341	55347	102499
# of observations filtered (>5mph, snapped)	96039	208600	155130	262550

Legend

Mean Speed (mph)

- No Data
- 0-10
- 11-20
- 21-30
- 31-40
- 41-50
- 51-60
- >61
- Tennessee

FIGURE A-9 Mean Speeds, October 16th – 18th



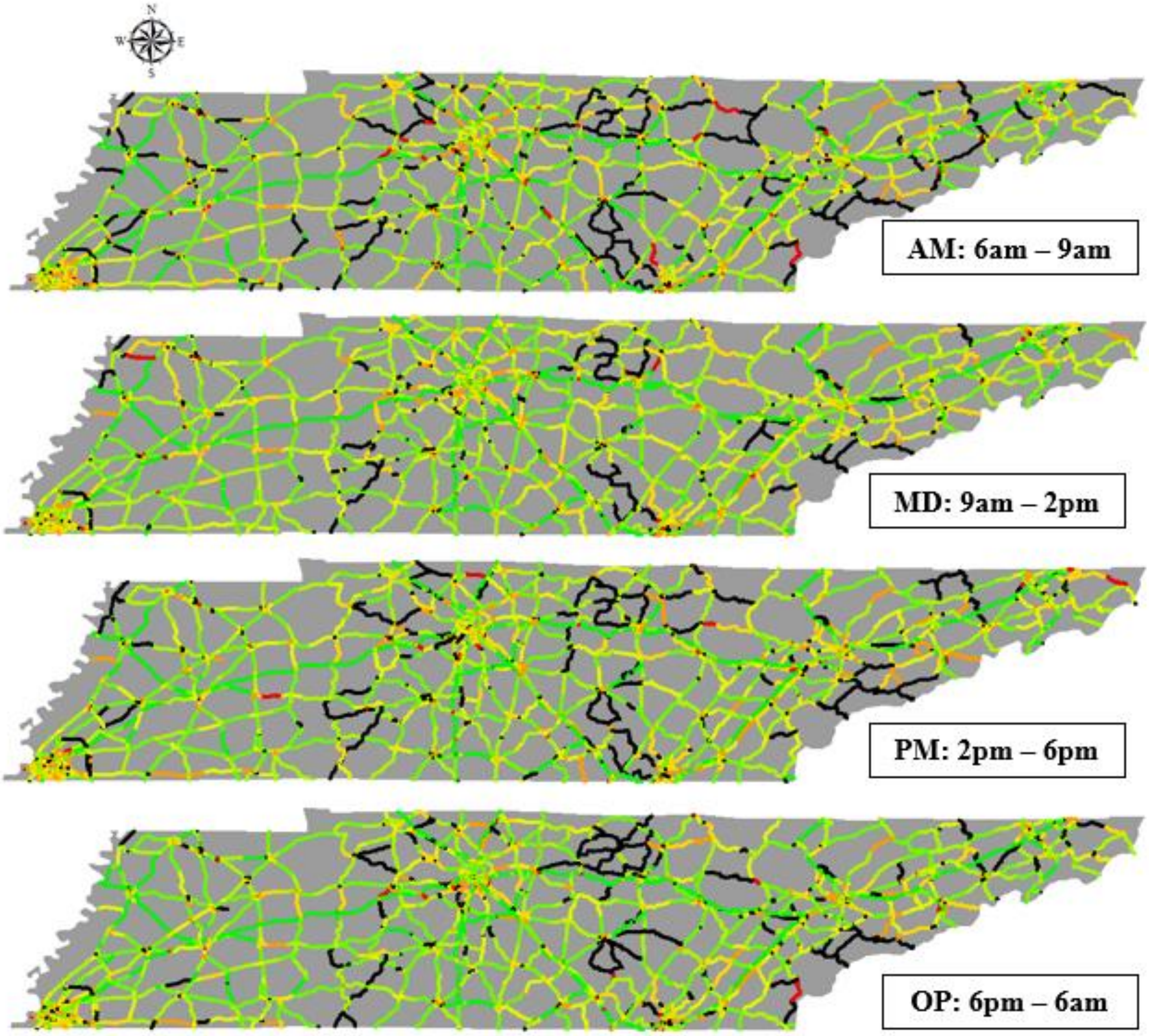
Features\period	AM	MD	PM	OP
Total # of observations	167509	337118	237437	425365
# of links with observations	2731	2998	2798	2844
# of observations with speed < 5mph	51790	95913	64524	130489
# of observations not snapped	38590	79181	53706	94414
# of observations filtered (>5mph, snapped)	100031	206264	149155	260417

Legend

Mean Speed (mph)

- No Data
- 0-10
- 11-20
- 21-30
- 31-40
- 41-50
- 51-60
- >61
- Tennessee

FIGURE A-10 Mean Speeds, November 6th – 8th



Features\period	AM	MD	PM	OP
Total # of observations	176393	355818	247408	443777
# of links with observations	2766	2996	2799	2846
# of observations with speed < 5mph	57295	103559	68022	141100
# of observations not snapped	42895	84648	58386	104846
# of observations filtered (>5mph, snapped)	102597	216332	154020	265803

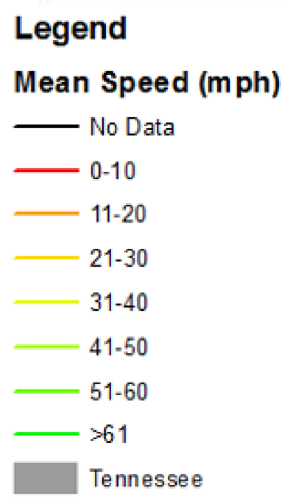


FIGURE A-11 Mean Speeds, December 4th – 6th

APPENDIX B
TOTAL MONTHLY TRUCK VOLUMES FOR TN ROADWAYS

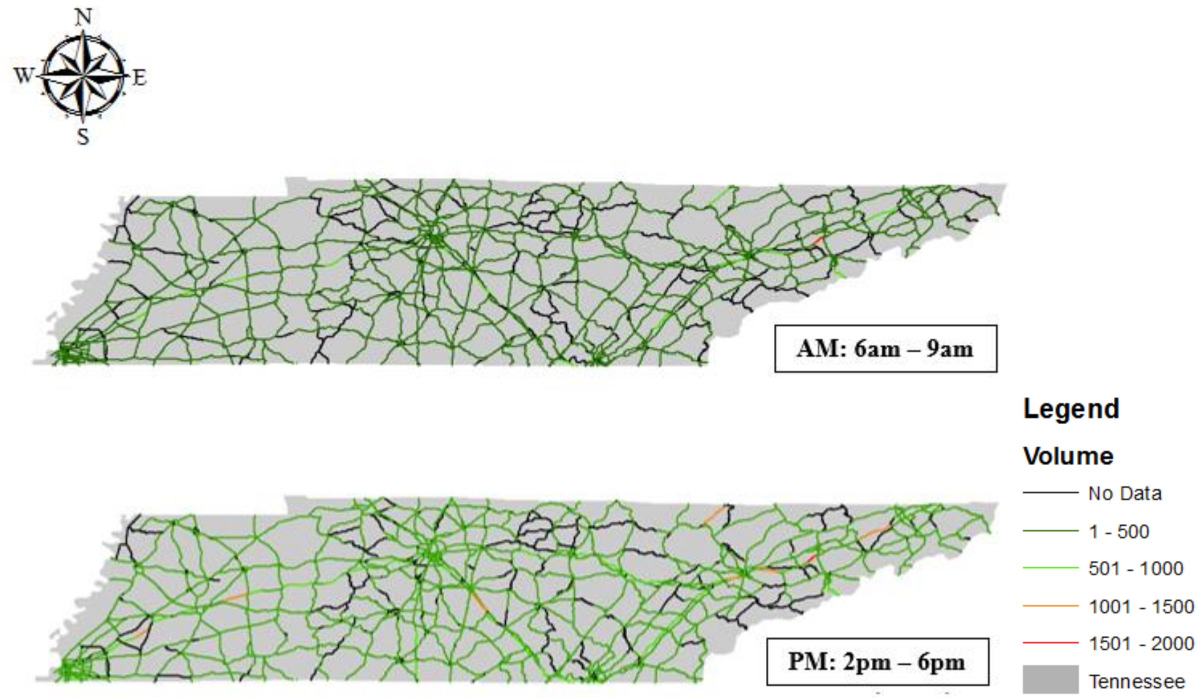


FIGURE B-1 Total Volumes, February 21st – 23rd, AM & PM Periods

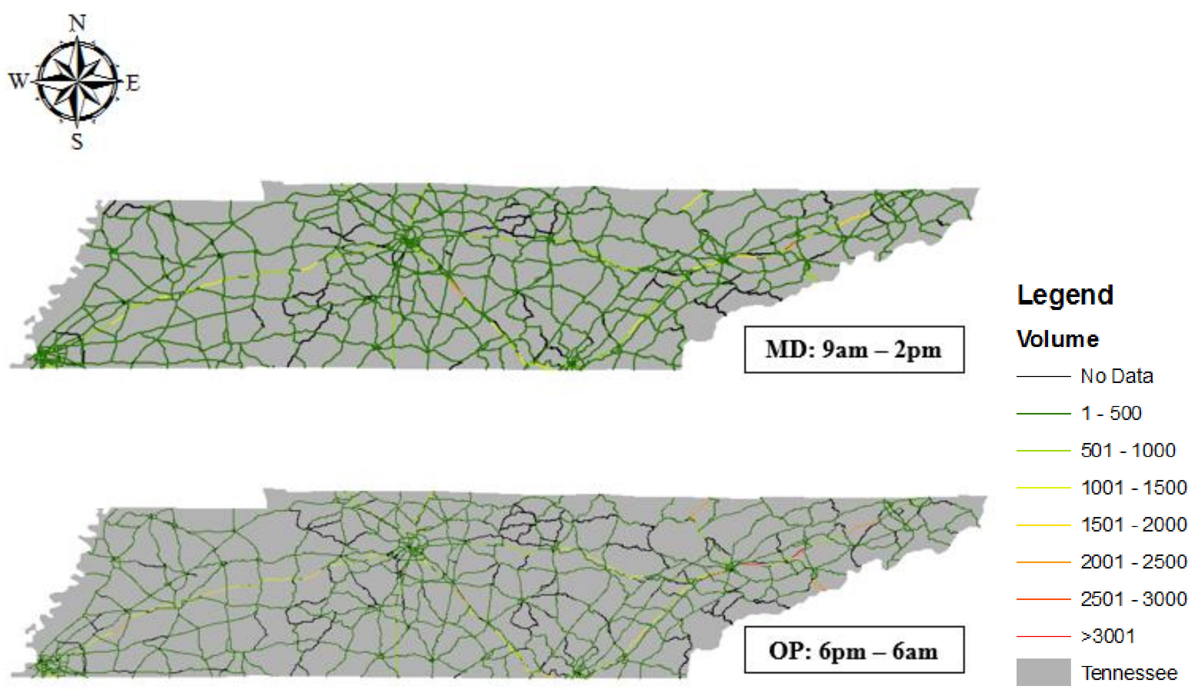


FIGURE B-2 Total Volumes, February 21st – 23rd, MD & OP Periods

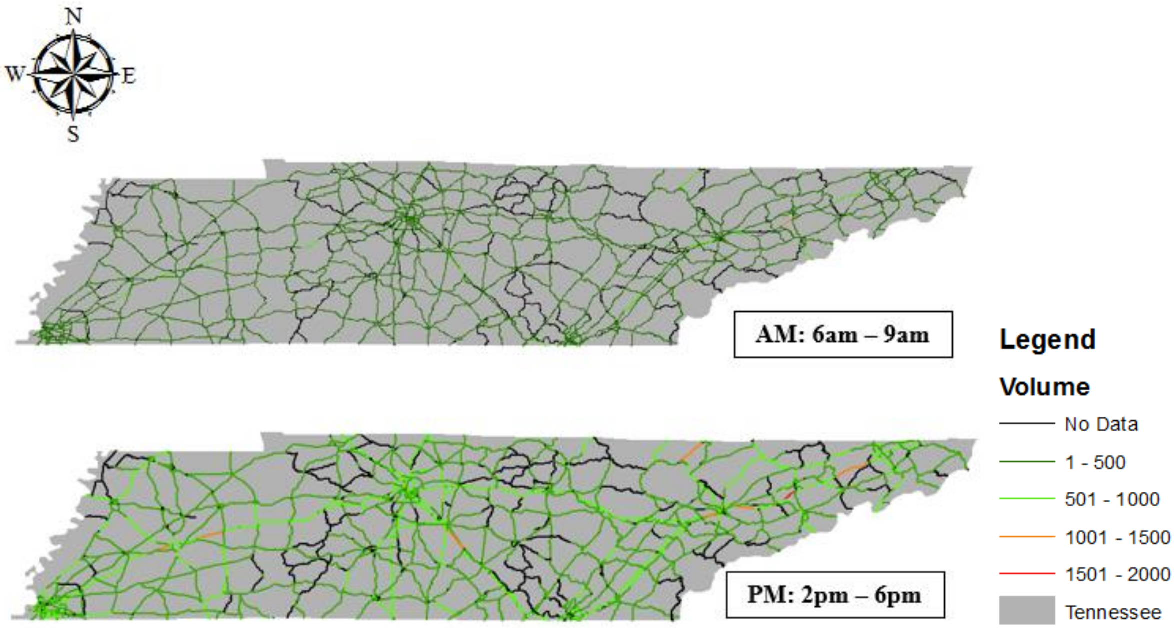


FIGURE B-3 Total Volumes, March 20th – 22nd, AM & PM Periods

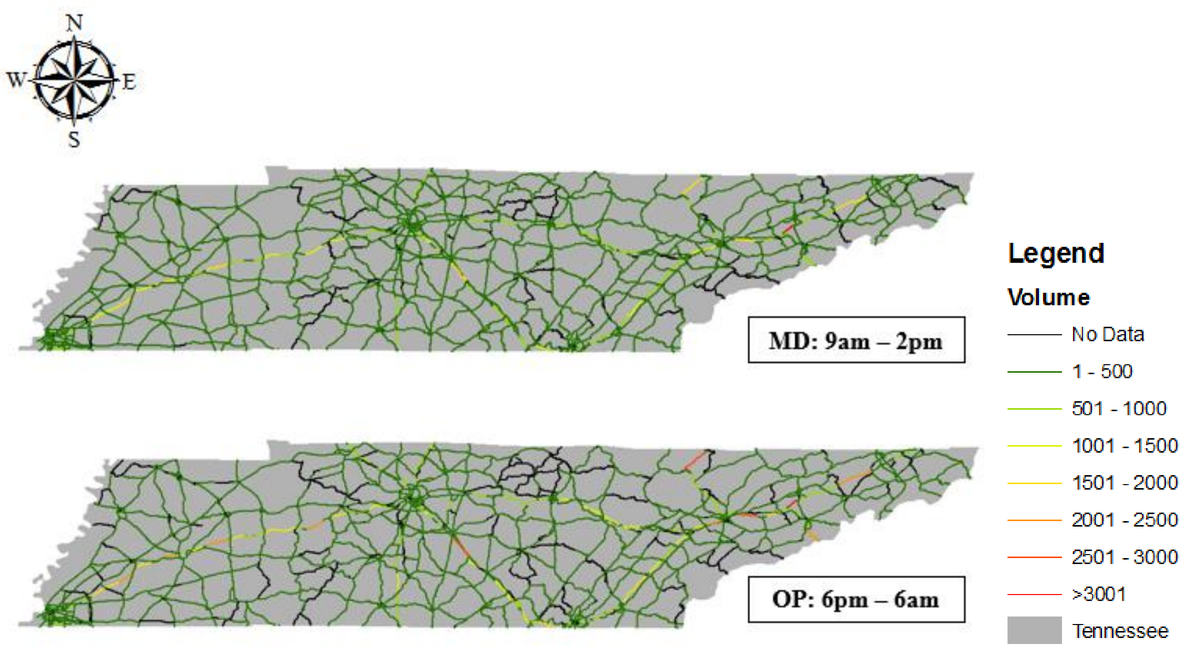


FIGURE B-4 Total Volumes, March 20th – 22nd, MD & OP Periods

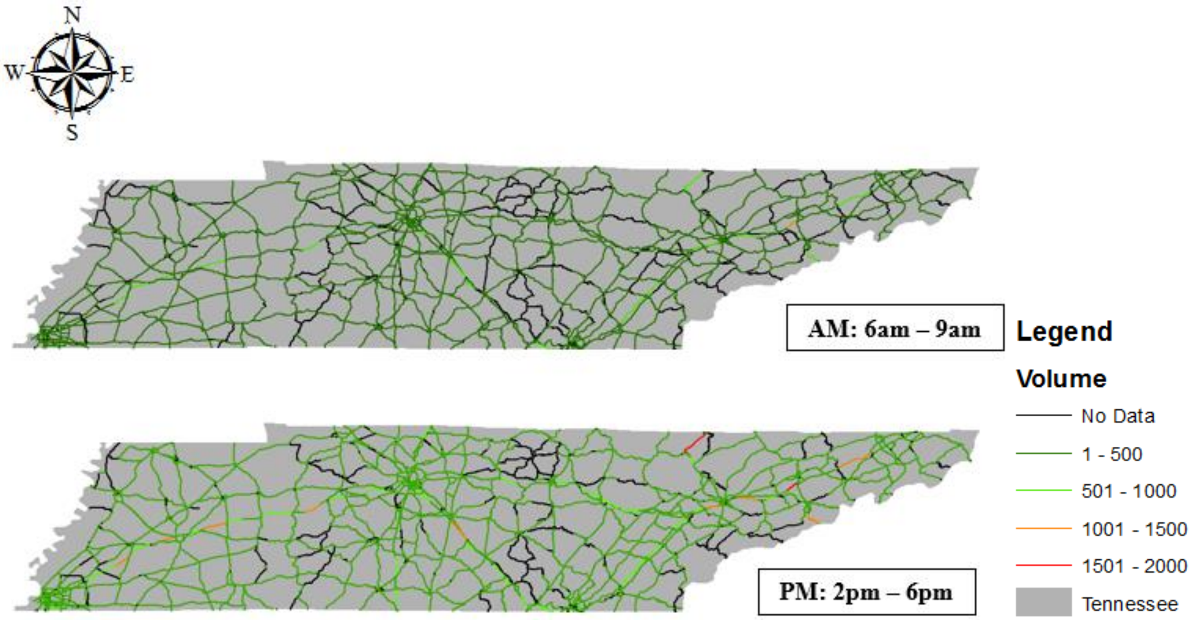


FIGURE B-5 Total Volumes, April 17th – 19th, AM & PM Periods

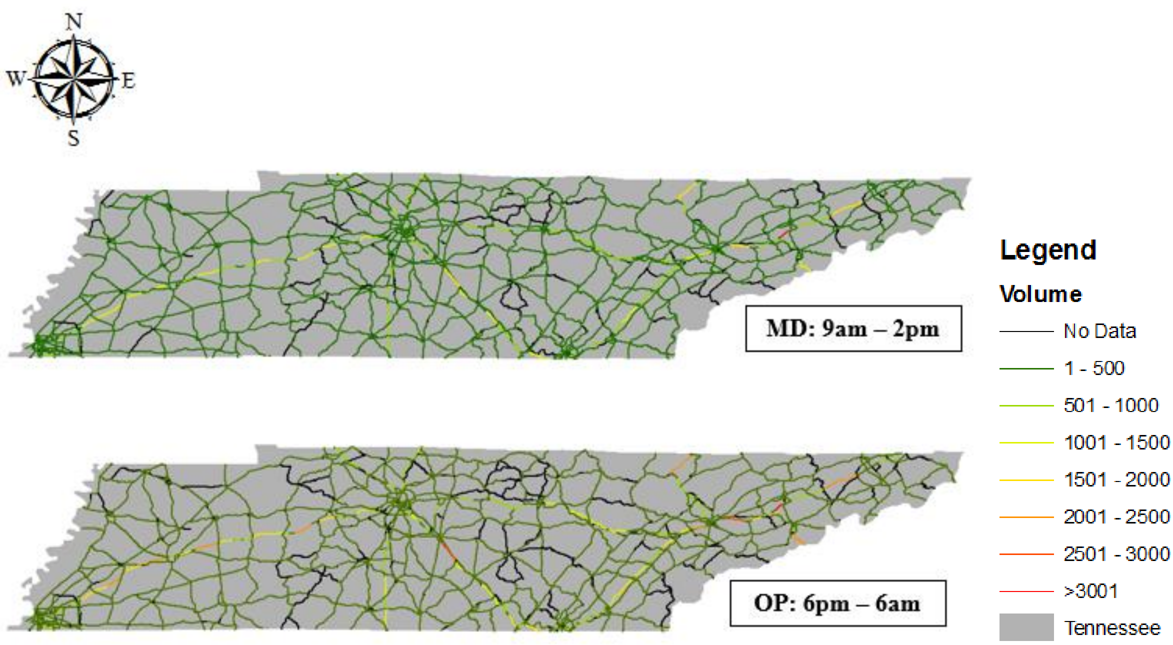


FIGURE B-6 Total Volumes, April 17th – 19th, MD & OP Periods

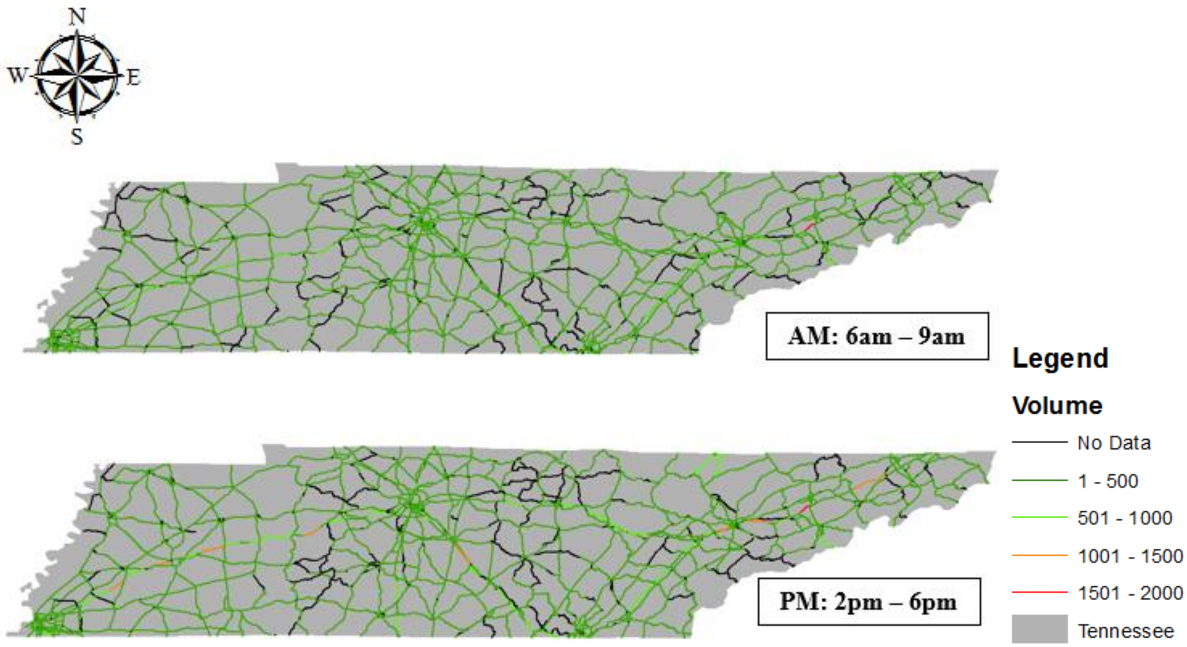


FIGURE B-7 Total Volumes, May 15th – 17th, AM & PM Periods

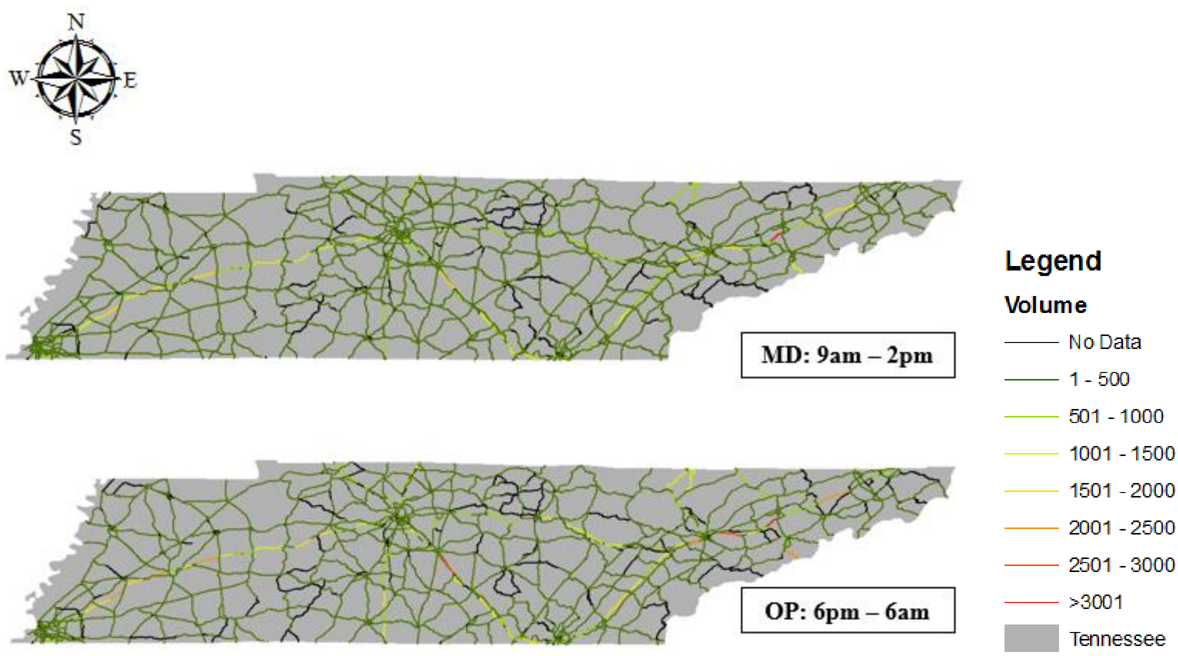


FIGURE B-8 Total Volumes, May 15th – 17th, MD & OP Periods

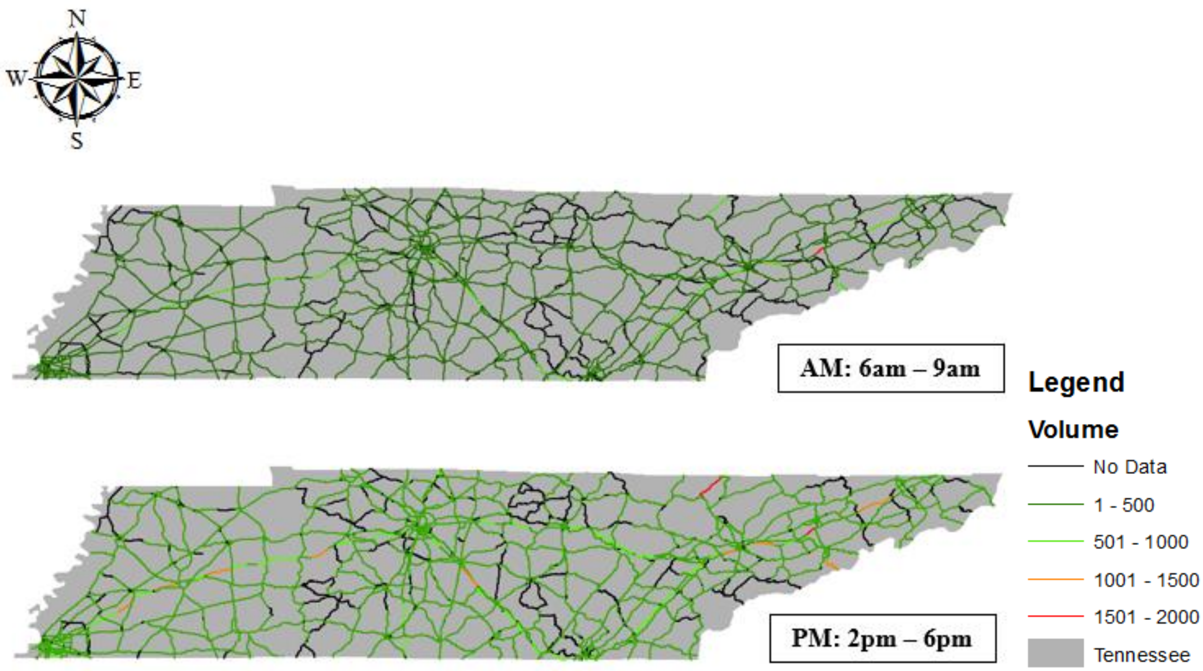


FIGURE B-9 Total Volumes, June 12th – 14th, AM & PM Periods

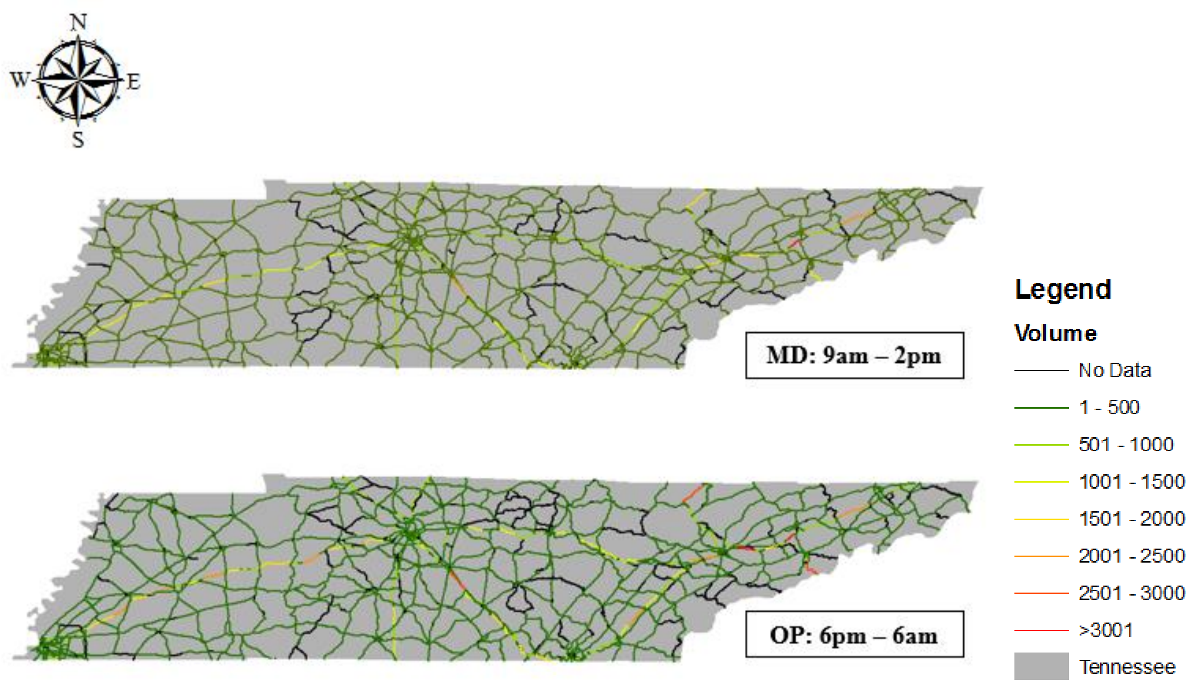


FIGURE B-10 Total Volumes, June 12th – 14th, MD & OP Periods

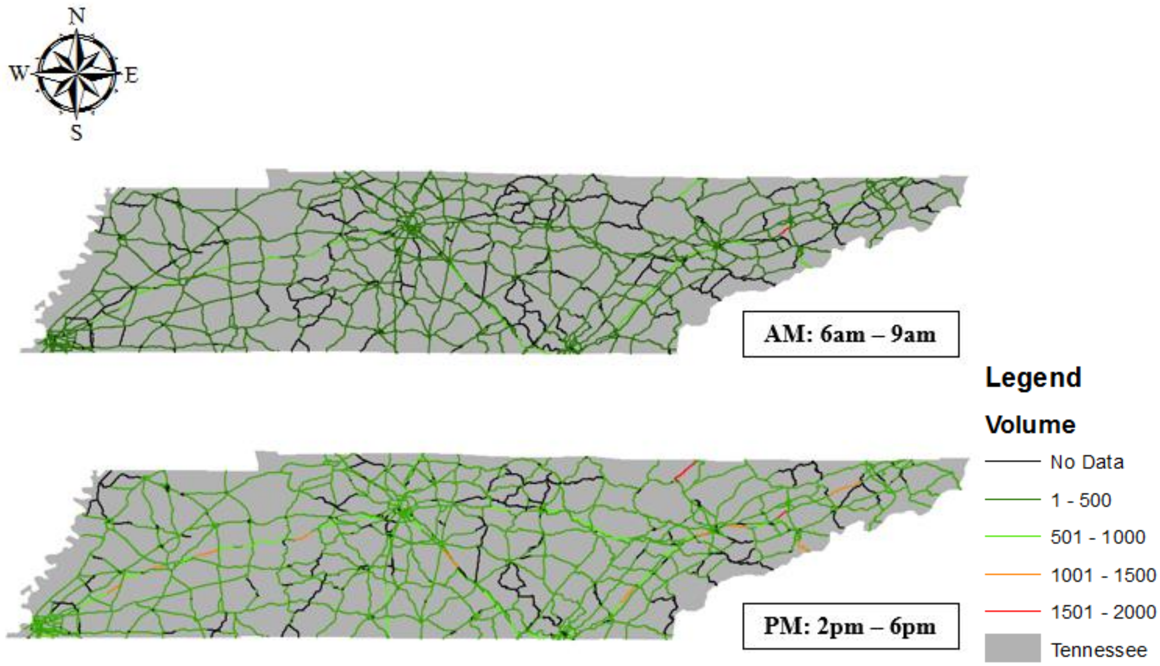


FIGURE B-11 Total Volumes, July 17th – 19th, AM & PM Periods

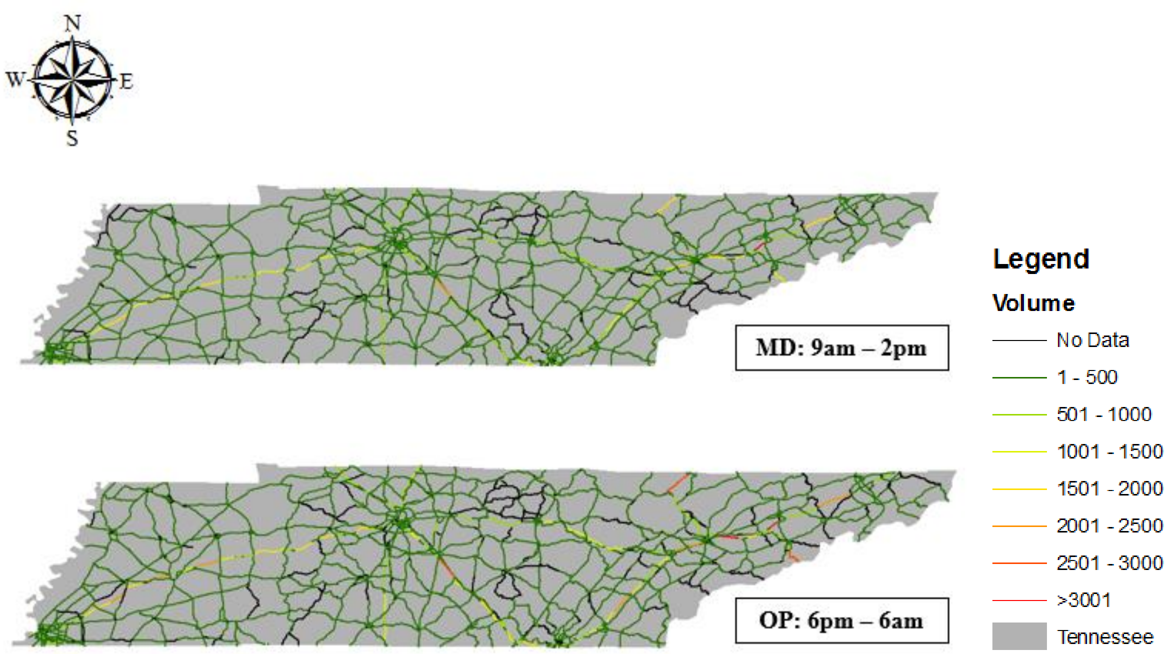


FIGURE B-12 Total Volumes, July 17th – 19th, MD & OP Periods

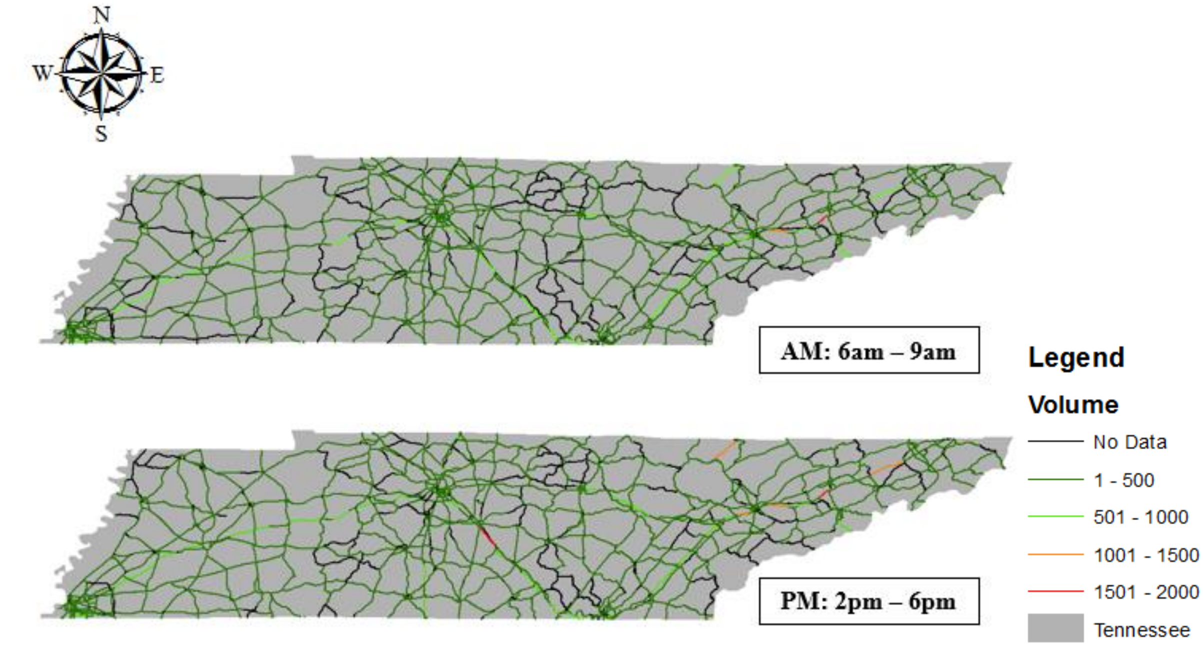


FIGURE B-13 Total Volumes, August 14th – 16th, AM & PM Periods

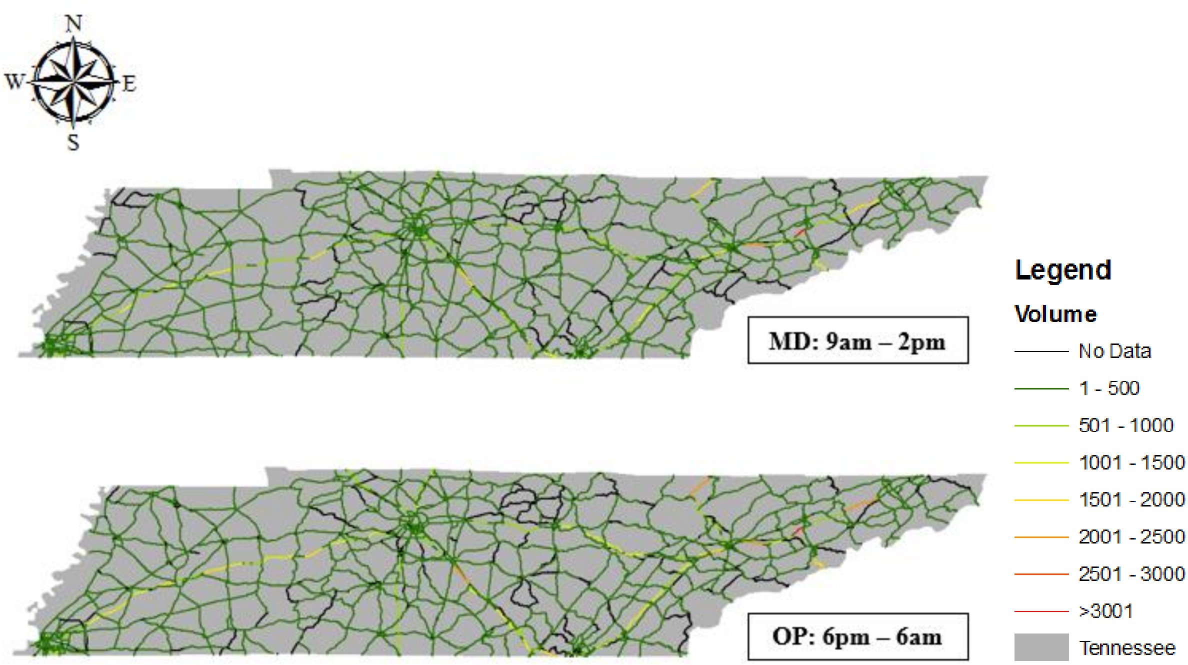


FIGURE B-14 Total Volumes, August 14th – 16th, MD & OP Periods

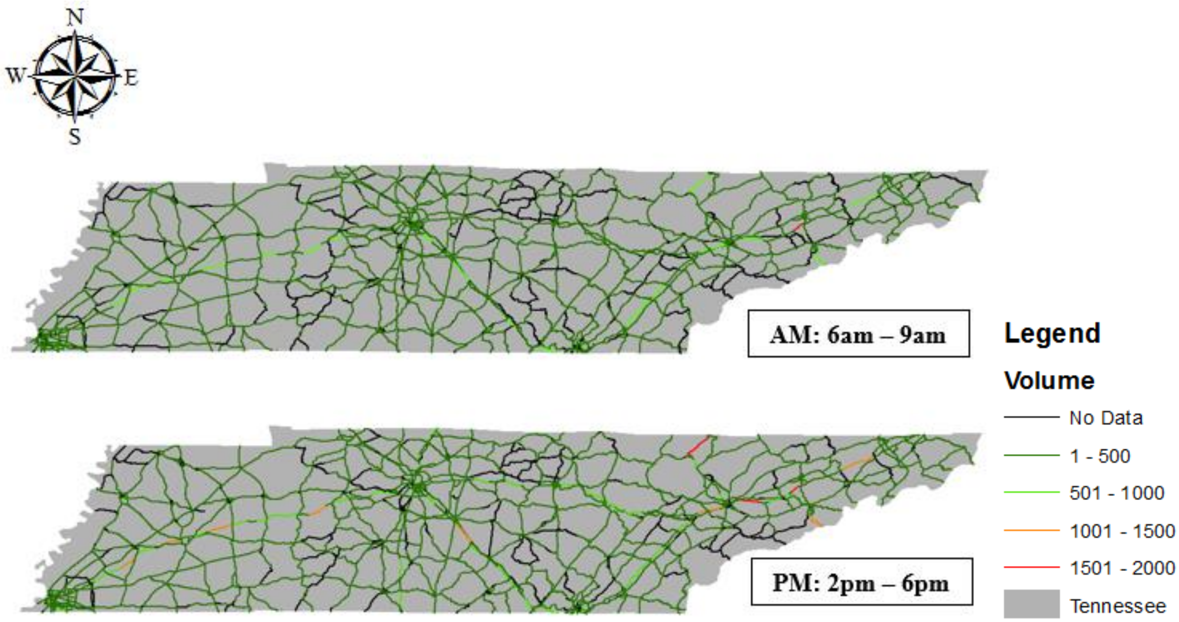


FIGURE B-15 Total Volumes, September 18th – 20th, AM & PM Periods

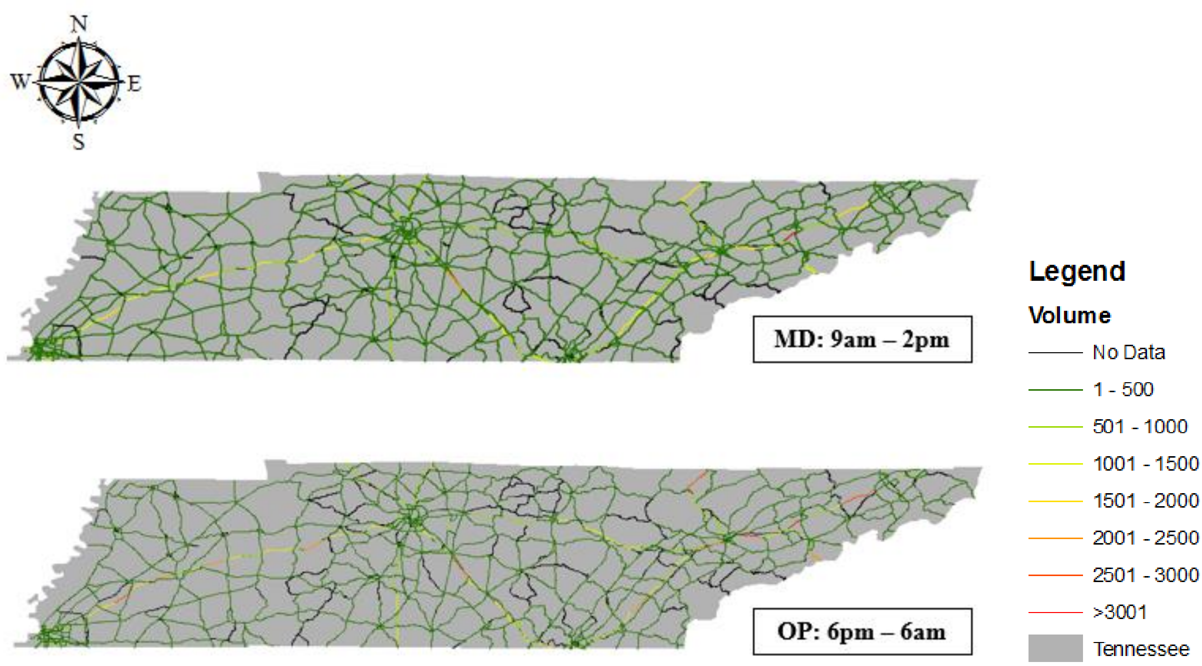


FIGURE B-16 Total Volumes, September 18th – 20th, MD & OP Periods

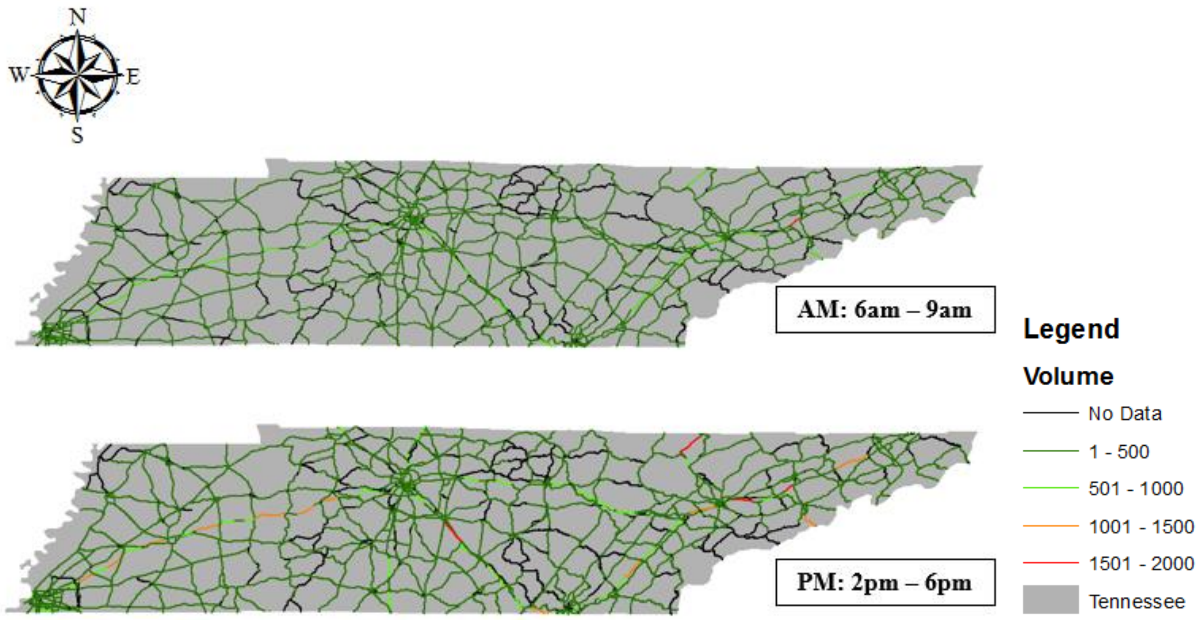


FIGURE B-17 Total Volumes, October 18th – 20th, AM & PM Periods

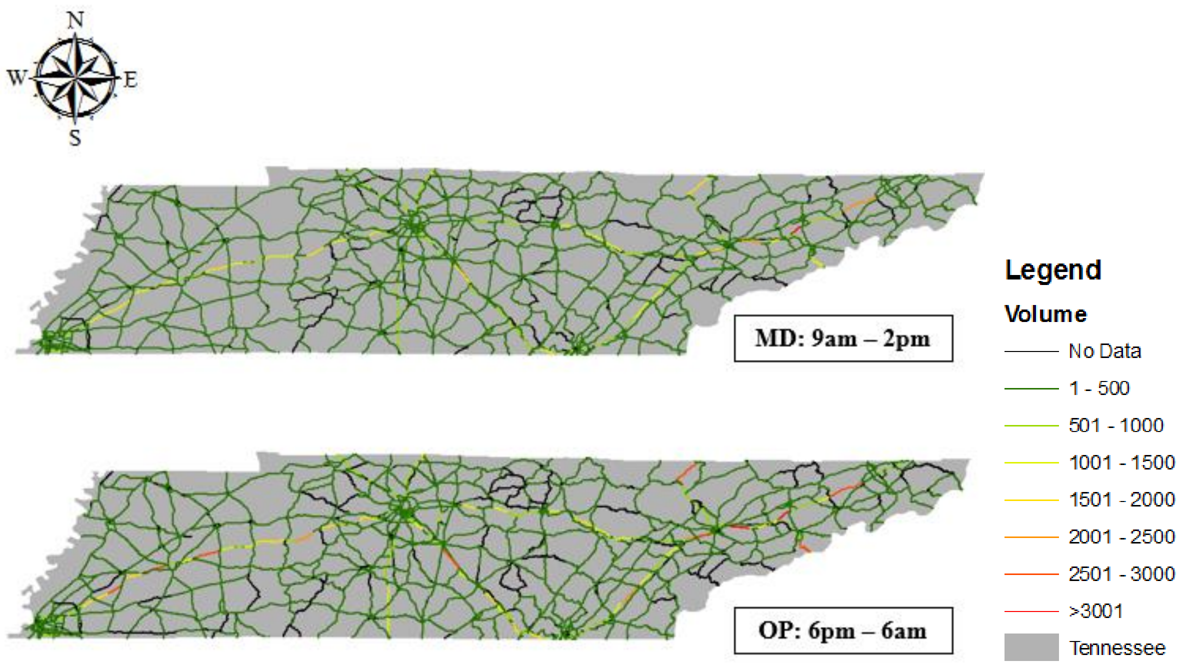


FIGURE B-18 Total Volumes, October 18th – 20th, MD & OP Periods

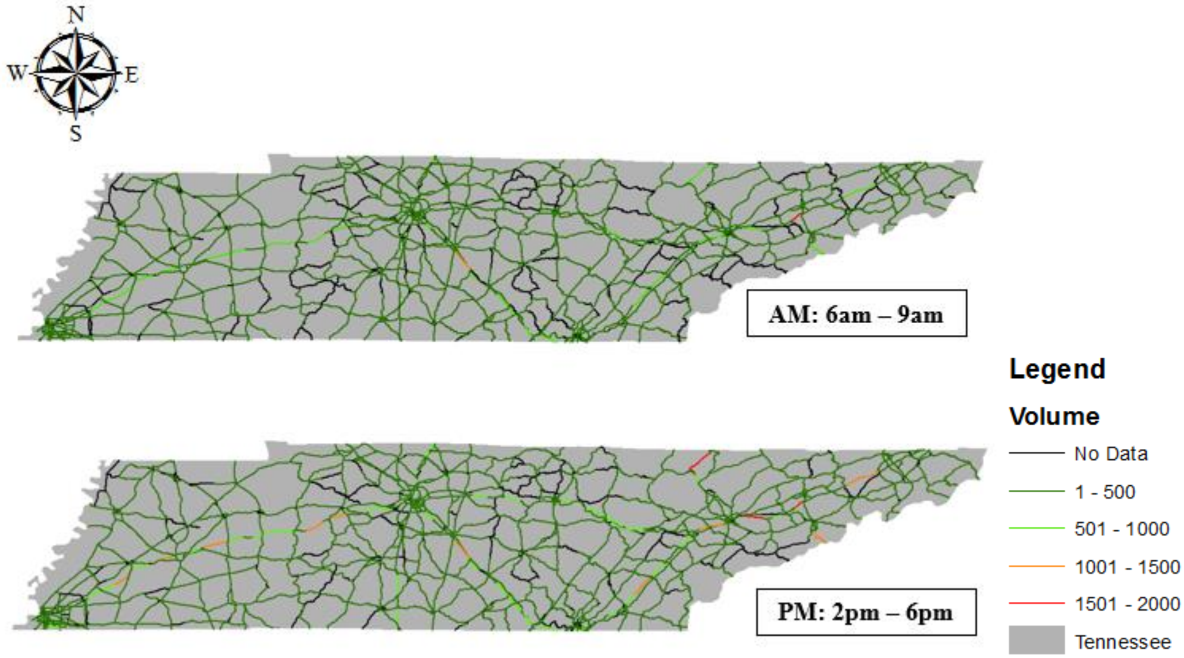


FIGURE B-19 Total Volumes, November 6th – 8th, AM & PM Periods

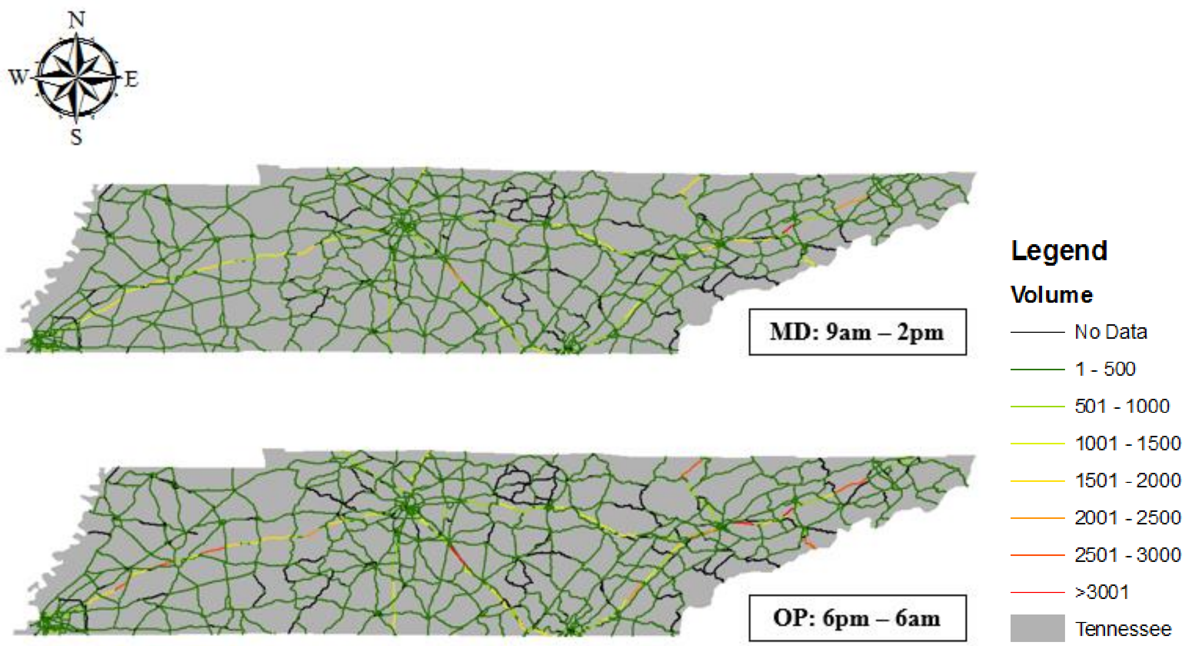


FIGURE B-20 Total Volumes, November 6th – 8th, MD & OP Periods

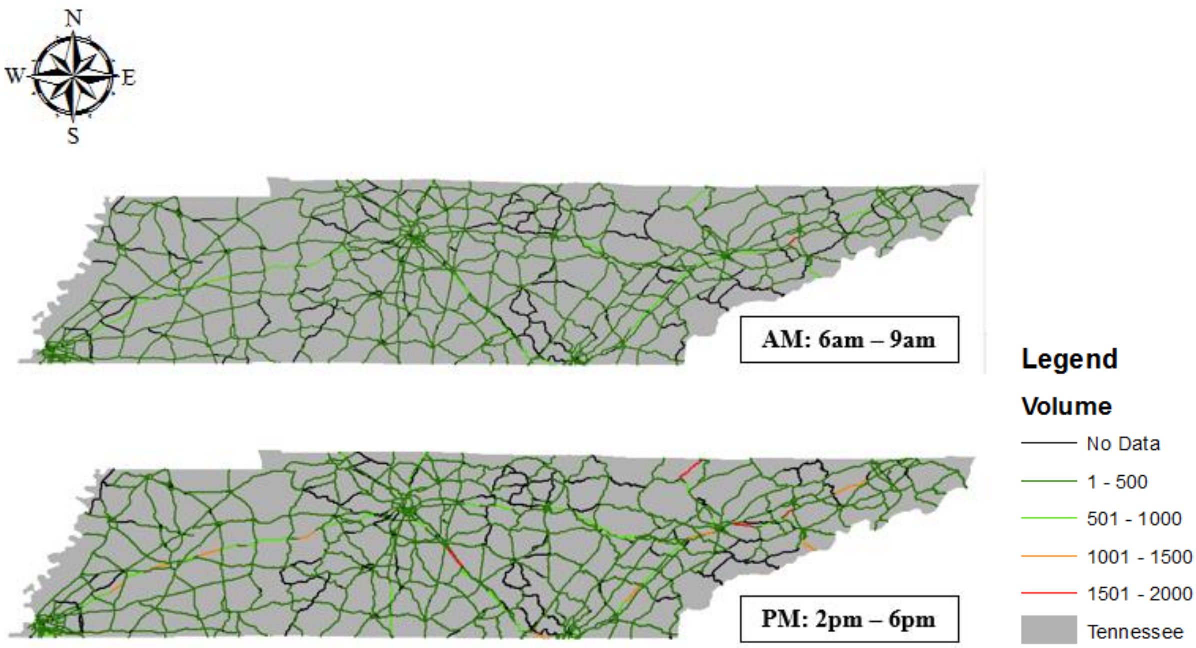


FIGURE B-21 Total Volumes, December 4th – 6th, AM & PM Periods

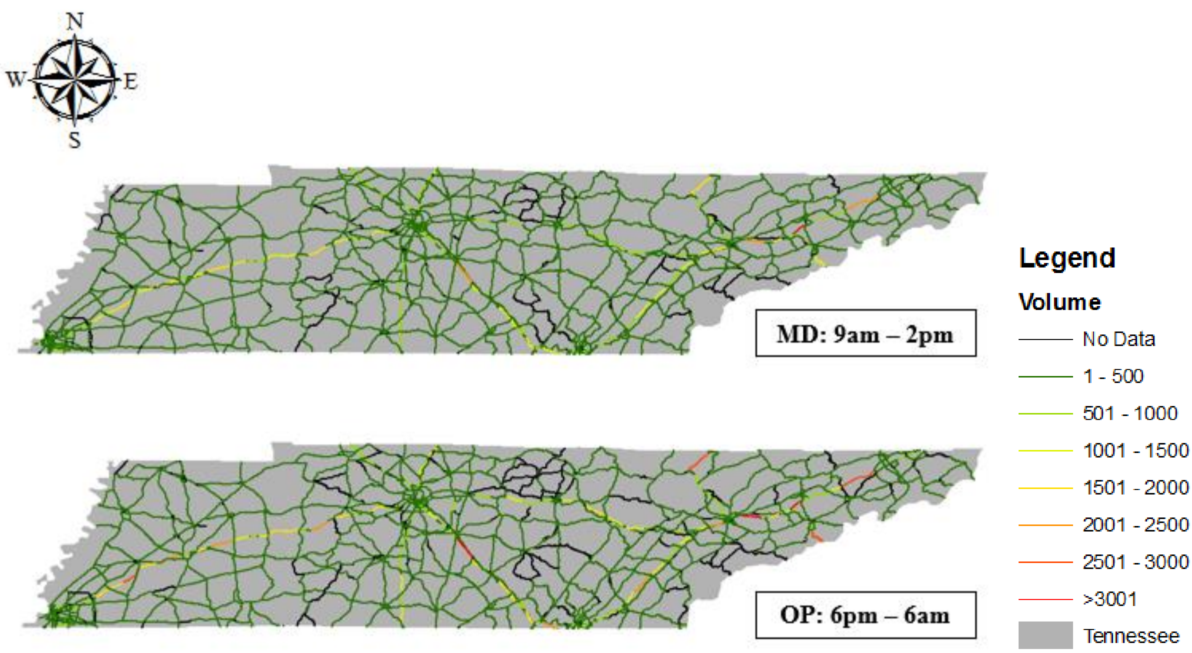


FIGURE B-22 Total Volumes, December 4th – 6th, MD & OP Periods

APPENDIX C
TRUCK TURN TIME HISTOGRAMS BY FACILITY (JANUARY 2012)

FIGURE C-1 Turn Time Histograms for Intermodal Facilities

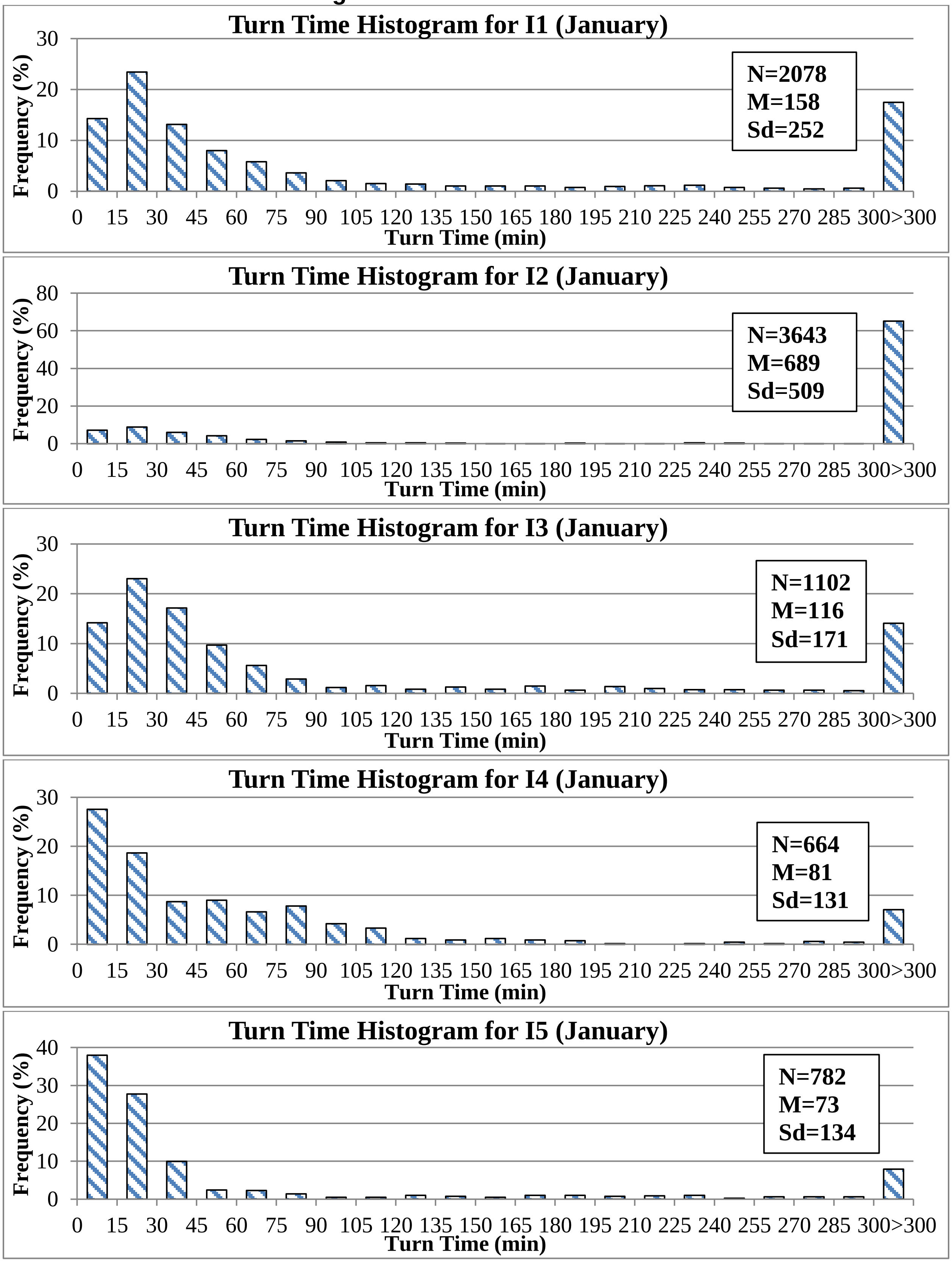
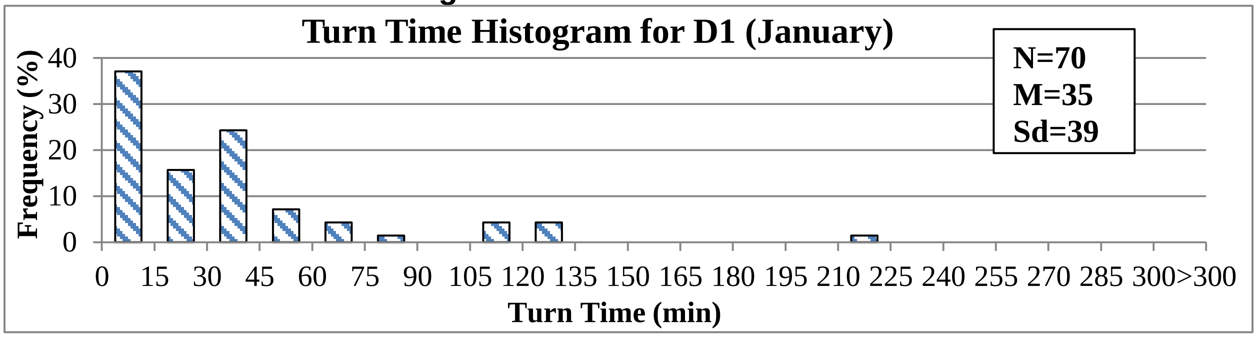
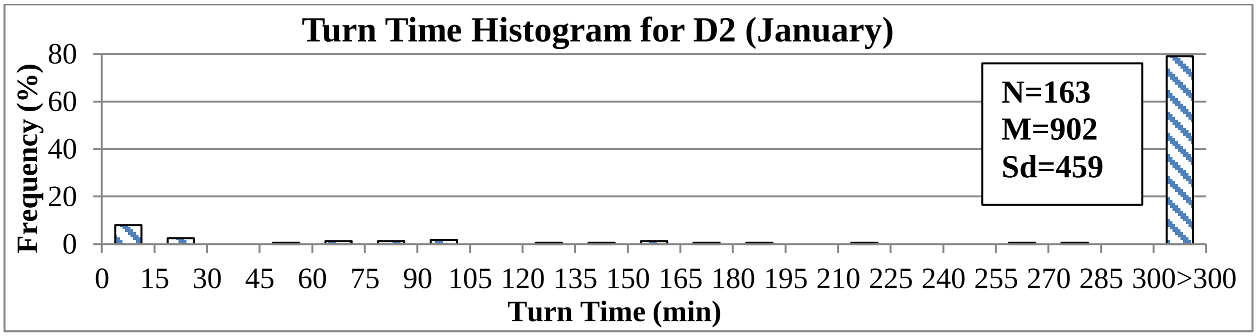
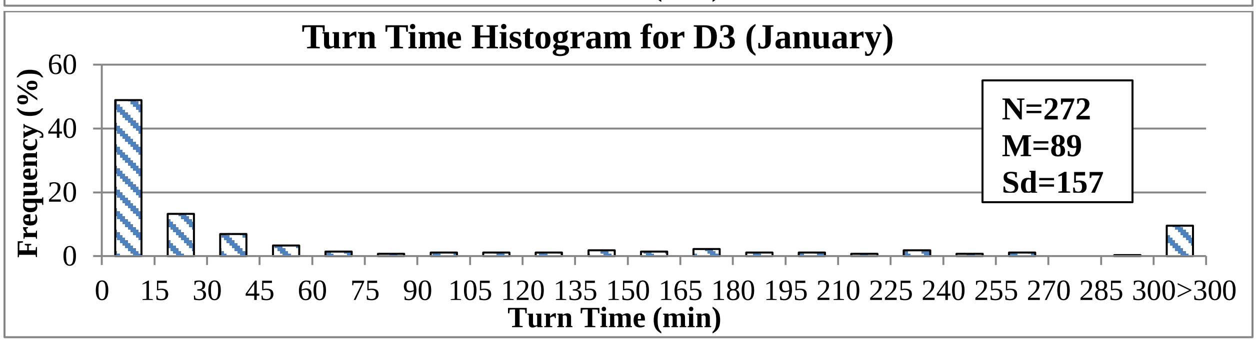
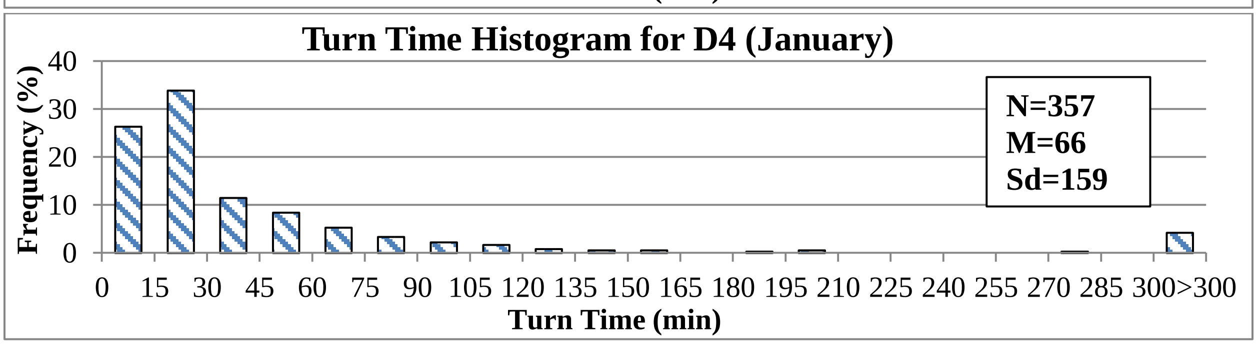


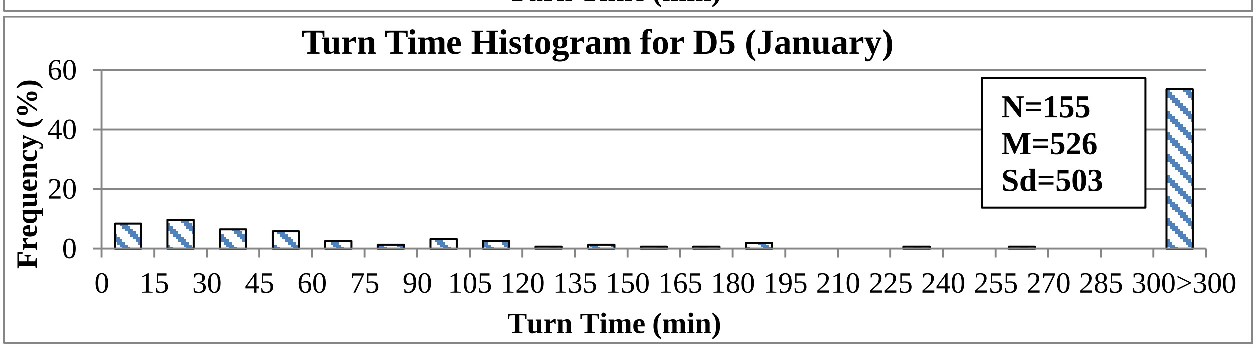
FIGURE C-2 Turn Time Histograms for Distribution Centers











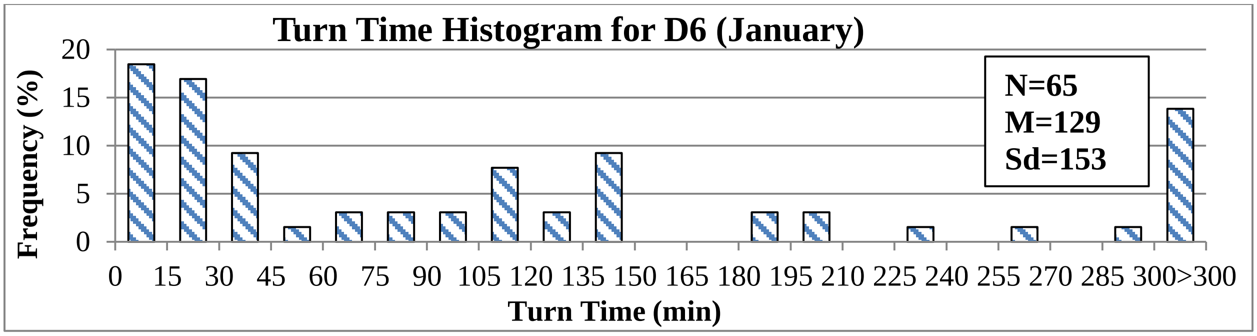
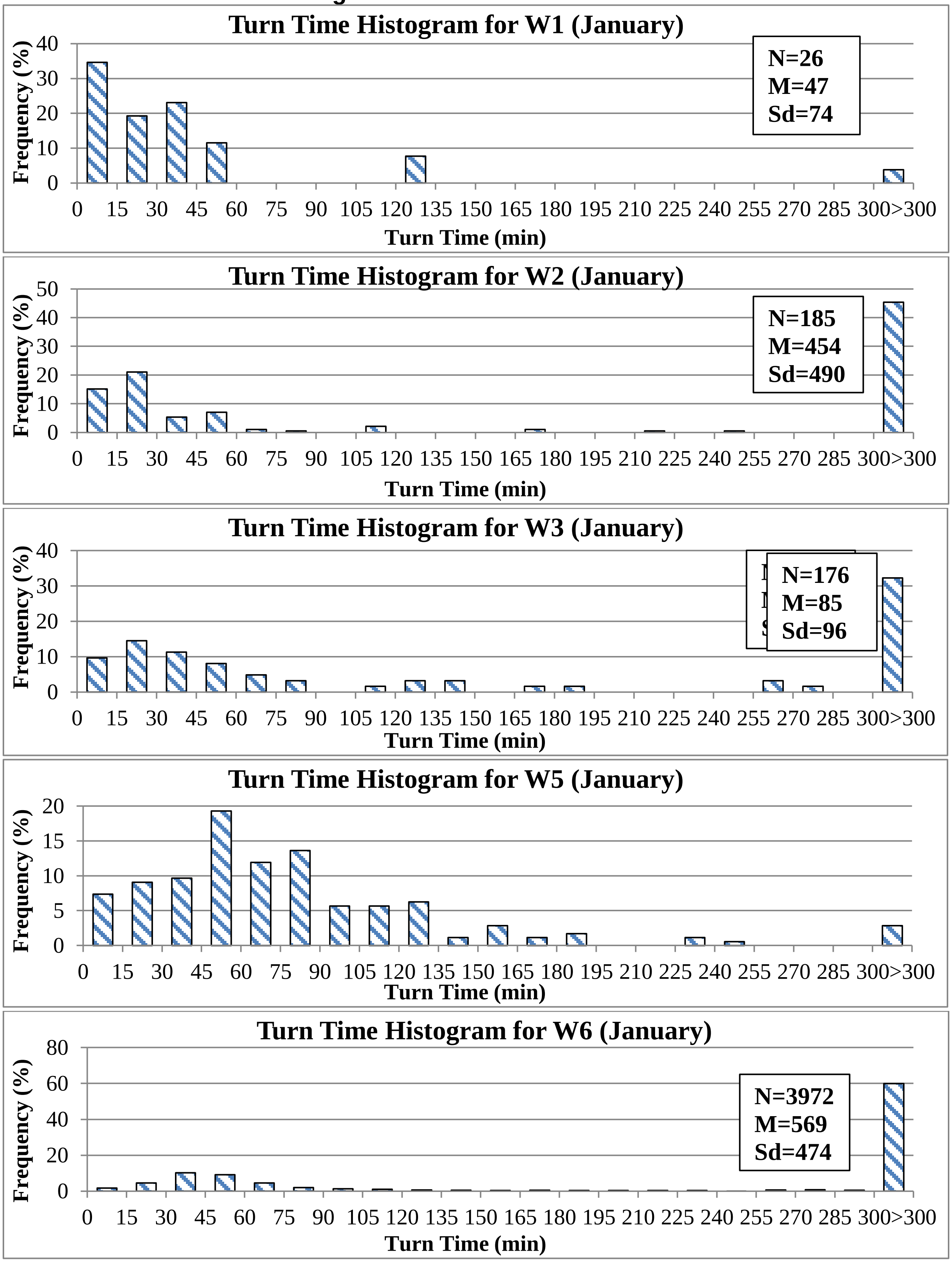
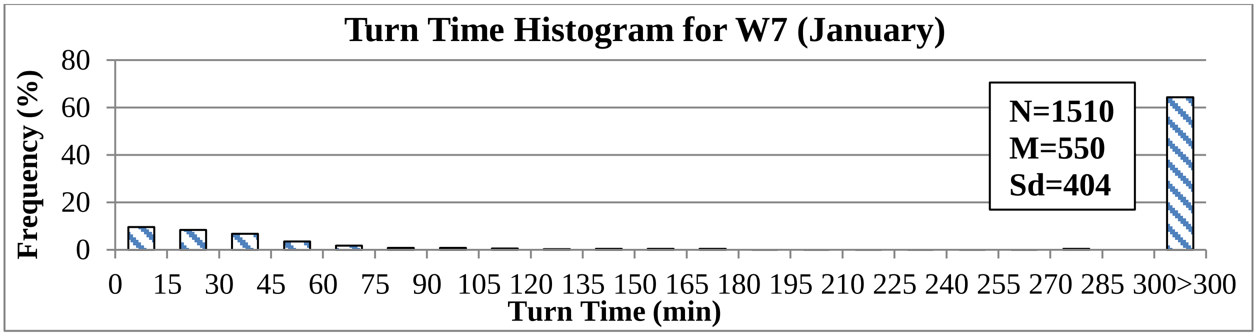
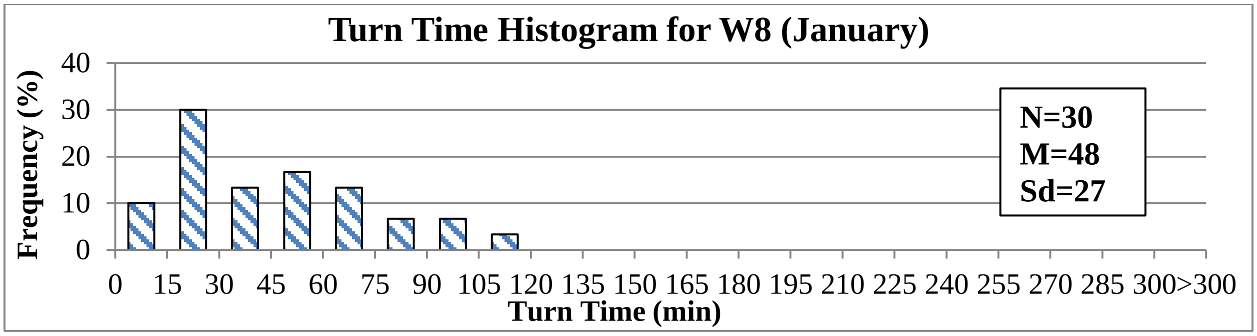

Turn Time Histogram for D6 (January)
N=65
M=129
Sd=153
Frequency (%)
20
15
10
5
0
0 15 30 45 60 75 90 105 120 135 150 165 180 195 210 225 240 255 270 285 300>300
Turn Time (min)

FIGURE C-3 Turn Time Histograms for Warehouses







Notations: N – number of unique trucks observed within a given facility; M – mean truck turn time (in hours); Sd – mean truck turn time standard deviation.

Histograms for facilities W4 and W9 are not provided due to lack of observations (only 3 and 5 GPS records respectively were available).

APPENDIX D
RELATIVE DAILY FREIGHT FACILITY OCCUPANCY AND ENTRY/EXIT VOLUMES
(JANUARY 2012)

Intermodal Facilities

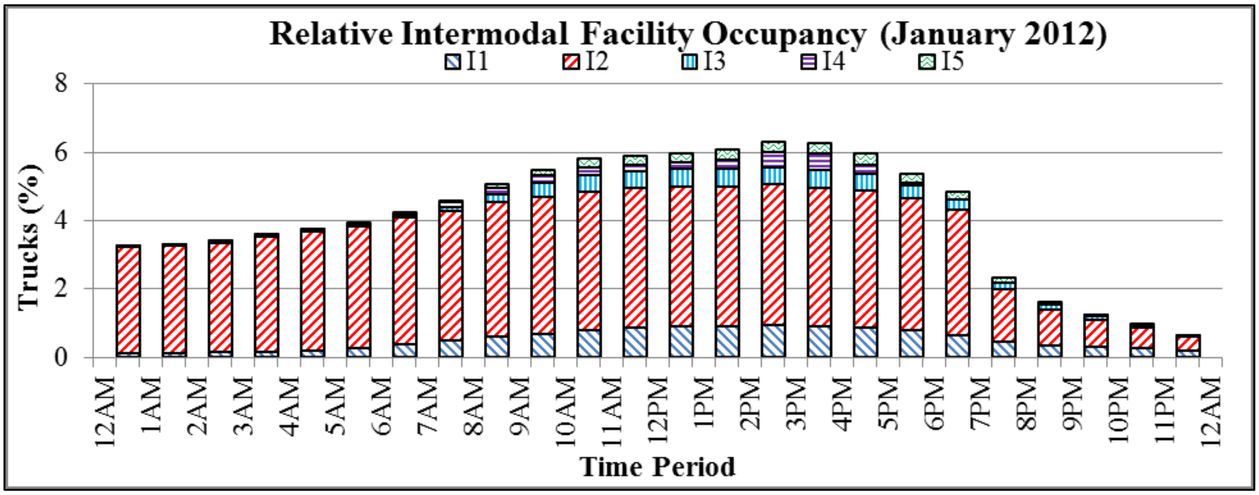


FIGURE D-1 Relative Daily Intermodal Facility Occupancy

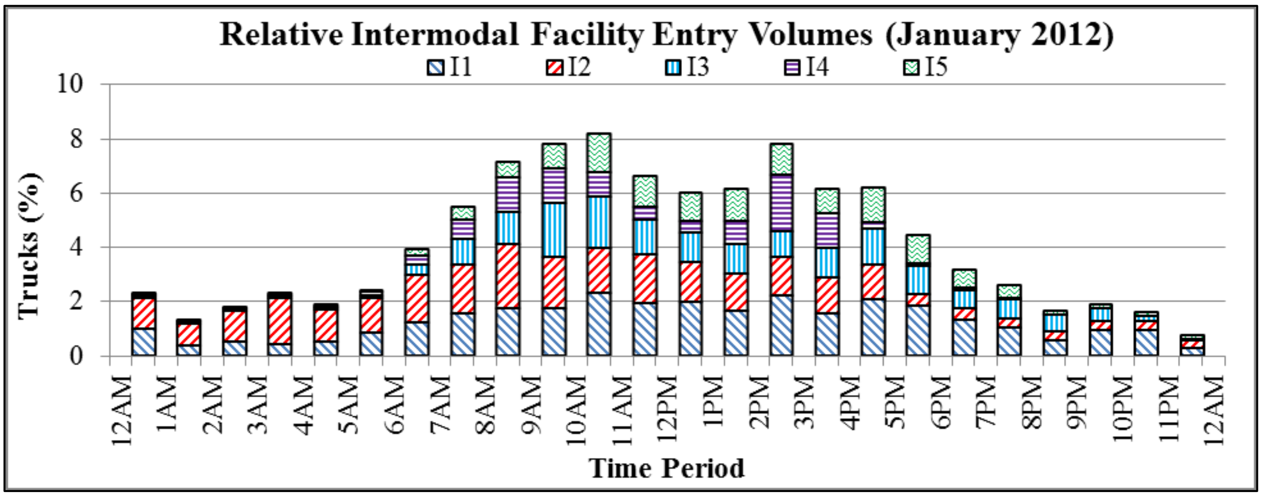


FIGURE D-2 Relative Daily Intermodal Facility Entry Volumes

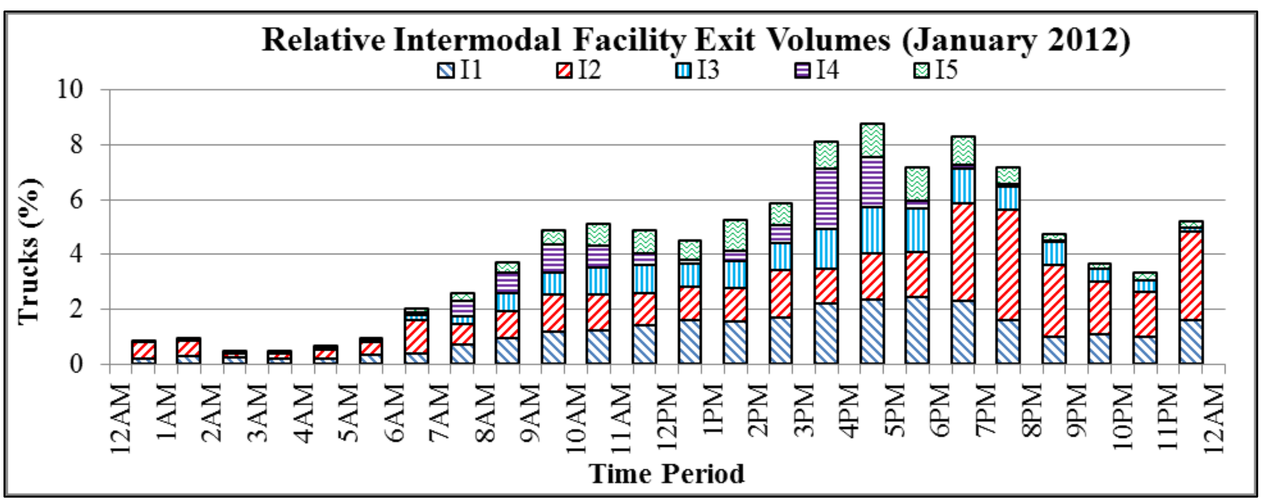


FIGURE D-3 Relative Daily Intermodal Facility Exit Volumes

Distribution Centers

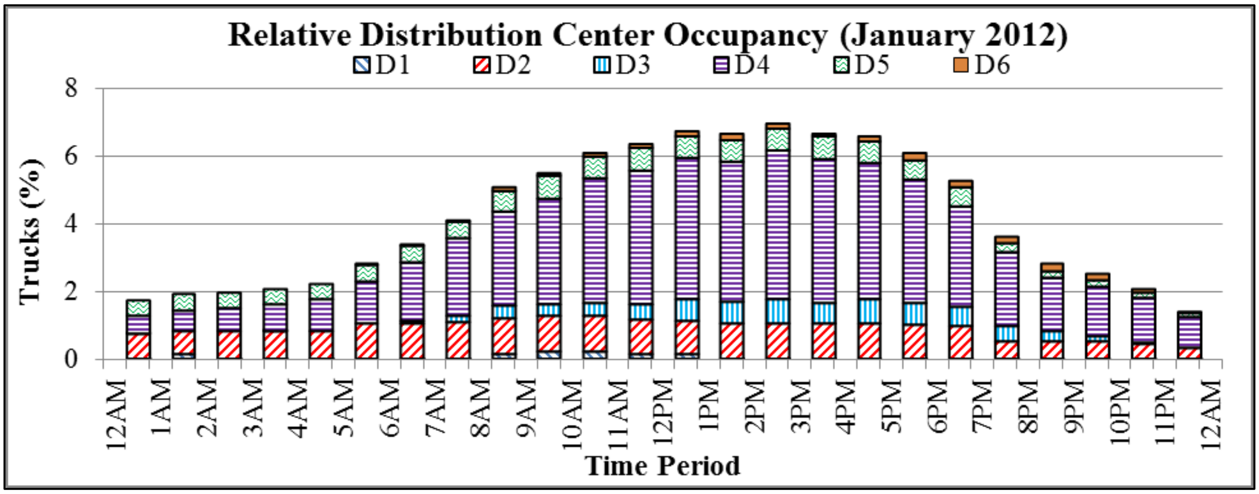


FIGURE D-4 Relative Daily Distribution Center Occupancy

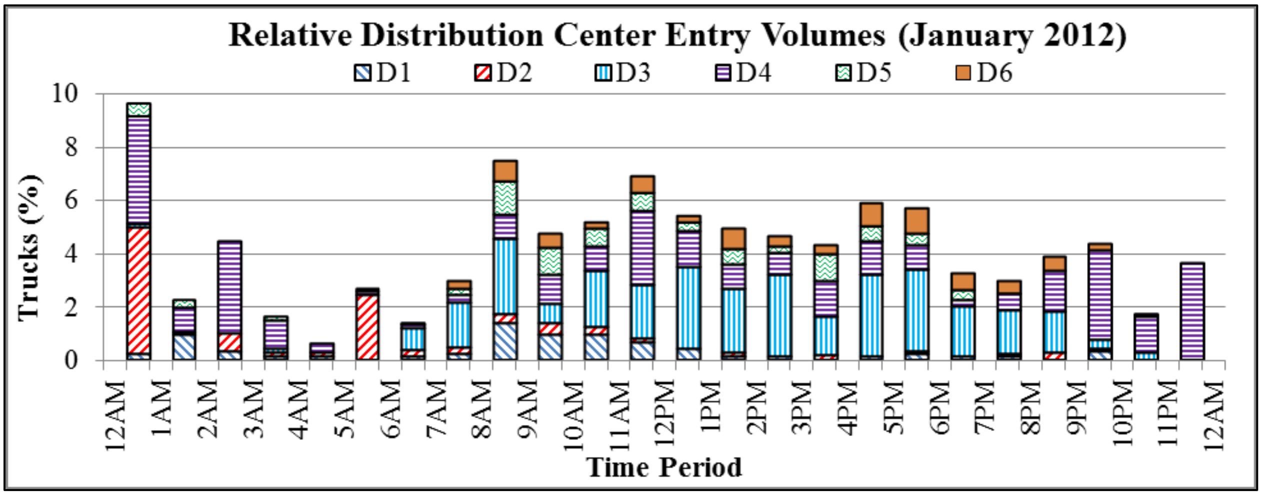


FIGURE D-5 Relative Daily Distribution Center Entry Volumes

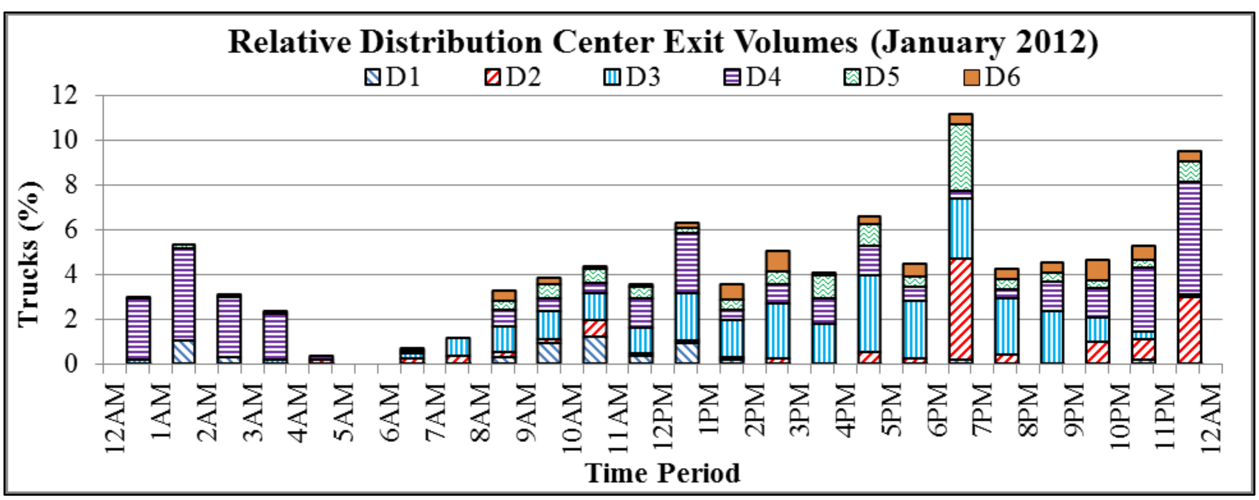


FIGURE D-6 Relative Daily Distribution Center Exit Volumes

Warehouses

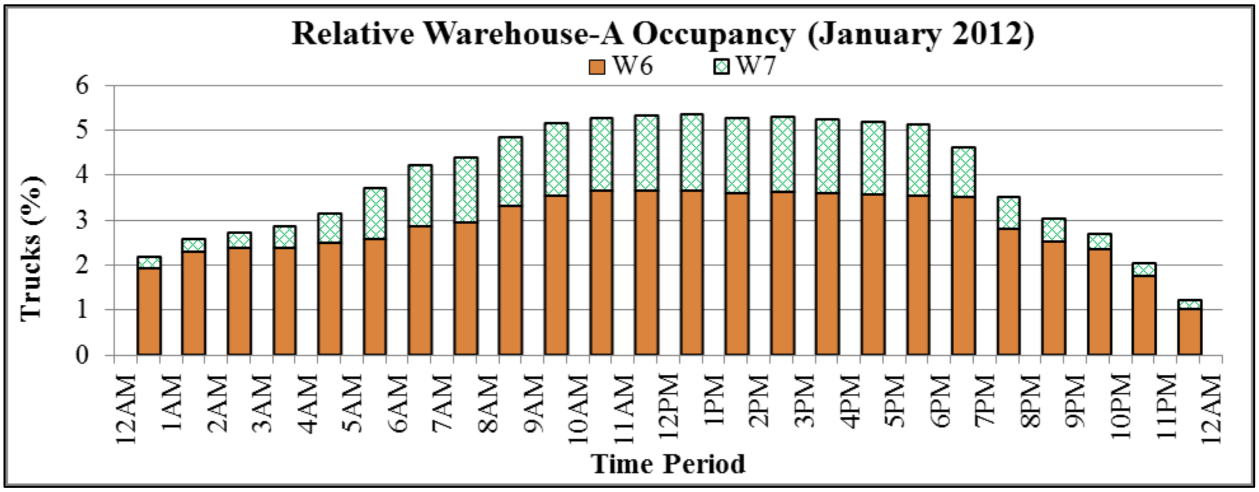


FIGURE D-7 Relative Daily Warehouse-A Occupancy

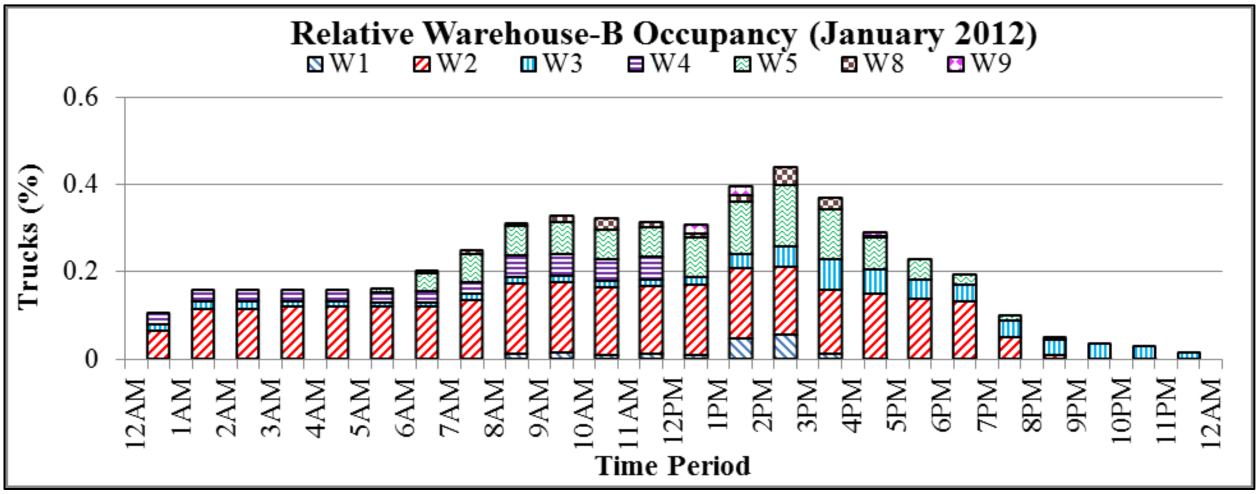


FIGURE D-8 Relative Daily Warehouse-B Occupancy

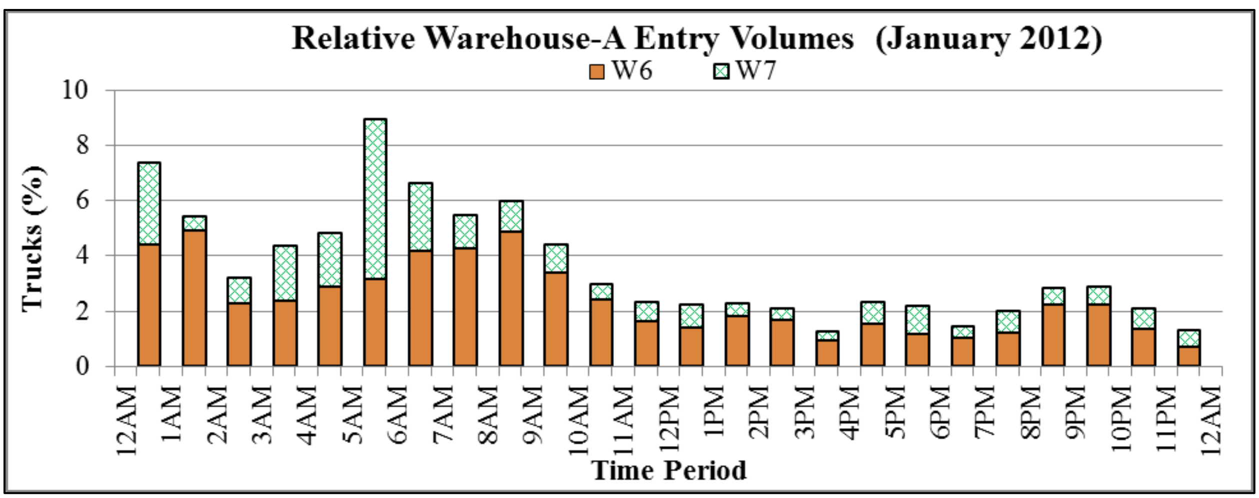


FIGURE D-9 Relative Daily Warehouse-A Entry Volumes

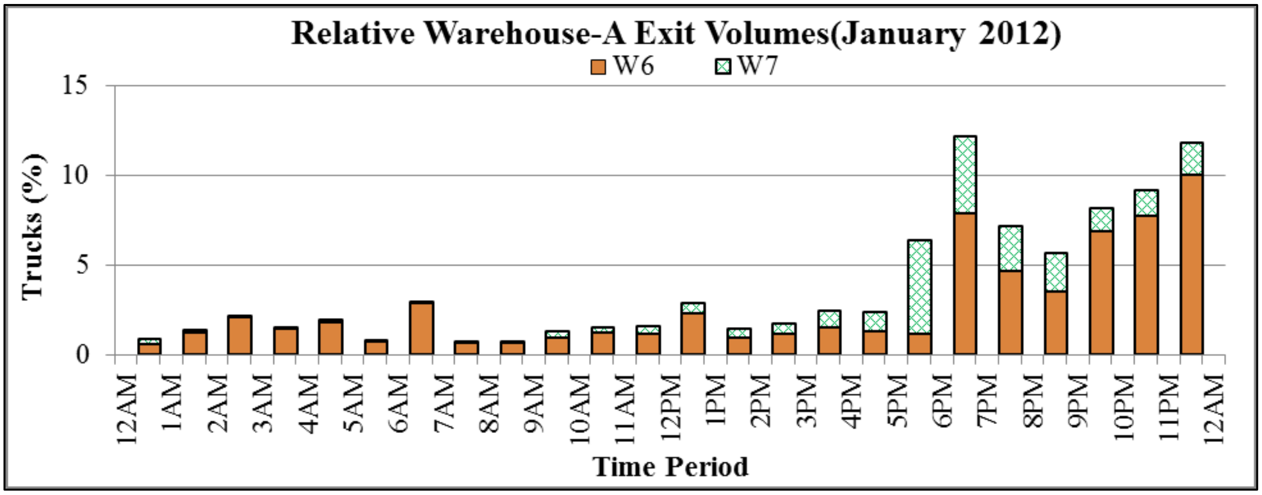


FIGURE D-10 Relative Daily Warehouse-A Exit Volumes

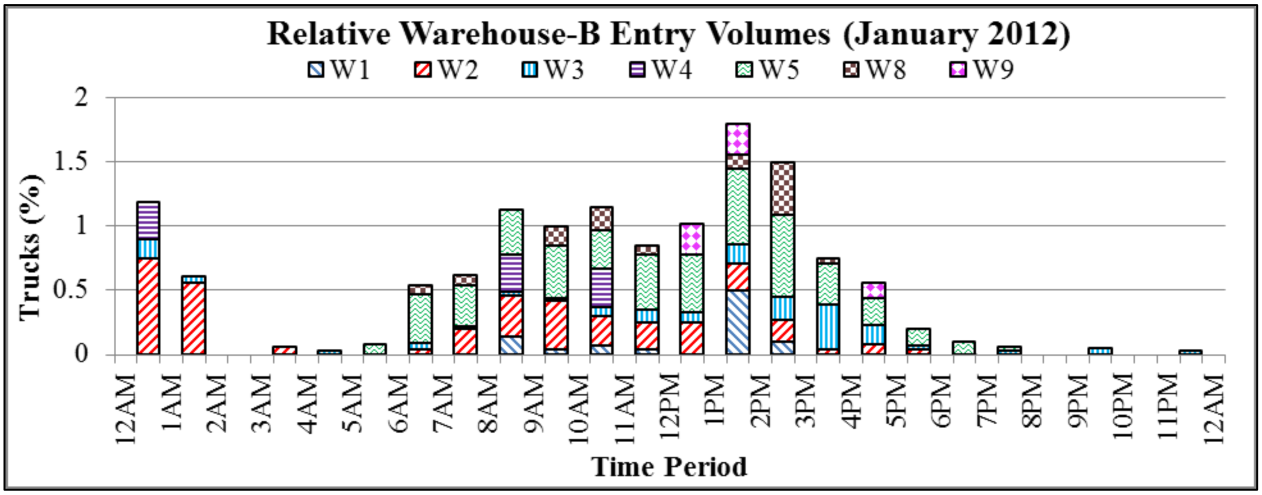


FIGURE D-11 Relative Daily Warehouse-B Entry Volumes

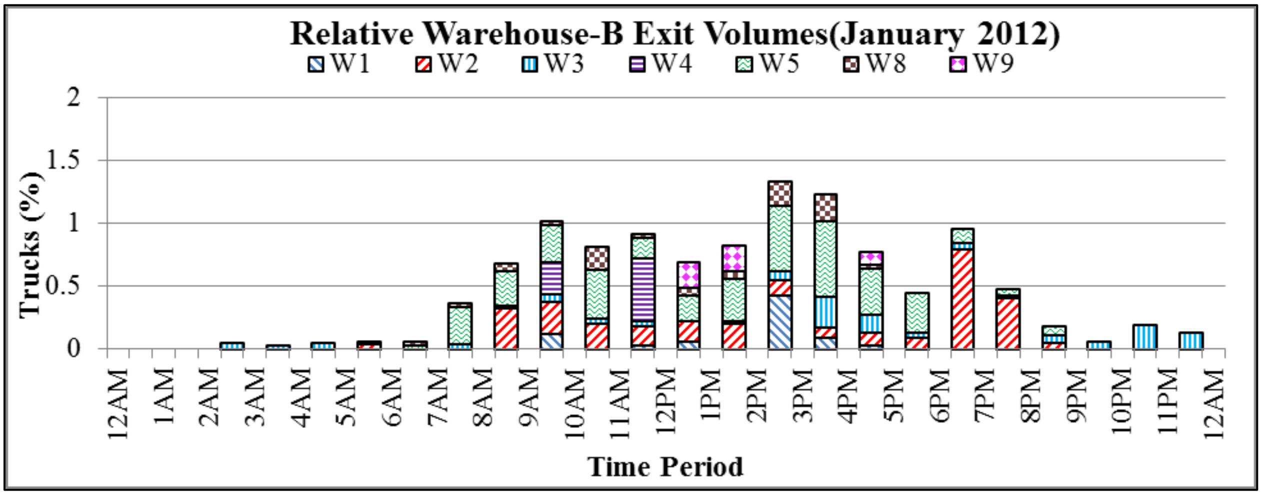


FIGURE D-12 Relative Daily Warehouse-B Exit Volumes

APPENDIX E
TDA EXAMPLE OUTPUTS

TABLE E-1 Trip Data for a Random Truck #1

Truck	TS(i)	TS(i+1)	tt	td	Status(i)	Status(i+1)	dtto	dttf	dtts	PotNewOr	dttstl	dttms	dttd
#1	0.077	5.294	5.217	0.033	AT ORIGIN	STAYS AT ORIGIN	5.217	0.000	0.000	0	0.000	0.000	0.000
#1	5.294	6.077	0.783	0.003	STAYS AT ORIGIN (SAO)	SAO	6.000	0.000	0.000	0	0.000	0.000	0.000
#1	6.077	9.577	3.500	0.001	SAO	SAO	9.500	0.000	0.000	0	0.000	0.000	0.000
#1	9.577	10.577	1.000	0.002	SAO	SAO	10.500	0.000	0.000	0	0.000	0.000	0.000
#1	10.577	11.794	1.217	0.004	SAO	SAO	11.717	0.000	0.000	0	0.000	0.000	0.000
#1	11.794	12.077	0.283	0.001	SAO	SAO	12.000	0.000	0.000	0	0.000	0.000	0.000
#1	12.077	14.714	2.637	0.055	SAO	MOVING	12.000	0.000	0.000	0	0.000	0.000	0.000
#1	14.714	14.817	0.102	0.780	MOVING	MOVING	12.000	0.000	0.000	0	0.000	0.000	0.000
#1	14.817	14.966	0.149	3.098	MOVING	AT FACILITY	12.000	0.000	0.000	0	0.000	0.000	0.000
#1	14.966	15.078	0.112	0.000	AT FACILITY	AT FACILITY	12.000	0.112	0.000	0	0.000	0.000	0.000
#1	15.078	15.434	0.357	0.052	AT FACILITY	AT FACILITY	12.000	0.468	0.000	0	0.000	0.000	0.000
#1	15.434	15.434	0.000	0.004	AT FACILITY	AT FACILITY	12.000	0.468	0.000	0	0.000	0.000	0.000
#1	15.434	15.577	0.143	0.001	AT FACILITY	AT FACILITY	12.000	0.611	0.000	0	0.000	0.000	0.000
#1	15.577	15.668	0.091	0.007	AT FACILITY	AT FACILITY	12.000	0.702	0.000	0	0.000	0.000	0.000
#1	15.668	15.684	0.016	0.041	AT FACILITY	AT FACILITY	12.000	0.718	0.000	0	0.000	0.000	0.000
#1	15.684	15.806	0.122	0.012	AT FACILITY	AT FACILITY	12.000	0.839	0.000	0	0.000	0.000	0.000
#1	15.806	15.815	0.009	0.004	AT FACILITY	AT FACILITY	12.000	0.849	0.000	0	0.000	0.000	0.000
#1	15.815	16.067	0.252	4.237	AT FACILITY	MOVING	12.000	0.849	0.000	0	0.000	0.000	0.000
#1	16.067	16.077	0.011	0.514	MOVING	MOVING	12.000	0.849	0.000	0	0.000	0.000	0.000
#1	16.077	16.131	0.053	0.558	MOVING	MOVING	12.000	0.849	0.000	0	0.000	0.000	0.000
#1	16.131	16.151	0.020	0.006	MOVING	STOPPED	12.000	0.849	0.000	0	0.000	0.000	0.000
#1	16.151	16.406	0.256	0.060	STOPPED	NO DESTINATION	12.000	0.849	0.000	0	0.000	0.000	0.000

Note: TS – time stamp (hr); tt – travel time between consecutive observations (hr); td – travel distance between consecutive observations (mi); dtto - truck origin dwell time (hr); dttf - truck dwell travel time at facilities (hr); dtts - truck dwell travel time at stops; PotNewOr – potential new origin (0 – no, 1 – yes); dttstl - truck dwell travel time at traffic light stops (hr); dttms - truck dwell travel time moving slowly (hr); dttd - truck destination dwell time (hr);

TABLE E-2 Trip Data for a Random Truck #2

Truck	TS(i)	TS(i+1)	tt	td	Status(i)	Status(i+1)	dtto	dttf	dtts	PotNewOr	dttstl	dttms	dttd
#2	10.250	10.425	0.175	0.010	AT ORIGIN	SAO	0.175	0.000	0.000	0	0.000	0.000	0.000
#2	10.425	10.561	0.136	0.166	SAO	MOVING	0.175	0.000	0.000	0	0.000	0.000	0.000
#2	10.561	10.583	0.022	0.040	MOVING	MOVING	0.175	0.000	0.000	0	0.000	0.000	0.000
#2	10.583	10.589	0.006	0.003	MOVING	MOVING	0.175	0.000	0.000	0	0.000	0.000	0.000
#2	10.589	10.667	0.078	1.901	MOVING	MOVING	0.175	0.000	0.000	0	0.000	0.000	0.000
#2	10.667	10.750	0.083	0.163	MOVING	MOVING	0.175	0.000	0.000	0	0.000	0.000	0.000
#2	10.750	10.833	0.083	3.681	MOVING	MOVING	0.175	0.000	0.000	0	0.000	0.000	0.000
#2	10.833	10.844	0.011	0.685	MOVING	MOVING	0.175	0.000	0.000	0	0.000	0.000	0.000
#2	10.844	10.917	0.073	3.738	MOVING	MOVING	0.175	0.000	0.000	0	0.000	0.000	0.000
#2	10.917	11.000	0.083	2.736	MOVING	MOVING	0.175	0.000	0.000	0	0.000	0.000	0.000
#2	11.000	15.833	4.833	1.966	MOVING	MOVING	0.175	0.000	0.000	0	0.000	0.000	0.000
#2	15.833	15.865	0.032	0.295	MOVING	AT FACILITY	0.175	0.000	0.000	0	0.000	0.000	0.000
#2	15.865	15.866	0.001	0.256	AT FACILITY	AT FACILITY	0.175	0.001	0.000	0	0.000	0.000	0.000
#2	15.866	15.871	0.006	2.276	AT FACILITY	AT FACILITY	0.175	0.006	0.000	0	0.000	0.000	0.000
#2	15.871	15.873	0.002	2.169	AT FACILITY	AT FACILITY	0.175	0.008	0.000	0	0.000	0.000	0.000
#2	15.873	15.901	0.028	0.481	AT FACILITY	MOVING	0.175	0.008	0.000	0	0.000	0.000	0.000
#2	15.901	15.907	0.006	1.284	MOVING	MOVING	0.175	0.008	0.000	0	0.000	0.000	0.000
#2	15.907	16.000	0.093	0.190	MOVING	MOVING	0.175	0.008	0.000	0	0.000	0.000	0.000
#2	16.000	16.083	0.083	0.301	MOVING	MOVING	0.175	0.008	0.000	0	0.000	0.000	0.000
#2	16.083	16.153	0.070	1.247	MOVING	MOVING	0.175	0.008	0.000	0	0.000	0.000	0.000
#2	16.153	16.167	0.013	0.729	MOVING	MOVING	0.175	0.008	0.000	0	0.000	0.000	0.000
#2	16.167	16.250	0.083	4.882	MOVING	MOVING	0.175	0.008	0.000	0	0.000	0.000	0.000
#2	16.250	16.333	0.083	4.901	MOVING	MOVING	0.175	0.008	0.000	0	0.000	0.000	0.000
#2	16.333	16.417	0.083	2.014	MOVING	MOVING	0.175	0.008	0.000	0	0.000	0.000	0.000
#2	16.417	16.470	0.053	0.113	MOVING	AT DESTINATION	0.175	0.008	0.000	0	0.000	0.000	0.000
#2	16.470	16.589	0.119	0.104	AT DESTINATION	AT DESTINATION	0.175	0.008	0.000	0	0.000	0.000	0.119
#2	16.589	18.089	1.499	4.009	AT DESTINATION	AT DESTINATION	0.175	0.008	0.000	0	0.000	0.000	1.619

Note: TS – time stamp (hr); tt – travel time between consecutive observations (hr); td – travel distance between consecutive observations (mi); dtto - truck origin dwell time (hr); dttf - truck dwell travel time at facilities (hr); dtts - truck dwell travel time at stops; PotNewOr – potential new origin (0 – no, 1 – yes); dttstl - truck dwell travel time at traffic light stops (hr); dttms - truck dwell travel time moving slowly (hr); dttd - truck destination dwell time (hr);