Analysis of Freight Corridors Using Truck GPS Data

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ABSTRACT

Trucks remain an important link of todays' supply chains as the majority of goods in the United States (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 objective of this paper is to develop a methodology for processing raw GPS data and to develop freight performance measures. Two algorithms are proposed to estimate bi-directional link speeds and to analyze truck trips respectively. A case study for the state of Tennessee (TN) is presented to evaluate the proposed methodology.

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 (*1*, *2*). 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 (*3*), Los Angeles, CA (U.S) is the third congested city in the world after Brussels (Belgium) and Antwerp (Belgium). According to USA TODAY (*4*), "*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 (*5*). 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 (*6*). 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 (*6*): 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 (*7-29*) developed various approaches for analyzing raw truck GPS data and estimating network and freight facility FPMs, which also have certain limitations (e.g., device 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 paper are to develop a methodology and algorithms to process GPS truck data and estimate network FPMs, identified from the literature. The contributions of the proposed research can be summarized as follows: 1) review of current practices using truck GPS records to evaluate traffic conditions on freight corridors, 2) analysis of existing procedures to process truck GPS records, and identification of FPMs commonly used by researches and practitioners; 3) development of algorithms to process GPS truck data and estimate FPMs; and 4) evaluation of the proposed algorithms using real world data.

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[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/

The rest of the paper is organized as follows. The next section presents an up-to-date literature review on freight transportation network analysis using GPS truck data. The third section presents the methodology proposed to process GPS truck data and to develop FPMs. The fourth section presents a case study in the state of TN. The last section concludes the paper and proposes future research avenues.

LITERATURE REVIEW

To date a number of studies and research papers have been published, where GPS truck data was used to evaluate performance of freight corridors, estimate various FPMs, identify network bottlenecks, and determine areas that require improvements. In the review presented herein, literature is classified in two groups based on the method used to calculate average travel time (TT). The majority of research focused on estimating average link TT (LTT). The remainder of the published studies proposed procedures for computing trip/tour TT. Some studies provided LTT along with truck trip characteristics (and are included in the second group).

Group 1: Average LTT

Quiroga and Bullock (*7*), and Quiroga (*8*) computed LTT and link travel speed (LTS) for Louisiana highways: Baton Rouge, Shreveport, and New Orleans. The segment length comprised 0.2-0.5 miles. It was found that shorter GPS sampling periods (1 to 2 seconds) decreased errors in travel speed 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 that may occur during peak hours. Storey and Holtom (*9*) used GPS data to calculate LTS and LTT at West Midlands roadways (UK). The GPS device provided information every 60 seconds, if the vehicle engine was on. It was assumed that segments between two GPS points had the same average speed. The analysis indicated congestion issues at major junctions, leading to the city center. Jones et al. (*10*) presented a methodology to measure performance of busy freight corridors. Top ten U.S. cities with the highest truck volumes were identified using ATRI satellite position reports. The busiest freight corridors were determined for each of those cities based on the information, provided by Cambridge Systematics. As a result of the study, a map was created, depicting average Travel Speed (TS) on the major U.S. corridors.

Schofield and Harrison (*11*) conducted a study to develop appropriate FPMs in the Texas area. GPS records were provided by ATRI for the entire year of 2005. The authors indicated that the spatial error for each observation could reach up to a quarter mile. Spatial errors increase the difficulty of accurately linking GPS observations to the roadway network (especially in dense network areas). TT, TS, and TT index (TTI) were estimated for each roadway segment. Changes in travel pattern were observed when the Hurricane Rita notification was announced. The report also provided average hourly truck volume percentage. Liao (*12*) evaluated performance of I-94/I-90 freight corridor between St. Paul, MN and Chicago, IL using GPS data, obtained from ATRI. The raw data were processed using the ArcGIS software, snapping records to the nearest route, and then the average speed was computed for each three mile segment. Results indicated that average speeds declined in areas approaching Chicago from 55 mph to 40 mph and under. A significant speed standard deviation and average speed drop were observed on I-90 toll highway, leading to Chicago. McCormack (*13*), the Washington DOT (*14*), McCormack et al. (*15*), and McCormack & Zhao (*16*) estimated LTT and its reliability at roadways in the state of WA. Efficiency of the Truck Performance Measure Program (TPMP) was highlighted (*14*). However, future success of TPMP would be highly dependent on the access to truck trip information, owned by trucking companies. The authors (*15-16*) also outlined a process for bottleneck identification and prioritization for the WA highways.

Figliozzi et al. (*17*) developed an algorithm for assessing TT reliability on the Oregon I-5 interstate based on GPS records, provided by ATRI. Traffic flows were estimated for every mile and direction of each segment for different time periods. Results demonstrated that differences between three types of TTs (i.e. 95th, 80th, and 50th percentile TT) were significant for urban areas and relatively small for rural areas. Wheeler and Figliozzi (*18*) assessed effects of recurrent and non-recurrent congestion on freight movements at the Oregon I-5 Interstate. Along with GPS records, the authors used corridor TT loop and incident data, provided by the Oregon DOT. A recurrent congestion analysis indicated that the highest TT and TT coefficient of variation (TTCV) were observed during evening peak hour. As for non-recurring congestion, it was found that incidents significantly affected truck TS in the incident area throughout the day. Wang et al. (*19*) 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 mapping method was able to analyze truck trips with large road segments consisting of multiple links. Both methodologies were assessed on the San Antonio corridor (TX) and the Milwaukee highway corridor (WI). The mapping method was found to be more efficient.

Group 2: Trip/Tour Average TT

McCormack and Hallenbeck (*20*) suggested two data collection methodologies to evaluate freight mobility improvement projects against benchmarks for the WA highways. The first technology relied on application of transponders, while the second one employed GPS devices. The information, collected by both types of devices, was processed to identify congested segments, trip TT, and TT reliability. It was highlighted that selection of each technique relied on the information required for a particular benchmark project. Greaves and Figliozzi (*21*) used GPS data to analyze truck movements in the Greater Melbourne region (Australia). The trip identification algorithm was developed to determine trip ends and tour characteristics. It was found that on average 12.2 stops were made per tour. The lowest average speeds were observed during morning and evening peak hours. A trip length distribution was provided in the paper as well.

Bassok et al. (*22*) demonstrated how truck GPS records could be used for the analysis of highway corridors in WA. The authors developed an algorithm for identifying trip ends. The analysis was performed for the Puget Sound region. It was found that each truck made on average nine tours and 10 trips per tour. Roughly two truck trips of each tour were made to grocery stores. Areas with higher population density produced more truck trips. Golias et al. (*23*) evaluated performance of roadways within the Greater Memphis area in TN using GPS data, provided by ATRI. The highest truck volumes on I-40 were observed during the evening peak hour between 4 pm and 5 pm. Trip durations were increasing for a period from 10 pm until 8 am. This was explained by the fact that most of truck drivers stopped for rest during that time interval. The authors developed regression models that could predict facility turn times based on truck volume per time interval and facility type (warehouse, distribution center or intermodal). 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.

Golias et al. (*24*) used truck GPS data from 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 along the TN road network. Existing truck trip patterns were developed by statistically analyzing the provided data, while future conditions were estimated using the methodology suggested in Highway Capacity Manual. By comparing the Level of Service (LOS) in both cases they found that the new HOS would worsen the LOS values leading to the increased delay. Pinjari et al. (*25-27*) underlined the importance of truck GPS records for freight transportation planning. A list of FPMs was suggested for the state of FL. Truck flows were estimated by month of the year and by day of the week. It was found that travel patterns during weekdays were different as compared to weekend travel patterns. A Trip Origin Destination Identification algorithm was designed. Trip length and trip duration distributions were provided in the report. You (*28*) studied tour-based models for drayage trucks at San Pedro Bay Ports, CA. The main objective was to develop a methodology, which could help to alleviate congestion at the gates, reduce truck turn times at the ports, and mitigate environmental impacts. GPS points for 545 drayage trucks were provided by the ports of Los Angeles and Long Beach. The 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.

Kuppam et al. (*29*) used truck GPS records for travel demand modeling in Phoenix area, AZ. The number of tours for each truck was determined using the information with truck coordinates, changes in TT and TS. The following tour-based models were developed: 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. It was found that the purpose of the previous stop influenced duration of the next stop.

The review of literature suggests that analyzing individual GPS truck data and estimating FPMs is still an evolving area of research. While several researchers attempted to use GPS truck data, there are several limitations in adequately finding the direction of each individual truck and attaching it's attributes to the highway network. Lack of efficient direction finding techniques may lead to elimination of valid records and consideration of misleading records which may result in estimation of misleading FPMs. This paper proposes efficient algorithms to adequately obtain truck GPS direction, determine FPMs for freight roadway networks and intermodal facilities, and analyze travel patterns of individual trucks.

METHODOLOGY

The majority of records provided by GPS enabled devices include information such as GPS waypoint, time stamp, heading, spot speed and a truck identifier. Eight unique headings for each record may be obtained (i.e. E, W, N, NE, NW, SE, and SW), while data are most of the times not known with high accuracy. Note that as various networks may be geocoded using different methods, accuracy of the same GPS data processing procedure may vary. The general rule follows that the longer the link length used, the less accurate the results will be, since in longer segments speeds may vary more within the link. Moreover, detailed roadway networks introduce more errors to the model as the snapping procedure is less accurate in cases where the observations for each truck are not as frequent.

Working with GPS truck data and developing FPMs for roadway networks and intermodal facilities requires four major steps: a) associating GPS points to links or areas usually involving procedures available in the GIS software (e.g. snapping of points to links using ArcGIS), b) identifying direction of movement of vehicles on each link, c) removing outliers, and d) analyzing travel patterns of individual trucks. In this paper we present two algorithms that can be used in latter three steps. Next we present the two algorithms developed to estimate direction of truck movement and remove outliers, and analyze individual truck trips from GPS truck data.

Direction and Outlier Identification (DOI)

DOI was developed to address the issue of multiple directions for GPS truck records associated with the same link. Figure 1A 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 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 (usually based on a predefined radius around each record)

Step 3: Remove outliers[3] 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 2)
- 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.

DOI Example

Figure 1B provides an example of step 4.2. for a fictitious link. First, start and end point coordinates are estimated for a given link (ArcGIS was used in this study). The link is then approximated by a straight line, connecting the start and end points. The next step calculates the angle (α), 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 1B) angle α lies between 0 and $\pi/4$, 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 2.

[3] Observations with spot speeds less than 5 mph, which is a common speed threshold used by other researchers (*18, 20, 23*), are considered as outliers.

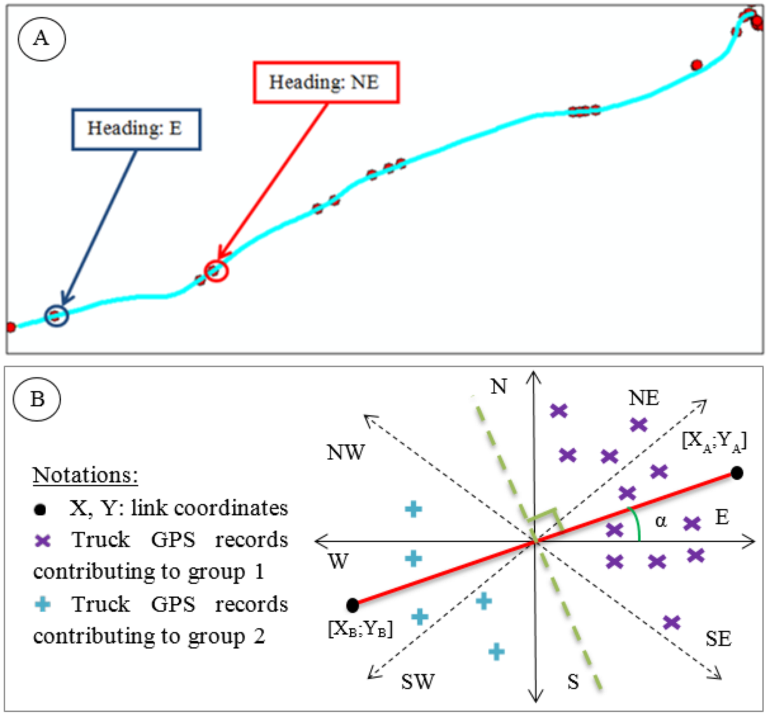
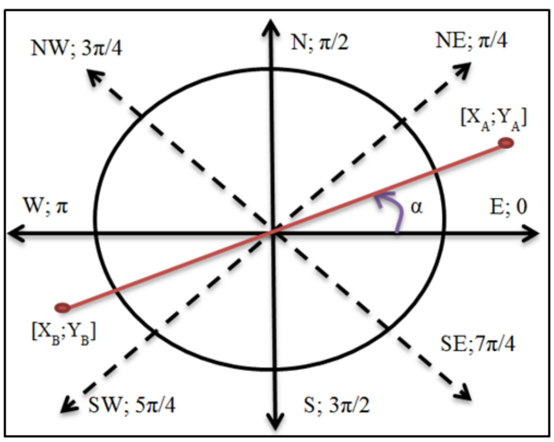


FIGURE 1 DOI for Resolving the Problem with Headings.



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 2 DOI Heading Assignment.

Outlier Detection: Chauvenet's Criterion

Detection and removal of outlier GPS truck records is important 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 using predetermined speed thresholds the Chauvenet's criterion was adopted (*30*). 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.

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 paper, include TS (in each direction), TT, and TT reliability measures (90^{th} percentile TT, 95^{th} 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 was 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). The next step was to investigate behavior of each truck individually by applying the TDA (will be described in this section later). Once FPMs are calculated for all links, it will be possible to identify areas where bottlenecks occur for a given time period.

DOI validation

DOI was validated on the Freight Analysis Framework (FAF) network with LTS obtained from 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: AM Peak: 6am – 9am, Midday Peak (MD): 9am – 2pm, PM Peak: 2pm – 6pm, and Off-peak (OP) period: 6pm – 6am. 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 each roadway segments length and shape.

Iterative DOI (IDOI)

Another issue discovered 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[4]. 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.

Trip Detection Algorithm (TDA)

TDA was designed to identify individual truck trips during 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

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

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 (=30 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 (=30 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 paper 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, [*18*, *20*, *23*]), 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 30 minutes. Those observations were flagged as stopped due to unknown reason – (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 30 min the algorithm will mark the corresponding GPS record as a potential new origin (PotNewOr).

CASE STUDY

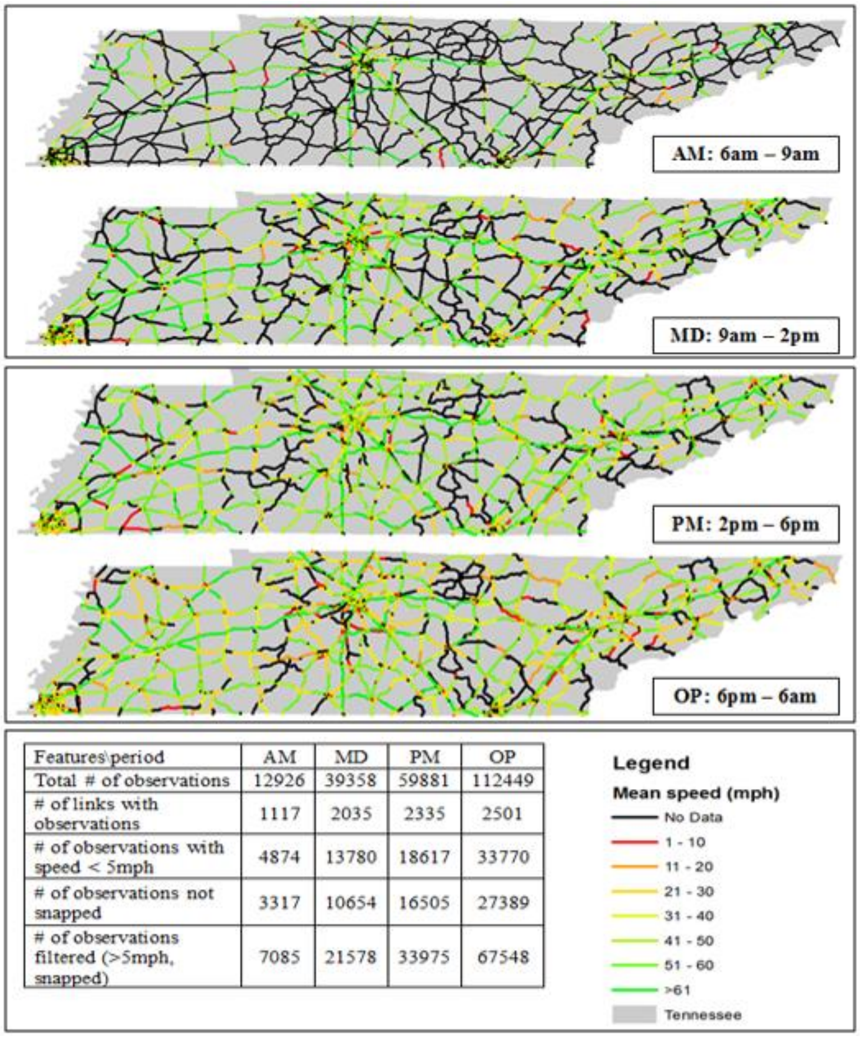
The proposed methodology was applied to the FAF network in the state of TN using truck GPS data (provided by ATRI) for selected weekdays of each month over the whole year of 2012. The FAF network included 3,393 road segments with average link length of 2.66 miles. In order to associate GPS points with the network, the Proximity Analysis Toolbox, of ESRI ArcGIS 10.0[5], was used. Since GPS truck 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 *10-11*), was assumed. In theory, the search radius for snapping observations should be equal to the device spatial error and the positional error of the used network. In FAF network this can be up to ±260 feet (*31*). In this paper we present the analysis of GPS records, for January 3rd, 2012 where 224,614 observations were available for a total of 6,103 unique trucks. Approximately, 3% of trucks 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 2,826 links. Around 28.6% of GPS points had spot speeds less than 5 mph. The total number of observations not snapped was 57,849 (25.8%), while the total number of filtered GPS records (snapped & spot speed more than 5 mph) was 130,199 records (57.9%). 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.

DOI Example

Average TS was estimated using the DOI for four time periods of the day: AM Peak: 6am – 9am, Midday Peak (MD): 9am – 2pm, PM Peak: 2pm – 6pm, and Off-peak (OP) period: 6pm – 6am. Results of the data analysis are presented in Figure 3. It can be noticed that fewer filtered records were obtained for the AM peak period (only 7,085 GPS points), while the maximum number of records were obtained for the OP period (67,548 GPS points); which may be explained from AM being the shortest peak period. On average bi-directional speeds were calculated for 67.5% links of the FAF network in TN (except for the AM peak hour, where only 32.9% of links were analyzed). 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. However, average speeds significantly decreased at links in the vicinity (or beltways / ring roads) of large metropolitan areas (i.e. Memphis, Nashville, and Knoxville TN). 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

[5] www.esri.com

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.

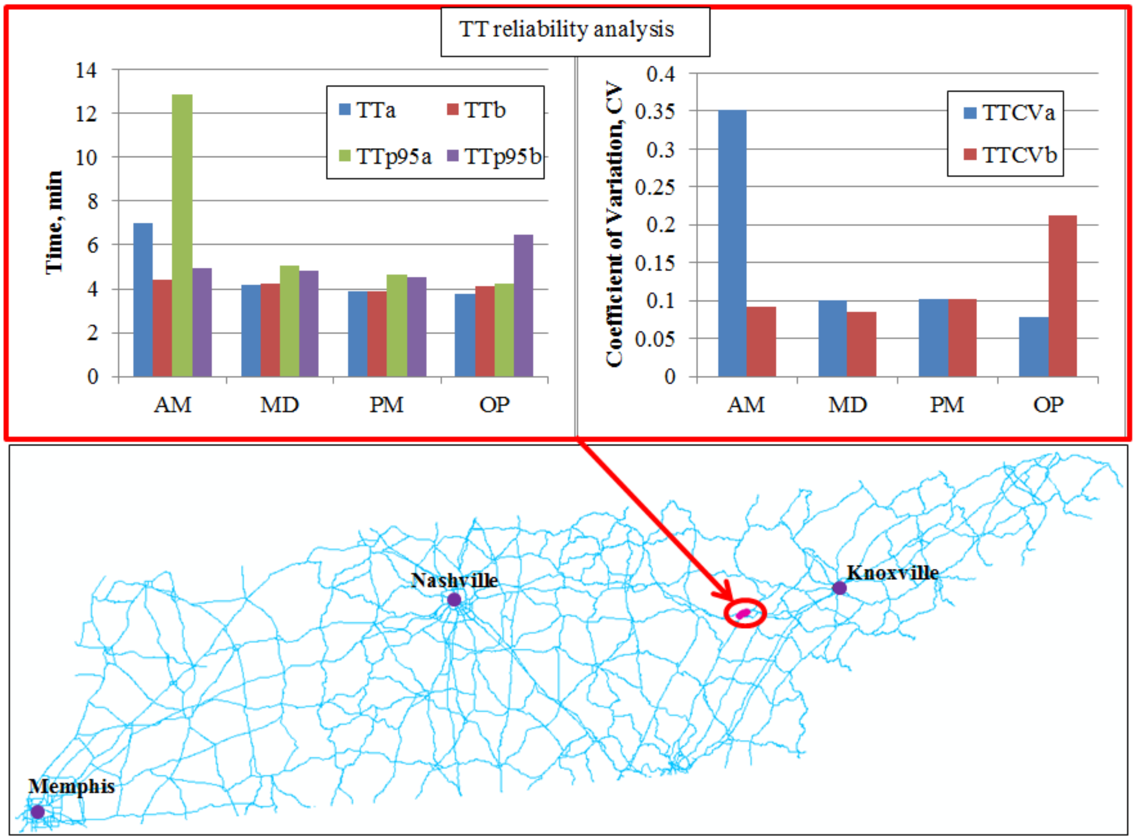


Features\period	AM	MD	PM	OP
Total # of observations	12926	39358	59881	112449
# of links with observations	1117	2035	2335	2501
# of observations with speed < 5mph	4874	13780	18617	33770
# of observations not snapped	3317	10654	16505	27389
# of observations filtered (>5mph, snapped)	7085	21578	33975	67548

FIGURE 3 Mean Speeds, January 3rd.

Travel Time Reliability Estimation

DOI output can also be used to estimate TT reliability measures of a transportation network. Results from an example of TT reliability analysis are presented in Figure 4 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 of the selected link increased substantially during the AM peak hour in the East direction (approximately 7.0 min). The 95th percentile TT in the same direction was approximately 13.0 min, while TTCV was 0.35. It is more likely that vehicles heading to Knoxville, TN faced traffic congestion during AM peak hour. As for the other time intervals, average TT in both directions didn't exceed 5 min.



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 4 TT Reliability Measures for Random Link

TDA Example

An example of TDA is demonstrated herein for a random truck, with 21 GPS records available, traveling in Memphis, TN on January 3rd between 12:23 am and 11:59 pm (Figure 4). TDA output was validated using Google maps and satellite images. The algorithm identified that the first four records were transmitted, when the truck was at its trip origin. A manual inspection (based on satellite images) indicated that the origin was at a freight facility. The truck spent around 8.5 hours at the freight facility and then started its trip approximately at 8:50 pm. TDA determined the first truck stop at 8:59 pm. Based on coordinates of the stop location, it was established that the truck was at a car wash location. After 20 min the GPS device indicated a vehicle movement. The second truck stop occurred at 9:29 pm near an intersection. A visual inspection of an aerial suggested two possible reasons for the stop: a) a gas station, or b) a traffic light stop. Since the next observation was received in 5 min and the truck was moving, it is more likely that it was a traffic light stop. The rest of the trucks' GPS records had spot speeds greater than 30 mph. Hence, the algorithm flagged those observations as "MOVING". The truck started moving at 9:34 pm, and the next GPS signal was received at 11:34 pm. Such gaps between records can be caused by various factors (overhead obstructions, inclement weather, device issues, etc.). The truck traveled approximately 3.55 mi within 2 hours. It is more likely that it stopped again somewhere between consecutive GPS points. However, the stop reason cannot be identified based on the given data.

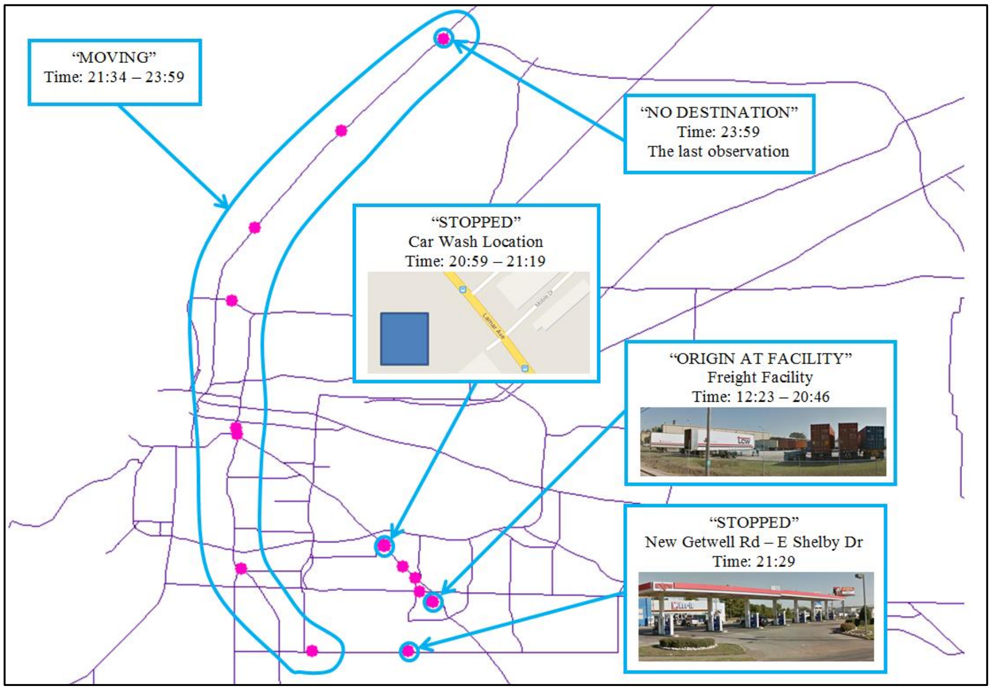


FIGURE 5 Trip of Random Truck on January 3rd.

Along with truck status TDA estimates additional trip characteristics. Based on this output, the truck spent around 8.5 hours at a freight facility, 20 min stopped, while no destination was detected. 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 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).

CONCLUSIONS

One of the main challenges in freight transportation planning is the lack of truck trip data. This paper demonstrated how truck GPS data can be used for estimating FPMs and analyzing freight corridors. Two algorithms were developed (DOI and TDA) to calculate FPMs and to investigate individual truck travel patterns. The methodology was applied using GPS records, available for the state of TN. Validation of the proposed methodology indicated that DOI accuracy was highly dependent on network link geometry, while TDA accuracy was highly dependent on the frequency of GPS records for each individual truck. On-going research is focusing on: a) computing monthly FPMs for different time periods; b) testing DOI application on various networks; c) analyzing truck flows between metropolitan areas in TN; and d) development of a GIS add-on tool that automates the proposed methodology.

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