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# A GPS Data Processing Framework for Analysis of Drayage Truck Tours

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## Abstract

A Clean Trucks Program (CTP) has been enacted at California's San Pedro Bay Ports (SPBP) of Long Beach and Los Angeles, to help address major environmental issues associated with port operations. "Clean trucks" (meeting 2007 model year emission standards) that utilized public funds to replace older, polluting drayage trucks were required to be fitted with GPS units for compliance monitoring, with an expectation that freight truck movements could be investigated more precisely. Such implementation also served as a prototype of emerging smart freight mobility concepts, which are often heavily data-driven processes, but which should provide data and insights that are useful to both researchers and practitioners. Accordingly, this paper reports on research to develop a comprehensive framework for processing SPBP clean truck GPS data, to both interpret tour behavior of clean drayage trucks, and to prepare sufficient tour data for clean truck modeling at the SPBP. An important finding is that clean trucks at the SPBP have distinct tour characteristics. First, most completed a tour within one day, but one day of travel behavior is not necessarily representative of any other day. Second, the identified tour types contain repetitive trip patterns while other commercial trucks mostly tend to travel as circulative patterns. These insights into clean truck behavior at the SPBP potentially provide more accurate depictions of current conditions and better projections of future conditions for freight related improvement plans and models.

Keywords: *drayage trucks; GPS data processing, freight transportation, tour behaviors, Clean Truck Program*

## 1. Introduction

Throughout the history of transportation research, freight movements have been responsible for a large share of the diverse problems in transportation. Traffic congestion created by active freight movements accelerates the increase of logistics costs, including travel time and fuel consumption. At the same time, the environmental impacts of freight trucks due to air pollution, noise, and safety are detrimental to the health and well-being of neighboring communities.

With such widespread problems caused by freight movements, many researchers in freight transportation have been dedicated to innovative modeling efforts that provide new insights into tours composed of multiple trips, whereas the traditional four-step approach assumes that trips are independent. Freight truck movements exhibit extensive trip chaining behaviors, which reflect interaction between shippers, receivers, carriers of goods, logistics constraints, and advanced information technology. Furthermore, the structure of supply chains and freight systems has rapidly evolved and whether or not their complexity can be accurately modeled has been a topic of debate for some time (Hensher and Figliozzi, 2007).

However, even though some promising models have been proposed with estimable functional forms, only a few studies of behavioral approaches to freight modeling have been estimated and applied due to difficulties in collecting accurate and detailed freight data. Traditional freight data collection methods include travel diary surveys, but diary surveys are known to be expensive and time consuming. Furthermore, low response rates (between 5% and 25%, from recently conducted surveys in Atlanta, Detroit, Denver, Greensboro, Alberta, Ohio, and the Region of Peel) are problematic because the period of urban commercial vehicle surveys is usually limited to a single day (Outwater *et al.*, 2005; Cambridge systematics, 2003; Hunt *et al*., 2006; Gliebe *et al.*, 2007; Roorda *et al.*, 2008). Some studies point out significant misreporting in self-report diaries (Roorda *et al.*, 2008; Stopher and Li, 2011; Greaves and Figliozzi, 2008). Empirical results indicate that conventional survey data should be used with corresponding commercial vehicle classes and collected in the same study area for deciding on policies and plans. Melbourne, Calgary, Guatemala, and Denver show different trip length distributions, numbers of trips per tour, and mix of commercial vehicle classes (Greave and Figliozzi, 2008; Holguin-Vera and Gopal, 2005; Hunt and Stefan, 2007). In addition, Holguín-Veras and Thorson (2000) noted the significant difference in travel distance between port and non-port flows with Guatemala's trip

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diary data.

Incorporation of GPS data into freight models is expected to allow for more sophisticated analysis that will accurately reflect the complexity of regional freight movements and overcome the limitations of conventional freight diary surveys. Furthermore, GPS tracking data can capture stop location and time information with frequently updated trajectories and even collect historical data over many years. Gonzales-Feliu *et al.* (2016) emphasized the importance of data-driven innovations in policy-oriented freight transport models and planning methods, and a series of studies including data processing, analysis and interpretation, to tackle the gap between researchers and practitioners. A number of researchers have attempted to complement conventional surveys with GPS data to estimate traffic performance measures, but only a few have implemented a post processing procedure for GPS data (Greaves and Figliozzi, 2008; Du and Aultman-Hall, 2007; Schussler and Axhausen, 2009; Joubert and Meintjes, 2015). Furthermore, the O/D identification procedure in these studies has been limited to just several freight facilities and trucking companies. Also, it is difficult to apply the resulting information to regional or local freight demand analysis. Therefore, a straightforward and efficient method is needed for freight modeling applications and for interpreting tour behaviors from GPS data. A systematic framework to process GPS data would provide more reliable and consistent results.

The objective of this paper is to interpret clean drayage truck tour behavior using GPS data collected from the San Pedro Bay Port (SPBP) complex in Sothern California. The paper describes a framework for GPS data analysis and investigates two critical tour criteria, the spatial allowance for Traffic Analysis Cells (TACs), and stop duration, for identifying tours. The resulting identified tours represent distinct tour patterns that are statistically significantly different by fuel type and monthly cargo moves. Finally, the insights and potential uses of such data in studying tour information of clean port trucks at the SPBP are discussed by considering current port truck related strategies and policies.

This paper is organized as follows: first, we introduce background information about the SPBP complex, relevant literature about GPS data, and provide a framework for GPS processing for tour identification of clean trucks. We then statistically summarize the resulting clean truck tour behaviors. After discussing the distinct patterns, we present concluding remarks and offer suggestions for future work.

## 2. Background

### 2.1 Clean Truck Program in the SPBP Complex

California state and regional government agencies, such as the California Air Resource Board (CARB) and the Southern California Association of Governments (SCAG), have proposed, in partnership with the SPBP, strategies for reducing traffic congestion and air pollution generated by the movement of goods in and out of the SPBP (CARB, 2006a; CARB, 2006b; POLB, 2010; SCAG, 2008a; SCAG, 2008b). In particular, under the SPBP CTP and California's Goods Movement Emissions Reduction Program, the SPBP is using California Proposition 1A bond funds and Ports funds to subsidize replacement of older heavily polluting port trucks with new trucks meeting 2007 model year emission standards (e.g., using Liquefied Natural Gas (LNG), Compressed Natural Gas (CNG) and clean diesel (CD), etc). Under the CTP, from January 1, 2010 the SPBP banned trucks with 1993 and older engines, in addition to almost all 1994-2003 trucks. All CTP truck owners must tag their vehicle with a Radio Frequency Identification Device (RFID) for compliance monitoring, and truck owners receiving public truck replacement funds must allow a GPS device to be installed on their new trucks for monitoring its movements. The collected RFID/GPS data has been utilized for representing simple statistics of clean truck activities. For example, the Ports of Long Beach and Los Angeles are reporting monthly cargo moves by truck characteristics such as fuel type and model year using RFID data (POLA, 2011; POLB, 2011) and attempting to estimate clean truck emissions directly from GPS speed profiles. PierPass, Inc., a non-profit company created by Marine Terminal Operators (MTOs), in conjunction with trucking companies, measures the truck turn time at terminals in order to improve the performance of terminal services (Pierpass, 2011).

After the enforcement of the CTP, LNG have been continuously increasing. In fact, LNG is a clean alternative fuel because nearly zero particulates are emitted due to a cooling down process. Although some short haul and regional trucking companies successfully use LNG to move their freight, allocating LNG fueling stations is one of the key factors blocking the increase of LNG long haul trucks. There are only around 76 LNG fueling stations currently operating in the United States (U.S. Department of Energy, 2016). Compared with over 120,000 gasoline stations, which includes around 4,000 truck stops selling diesel fuel, there is a large infrastructure gap for LNG and diesel trucks. However, at the time the data used in this study were collected, there were 34 LNG stations in California to fuel LNG trucks; 11 of these stations were in our main study area, 6 in Eastern California, 13 in Northern California, and 4 in Los Angeles and Orange counties (Krupnick, 2010). Since trucks usually travel predictable routes, the infrastructure for an LNG fleet could be concentrated in specified areas, and the placement of LNG stations was oriented toward facilitating the operation of LNG trucks in California.

The SPBP is not only one of the busiest ports in the US, but also a leader in developing new emission mitigating strategies such as PierPass, CTP, and On-Dock capacity improvements. Because of the impact of continuous efforts at the twin ports, clean port truck tour patterns must be separately analyzed and carefully reviewed. For example, the increase of LNG trucks and LNG fueling stations would provide a good opportunity to evaluate the benefits to air quality and the change of Vehicle Miles Traveled (VMT). In addition, GPS data collected under the CTP are the best resource for investigating tour patterns and can provide insights for a particular commercial vehicle tour behavior that heavily effects traffic conditions and health in the neighboring communities.

### 2.2 Literature Review

GPS studies have noted that GPS-based surveys are most likely to replace paper based travel surveys. In fact, compared with traditional travel surveys, GPS data offer more accurate and reliable information to capture disaggregate data on vehicle movements. As GPS unit costs decrease and availability increases, commercial GPS tracking records are more readily and continuously collected and stored. Consequently, the tremendous amount of GPS data becomes a new issue. Therefore, extracting meaningful information from large amounts of data is a critical procedure for research using GPS data.

A number of agencies and firms, including the Ports of Long Beach and Los Angeles, subscribe to continuous long-term GPS tracking services from third party providers. Third party providers usually collect and record GPS data using their own definitions/formats and generate information requested by their clients. For example, the third party provider of the CTP GPS data generates basic statistics and estimates of individual truck emissions using the GPS speed profile. PierPass Inc., in partnership with trucking companies, conducts truck turn time studies at terminals to monitor and improve terminal services. Years earlier, Battelle Memorial Institute outfitted trucks with GPS to measure truck travel activities focusing on idling time with the purpose of developing emissions factors in California (Battelle, 1999). In Washington State, McCormack and Hallenbeck measured the effect of infrastructure improvements on truck travel times and highway speeds, Ma *et al.* (2011) developed a web-based truck performance measure program, Zhao *et al*. (2011) estimated truck travel speeds using GPS data, and Wang *et al*. (2016) predicted freeway truck travel time using truck probe GPS data. In Oregon, Logendran and Peterson (2006) evaluated the capability of GPS data as a tool for freight truck movement data collection such as truck route and counts, and Bell and Figliozzi (2013) evaluated the accuracy of the Truck Road Use Electronic (TRUE) system by Oregon DOT and developed trip generation rate using Smartphone with GPS devices.

Only a few researchers have introduced methodologies for post-processing GPS data to obtain tour information or connectivity. Greaves and Figliozzi (2008) provided commercial vehicle tour information but only used GPS data to complement a major update of the commercial vehicle survey in Melbourne, Australia. The authors highlighted that second-by-second truck travel information such as tour duration, speed, number of stops, and travel distance give better insight into truck tour patterns. Bassok *et al.* (2011) estimated truck trip rates by land use and developed a trip generation model using GPS data. In the Region of Peel commercial travel survey, two methods for commercial vehicle data collection, GPS data and paper based survey were compared. Results showed a significant under-reporting of stops in paper surveys (Roorda *et al.,* 2008). Finally, Sharman and Roorda developed a two-step clustering method for identifying GPS trip ends into destinations in Canada (Sharman and Roorda, 2011).

## 3. Methodology

### 3.1 Description of Study Area and Data

To keep our study manageable while capturing port clean truck tours, we selected a primary study area that extends from the SPBP complex to the edge of downtown Los Angeles. The study area is shown on the left panel of Fig. 1, where most of the home depots (or depots) of the clean trucks are located. Regarding truck operations, we selected a second study area, which extends to the rest of California where port related trucks visit: the San Francisco Bay Area, San Bernardino, and San Diego. Based on our empirical results from a year of GPS data for 2010, approximately 40% of clean port truck trips are made outside the primary study area.

According to a SPBP report (19-20), in November 2010, 8,417 SPBP trucks (or 77.4% of trucks in-service) were clean trucks and 94% of cargo moves were already being made by clean trucks. For this research, access was obtained to a year of GPS data for all of 2010, consisting of 545 clean trucks, 88% of which were LNG trucks. Even though the collected GPS data represents only a small percentage of in-service clean trucks at the time (about 7%), the importance of the analysis in this paper is related to the fact that there is a year's worth of GPS data (over 25,800,000 records per year, in 2010), and these data have not

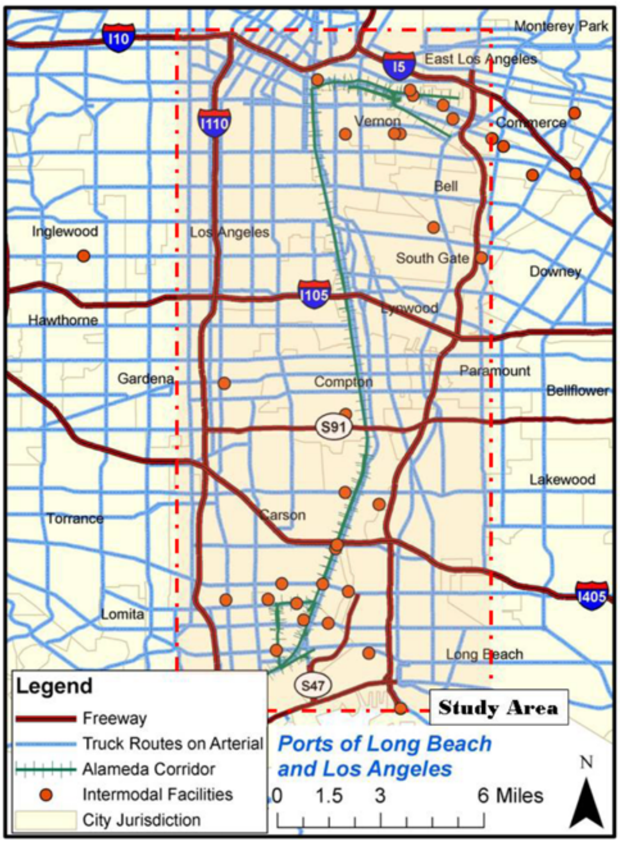
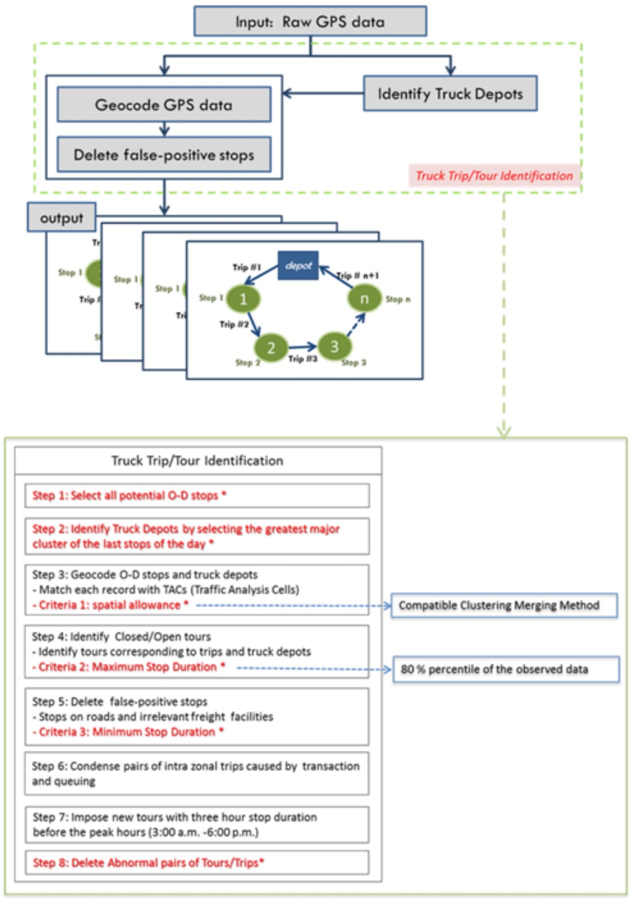



Fig. 1. Study Area

previously been analyzed in such detail. Further, considering that in the future GPS truck data will become more readily available to researchers, it is important to formulate a methodology to process large amounts of GPS data for the purpose of analyzing tours.

### 3.2 A Framework of GPS Data Processing

To utilize GPS data for freight modeling and truck tour behavior analysis, a systematic framework for GPS data processing is required with a clear definition of a tour. Most freight and passenger demand is oriented toward single trips, but commercial vehicles tend to make long tours composed of multiple trips, which may start from a depot and return to the same location (closed tour). A tour is more complicated than a trip since tours store sequential information about corresponding trips, while trips interact independently. Furthermore, in reality, trucks often do not return to their depot. In those cases, the tour does not satisfy the given definition of a closed tour. To overcome the inconsistency between what happens in reality and how tours are defined in this study, we introduce the idea of an open tour. An open tour limits excessive tour lengths caused by trucks not returning to their depot. Using both definitions, our proposed framework for GPS data processing follows the eight steps shown in Fig. 2.




* the main modules to be addressed in detail

Fig. 2. Framework to Process Clean Truck GPS Data

From Step 1, 5,349,499 records were selected as potential O-D stops. Step 2 identified each truck's depot in order to define the tour as closed or open. In Step 3, we geocode all potential O-D stops and each truck's depot according to its Traffic Analysis Cell (TAC), which is a block group level geographical boundary that is at a higher resolution than a Traffic Analysis Zone (TAZ). TACs make it easier to store demographic and social information for each GPS record according to the block group and TACs can be converted to TAZs by a single TAC or merging multiple TACs. During the geocoding procedure, falsely detected GPS data are eliminated. For example, GPS points located in the Pacific Ocean are ruled out as false detections. Steps 4 and 5 consist of the core procedure to identify tours using spatial and temporal criteria. Due to waiting for service and transaction, trucks often repeat the pattern of a long wait followed by a short stop within the same TAC. Although they are a part of tours, those activities do not contribute to traffic congestion or on-road emissions, but only increase the number of trips per tour. Therefore, such intra-cell trips are considered as waiting activities without counting toward a tour operation. In Step 6, we condense consecutive waiting activities, that is, two or more waiting activities not separately followed by a moving activity. Some trucks wait for their next shift or their appointments with their ignition on, to avoid the PierPass Traffic Mitigation Fee (TMF) during the peak hours (3:00 a.m. to 6:00 p.m.). We assign new tours to the long waiting activities lasting longer than three hours to avoid a false-positive tour in Step 7. Finally, we cross-check average speeds, travel distance, and travel time from the identified tours for abnormal pairs of trips/tours and present the final set of clean truck tour data (Step 8).

#### 3.2.1 Step 1: Selected Potential O-D Stops

The clean truck GPS data were collected and recorded either every 15 minutes during truck operation or with the special requests in Table 1. Our interest in the GPS data is to understand trip distribution and trip chaining behavior. Therefore, effective GPS points were extracted so that we could save processing time. Reason codes one through four were selected and the corresponding GPS data was used to determine effective stops, which could be potential trip origins and destinations.

#### 3.2.2 Step 2: Identifying Truck Depots

In order to determine if a tour is closed or open, each truck's depot needs to be identified. Assuming that all trucks return to depots at the end of the day, we select the records corresponding to the last trip at the end of the day and match them with TACs. The most frequently visited locations are found by minimizing the Mahalanobis distance (Formula (1)) and then selected them as the initial truck depot.

$$Min\sum_k \sum_j [\text{disstance}(T_j^k(x,y), T_i^k(x,y))] \quad (1)$$

Where, $T_i^k(x,y)$ : x, y coordinates of GPS point i(or j) in a truck k

Once the initial depots were identified, they were confirmed as

Table 1. Reason Codes for Recording GPS Data

| No. | Reason/Event | Description |
|---|---|---|
| 1 | Ignition On | Created when the vehicle's ignition is turned on and the Locator is powered up |
| 2 | Ignition Off | Created when the vehicle's ignition is turned to the off position |
| 3 | Stop | Created when the vehicle has moved less than 25 meters for longer than the setting of the "travel stop" parameter (2 minutes) |
| 4 | Start | Created when a GPS Global Positioning System when the vehicle has moved outside the default value of 25 meters |
| 5 | Time Send | Created every five minutes and only when a vehicle is moving |
| 6 | Distance | Created when a vehicle travels a set distance like "Time Send"; every 100 meters |
| 7 | Wakeup | Created for two reasons: 1) When the Locator is powered up and the vehicle is parked for a 24 hour period, and 2) When the internal battery wakes-up the Locator every five minutes |
| 8 | Crossing Geofence | Created when a vehicle enters or exits a Geofence assigned to the vehicle. |
| 9 | Demand | Created when a vehicle is polled for its location using the Poll The Poll button function retrieves current location information for a vehicle or fleet of vehicle |
| 10-39 | Additional Reasons | Error Report, External Data Report, OBII fault, Server closed, Server Open, Telemetry, Temperature report alarm, Over Speed, Under Speed, and etc. |

depots if the 80th percentile of each truck's daily destination records fell into the TAC corresponding to the identified truck depot coordinates. Otherwise, they were considered as trucks without regular depots.

### 3.2.3 Step 3: Tour Criteria 1 - Spatial Allowance

The initial TACs consist of the block groups surrounded mostly by major streets and in some cases by minor streets. The advantage of the TAC system is that detailed spatial boundaries are maintained while TACs can be readily aggregated into TAZs or coarse zones for more aggregate level studies. Merging TACs is necessary in order to handle GPS processing errors and the irregular shapes of freight facility boundaries. Irregular freight boundaries exist for two reasons: 1) a large freight related facility is split into multiple TACs because of geographical limits (See Fig. 3) and 2) a larger complex or industrial area often consists of smaller facilities located closely together, which are hard to differentiate for each truck O/D. Merging TACs makes it easy to identify intra or inter cell trips and a well-defined TAC system eventually assists in determining closed and open tours. Additionally, tour characteristics are better if available by individual TACs/freight facilities. The goal is to merge TACs such that each TAC has identical freight facilities, while keeping TACs as small as possible for detailed analysis. Once a TAC system is determined, GPS data can then be geocoded into the system by locating the TAC for each GPS point. The detailed procedure is as follows.

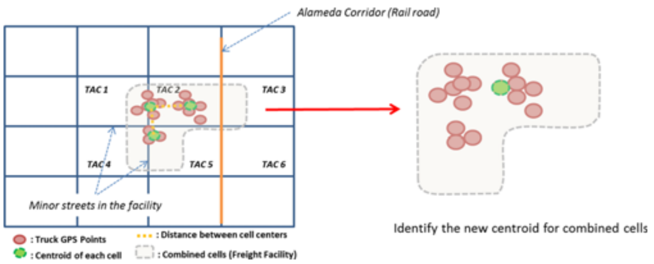



Fig. 3. The Example of TACs to be Merged and Procedure of Merging TACs

#### 3.2.3.1 Find the Centroid of each TAC

For the initial TAC group, an individual TAC centroid is found by minimizing the Mahalanobis distance (Formula (2)) among GPS coordinates within the same TAC.

$$\min_k \sum_{j=1}^{n} \sum_{i=1}^{n} [distance(T_j^k(x,y), T_i^k(x,y))] \tag{2}$$

Where,

$T_j^k(x,y)$ = x, y coordinates of truck GPS point i (i = 1, 2, …, n) where is located in TAC k

$T_j^k(x,y)$ = x, y coordinates of truck GPS point j (j = 1, 2, …, n) where is located in TAC k

#### 3.2.3.2 Calculate Z scores by TACs

Z scores by TACs are calculated as follows:

$$z_k = \frac{\bar{X}_{km} - \mu_k}{\sigma_k / \sqrt{n_k}} \tag{3}$$

Where,

$n_k$ = Number of truck GPS points in TACk

$\bar{X}_{km}$ = Distance between the centroid k and the centroid m, i.e. Mahalanobis distance if assuming m is a new element of cluster k ($m \neq k$)

$\mu_k$ = Mean of the distance between the centroid and individual GPS points in zone k

$\sigma_k$ = Standard deviation of the distance between the centroid and individual GPS points in TAC k

$$\bar{X}_{km} < \mu_k + \frac{z_k \sigma_k}{\sqrt{n_k}} \tag{4}$$

If the centroid of the TAC (m) is close enough to the centroid of the TAC (k) such that $\bar{X}_{km}$ exists within the criteria of formula (4), TAC (m) and TAC (k) are the subjects to merge. After evaluating a normal distribution with Kurtosis (g2<3), Skewness, and n<30, unqualified subjects were excluded for merging TACs.

#### 3.2.3.3 Check the validity and generate new GPS clusters

For the merging subjects for TACs, a new group centroid was found using formula (2). After finding the centroid of the new

TACs and checking the validity using formula (5), the final merging clusters were determined if the separation index of the new TACs was smaller than the separation index of the initial one, otherwise the given TACs would stay with initial TACs.

$$S(k) = \frac{\sum_{i=1}^{n} \mu_{ik}^{m} \|x_i - v_k\|^2}{\mathrm{N}\min_{\mathrm{k,t}} \|v_k - v_t\|^2} \tag{5}$$

Where,

$N_k$ = The number of elements in the cluster $k$; $i \in [1, N_k]$

$\|x_k^i - v_k\|$ = The distance between the elements within the cluster $k$ ($x_k^i$) and the centroid of the cluster $k(v_k)$

Sharman and Roorda (2011) proposed Ward's Hierarchical Agglomeration Clustering (HAC) method to determine the repeated visits to common destinations and a single distance threshold throughout the study region was identified. However, we represent individual distance thresholds for each TAC.

In order to check how well the proposed method performed, several conventional clustering methods were compared against the proposed method using GPS data. The partition coefficient indicates the amounts of "overlapping" between clusters. If the cluster is not overlapping at all, the measure is 1; otherwise it is less than 1. The partition index is the ratio of the sum of compactness and separation of the clusters and is a useful criterion when comparing different partitions having an equal number of clusters. Furthermore, the separation index is the criterion using a minimum distance and is useful when searching for the "right number of clusters." As shown in Table 2, considering that smaller numerical values means a better model, the proposed algorithm is relatively competitive.

Furthermore, the proposed method is effective and precise enough for tour analysis compared to more advanced methods for three reasons. First, the GPS data for tour analysis are pre-clustered data by TACs, which violates the definition used in clustering methods, i.e. that it is an unsupervised algorithm. The cardinality of TACs highly relies on the number of the freight facilities. Second, while the conventional clustering methods use exhaustive iterative calculations, our algorithm is straightforward. Third, after the acceptance allowance for each TAC is obtained, a repeated clustering procedure is unnecessary whenever a new GPS dataset is updated. Our method would save expensive computational time and resources as the amount of data increases.

#### 3.2.4 Step 4: Tour Criteria 3 – Maximum Stop Duration for Terminating Open Tours

There are two criteria for the stop duration to determine whether the open tour has ended; 1) the tour ends in a port related TAC, and 2) the other TACs in the tour indicate an open tour. For this study, we focus mainly on trucks with frequent operations and weekday travel and not on trucks with infrequent operation and weekend travel, since the latter tend to have stop durations greater than one day. From the cumulative stop duration histogram, we select the 80th percentile as the maximum stop duration, which covers 99% of queue times at the port terminals (PierPass, 2011). The maximum stop duration was 4.4 hours at the ports and 4.5 hours at the other freight related companies and facilities.

Table 2.The Numerical Values of Validity Measures

| | Partition Coefficient | Partition Index | Separation Index |
|---|---|---|---|
| The Proposed Method | 1 | 1.90E-03 | 1.98E-08 |
| K-Means | 1 | 7.36E-02 | 6.55E-07 |
| K-Medoid | 1 | 7.33E-02 | 6.53E-07 |
| Fuzzy C-Means (FCM) | 0.77 | 2.00E-01 | 1.20E-06 |
| The Gustafson-Kessel (GK) | 0.79 | 1.47E-01 | 8.73E-07 |

#### 3.2.5 Step 5: Tour Criteria 2 – Minimum Stop Duration for the False Positive Stops

False positive stops often occur as failing GPS signals and wrong GPS coordinates, or when trucks are temporarily stopped due to heavily congested freeways or signalized intersections. First, some of false positive stops are simply removed when GPS records fall into the TACs which hold only freeways and ramps. Second, by providing minimum stop duration between consecutive trips at each stop, false positive stops are ruled out. In a study of the SPBP, Giuliano and O'Brien (2007) indicate that the minimum processing time at the port terminals is 10 minutes. Considering that the terminal service at SPBP provides one of the fastest from the PierPass study, we reasonably assume that a stop less than 10 minutes between the two consecutive trips is not caused by freight related loading/unloading but rather by congested traffic conditions.

#### 3.2.6 Step 8: Deleting Abnormal Pairs of Trips/Tours

Although abnormal pairs of trips/tours are mostly taken care of throughout the proposed framework (Step 1-7), the following items are revisited to further remove abnormal pairs from the final tour set.

##### 3.2.6.1 Non-freight Activity Related Tours

Since our GPS data contain a year's worth of records, non-freight related movements are sometimes observed. For example, truck maintenance activities are detected as tours with recursive intra-cell trips due to repeated ignition on and off detections, which obviously are unrelated to freight movement activities or traffic conditions. Non-freight activity related tours are a combination of intra-cell trips since we define a tour as consisting of an operation tour and a waiting/transaction tour.

##### 3.2.6.2 Trips with Extremely Low or High Speeds

The CTP GPS data provide travel distance and travel time per tour. Shortest paths are found based on the GPS coordinates of each O/D. Two methods are used to find shortest path routes; 1) the MapQuest route search function and 2) Dijkstra's search algorithm using high-resolution SCAG network information. By comparing the average speed from GPS data to the low and high speed limits, and the speed information from two algorithms, unrealistic trips are eliminated.

### 3.3 Validation

In order to validate the proposed framework with this limited information, our validation procedure relies on eliminating unreasonable doubts since it is difficult to obtain ground truth.

The first step of the validation is to find whether the identified depots are located at truck accessible places such as trucking companies participating in the CTP and/or intermodal facilities. The land use of each TAC is found by geocoding the trucking companies participating in the CTP and intermodal facilities. Next, the TACs whose land uses do not fall under CTP or intermodal purposes are found manually using Google Earth. This includes LNG fueling stations, school zones, and residential areas, which are isolated as non-freight related activity TACs. Filtering though these steps resulted in 94.6% of truck's depots falling into truck accessible TACs within the study area and 5.4% falling in the secondary study area or commercial vehicle parking lots. The second check was to confirm whether the identified O-D stops were located in truck accessible locations in the same procedure as the first check and resulted in 90.6% of O-D stops linking to truck accessible TACs within the study area. The third step was to determine whether trucks belonging to the same Licensed Motor Carriers (LMCs) used the same depot. After grouping all trucks by owner group, we compared the identified depot of the members in each LMC. An average 94.4% of trucks within the same owner group used the same depot. Finally, we randomly sampled trucks and selected one day of operation for the sampled trucks. We compared their GPS trajectories with the sequence of the identified stops obtained from the proposed method. As shown in Fig. 4, the purple circles containing a letter are labeled in alphabetical order according to the recorded time from the GPS data and the green circles indicate the identified stops (E-G-H-M-N-P-R-V-X-E). Based on the selected samples, the identified tour information is in accordance with raw GPS trajectories. Therefore, the proposed framework was validated for the clean truck GPS data at SPBP.

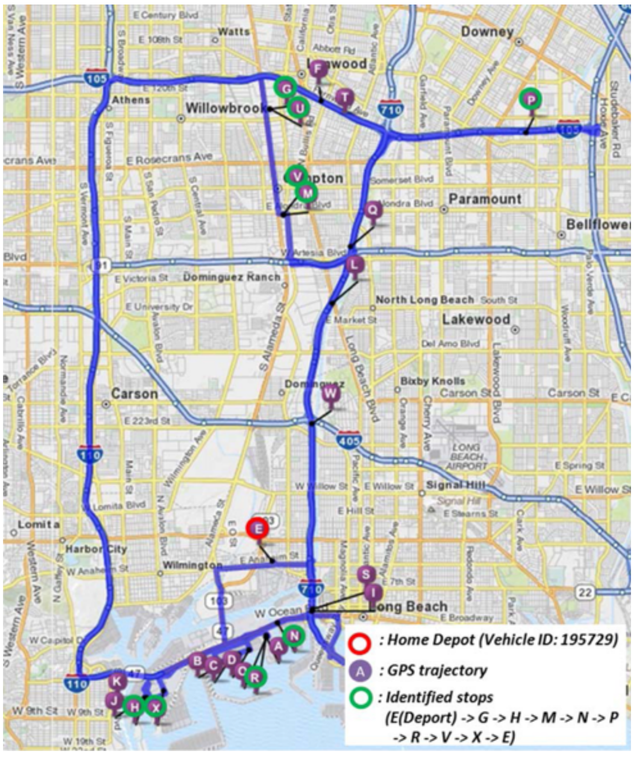



Fig. 4. Comparison of GPS Trajectories with the Identified O-D Stops Per Tour

## 4. Results

The identified tours using the proposed framework are summarized in this section along with a discussion of the observed trip chain behaviors of port CTP trucks and the relationship between tours and external factors such as fuel types and cargo moves. To evaluate the statistical differences between tour characteristics of CTP trucks by cases, two-sample z-tests were conducted at the $\alpha = 0.05$ significance level. These tests can be described as follows:

Two-sample z-test (Case A vs. Case B)

$$H_0: \mu_{\text{case A}} = \mu_{\text{case B}} \; vs. \; \mathrm{H}_1: \mu_{\text{case A}} \neq \mu_{\text{case B}}$$

$$Z = \frac{(\hat{X}_{\text{case A}} - \hat{X}_{\text{case B}}) - (\mu_{\text{case A}} - \mu_{\text{case B}})}{\sqrt{(\sigma^2_{X_{\text{case A}}} + \sigma^2_{X_{\text{case B}}})}} \tag{6}$$

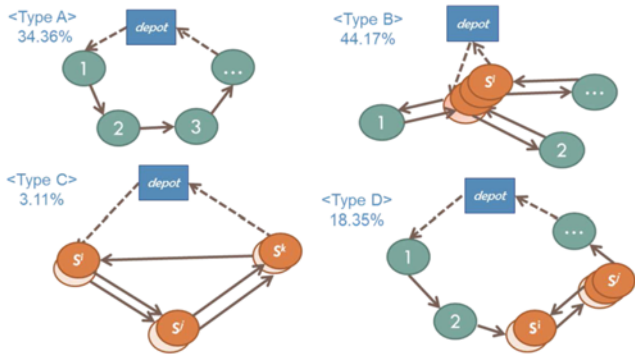
Where, $\hat{X}_{\text{case A}}$ is the average rate of each tour measure (e.g., travel time per trip/tour, waiting/transaction time, and tour distance) by Scenario; $\sigma^2_{X_{\text{case A}}}$ is the variance of each tour measure by case; and n is the number of observations (here $n > 30$).

### 4.1 Observed Trip Chain Behaviors of Port CTP Trucks

As mentioned earlier, tours consist of multiple trips and some port trucks repeatedly visit the same TACs within a given tour. Considering the recursive patterns as part of the same tour, we found four tour types (See Fig. 5). While the type A visits once at each stop, the other types contain S* which is frequently visited locations: ports and intermodal facilities such as the Union Pacific's Intermodal Container Transfer Facility (ICTF) and Commerce rail yards. For example, trucks in the type B drop by ports before and after delivering containers. In the type C, trucks travel among ports and intermodal facilities. Finally, the type 4 is the mixed pattern between the type B and C.

Although tours consist of the same recursive patterns, they can be identified as two different tours by the number of the repetition and stop locations. During 2010, 169,018 tours were made by 545 CTP trucks; the tours of the unique set are 92,912 and 10.8% of them were repeated more than once. From the results, the clean trucks at the SPBP followed a daily-based operation and one day of travel behavior does not represent any other days' behavior.

From the resulting clean truck tours, closed tours and open tours are 61% and 39%, respectively, of tours. The CTP trucks operate an average of 1.7 tours per day and 6.2 trips per day. The two-sample z-test indicates that the number of tours per day is




$S^i$, $S^j$, and $S^k$ : a location indicator for the ports of Long beach and Los Angeles, near-dock, and off-dock intermodal facilities ($i \neq j \neq k$)

Fig. 5. Drayage Truck Tour Types

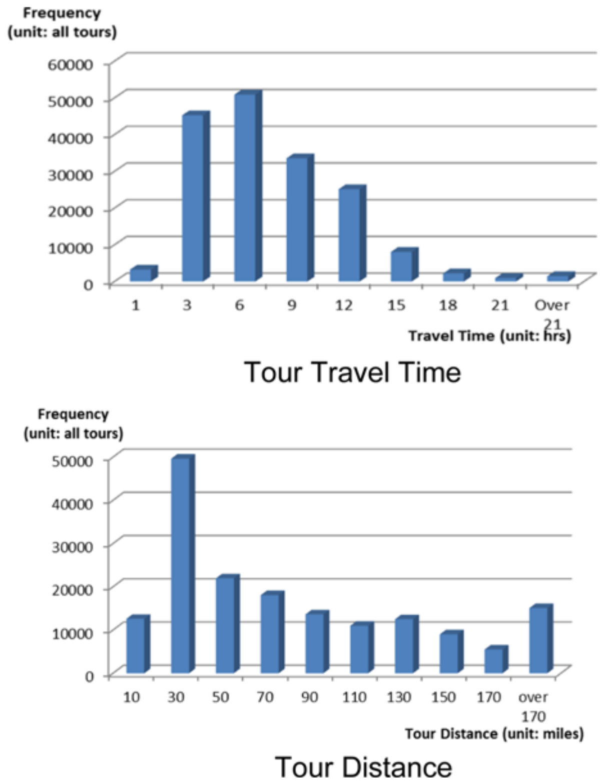



Fig. 6. Distribution of Tour Characteristics

statistically the same throughout the year, but the number of trips per day is significantly different between the first and second halves of the year. Tours during the second half of the year tend to have more trips per tour thus increasing the total number of trips. In order words, the CTP trucks make more stops to load and unload containers during summer and fall seasons.

For overall commercial vehicles, the City of Calgary reported approximately 6 stops per tour, Denver reported 5.6, Amsterdam reported 6.2, and Melbourne reported an average of 12.2 stops per tour (Hunt and Stefan, 2006; Glibe *et al.*, 2007; Greaves and Figliozzi, 2008). Comparing clean trucks to other commercial vehicles, CTP trucks at the SPBP make fewer stops or trips: 3.1 stops per tour (or 4.1 trips per tour) for closed tours, and 3.9 stops per tour (or 4.9 trips per tour) for open tours. The lower average number of stops of SPBP trucks compared to what has been reported in other studies is likely due to the use of drayage trucks which are often involved in lengthy loading/unloading of containers in and out of SPBP and at each stop.

As shown in Fig. 6, the travel times per tour mostly stayed in the 3 to 9 hour period although some tours lasted more than 18 hours. For the travel distance per tour, there was a major peak around 30 miles and a minor peak around 130 miles. The main study area contributed to tours with recursive and short travel patterns such as near-dock and off-dock operating trucks while tours over the 30-mile range indicate commercial vehicle travel to the secondary study area or even further.

### 4.2 Observed Tour Characteristics by Fuel Type

As shown in Table 3, diesel truck tour patterns were found to be significantly different from those of LNG trucks in terms of travel time and travel distance. Diesel trucks have longer travel

Table 3. Statistical Result of LNG and Diesel Trucks' Trip/Tour (unit: travel time (hours), travel distance (miles))

| | | Two-sample z-test | LNG Trucks (n=481) | Diesel Trucks (n=64) |
|---|---|---|---|---|
| Trip | Travel Time | DIFFERENT | 0.65 | 0.79 |
| | Travel Distance | DIFFERENT | 16.37 | 23.57 |
| Closed Tour | Tour Time | DIFFERENT | 5.61 | 6.89 |
| | Operation Time* | DIFFERENT | 2.70 | 3.56 |
| | Travel Distance | DIFFERENT | 67.63 | 103.15 |
| | Trips per Tour | DIFFERENT | 4.11 | 4.33 |
| Open Tour | Tour Time | DIFFERENT | 6.86 | 7.11 |
| | Operation Time | DIFFERENT | 3.19 | 3.39 |
| | Travel Distance | DIFFERENT | 80.23 | 105.27 |
| | Trips per Tour | DIFFERENT | 4.94 | 4.54 |
| Tours Per Day | | DIFFERENT | 1.75 | 1.46 |
| Trips Per Day | | SAME | 6.19 | 6.22 |

Notes Two-sample z-test at the $\alpha = 0.05$ significance level
Operation Time =Tour Time-Transaction Time

times and further travel distances per tour while the number of diesel truck tours per day is less than that of LNG trucks.

LNG fuel consumption is around 5.6 miles/gallon, less than that of diesel trucks (Clean Energy Fuels, 2011). Therefore, LNG trucks require more frequent fueling than diesel trucks leading to different tour patterns that are more reliant on the location of fuel facilities. This is supported by the statistical analysis which showed a significant difference between tours based on fuel type. It is important to note that the study area had more LNG fueling stations than other parts of the country, so the difference is expected to be even greater in other parts of the U.S.

### 4.3 Observed Tour Characteristics by Month

Before getting into the point, observed tour characteristics by month were performed with the LNG clean trucks. As breaking down the sample into dataset by month and season, the number of diesel trucks reduced into less than 30 because of collecting discontinuous dataset through a whole year. We concerned that it may lead the false cognition without statistical and it does not meet the central limited theorem. Although we introduced the concept of closed and open tour, the results in Table 4 and Table 5 were focused on the trip chaining behavior by itself, but not into the two types of tour. Note that the following results were from the LNG clean trucks including both closed tour and open tour.

From our findings (See Table 4), the tour characteristics of the 3rd quarter in 2010 were significantly different from those of other quarters, and the tour patterns of this season dominated annual average patterns. Although the busiest season of container movement was 3%~5% higher than the other seasons, longer tour times and further tour distances were reported in the 4th quarter's trip chain behavior.

For a better understanding of the relationship between trip chaining behavior and cargo moves, we closely examined the tours at monthly levels. In order to confirm whether the relationship between monthly container volumes and monthly CTP truck tour patterns are independent, the correlation coefficients were

Table 4. Statistical Result of Seasonal Clean Truck Behavior (unit: travel time (hours), travel distance (miles))

| | | Annual Average | Quarter 1 | Quarter 2 | Quarter 3 | Quarter 4 |
|---|---|---|---|---|---|---|
| Tour | Tour Time | **6.18** | 5.81** | 6.01** | **6.34** | 6.43** |
| | Operation Time* | **2.95** | 2.51** | 2.69** | **3.20** | 3.23** |
| | *Travel Distance* | ***75.79*** | *70.81*** | *75.42*** | ***77.06*** | *78.17*** |
| | Trips per Tour | 4.43 | 4.21** | 4.23** | **4.57** | 4.60** |
| Cargo Moves | Share (%) | 100.00% | 20.97% | 25.15% | **28.24%** | 25.95% |

*Operation Time =Tour Time-Transaction Time
( )** : Significantly different with Two-sample z-test, $\alpha = 0.05$

Table 5. Statistical Result of Monthly Clean Truck Behavior (Unit: hour or mile)

| Month | Level | Cargo Moves (S factor**) | Tour Time (S factor**) | Operation Time* (S factor**) | Travel Distance (S factor**) | Trips per Tour (S factor**) |
|---|---|---|---|---|---|---|
| Jan | Level 1 | 1,001,774 (0.73) | 5.96 (0.94) | 2.56 (0.80) | 71.18 (0.94) | 4.34 (0.94) |
| Feb | Level 1 | 938,593 (0.68) | 5.95 (0.94) | 2.55 (0.80) | 72.46 (0.96) | 4.26 (0.93) |
| Mar | Level 1 | 973,024 (0.71) | 5.58 (0.88) | 2.43 (0.76) | 69.15 (0.91) | 4.07 (0.89) |
| Apr | Level 1 | 1,080,343 (0.79) | 5.63 (0.88) | 2.52 (0.79) | 73.57 (0.97) | 4.19 (0.91) |
| May | Level 2 | 1,214,136 (0.88) | 6.32 (0.99) | 2.89 (0.91) | 72.74 (0.96) | 4.13 (0.90) |
| *Jun* | *Level 3* | *1,250,418* (0.91) | *6.08* (0.96) | *2.68* (0.84) | *78.83* (1.04) | *4.34* (0.94) |
| *Jul* | *Level 3* | *1,318,627* (0.96) | *6.24* (0.98) | *3.13* (0.98) | *76.29* (1.01) | *4.48* (0.98) |
| ***Aug*** | ***Level 3*** | ***1,374,839 (1.00)*** | ***6.37*** **(1.00)** | ***3.19*** **(1.00)** | ***75.84*** **(1.00)** | ***4.59*** **(1.00)** |
| Sep | Level 3 | *1,286,402* (0.94) | *6.41* (1.01) | *3.27* (1.03) | *79.13* (1.04) | *4.64* (1.01) |
| Oct | Level 3 | 1,296,006 (0.94) | 6.35 (1.00) | 3.25 (1.02) | 79.44 (1.05) | 4.66 (1.01) |
| Nov | Level 2 | 1,225,278 (0.89) | 6.58 (1.03) | 3.19 (1.00) | 76.88 (1.01) | 4.59 (1.00) |
| Dec | Level 2 | 1,135,963 (0.83) | 6.37 (1.00) | 3.24 (1.02) | 78.13 (1.03) | 4.56 (0.99) |

*Operation Time = Tour Time-Transaction Time
**S factor: a Scale factor based on each measure of trip/tour characteristics in August

calculated (Formula (7)) and the monthly container volumes were highly related to the clean truck behaviors:

1) Correlation between travel time per tour and container volumes was 0.80,

2) Correlation between the number of trips per tour and container volumes was 0.68, and

3) Correlation between travel distance per tour and container volumes was 0.75. According to the given correction coefficients, the travel time per tour is the most sensitive to cargo movement. This is because travel time per tour takes into account the travel distance, waiting time, and number of trips per tour. For example, as travel distance and number of trips per tour increase, travel time per tour gets longer.

$$r_{xy} = \frac{\sum_{i=1}^{12}(x_i - \bar{x})(y_i - \bar{y})}{(n-1)s_x s_y} = \frac{\sum_{i=1}^{12}(x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum_{i=1}^{12}(x_i - \bar{x})^2 \sum_{i=1}^{12}(y_i - \bar{y})^2}} \quad (7)$$

Where,

$\bar{x}$ and $\bar{y}$ = Annual averages of the case X and the case Y

$x_i$ and $y_i$ = Mean of the ith month of the case X and the case Y

$s_x$ and $s_y$ = Standard deviations of X and Y

According to the SPBP studies, the peak period is roughly July to October (POLB, 2011). Considering that off-peak shifts encouraged by the PierPass program are reinstated every year around May, the peak season starts even earlier than the SPBP's definition. As shown in Table 5, we create S-factors for comparing the changes in several tour patterns by scaling based on the measures of clean truck tour characteristics during the busiest month, August 2010. The S-factor is calculated using actual cargo statistics and provides more insight into the results. We divide the months by the calculated cargo moves' S-factor using three levels:

1) Level 1: less than 0.8,

2) Level 2: between 0.8 and 0.9,

3) Level 3: over 0.9.

Level 1 consists of the least busy months; January through April. Level 3 contains the extremely busy months; June through October. The remaining months fall into level 2.

Using the tiered categorization, the relationship between tour behaviors and cargo moves becomes even clearer. In 2010, MTOs suspended an off-peak gate from February to April, which is almost in accordance with our proposed period for Level 1. During the non-peak period, tour behaviors such as travel time and distance grew although they did not change as dramatically as the cargo volumes did. A time delay exists between cargo movement volume and tour behavior change. As shown in Fig. 7, the tour behaviors in the non-peak period shifted about one month after the cargo volume increased. During continuous peak periods, it is hard to distinguish the impact on tour behaviors but once the cargo volume reaches its highest peak, travel distance and tour time peak in the following month. As a result, continuously monitoring cargo volumes is one of the important factors for predicting clean truck tour behaviors.

## 5. Conclusions

The objective of this paper was to introduce an effective analytical framework to process GPS data. With GPS data from clean drayage trucks at SPBP, we could interpret complex port related freight movements and prepare sufficient tour data for clean truck analysis. The proposed framework consists of eight steps by which to identify a tour, and three criteria for eliminating noise:

1) spatial allowance for TACs,

2) false positive stops, and

3) maximum stop duration for terminating open tours.

Through the eight steps, the tour data are generated and calibrated for comprehensive tour analysis and a tour based freight model (in the next phase of this research). Using the tour data, this paper presented trip chaining behaviors and compared the characteristics of clean truck trips/tour by:

1) open/closed tours,

2) fuel types, and

3) monthly cargo volumes.

According to PierPass reports, the ports experience heavy congestion at 8:00 a.m., 1:00 p.m., and 6:00 p.m. (PierPass, 2011). During these times, trucks often idle outside the ports to avoid TMF. Although MTOs find that the turn time inside the ports is 37 minutes on average, the overall perception of the dwell time at the twin ports is about 3-4 hours because waiting time outside

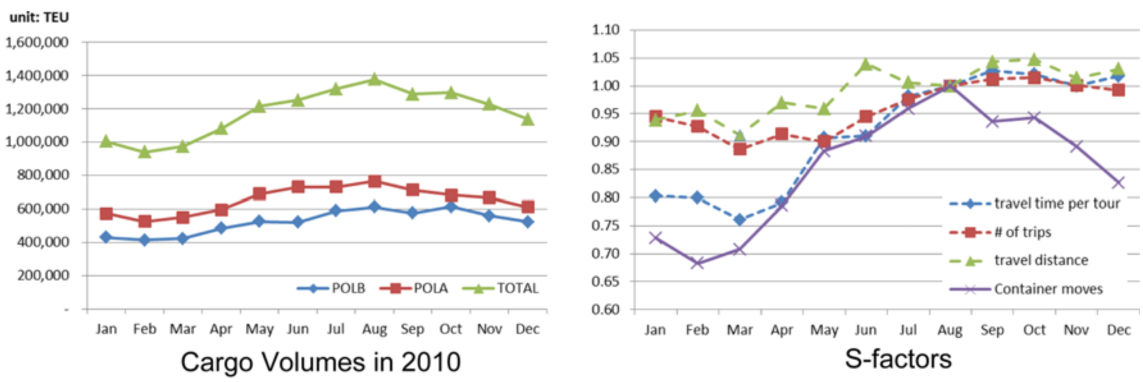



Fig. 7. Monthly Distributiona

of the ports is added. Our clean truck tour data calibrated by the proposed framework support the perceived time since the given tours consist of moving and waiting activities. Waiting/transaction tour time calculated in the framework to process GPS data would keep tracking the overall perception of the dwell time at each stop.

Furthermore, newer diesel trucks tend to travel further and longer than LNG trucks, and the monthly changes of cargo volumes have a great effect on the characteristics of clean truck tours. The tour time is the most sensitive factor corresponding to monthly distribution of cargo moves. Such tour characteristics would guide how to forecast drayage truck tours and corresponding emissions. This is because our tour data are capable of capturing the change of the tour travel time and distance as cargo volumes increase and as the share of LNG trucks and Diesel trucks changes.

From our findings, the CTP drayage truck tour behaviors are distinct in several ways. First, while commercial vehicles in some existing studies visit from 5.6 stops per tour up to 12.2 stops per tour, the SPBP clean trucks visit around 3.1-3.9 stops per tour because of lengthy loading/unloading of containers in and out of SPBP and at each stop. Second, the four tour types including recursive patterns reflect drayage trucks operational processes and are differentiated from other commercial vehicles circulative movements. Third, clean trucks at the SPBP rely on daily-based operations and one day of travel behavior is not necessarily representative of any other day. Due to these characteristics, which are distinguished from other commercial vehicles, it is strongly recommended to independently develop a tour based model for drayage trucks. Due to the long term GPS data collection, all possible tour sets were explicitly identified so that annual and seasonal behavioral attributes could be well captured. With these insights into clean trucks at the SPBP, it is clear that a tour based freight model could provide more accurate measures by which to assess current and projected conditions, such as PierPass, CTP, On-Dock capacity improvements, and an inland port location-allocation model for a regional intermodal goods movement system.

Among the abovementioned potential applications, the authors invested aggregate and disaggregate approaches for a tour based model. In the aggregate approach, we utilized a tour based entropy maximization model with GPS data to convert trip based demand from state and regional government agencies to a tour based model. In the disaggregate approach based on the collected GPS data, we developed a tour based freight model for forecasting purposes by solving the inverse selective routing problem. Further detail can be founded in You (2012).

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