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Freight Traffic Analytics from National Truck GPS Data in Thailand

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Abstract

Recently, demand of freight transport increases tremendously and cause serious impacts on traffic congestion and air quality. In 2015, The Department of Land Transport of Thailand has introduced a project named "Nationwide Confidence with GPS Onboard" to install GPS tracking system on all trucks in Thailand. This project provides new sources of data in analyzing the freight-related traffics and designing remedial measures for freight-related issues. This paper aims to demonstrate the use of GPS data in determining truck activities, estimating truck origin-destination matrix and estimating the flow of different commodities. Thailand is used as a case study to demonstrate the results.

Keywords: Truck activities; freight origin-destination matrix; commodity flows; global positioning system data;

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1. Introduction

Owing to the advancement of transportation and communication technologies, globalization is the hot topic in various aspects (e.g., economy) for the recent decade. In contrast to several decades ago, most of the goods consumed nowadays are produced over hundreds kilometers away. Thus, the demand of freight transport increases tremendously and cause serious impacts on traffic congestion and air quality. To manage freight traffics for removing their adverse impacts, engineers and researchers have adopted various methods to collect/generate freight-related information for their design of remedial measures. As the traditional sources of data for freight-related studies are mainly from planning-related sources (e.g., land use data) and require substantial manual operations, the evaluation of freight-related information will be highly inefficient and the results could be easily outdated. Recently, with the increasing use of new data sources (e.g., Global Positioning System (GPS), Bluetooth, WiFi, RFID, etc), which in nature are more real-time and disaggregated, new methods are developed for the freight-related studies to improve their accuracy and efficiency. In 2015, The Department of Land Transport of Thailand has introduced a project named "Nationwide Confidence with GPS Onboard" to install GPS tracking system on all trucks in Thailand. As of January 31, 2017, 23.2% (91,361) of the targeted trucks/trailers are installed with GPS tracking system and the installation is expected to finish in 2019. The installed GPS devices will send back GPS data to the authority's database for every 1 minute through 3G wireless mobile network and internet. Each record of GPS data is consist of a timestamp, device ID, latitude, longitude and speed. In this study, these records of truck GPS data is the basis for various freight traffic analyses.

The estimation of trip table information, or origin-destination (OD) matrix, has long been a major area of research in the literature of transportation network analysis. The estimation of trip table can be classified into two different approaches: (i) top-down approach, and (ii) bottom-up approach. For the top-down approach, four-step model is generally used to reproduce the OD trips for the internal and external traffic zones. Furthermore, the trip table is heuristically adjusted, or calibrated, to fit with the collected traffic counts (e.g. applying of origin-destination K-factors in Ortuzar and Willumsen, 2011). To adopt statistical approach in the estimation of trip tables, the observed data from road network (e.g. link counts) is directly used in the calibration procedures for the bottom-up approaches. By defining the observed data on road networks as the preferred outputs of the model, the parameters of the model (trip table) are then adjusted accordingly. For instance, traffic counts and prior trip tables are used directly in the model to statistically estimate/update a trip table in this bottom-up approach (Bell, 1991; Cascetta, 1984, 1993; Maher, 1983; Watling, 1994; Yang et al., 1992, 1994; Yang, 1995).

In the context of intelligent transportation systems (ITS), Hu et al. (2001) extended the problem of trip table estimations by using adaptive Kalman filtering to estimate dynamic assignment matrices and OD demands. In considering models to estimate/predict different types of traffic characteristics and/or information, Lao et al. (2012) developed a Gaussian mixture model to estimate travel speeds and type-dependent vehicle volumes using loop detectors. Also, Yuan et al. (2014) adopted a traffic flow model to predict the travel speeds by using two sources of traffic data (loop detector and floating car data) with Kalman filtering. Ideally, data used in the estimation of OD flows should be collected by GPS-based travel surveys. For example, the activity-travel data collected by GPS equipments installed on probe vehicles or carried by travelers. Wolf et al. (2004) developed an automated process to predict travelers' destinations and trip purposes from vehicle GPS traces. In addition, Frignani et al. (2010) has also collected highly accurate activity-travel data (e.g. the chosen activity type, destination and mode) from internet-based interaction travel feedback systems enhanced with GPS data. To identify the chosen paths from GPS traces of tracked vehicles, a topological map-matching method is normally used (Felipe et al., 2016). Apart from tracing the chosen paths, Greaves and Figliozzi (2008) used the difference of time stamps between GPS-to-satellite communications to determine the running and stopping status, which are the two major statuses, of the tracked vehicles. According to their investigations, 240 seconds can be taken as an acceptable threshold to distinguish the stopping and running status of vehicles. In addition, McCormack et al. (2010) suggested that there exist insignificant truck movements at Washington metropolitan area, which could be resulted from the short movements inside large plants/industrial zones or the GPS signal inaccuracy. Such insignificant truck movements are spurious trips that could lower the accuracy of trip table estimation. In McCormack et al. (2010), to eliminate such trips, distances between two consecutive GPS records, which are the records feedback from the GPS devices with the frequency of every 0.5 ~ 15 minutes, were adopted for screening the collected GPS data and trips. For instance, trips will be removed if the distance between two consecutive GPS records is less than 65 feet (McCormack et al., 2010). Recently, Yang et al. (2014) adopted a support vector machine method (SVM) to identify freight delivery stops using GPS data in New York City. Stop features (e.g. stop durations and distances to center of city) are used to classify all stops into delivery stops and non-delivery stops (e.g. stops due to traffics or rests).

This paper is organized as follows. The next section shows the results of truck activities in Thailand based on the analysis from the collected GPS data. Section 3 shows the estimated truck OD flows in Thailand from the passive GPS data and traffic counts. The results of the commodity flows in Thailand will be described in Section 4. Lastly, concluding remarks will be given in Section 5.

2. Analysis of Thai truck activities from GPS data

Data/information, depending on the characteristics of data collection methods, is suffered from different types and degrees of error. Thus, basically there is no collected data/information that could be completely accurate. To improve the accuracy of collected data/information, various criteria/procedures, which are developed based on experience and the characteristics of application, are adopted in accordance to different data collection methods to screen out the inaccurate data/information. For example, missing, incomplete and unreasonable (e.g., speed is larger than 200 km/h) GPS data, and abnormally high link counts (say 20,000 veh/hr) from loop detectors will be screened out to improve accuracy. Moreover, some systematic errors of the data collection methods (e.g., inaccuracy of GPS location, missing counts in loop detectors, etc) cannot not be easily removed. Thus, there is no simple conclusion on which type of data/information is more accurate, the accuracy of data/information relies on the collection methods, screening procedures adopted, and the required application of the data/information. Despite the possibility of introducing data inconsistency, which is a challenging task to tackle, recent studies tend to fuse multiple sources of data/information for improving accuracy, especially lowering the impact of systematic errors from each source of data/information.

In this section, the truck GPS data from Thailand will be analyzed to determine the corresponding activities. To effectively and efficiently analyzing the GPS data, the collected GPS data should first be screened, which aims to remove the incomplete data (e.g., missing GPS time logs or large time gap between GPS records), and sorted in accordance to the time stamp. Distance and difference of time stamps between any two consecutive GPS records of the sorted GPS data are then determined for identifying the potential truck stops. Potential truck stops from raw GPS data are defined by the locations where the trucks stop and do some activities (e.g., loading goods), which exclude the delay from traffics. To eliminate unwanted truck stops due to traffic stops, this study has adopted a 20 minutes dwell-time buffer to determine a potential truck stop. In addition, for the distance between two consecutive potential truck stops that is less than 2 kilometers, the movement is considered as insignificant movement (e.g., movements within an industrial estate) and the latter potential truck stop will be removed. After removing the unwanted potential truck stops due to insignificant movements, a list of effective truck stops, which trucks are performing some activities, are formed.

With the processed GPS data, the type of activity for each of the effective truck stops will be determined by using the maximum likelihood estimation method proposed in Siripirote et al. (2017). In Siripirote et al. (2017), the vehicle stop duration (y) and the distance from the nearest road to stop points (x) for each of the activity type (f) are taken as log-normally and independently distributed random variables. In this study, the definition of road is taken as all the vehicle accessible roads in Thailand that are extracted from the geographic information system (GIS). The attributes (i.e., mean and variance) of these random variables are estimated by a maximum likelihood problem defined by the joint probability density function of the random variables that reproduce the observations (i.e., the dwell time from the GPS data, actual activity carried out, etc). With the calibrated attributes, the probability density functions for the random variables are defined. Thus, the joint probability of each activity types for each effective truck stop extracted from the GPS data could be calculated and the activity type with the highest probability is chosen as the activity type for that effective truck stop. Similar to Siripirote et al. (2017), this study will consider an update of activity type probability, by applying the Bayesian rule, based on the known land use information (e.g., sea/river port, container yards, container depot, cargos, etc.) from the GIS map of the stop location.

In this study, 10,190 effective truck stops, which cover 3% of all the identified effective truck stops within Thailand, was randomly selected for calibrating the probability density functions of the random variables. Types of activity for the effective truck stops are illustratively classified into 2 main categories: rest and load-unload. Also, the model parameters are divided into 7 subclasses based on specific types of major commodities of Thailand: Beverage, sugar, rice, animal fees, paper, mixed concrete, and container freight. The estimated mean and standard deviations of stop durations(y) and distance from major road/highway to stop points (x) are estimated and shown in Table 1.

Table 1. Summaries of model parameters classified by 7 types of commodities.

Parameter	Activity type	Types of goods							
		Beverage	Sugar	Rice	Animal feed	Paper	Container freight	Mixed concrete	All type
Mean distance to road (m)	Rest	23.43	20.62	26.42	29.37	31.82	32.53	67.10	45.28
	Load-unload	378.04	243.73	173.68	197.79	642.26	430.52	520.61	426.24
SD of distance to road (m)	Rest	5.22	4.81	5.88	5.93	6.43	6.91	12.18	7.29
	Load-unload	37.90	26.89	20.92	23.82	64.39	43.16	52.19	42.73
Mean activity duration (min)	Rest	60.42	76.04	70.09	42.71	68.12	41.26	37.44	43.81
	Load-unload	100.46	115.41	139.55	151.18	115.56	73.79	117.74	73.06
SD of activity duration (min)	Rest	9.11	11.47	9.86	7.31	10.28	5.80	6.03	6.16
	Load-unload	14.13	15.07	18.22	19.74	16.26	11.13	15.37	11.02
Number of truck stops		1447	878	1401	240	651	3447	1198	10190

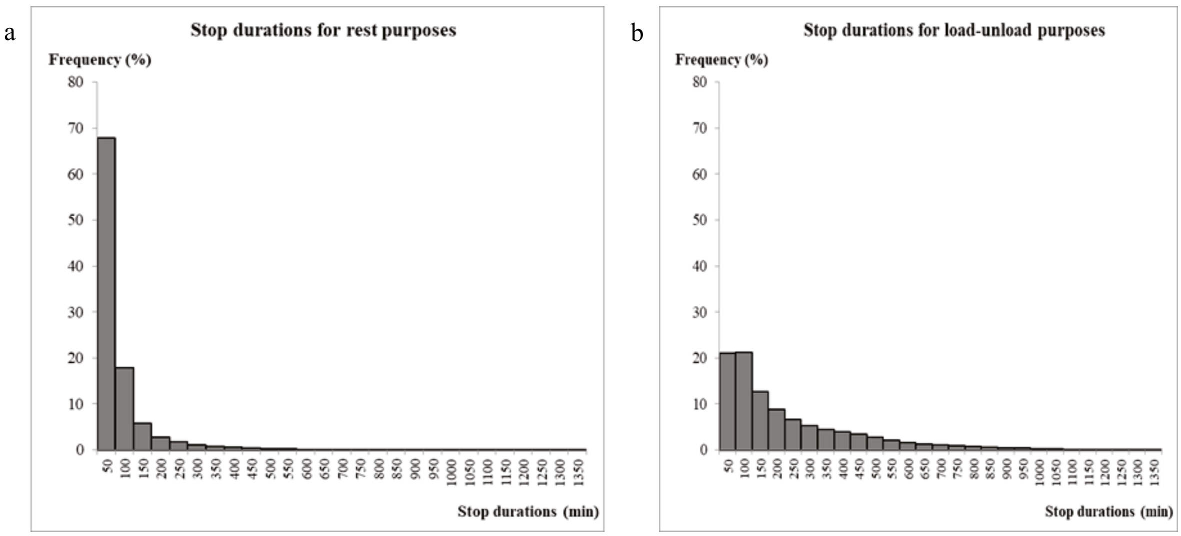

Fig. 1. (a) distributions of stop durations for rest purposes; (b) distributions of stop durations for load-unload purposes.

In Table 1, it could be seen that the mean stop (activity) durations for load-unload purpose are much higher than that for the rest purpose. The mean activity durations fall in a wide range (i.e., ranging from 73.79 minutes to 151.18 minutes) with animal feeds and rice are the two commodities with the longest load-unload duration for more than 2 hours. Such large range of mean activity duration of load-unload activities for different commodities could be explained by the different packing, size of trucks and handling requirements for these commodities. The standard deviations of stop (activity) durations for rest purpose and load-unload purpose are about 6.16 minutes and 11.02 minutes, respectively. For the estimated parameters for the distances (x) from the stop point to road, the mean distances for rest purpose is substantially less than the mean distance for load-unload purpose. Thus, it means that the locations where the trucks tend to stop for rest purpose are nearby roads while the load-unload locations (e.g.

factories, warehouses, or ports) are located further from roads. The SDs of the distance to road for the rest activities (i.e., between 18% and 23% of the corresponding mean) are in general larger than that for the load-unload (i.e., between 10% and 12% of the corresponding mean) as the locations for truck drivers to take their rest is not necessary fixed and, thus, more random. With the calibrated model, the identified effective truck stops from the truck GPS data are classified into rest and load-unload purpose with the corresponding distribution of stop durations shown in Fig. 1.

In Fig. 1(a), it could be seen that the majority (over 65%) of the stops for rest purpose have a duration less than 50 minutes, while none of these stops have a duration over 550 minutes. In contrast to the rest purpose, the stop durations for the load-unload purpose (Fig. 1b) is more spread out with the group of largest proportion (50 ~ 100 minutes) is just only around 20% of the total number of stops. Also, the stop duration for the load-unload purpose is up to 1050 minutes. Such spread out of the load-unload duration could be explained by the wide variety of the weights, packing and bulkiness of the commodities that directly affect the loading and unloading time. Based on the geographic location (from GPS information) of the effective truck stops, the stop durations could be categorized into different provinces. Considering the 76 provinces and 1 special administration area (Bangkok) in Thailand, it is found that the average stop durations for loading and unloading is ranging from 143.5 minutes (Rayong) to 249.5 minutes (Nan). On the other hand, the average stop duration for the rest purpose is ranging from 41.6 minutes (Phetchaburi) to 114.6 minutes (Yala).

3. Estimation of truck origin-destination flows in Thailand from GPS data

With the estimated loading and unloading activities of the tracked trucks from the GPS data, the origins and destinations of these tracked truck trips could be established. In this section, these OD flow information (around 10% sample of the total 1 million trucks registered in Thailand), together with the roadside traffic counts, are adopted to estimate the truck OD flows in Thailand based on the approach proposed in Siripirote et al. (2017). Similar study in using GPS data and traffic counts for the estimation of OD flows could be found in Kim et al. (2018). In Siripirote et al. (2017), it is proposed that the sampled truck OD flows ($\hat{\mathbf{t}}$), which are estimated from the GPS data and by the method introduced in the previous section, and the populated truck OD flows ($\mathbf{t}$), which are the total flows for all trucks in Thailand, are related by a scalar matrix that gives the ratio between the corresponding flows. On the other hand, Siripirote et al. (2017) evaluates the link flow ($\mathbf{v}$) of the OD flow ($\mathbf{t}$) based on stochastic traffic assignment (Watling, 2006). Based on such settings, a maximum-likelihood estimation problem is setup for estimating truck OD flows of Thailand that will give the best fit of the sampled OD flows from GPS ($\hat{\mathbf{t}}$) and the observed link counts ($\hat{\mathbf{v}}$).

In the traditional approaches, link counts are the only information adopted in estimating OD matrices. In adopting these approaches, some components of OD matrices may be omitted as the used paths of these components (i.e., OD pairs) may not pass through the link count stations. The OD estimation approach in Siripirote et al. (2017), and also in this paper, tackle this issue by including the sample truck OD flows, which are estimated from the GPS data, together with the link counts in the estimation of populated truck OD flow. As the sample OD flows, which are estimated based on the GPS data of the 10% trucks in Thailand, have a larger coverage than the link counts in terms of describing the truck OD matrix, the observability of flows for the minor components in the truck OD matrix will be substantially improved. Thus, the adopted truck OD estimation approach in this paper is able to provide a more accurate estimation of the minor components of the truck OD matrix. On the other hand, such high coverage could also helps to lower the chance of over-estimating the major components of the truck OD matrix as in the traditional approaches. Ultimately, with 100% of trucks are installed with GPS devices, which is the goal of "Nationwide Confidence with GPS Onboard" that have to be completed in 2019, all components of the truck OD matrix could be observed from the GPS data and no additional estimation is needed.

In the test case, the sampled OD–populated OD ratios were calculated from the numbers of GPS-installed trucks divided by the total number of trucks registered in Thailand, which is around 0.1 in this study. The sampled truck OD flows ($\hat{\mathbf{t}}$) is input from the results of the previous section with the origins and destinations are classified into 926 different traffic analysis zones (i.e., 926 sub districts of provinces called "amphoes"). For the observed traffic counts, one-day traffic counts of trucks on road network are adopted. The traffic count stations are selected by OD covering flow rule such that a certain portion of trips between any OD pair will be observed (Yang and Zhou, 1998). After the OD flow estimations are carried out for the test case, the estimated truck volumes at chosen traffic counting locations are compared with the observed truck volumes (Fig. 2a). In Fig. 2(a), it could be seen that the estimation of populated truck OD flows (**t**) are reliable with high coefficient of determination (R-squared = 0.83). In this estimation, the total daily truck OD trips, excluding intrazonal trips (i.e. origin-destination trips travelling within same zone), is equal to 768,170 trips/day.

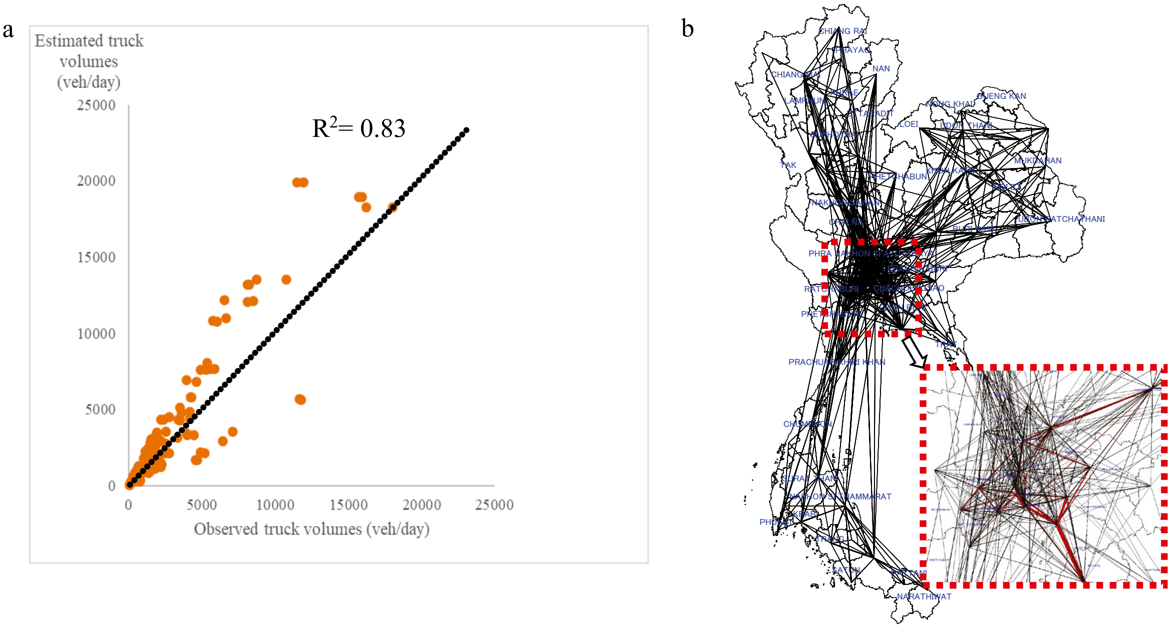

Fig. 2. (a) observed truck volumes vs estimated truck volumes at chosen traffic counting locations; (b) estimated one-day OD trips.

The estimated daily truck OD flows is grouped into different province and geographically plotted in the map of Thailand (Fig. 2b). It appears that the majority of OD trips are occurred between areas with high density of industries and/or factories. For instance, the two highest amounts of truck OD trips are travelling between Chonburi and Rayong (38,630 trips/day) and between Bangkok and Samuprakan (37,650 trips/day). Chonburi, where contains many industrial estates, has highest amounts of truck trips (94,047 trips/day) generated. The major destinations of truck trips generated from Chonburi are Rayong, Samutprakan, and Chonburi itself. Beside Chonburi, Bangkok (76,062 trips/day), Samut Prakan (73,351 trips/day), Saraburi (47,748 trips/day), Ayutthaya (45,819 trips/day), and Rayong (44,907 trips/day) are the other five major provinces in generating truck trips.

4. Estimation of commodity flows in Thailand from GPS data

In section 2, truck GPS data is analyzed to distinguish the rest and loading/unloading purpose of the tracked trucks. In this section, stops related to loading and unloading is further analyzed in order to estimate different commodity flows in Thailand (Siripirote et al., 2017). From the effective truck stops of a tracked truck, list of locations where this truck visited were recorded and considered as the travel patterns of this truck. To further identify between the loading and unloading activities, the location types of the visited locations, which could be extracted from GIS, and known travel patterns among such location types are considered. For instance, the travel pattern of trucks carrying rice consists of loaded truck trips from rice mills to distributors, rice exporters and animal feeds, and unloaded truck trips from these locations back to the rice mill. By considering the target locations of the commodity (e.g., rice mills, distributors, rice exporters and animal feeds for rice), the truck trips could classified into different commodities.

In this study, 7 types of commodities (rice, sugar, paper, animal feed, alcoholic beverage, oil, and mixed concrete) are selected to distinguish the commodity flows from the given travel patterns. Major stopping areas of these commodities (e.g. plants, cargo, warehouse, and port) are marked in GIS map to identify the location types of the effective truck stops. 9,601 effective truck stops (collected from 3,855 trucks), which are extracted from major stop locations, were individually examined to find out their travel patterns. Similarity, 20-minute stop duration and 2-kilometer movement are set as criteria in defining these effective truck stops. In this study, the trip status is defined as the status between 2 consecutive effective truck stops and is classified into loaded trips, unloaded trips, and stationary trips.

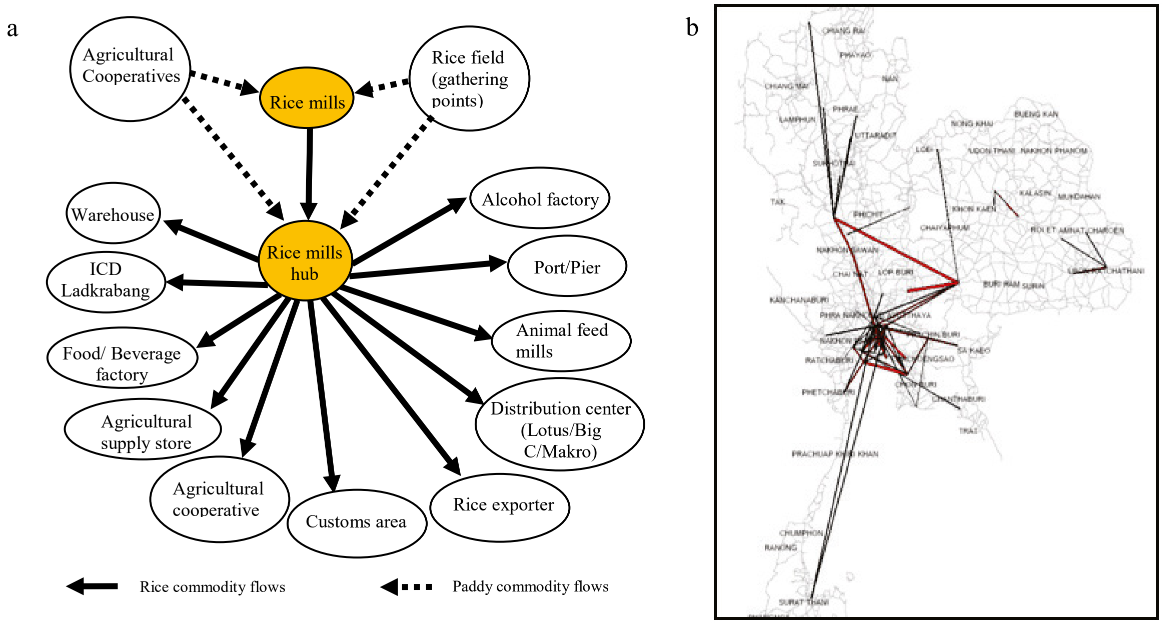

Fig. 3. (a) directions of commodity flows related with rice mills; (b) loaded trips of beer and alcoholic beverage (3 August 2017).

Analyzing the GPS data based on the aforementioned approach, the direction and, as well, the pattern of commodity flows for the 7 considered commodities could be established. For instance, Fig. 3(a) shows the directions of commodity flows related to rice mills. In term of the pattern of commodity flows, the proposed approach in Siripirote et al. (2017) has identified different flow pattern for each of the commodity (e.g., 14 different flow patterns for rice). For example, for a flow pattern of rice, the truck will first be loaded at rice mill. Then the truck will travels to food/beverage factory and warehouse to unload. Lastly the truck will travel back to rice mill. In this test case the proposed algorithm in Siripirote et al. (2017) could classified 72~ 90% of trip into the given patterns. By spatially aggregating the loaded truck trips, the flow of commodities within Thailand could be estimated and is found to be different for different commodities. Fig. 3(b) shows the loaded truck trips for beer and alcoholic beverage within Thailand. The ratios between loaded and unloaded trips (or simply called the load-unload ratios) are also calculated for evaluating the utilizations of trucks. If these ratios are high, the trucks, which travel along the roads, are more likely to have commodities. The current test case shows that the load-unload ratios of papers are less than one due to the long waiting time for unloading papers at the port. In addition, load-unload ratios of mixed concretes are almost one due to the unique travel patterns of mixed concretes between the concrete plants and construction sites.

5. Conclusions

In this paper, different freight related analytics are extracted and estimated from the Thai national truck GPS data. To efficiently analyzing the GPS data, the data is first screened to remove the incomplete data and sorted in accordance to the time stamp. The screened and sorted GPS data is applied to a maximum likelihood estimation model for finding the probabilities of the rest and load-unload activities that are used to determine the truck activity. It is found that, depending on the types of commodity, the stop durations for the loading/unloading activity are different. By considering the partial (sampled) truck OD flows from the GPS data and the link counts at different counting stations, this study has adopted a maximum-likelihood estimation approach to estimate the daily truck OD flows in Thailand. Based on the estimation, the total daily truck OD flows within Thailand is 768,170 trips/day. With the characteristics of the locations from GIS database, this study further analysis the GPS data to determine the commodity flows. It is found that, depending on the types of commodity, the flow pattern (e.g., rice mill→port→rice mill) and the spatial distribution of these commodity flows within Thailand is different.

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