ScienceDirect

Research in Transportation Business & Management
Volume 45, Part C, December 2022, 100908

GPS data as a basis for mapping freight vehicle activities in urban areas – A case study for seven Norwegian cities

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Abstract

Purpose

The current paper addresses how GPS data from freight vehicles can give detailed information on freight activities in urban areas, with examples of delivery/pickup activities in seven Norwegian cities. Such information is key when planning for freight activities in urban areas–e.g. when dimensioning the capacity of loading/unloading zones.

Design/methodology/approach

For 2019, a dataset of 79 million GPS positions was retrieved from 1200 freight vehicles. We present a method to convert GPS data into information on freight vehicle movements, including an approach to separate delivery/pickup activities from other stop activities in urban areas.

Findings

The study shows that detailed information on delivery/pickup activities in urban areas may be obtained from GPS data. We find that dwell time averages differ between outer and inner-city areas and vehicle types in Norway.

Practical implications

Today, most studies of this type are based on data from voluntarily participating firms, resulting in sample biases. However, as almost all new heavy goods vehicles include a possibility of GPS tracking, there is a vast future potential of such data, and this study illustrates how such data can provide transport authorities/planners with information at a more detailed level than traffic counts and at a lower cost than traditional observation studies.

Original/value

Several studies have addressed the issue of converting GPS data to trip information and identification of stop activities. However, we find less work on how such data may provide new insights into freight vehicle movements and activities in urban areas, and, in turn, how it may contribute to improved policy making towards the goal of greener and more efficient freight transport in urban areas.

Previous

Next

Keywords

GPS data; Urban logistics; Road transport; Delivery times

1. Introduction

Understanding freight activities in urban areas is key if policy makers are to implement effective measures towards cleaner and more efficient freight transport in city centres. Such measures are becoming increasingly relevant, as the European Commission (EC) has set ambitious GHG reduction targets. Like the EC, Norway has a stated objective of achieving virtually zero emission distribution in city centres by 2030 and is working towards more efficient city logistics and increased utilisation of transport capacity in urban areas (Norwegian Public Road Administration, 2008). To achieve these objectives and to facilitate the phase-in of zero-emission commercial vehicles, several urban logistics measures are necessary. Examples can include City Hubs, consolidation centres, dedicated loading and unloading sites, fast-charging infrastructure for electric vehicles, or zero-emission zones (Hovi, Pinchasik, Mjøsund, & Jensen, 2019).

Regardless of the different approaches towards greener and more efficient city logistics, there is a knowledge gap regarding user patterns for commercial vehicles in urban areas. Even though several studies and official statistics are carried out to map such information, a challenge is collecting sufficiently detailed data to fully describe the complex city logistics, which typically involves numerous deliveries/pickups and varying daily routes for the vehicles involved (Van den Bossche, Maes, Vanelslander, Macário, & Reis, 2017). From a planning point of view, there is for example a need for more detailed information about delivery and pickup activities in urban areas, e.g. activity locations, dwell time duration, and how such patterns can change over time due to infrastructure investments, traffic conditions, changes in transport demand, political objectives, or other reasons.

New data sources can help to fill this information gap. Almost all OEMs have offered Fleet Management Systems (FMS) as a standard in heavy goods vehicles (HGVs) produced after 2013, based on sensors installed in-vehicle. Such FMS enable collection of data from a vast number of vehicles, including position (GPS) data, date and time of day, operational time, distance driven, fuel consumption and parameters on driving behaviour. However, to access such data, vehicle owners must subscribe to FMS as a service from the vehicle supplier or third-party FMS service providers. GPS data may give detailed information on freight vehicle movements and delivery/pickup activities, making it possible to study urban logistics in detail. Although observation field studies may also provide such information, these are usually time consuming and expensive, and, as a result, often have relatively small sample sizes and/or are not conducted frequently. On the other hand, automatic traffic counts from inductive loops in the road network can provide information on traffic flows, broken down by vehicle length categories. However, such traffic counts do not yield information on the activities and movements performed by the individual vehicles and donot differentiate between passenger cars and vans, nor between buses, trucks and light vehicles with trailer. Traffic counts are also more common on highways and other main roads than in downtown areas, meaning that data are not detailed enough for understanding freight vehicle activities in urban areas.

The research question investigated in this article is: *How can GPS data provide detailed information about commercial vehicles' activities in urban areas and through this contribute to improved policymaking?*

2. Literature review

While modern research on freight transport modelling in urban areas can be traced back to the 1970's, development has lagged compared to passenger transport models and freight models on the national and regional level (Gonzalez-Feliu, 2019; Kaszubowski, 2019). There are several reasons for this: Firstly, urban logistics is characterized by a higher degree of complexity in terms of for example delivery patterns, distribution routes and loading and unloading activities. This makes it more difficult to collect data and to model detailed urban logistics, while at the same time keeping the models and statistics user-friendly (Kaszubowski, 2019). Secondly, data access is more limited, since relevant data usually are proprietary and contain information that is competitively sensitive for private enterprises and logistics service providers (Southworth, 2018). Furthermore, official statistics on freight transport, such as the road freight transport survey carried out in all EU/EEC member states (Eurostat, 2022), are designed to give information on transport patterns at a regional and national level, and therefore do not contain sufficiently detailed information to represent city logistics. The sample for these surveys (HGVs with over 3.5 t in loading capacity, which corresponds to approximately 7.5 t gross weight) also consists of vehicles that are larger than the vehicles typically used in (European) cities. Toilier, Gardrat, Routhier, and Bonnafous (2018) further posit that urban logistics is not prioritized highly enough in cities' policy making, which in turn may originate from the lack of detailed data.

Several studies have been conducted to better understand the structure of urban logistics. The data they are based on can roughly be divided into GPS data and other forms of sample surveys, such as trip generation and/or dwell times models. Holguín-Veras, Kalahasthi, and Ramirez-Rios (2021) estimated service trip generation models to assess how commercial establishments attract vehicle movements in terms of frequency, purpose, time of day and dwell time duration, by industry. Based on data collected for two metropolitan areas in the USA, the authors estimated econometric models that express the number of service trips to commercial establishments, divided into freight- and service-intensive sectors, as a function of the establishments' characteristics, and assessed the geographic transferability of the models obtained. They found that 36% of freight trips have a parking limit of 5 min, 59% of 10 min, 71% of 15 min and 96% of 1 h. They also found that parking times for service trips are five to nine times higher than for freight trips, with the highest ratio for the shortest parking durations.

The dwell time models presented by Kim, Goodchild, and Boyle (2021) aim to identify factors correlated with dwell times for commercial vehicles by using generalized linear models with data on commercial vehicle activities collected from five buildings in the downtown area of Seattle (USA). Their models showed that average dwell times for deliveries of documents tended to be shorter (14 min) than oversized supplies deliveries (21 min). Passenger vehicle deliveries had shorter average dwell times (8 min) than deliveries with vans and HGVs (15–18 min), and deliveries made to multiple locations within a building had significantly longer dwell times (29 min) than deliveries to one location in a building (13 min). Cherrett et al. (2012) investigated 30 UK surveys and found estimates for different characteristics for goods deliveries to establishments, including variations in deliveries over the year, day of the week and time of day, types of vehicles used to make the deliveries, and dwell times of goods delivery vehicles. For the latter, said study reported loading/unloading dwell times between 6 and 50 min, dependent on the study area and vehicle type. For vans, the study reported a median dwell time of 10 min, while for HGVs, medians were 19 min (rigid HGVs) and 31 min (articulated HGVs).

Nadi, Van Lint, Tavasszy, and Snelder (2020) developed a decision tree method to model departure time and trip type in the Netherlands. Their model was based on XML data of truck diaries provided by Statistics Netherlands, combined with location data (post zone level) for distribution centers and transshipment terminals, and data from road vehicle counts. The authors found that departure times are sensitive to congestion in tpickup and delivery zones, that trips with high trip distances are most likely to depart in the early morning or night periods, that direct tours are usually planned for the uncongested zones, and that the number of stops on distribution trips is higher, the shorter the total distance.

As GPS data from freight vehicles gradually has become more available for data analysis and transport planning, many studies have addressed the issue of how raw GPS data may be converted into datasets more applicable for analysing freight vehicle movements and activities. Typically, raw GPS datasets consist of large data streams that contain, at a minimum, observations that connect a vehicle with a set of geographic coordinates (for instance latitude and longitude positions), and timestamps. To provide insights, data must therefore be processed. The first stage in such processing (linking GPS position observations together in chronological order and calculating time intervals and distance between consecutive observations) is rather straightforward. The literature therefore focuses on developing methodologies for trip generation and stop identification, that is crucial both for defining the start and end of trips and for detecting freight delivery and pickup activities (Yang, Zhanbo, Xuegang, & Holguín-Veras, 2014).

Stop identification in GPS data is complex for several reasons; For instance, the present quality standard of GPS data streams gathered from freight vehicles often involves significant time intervals between observations. This is confirmed by Laranjeiro et al. (2019), who used five different sources of GPS data in a study of freight transport in the São Paulo Metropolitan Region, and found that time intervals between consecutive observations differed substantially between sources, ranging from 2.3 s (app-based data collection) to 17 min (dataset from a retail company).

GPS data pings may also be event-triggered, with logging occurring on events such as engine start, start/stop of vehicle movement, etc. To deal with these challenges, most studies introduce a maximum threshold speed between two GPS observations that defines when a vehicle has come to a stop. For instance, Thakur et al. (2015) use a threshold value of 5 miles/h (equivalent to 8 km/h) in their study of HGV movements in Florida. Flaskou, Dulebenets, Golias, Mishra, and Rock (2015) also use 5 miles/h, Laranjeiro et al. (2019) use 5 km/h, while Yang et al. (2014) introduce a 14 km/h threshold in their study of data from delivery trips in New York. All consecutive GPS observations with a calculated speed below the threshold value are then accumulated until the speed again surpasses the threshold value, to yield a total time for the stop observation. Minor vehicle movements within limited geographical areas should usually be considered as belonging to a single stop observation, because movements may be a result of GPS positioning inaccuracy, or because of (minor) vehicle movements related to the loading/unloading process on a particular site. To allow temporary movements over the threshold speed, both Gingerich, Maoh, and Anderson (2016) and Laranjeiro et al. (2019) introduced a distance buffer where the vehicle has to move a certain distance before the stop observation is considered complete. Gingerich et al. (2016) suggest a buffer value of 250 m, while Laranjeiro et al. (2019) use a value of 200 m.

Holguin-Veras, Encarnacion, Pérez-Guzmán, and Yang (2020) go one step further and present a procedure based on the physics of driving patterns, to identify freight activity stops from raw GPS data. The procedure, using machine learning, was implemented to identify stops in three metropolitan areas, representing a wide range of traffic conditions. The method utilized three different parameters: 1) the number of GPS data points to be used in the calculations of speed and acceleration (typically between 25 and 40); 2) the cutoff acceleration, below which the HGV is considered not to be accelerating (typically between 0 and 8 km/h^2); and 3) the cutoff speed parameter, below which the HGV is considered to have stopped (typically between 0 and 10 km/h). Their results show that the procedure achieves an average accuracy of above 98.6% when identifying freight activity stops.

Identifying stop patterns based solely on GPS data is challenging when deliveries and pickups are done quickly, which is often the case during distribution routes, and particularly in urban areas, with several small deliveries. As a result of data shortcomings, studies have developed different techniques to identify primary stops based solely on stop times and their corresponding locations derived from GPS data. Hess, Quddus, Rieser-Schüssler, and Daly (2015) consider stops of 45 min or more to be stops between trips, while Flaskou et al. (2015) and Thakur et al. (2015) use 30 min for this purpose. Gingerich et al. (2016) introduce a 15-min minimum stop time and used the method of entropy to identify primary stops. Hess et al. (2015) consider all stops between 2 and 15 min to be primary stops, while stops between 15 and 45 min are considered to be primary stops if the stop location does not match with a look-up in a geo-coded database of service stations/truck-stops. Laranjeiro et al. (2019) consider stops of over 20 min to be primary stops. These values seem plausible for long-haul vehicles, but for distribution, especially in urban areas, they seem too high, which is also supported by findings in Cherrett et al. (2012).

Although several studies have addressed how raw GPS data from trucks can be converted into trip information and how stop activities can be identified, we find less work where such data provide new insights into urban logistics. On the other hand, it is when studying the complicated urban logistics, that GPS data have a great advantage over other types of data. Urban distribution, and particularly of parcels and small shipments, is often performed by vans, where data availability is even more limited than for trucks, because these vehicles to a lesser extent than trucks have installed hardware for FMS and GPS. Deriving stop information from GPS data in urban areas requires some adjustments to the established methods of identifying primary stops and measuring stop times. Our study contributes to the literature by 1) adapting established methodology to be better suited for studying the stopping pattern of trucks in urban areas and 2) adapting it further to be applied to GPS data from vans. Finally, we use a case to illustrate how dwell times and activities differ within small geographic areas, depending on the kind of businesses and freight facilities situated in the area. This emphasizes how important it is that policy makers have insight into today's freight transport activities in the relevant areas before they introduce measures to promote greener and/or more efficient freight transport in urban areas.

3. Methodology

3.1. Trip generation and stop times calculation

To utilise the GPS data for analysing purposes, it is necessary to convert data into trips and separate driving activities from stop activities. This is done in several steps using the information on position coordinates (x,y) and timestamps for the consecutive observations for each vehicle. The Haversine formula is used to calculate the distance (d) between two coordinates and considering the curvature of the earth's surface:

$$d = 2r\ \arcsin\left(\sqrt{sin^2\left(\frac{\Phi_2 - \Phi_1}{2}\right) + \cos(\Phi_1)\cos(\Phi_2) sin^2\left(\frac{\lambda_2 - \lambda_1}{2}\right)}\right)$$

where Φ represents latitude coordinates, λ represents longitude coordinates, and r is the radius of the earth (≈6371 km) (Chopde & Nichat, 2013).

By combining the GPS timestamps to retrieve the time between observations, and the calculated distance, we derive the speed (km/h) between each observation. However, by using the geodetic distance to calculate speed, the actual vehicle speed will be underestimated whenever the vehicle does not move in a straight horizontal line between two GPS observations. This underestimation will decrease with increasing GPS ping frequency. However, low GPS frequency, when calculating delivery/pickup times, will also increase uncertainty regarding estimated stop times, and regarding the location of vehicle stops. This is particularly relevant for cities, where GPS signals can be disturbed by tall buildings. For this reason, GPS data with a frequency lower than every 5th minute are excluded from this analysis.

Following the methodology suggested by Gingerich et al. (2016), and to avoid breaks in total stop times due to GPS inaccuracy or minor vehicle movements at the same loading/unloading location, stop times are accumulated as long as the vehicle is observed to be inside a radius of 250 m from the first stop observation, illustrated in Fig. 1. Vehicle stops are identified based on the calculated speed between GPS observations. Because a stop for pickup or delivery also implies that the vehicle must decelerate, and to avoid GPS signal jiggle, a threshold of maximum 8 km/h is used to identify the first stop observation, and is in line with most of the studies presented in the literature review. The cumulative time for all consecutive stop observations is then calculated to establish the total stop time before the vehicle starts moving again. Trips are generated based on the estimated dwell times. A threshold value of 60 min is used to identify new trips. Dwell times under 60 min are considered to be temporary stops during the trip or distribution route.

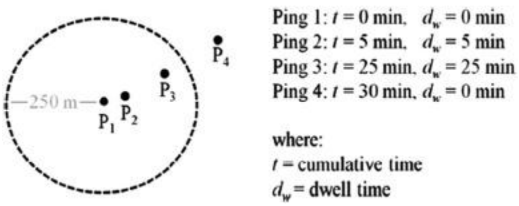

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Fig. 1. Distance-based stop time calculation (Gingerich et al., 2016).

The 250-m radius buffer is preferable in most cases where some distance between different consecutive loading/unloading locations for a vehicle is expected, e.g. for an articulated HGV, where the trailer must be parked before loading/unloading can start, as well as for stops at sites such as consolidation centres, larger warehouses, manufacturing and industrial sites or other logistics centres. This is to avoid splitting up operations and vehicle movements at the same locations, into separate stops. For freight vehicle movements in urban areas, such as in this study, a 250-m radius seems too large for stop identification, particularly if vehicles used are smaller HGVs or vans. Indeed, articulated vehicles are hardly used in urban logistics, and delivery and pickup locations may be close to each other in city centres. Here, different delivery and pickup stops within a radius of 250 m would merge into one single stop with an incorrectly high stop time. Therefore, we introduced a 50-m radius for stops that take place inside defined inner-city areas, while using the 250-m radius outside these areas. The definition of inner-city areas is explained in more detail in chapter 3.3.

Standard values for driving times are estimated based on the observed speed for the last stop observation before exiting the stop buffer radius in the inner cities and outside the inner cities, and are derived from the GPS observations and time stamps. To avoid overestimation of dwell times through distance-based stop time calculation, estimates of the driving time are adjusted to bear in mind that vehicles need time to exit their defined stop radius. Based on the available dataset, we find an average speed of 18 km/h in the inner cities and 20 km/h outside the inner cities, which equals to respectively 10- and 45-s driving time for the relevant radius distances, which is then subtracted from the dwell time. This step is performed to compare dwell times for inner city stops with dwell times for stops outside the inner city.

3.2. Identifying delivery and pickup stops

To separate short primary stops from other short stops, for example due to traffic congestion or traffic signals, different potential techniques have been tested. First, we plotted all identified stops shorter than 60 min on a map and studied the detailed stop locations in different dwell time intervals. We found that most of the shortest stops (<2 min) are typically situated along larger roads, near traffic junctions and known bottlenecks, and other places where deliveries and pickups do not occur. Based on this evaluation, the minimum dwell time for a primary stop was set to 2 min, while shorter stops are considered as part of the driving activity. For stops between 2 and 5 min, the picture is less clear. On the one hand we still found several observations at the same locations where deliveries and pickups are not expected to take place, but on the other hand there are also stops in areas and along routes that are part of distribution routes and which should therefore be defined as primary stops.

Our approach is to separate the minimum allowed dwell time based on vehicle type. For vans, stops with a duration between 2 and 60 min are defined as primary stops, whereas for HGVs, the minimum allowed time is set to 5 min. The rationale behind defining a primary stop based on vehicle type is that vans are more frequently used for urban distribution and deliveries and pickups of parcels and small shipments, which in turn implies shorter dwell times.

HGVs are also used on distribution routes, but usually carry pallet goods and larger shipments that take a longer time to load and unload, often involving use of a jack trolley and operating of a tail lift (twice). This assumption is in line with observations by Cherrett et al. (2012) and Holguín-Veras et al. (2021).

Fig. 2 shows stop observations in the district of Torshov in Oslo. Panel ‘A’ shows all stop observations over 2 min, while panel ‘B’ shows stop observations over 2 min for vans and over 5 min for HGVs.

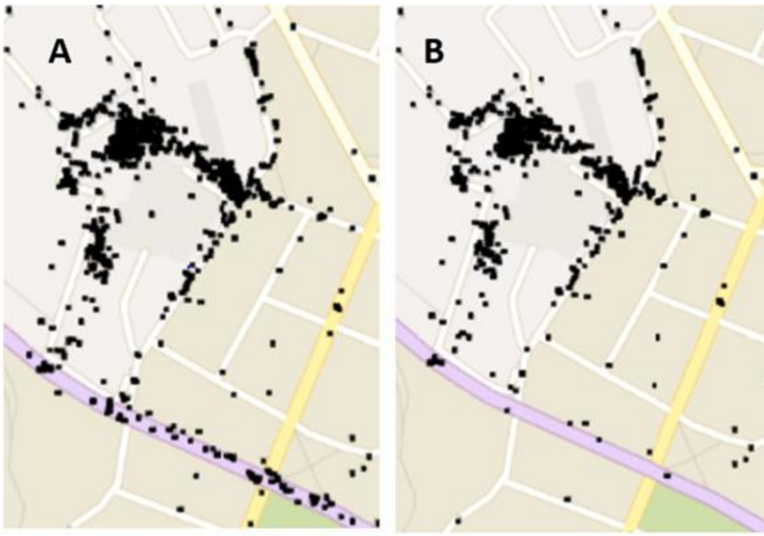

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Fig. 2. Map of stop observations in the district of Torshov in Oslo. A) All stops over 2 min, B) Stops over 2 min for vans and over 5 min for HGVs (Google Maps, 2020).

Most stop observations are clustered around buildings that house shops and service providers that attract freight transport, such as a postal office, a grocery store, and other retail outlets. Such observations should therefore be defined as deliveries/pickups. The purple road is a ring road ('ring road 2') where deliveries/pickups will most likely not take place. Panel B shows that most observations along the ring road are removed when HGV stops below 5 min are not considered as deliveries/pickups. However, there are still several observations along the main road, which is probably a result of days with major traffic delays, but are erroneously classified as deliveries/pickups, rather than secondary stops. This challenge indicates a potential for further development of the method, e.g. by additionally considering land-use data.

3.3. Classification of urban areas

Spatial differences in vehicle movements in urban areas are studied for seven of the largest cities in Norway (Oslo, Bergen, Trondheim, Stavanger, Kristiansand, Drammen and Tromsø respectively). We distinguish between areas inside and outside of the inner cities, based on an assessment of areas of postal zones with a high density of shops and services for each individual city, determined in collaboration with the Norwegian Public Road Administration (Pinchasik & Hovi, 2018). For the city of Oslo, the area inside a major ring road ("ring road 3") is defined as the inner-city area. The remaining area within the city municipalities' administrative borders is defined as the outer city area. Fig. 3 shows examples of the defined inner (orange) and outer (blue) areas for the cities of Oslo and Bergen.

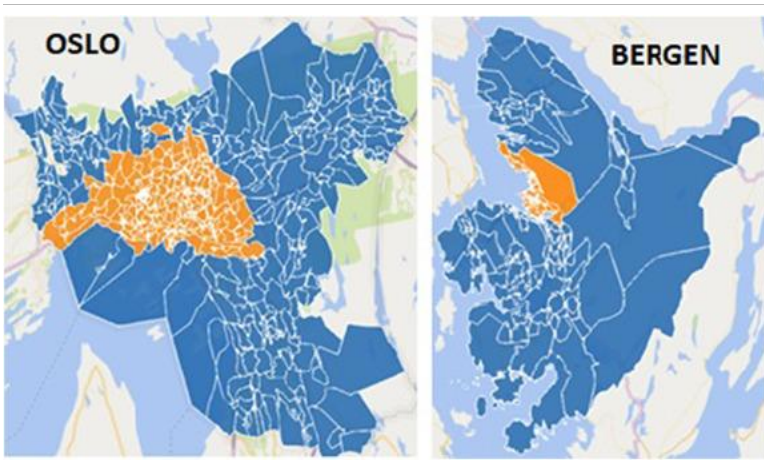

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Fig. 3. Definition of inner and outer city areas in Oslo and Bergen (Google Maps, 2020).

The selected cities in Norway vary greatly in terms of both population numbers and density. While the capital Oslo had a population of 693,000 and a density of 1628 inhabitants per square kilometre inside its municipal administrative border (per 01.01.2020), the second largest city, Bergen, had 284,000 inhabitants and a density of 638 inhabitants per square kilometre. In turn, the seventh largest city, Tromsø, had a population of 77,000 and a density of 31 per square kilometre (Statistics Norway, 2020).

3.4. Data collection and cleansing

Data used in this study was collected from February 2019 to December 2019 and consist of 79 million GPS observations distributed over approximately 94 thousands vehicle days. Data originate from two different sources, the first is collected by a Norwegian FMS provider, utilising the built-in API from 476 HGVs owned by 18 different Norwegian freight forwarders. This source accounts for 38% of the GPS observations. The other data source, accounting for the remaining 62% of GPS observations, is based on externally installed hardware in 717 vehicles performing transportation for a large Norwegian forwarder. Although the majority of the sampled vehicles were HGVs, the sample also included 168 vans.

In other words, the distribution between trucks and vans in this study is not necessarily representative for the vehicle population in Norway as a whole or the distribution of vehicles used in cities. This is partly due to the fact that GPS data from trucks have a somewhat better availability than for vans since they to a greater extent are equipped with factory-fitted FMS-APIs including a GPS tracker, while data from the vans included in this study stems from externally equipped FMS hardware. Our purpose is not to derive representative distributions of trips divided between vans and trucks, but rather to test whether the methodology for identifying trips and stops based on GPS data from trucks with some adaptations can be adopted for urban logistics in general and vans in particular.

Table 1 gives an overview of the vehicles in terms of vehicle types and max. gross weights. Technical information about the vehicles is extracted from the national vehicle register. Although we only have access to deidentified information about the vehicles, the FMS providers have organised fictitious vehicle links and corresponding information from the vehicle register for each vehicle.

Table 1. Distribution of tracked vehicles by vehicle type and weight classes.

					Shares in %		
Vehicle type	**Max Gross Weight**	**Vehicles (number)**	**Vehicle days**	**GPS ping interval (minutes)**	**Vehicles**	**Vehicle days**	**Primary stops**
Vans	3,500 kg	168	9,423	2.9	14%	10%	27%
	≤ 16,000 kg	73	5,677	0.6	6%	6%	14%
Single unit trucks	16,001–27,000 kg	460	39,882	3.7	39%	43%	41%
	>27,000 kg	208	12,783	1.4	17%	14%	7%
Tractors with trailers	16,001–27,000 kg	131	12,324	2.1	11%	13%	6%
	>27,000 kg	153	13,551	0.9	13%	14%	5%
In total		**1,193**	**93,640**	**2.5**	**100%**	**100%**	**100%**

Vans make up 14% of the total number of tracked vehicles, 10% of vehicle days and 27% of the number of trips. Given that Norway counts ca. 70,000 registered trucks and 500,000 vans, it is obvious that the composition of vehicles in this study is not representative for the population, even if taking into account that only a fraction of the vans are used for distribution. This was also expected, as our data access was dependent on the willingness of carriers to cooperate, and because our efforts to establish access to data were primarily directed at data for trucks. The data capture for vans was therefore a side effect of the fact that one transport companies had installed hardware for FMS in part of their vans.

Some data cleansing was necessary to avoid errors in the raw data affecting our analyses. This involved removal of observations with a timestamp identical to the consecutive observation, for which it would be impossible to calculate speeds between GPS positions. For some observations, the GPS positioning is clearly wrong, for instance indicating that a vehicle is moving over long distances in a short amount of time. To exclude such observations, the maximum allowed speed in the Norwegian highway network (110 km/h) was used as cut-off.

Following the methodology described in 3.1 Trip generation and stop times calculation, 3.2 Identifying delivery and pickup stops, we were able to generate several trips and stops for deliveries/pickups based on 18 million GPS positions in the seven largest Norwegian cities. The time interval between consecutive observations for vehicles in urban areas differs between vehicle segment but was 2.5 min on average, with the lowest time interval being 0.6 min for single unit trucks up to 16 t.

In total, 242 thousand trips were generated, of which 108 thousand take place entirely outside the inner city areas, while 127 thousand trips take place both in outer and inner city areas, wherein the trip typically starts in the outer city before entering the inner city area. 7.5 thousand trips take place entirely within the inner cities. Further, the method identified 513 thousand deliveries/pickups, of which 135 thousand take place in inner cities and the remaining 378 thousand in the outer city areas.

Fig. 4 summarises the distribution of derived delivery/pickup stops with respect to vehicle type for the seven cities. The corresponding numbers, also divided into inner and outer urban areas, are provided in Table A1.

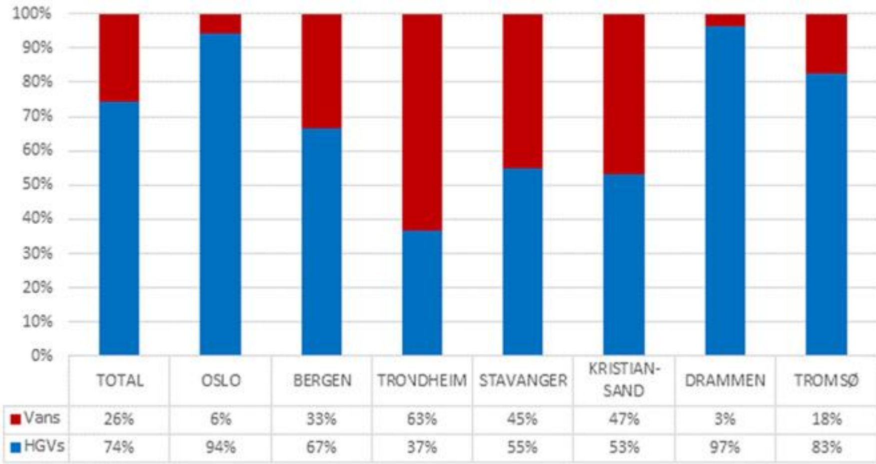

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Fig. 4. Distribution of deliveries/pickups in urban areas with respect to HGVs and vans (percent).

It appears that all areas have a selection of deliveries/pickups for both types of vehicles. However, this distribution differs considerably between the cities. In Trondheim, for instance, 63% of the stops in the sample are performed by vans, while in Drammen this share is only 3%. As a result, mean values for the different urban areas will vary according to the sample's vehicle compositions. Because of this bias, results in the remainder of this article present results for HGVs and vans as own categories, rather than weighting them into one category.

4. Results

4.1. Delivery and pickup activities in Norwegian cities

Up-to-date information on delivery/pickup activities in urban areas is useful for the planning and evaluation of measures towards greener and/or more efficient freight transport in urban areas. Fig. 5 presents the median dwell times for deliveries/pickups in the different urban areas for HGVs and vans.

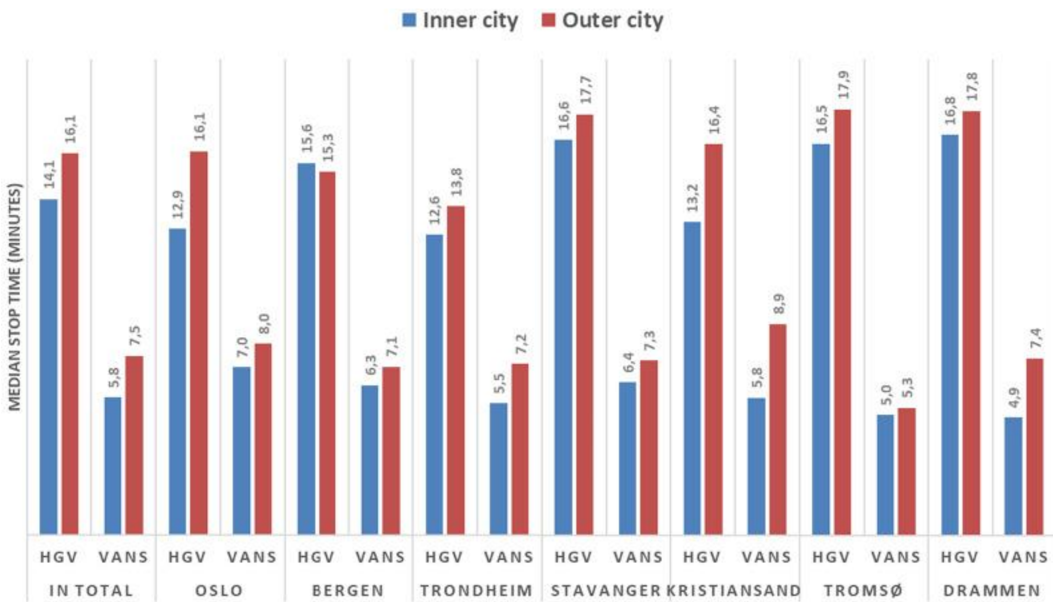

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Fig. 5. Delivery/pickup times in Norwegian urban areas for HGVs and vans. Median dwell time (min).

In aggregate, the median dwell time for HGVs is estimated to be around 14 min in inner city areas and 16 min in outer city areas. Vans have considerably shorter dwell times. For these vehicles, the median dwell time is 5.8 min in inner city areas and 7.5 in outer city areas. The results are in line with Cherrett et al. (2012), cfr. Section 2 (dwell time variation between 6 and 50 min, dependent on area and vehicle time, with median dwell times of 10 min for vans and 19/31 min for HGVs (rigid and articulated HGVs respectively).

Table 2 shows dwell time statistics in more detail, indicating that 75% of the primary stops performed by vans in inner cities are completed within about 11 min, whereas 95% are completed within 32 min. For outer cites 75% of the primary stops performed by vans are completed within 15 min, whereas 95% are completed within 39 min. There is relatively little variation across cities, where Tromsø has the lowest values, while Kristiansand and Oslo have the highest. Not unexpectedly, HGVs tend to have longer stops; here, 75% of stops are completed within 24 min, whereas 95% are completed within 47 min in inner cities, with small variations to outer cities. To compare (cfr. Section 2), Holguín-Veras et al. (2021) found that 36% of freight trips with vans have a dwell time of 5 min, 59% of 10 min, 71% of 15 min, and 96% of 1 h. Also for Norway, an observation study from 2008 in the Oslo urban area reported that a third of the deliveries had dwell times in the range of 1–10 min, nearly 40% had dwell times in the range of 11–25 min, and the remaining 30% of deliveries had dwell times of over 25 min (Norwegian Public Road Administration, 2008).

Table 2. Delivery/pickup times in Norwegian urban areas for HGVs and vans. Mean values (min), standard deviations and percentiles.

Urban area		Vehicle type	Mean	St.dev.	%tile 05	%tile 25	Median	%tile 75	%tile 95
Oslo	Outer city	HGVs	20.4	13.5	5.9	9.6	16.1	28.0	49.4
		Vans	13.0	12.6	2.5	4.5	8.0	16.4	43.3
	Inner city	HGVs	16.6	11.3	5.7	8.4	12.9	20.9	41.8
		Vans	11.1	10.4	2.6	4.4	7.0	13.7	34.6
Bergen	Outer city	HGVs	20.0	13.8	5.8	9.0	15.3	27.8	49.9
		Vans	11.0	10.6	2.4	4.0	7.1	13.5	35.2
	Inner city	HGVs	20.2	14.1	5.6	8.7	15.6	28.2	50.0
		Vans	9.7	9.2	2.4	3.9	6.3	11.9	28.5
Trondheim	Outer city	HGVs	19.0	13.6	5.8	8.9	13.8	25.3	49.4
		Vans	11.8	11.7	2.4	4.0	7.2	14.8	39.0
	Inner city	HGVs	17.0	11.9	5.8	8.6	12.6	21.3	44.8

Urban area		Vehicle type	Mean	St.dev.	%tile 05	%tile 25	Median	%tile 75	%tile 95
		Vans	9.6	10.4	2.3	3.4	5.5	11.0	33.5
Stavanger	Outer city	HGVs	22.1	14.6	5.8	10.1	17.7	31.6	51.8
		Vans	11.4	10.8	2.3	3.9	7.3	14.8	35.4
	Inner city	HGVs	20.3	13.2	5.8	9.3	16.6	28.2	47.5
		Vans	10.6	10.6	2.4	3.7	6.4	12.5	34.9
Kristiansand	Outer city	HGVs	21.0	14.3	5.8	9.2	16.4	30.0	50.9
		Vans	13.8	12.7	2.5	4.7	8.9	18.4	42.9
	Inner city	HGVs	17.1	12.0	5.5	7.8	13.2	21.8	43.3
		Vans	9.4	9.7	2.3	3.5	5.8	11.0	30.4
Tromsø	Outer city	HGVs	21.7	13.2	6.5	11.2	17.9	29.5	50.0
		Vans	7.5	6.9	2.3	3.3	5.3	8.9	20.3
	Inner city	HGVs	20.9	13.9	6.0	9.6	16.5	29.1	50.1
		Vans	8.1	8.6	2.2	3.2	5.0	8.9	25.3
Drammen	Outer city	HGVs	21.7	13.5	6.3	10.8	17.8	30.0	49.8
		Vans	10.5	9.8	2.4	3.8	7.4	13.1	30.0
	Inner city	HGVs	20.5	13.0	6.0	9.8	16.8	28.6	47.1
		Vans	9.6	10.0	2.6	3.2	4.9	12.0	31.3
In total	Outer city	HGVs	20.5	13.7	5.9	9.5	16.1	28.3	49.8
		Vans	12.1	11.8	2.4	4.2	7.5	15.4	39.4
	Inner city	HGVs	18.5	12.7	5.8	8.8	14.1	24.4	46.6
		Vans	9.6	10.0	2.3	3.5	5.8	11.2	32.3

4.2. Trip characteristics: Freight vehicle movements and activities in Norwegian inner cities

To gain more insight into freight vehicle movements and activities in inner city areas, we investigated all trips that had deliveries/pickups in the defined inner cities. By separating the part of the trips taking place in the inner-city areas, we calculated how long the vehicles stay in inner cities, and further, how much time they spend driving or stopping for deliveries/pickups, respectively. We also summarized the number of deliveries/pickups for each inner-city trip. Table 3 shows the median values for the different inner-city areas and vehicle types.

Table 3. Freight vehicle movements in inner city areas. Median values in minutes, for time spent in inner city, dwell time and driving time, and number of deliveries/pickups in inner city areas.

City area /vehicle type	Time spent in inner city (min)	Dwell time (min)	Driving time (min)	Number of deliveries/pickups per trip
Oslo	**58**	**32**	**25**	**2**
HGVs	58	32	25	2
Vans	69	44	23	3
Stavanger	**44**	**25**	**17**	**1**
HGVs	42	21	16	1
Vans	58	38	18	4
Drammen	**46**	**26**	**17**	**1**
HGVs	49	28	18	1
Vans	13	5	7	1

City area /vehicle type	Time spent in inner city (min)	Dwell time (min)	Driving time (min)	Number of deliveries/pickups per trip
Bergen	**56**	**36**	**19**	**2**
HGVs	54	34	18	1
Vans	76	50	25	6
Tromsø	**82**	**53**	**28**	**3**
HGVs	82	54	27	2
Vans	78	42	38	6
Trondheim	**51**	**30**	**19**	**2**
HGVs	45	24	18	1
Vans	63	39	21	4
Kristiansand	**59**	**43**	**16**	**2**
HGVs	59	42	16	2
Vans	59	45	16	4
In total	**57**	**35**	**22**	**2**
HGVs	56	34	22	2
Vans	64	41	22	4

In total, the median vehicle spends 57 min per trip in the inner-city areas, of which 22 min in motion and 35 min related to delivery/pickup activities. The median number of deliveries/pickups in the inner city is two per trip before leaving this area. A distribution trip usually consists of deliveries both inside and outside the inner city. For vans, the number of deliveries/pickups is higher; these vehicles on average perform 4 deliveries/pickups per trip in the inner-city areas. For vehicles performing city logistics, this figure seems too low, but may be correct, for example because stops within inner city areas may entail deliveries to several receivers, because it is often difficult to find suitable areas for parking. Deliveries in inner city areas might also be part of longer distribution rounds.

The statistical distribution of deliveries/pickups per trip in inner-city areas is shown in the histograms in Fig. 6 for HGVs and vans, respectively, including values for mean and standard deviation; A large share of the trips only includes one or a few delivery/pickup activities, which explains the low median figures in Table 3. The distribution is right-skewed for both HGVs and vans. For vans, half of the trips include 4 or more deliveries/pickups, with some trips exceeding 20 primary stops in inner cities. For trucks, 50% of the trips in inner city consists of one single stop. Given the limited areas defined as inner cities, this indicates a very high stop frequency and short distances between each stop for vans. Considering that freight bicycles are also used in several of the cities studied, there is also a division between vans and bicycles, where the latter are used to distribute the smallest packages and with the shortest distances between each stop, such as in pedestrian areas.

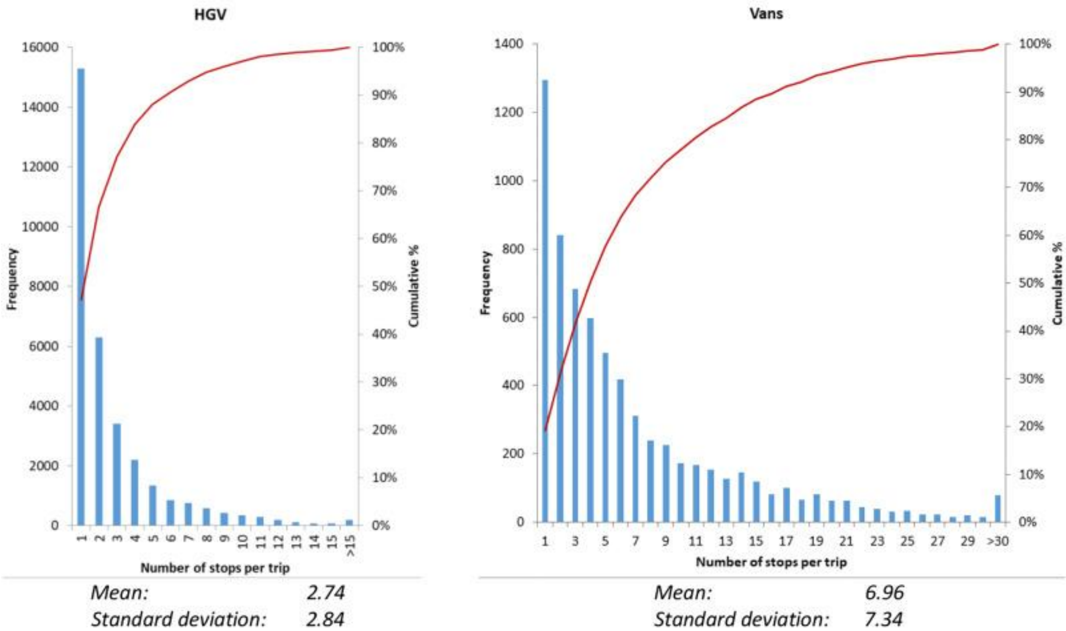

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Fig. 6. Distribution of number of deliveries/pickups per trip in inner city areas for HGVs and vans.

4.3. Insight into inner city freight activities: the case of Bergen central business district

While aggregated figures on a city-level give some indications as to freight vehicle movements in different urban areas, new measures are often more local in nature, e.g. when planning for loading/unloading zones/spaces, or introducing vehicle-free zones in particular areas of the city. In such cases, there is a need for more detailed information on freight vehicle activities in particular areas, including information on where the vehicles stop, for how long they occupy space, and the origin and destination of the trip. As an example of the extent to which GPS data may be a source of such information, freight vehicle movements in the inner city of Bergen are studied in greater detail. Fig. 7 shows a plot of every delivery/pickup observation in the inner-city area of Bergen, categorized into dwell time intervals.

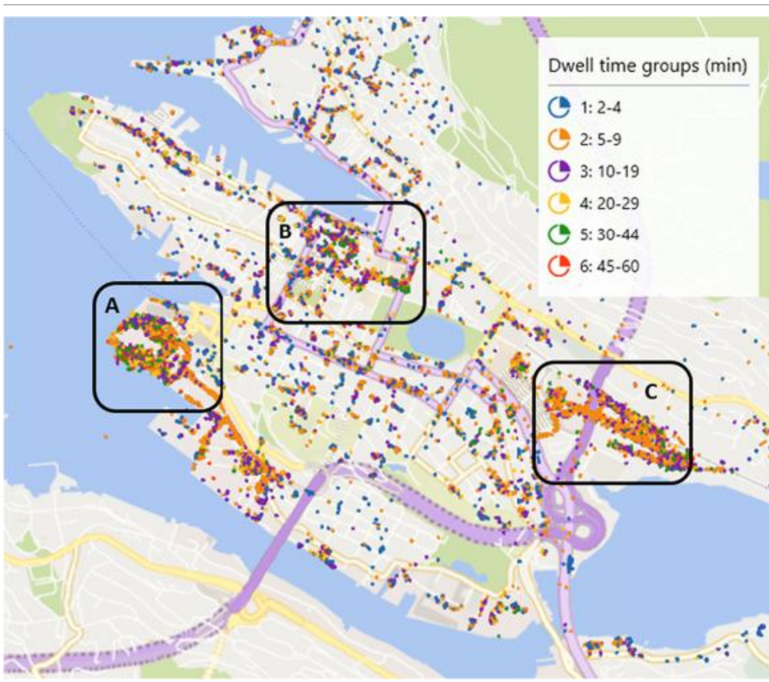

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Fig. 7. Delivery/pickup observations in the inner city area of Bergen. Dwell time intervals in minutes (Google Maps, 2020).

Although the median delivery/pickup time in the inner city area of Bergen is estimated to 6 min for vans and 16 min for HGVs (from Fig. 5 and Table 2), the grouped dwell time observations plotted on the map reveal significant variations. Most parts of the inner city seem to have a mixture of observations across the different dwell time intervals. Some areas of the inner city are worth mentioning. The area marked with an "A" is Dokken/Jekteviken, a busy port with several daily calls, and the location of the distribution terminal of Norway's largest forwarder, Bring. Unsurprisingly, there are a lot of stop observations in this area, and the dwell time spans from short stops of a couple of minutes to stops lasting one hour. The median delivery/pickup time in this area is 6 min for vans and 14 min for HGVs. The area marked with a "C" is another freight hub located in the inner city of Bergen. This is Nygårdstangen rail freight terminal and the location of PostNord's and DB Schenker's distribution terminals (also two of the largest forwarders in Norway). For this area, the data show many stops lasting 5–9 min, which is expected, considering the amount of shuttling to and from the freight rail terminal for container pickups and deliveries. Consequently, HGVs have a lower median delivery/pickup time in this area and spend on average 10 min per stop. In turn, vans spend 7 min on average per stop in this area. The area marked with "B" is the Central Business District (CBD) of Bergen, the most densely built area with a mixture of office buildings, retail outlets and service industries such as hotels and restaurants. This area has a high density of stop observations, and the duration of the stops spans across all time groups. In this area, vehicles tend to spend more time when delivering/picking up goods. The median stop time is 10 min for vans and 20 min for HGVs. The plot also shows that deliveries/pickups take place at many different locations, and there is no indication of dedicated areas for loading/unloading in this area.

The example illustrates that stop activities and dwell times differ within small geographic areas, depending on the kind of businesses and freight hubs situated there. For policy makers who want to introduce measures to promote greener and/or more efficient freight transport in urban areas, having an insight into today's freight transport activities in the relevant areas is important. For instance, in a *hypothetical* scenario where the local authority wants to introduce a vehicle-free zone in the CBD-district of Bergen, there would be a need for establishing loading/unloading zones nearby to facilitate the delivery and pickup of goods in the district. GPS data can be a useful source of information when deciding where such zones should be located, as well as for capacity dimensioning (based on dwell times and number of stops per hour for different classes of vehicles). In Fig. 8, we map freight vehicle activities for all trips that included a delivery/pickup in the CBD-area, to analyse where else these vehicles performed activities in the inner city. Panel A shows all the delivery/pickup observations for these trips, while Panel B shows all GPS observations for these trips as a heat map, where the red colour signifies the highest activity densities.

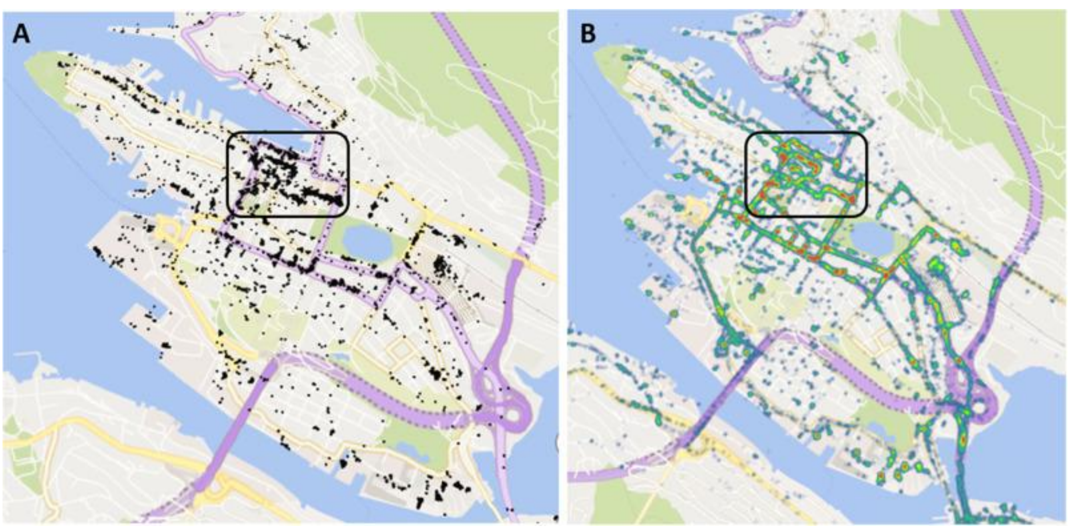

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Fig. 8. A) Delivery/pickup observations for trips to the Bergen CBD; B) Heat map of GPS observations for trips to the Bergen CBD. (Google Maps, 2020).

The figure shows that trips with deliveries/pickups in the CBD-area also had deliveries/pickups elsewhere in the inner city, but considerable fewer in the Dokken/Jekteviken port area as compared with the whole set of observations plotted in Fig. 7. The heat map shows that much of the vehicle movements related to deliveries/pickups in this area can be narrowed down to quite a limited part of the inner city. Furthermore, the heat map also shows that the main corridor for trips to the CBD is in the south-eastern direction, suggesting that loading/unloading zones should be located in areas with good access to this corridor in order to minimize traffic in the inner city area.

5. Conclusions and discussion

Insights into freight vehicle movements and activities in urban areas are necessary for local authorities if they are to develop effective measures towards sustainable future city logistics. Several studies have been conducted to better understand the structure of urban logistics, and data they are based on can roughly be divided into GPS data and other forms of sample surveys, such as trip generation and/or dwell time models. For the purpose of city logistics, GPS data provide a suitable source, making it possible to study vehicle movements and activities at a more detailed level with respect to geography and time, than is possible through e.g. traffic count data, basic data from sample surveys (such as the Eurostat road freight transport survey carried out in all EU/EEC member states), or other official statistics on freight transport.

Building on mostly established methodology introduced by Gingerich et al. (2016) and Laranjeiro et al. (2019), for converting raw streams of GPS data into trips, stops and deliveries/pickups for HGVs in general, we developed adaptations with improved suitability for urban logistics in particular. To deal with challenges of GPS positioning inaccuracy and at the same time consider the possibility that subsequent deliveries can take place within short distances in urban areas, our methodology downscales the distance buffers introduced in above studies, from the first to the last stopping point observation, from 200 to 250 to 50 m. We also found that vehicle type can be used as a determinant when identifying and separating primary stops from secondary stops: Since vans spend considerably less time per delivery/pickup point than HGVs, all stops over 2 min by vans are categorized as deliveries/pickups, while for HGVs, this threshold is set to 5 min.

However, it is important to be aware that reducing distance buffers and time threshold values also introduces a risk of erronegously identifying rearrangement driving at terminals or some secondary stops, as deliveries/pickups (e.g. traffic jams or service stops where vehicles stand still for >2/5 min). It is therefore important to distinguish between areas where transport is mainly linked to distribution without trailer, as is usually the case for city distribution, and to a lesser extent deliveries at terminals or larger warehouses. In order to further develop our extended methodology, one could consider utilising land use data, even though this could also entail new challenges. Since some loading and unloading takes place along the road network, and because some terminals can also be located close to city centres, it will be difficult to eliminate errors completely without including more information. For urban logistics, further challenges include identifying and distinguishing between stops and deliveries when delivery addresses are close together and where walking distances between parking locations and goods deliveries can be significant, in particular for deliveries by vans (i.e. often parcels and other small shipments).

Results from our study and our sample of vehicles, and for the seven largest Norwegian cities, show a median dwell time for HGVs of 14 min in inner-city areas and 16 min in outer city areas, while vans have considerably shorter dwell times, with a median stop time of 5.8 min in inner city areas and 7.5 min in outer city areas. These results are in line both with earlier international results (e.g. Cherrett et al., 2012; Holguín-Veras et al., 2021), and also results from dwell time models presented by Kim et al. (2021), with shorter average dwell times for deliveries of documents (14 min) than oversized supplies deliveries (21 min).

This indicates that GPS data and the method applied may serve as a potential source of information on freight vehicle delivery/pickup times in urban logistics and for understanding transport patterns in these areas. Trip characteristics based on GPS data provide information on how freight transport is performed in different areas, and therefore highlight activities that must be replaced or performed differently to achieve the objective of emission-free city logistics.

Analysis based on our samle of vehicles and for trips that include deliveries/pickups in inner cities shows that the median time vehicles spend in these areas is just below one hour, of which the stopping time is 35 min and the driving time is 22 min. These values are almost the same for HGVs and vans, but the latter spend some more time dwelling and have twice as many deliveries/pickups stops per trip than the larger vehicles. This is not surprising considering the frequent use of vans in city logistics, and differences in the types of deliveries (more often small shipments like parcels and documents for vans, vs. pallets and large units for HGVs).

Median values are influenced by numerous factors, and for thorough insights into urban logistics, it is necessary to study each city in more detail. For instance, an investigation of all stop observations in the inner city of Bergen showed that dwell times and activities can differ within small geographic areas, depending on the kind of businesses and freight facilities situated there. In a hypothetical scenario where local authorities want to introduce a vehicle-free zone in the CBD district of Bergen, information on freight vehicle movements from GPS data could support the local authority's decision-making when planning for loading/unloading zones, because the data can provide up-to-date information on vehicle activities in the local area.

Even though this study is based on a relatively large sample of commercial vehicles, the results will most likely not be representative for the true population because of sample bias. This is a challenge that most studies of this type suffer from, and is a result of private ownership of data. Studies like the current one are dependent on cooperation with private enterprises to access data. To correct for sample biases, sampled vehicles must be linked to the national vehicle register. However, as most new HGVs include an on-board factory-fitted API with GPS capability, there is a vast future potential of such data. This article is a step on the way in developing methods for using GPS data as a basis for analyzes of the use of HGVs and vans in city logistics. Further development of methods to transform GPS data into information on freight activities and vehicle movements in urban areas would be useful. This also includes the exploration of different collaboration agreements between public and private entities to make such data available.

Author contributions (credit author statement)

Conceptualization, C.S.M. and I·B·H; Methodology, C.S.M. and I·B.H. Validation, C.S.M. and I.B.H.; Formal analysis, C.S.M. and I.B.H.; Investigation, I.B.H.; and C.S.M.; Data curation, C.S.M. and I.B.H.; Writing – original draft, C.S.M. and I.B.H.; Writing – Review & editing, I.B.H.; Visualization, C.S.M. and I.B.H.; Supervision, I.B.H.; Project administration, I.B.H.; Funding acquisition, I.B.H.

Acknowledgements

This work was performed within LIMCO, a knowledge-building project for industry (KPN), co-sponsored by The Research Council of Norway (grant number 283333) and the Norwegian Public Road Administration and 12 partners from research, industry, and public sector. We are grateful to the carriers who made their data available for analysis.

Annex

Table A1 shows the distribution of delivery/pickup stops by vehicle type for the different urban areas.

Table A1. Number of deliveries/pickups in urban areas for HGVs and vans (thousands).

	In total			**Inner city area**			**Outer city area**		
	In total	**HGVs**	**Vans**	**In total**	**HGVs**	**Vans**	**In total**	**HGVs**	**Vans**
Oslo	240.7	227.1	13.6	200.2	189.9	10.2	40.6	37.2	3.4
Bergen	48.1	32.1	16.0	34.2	25.0	9.2	13.9	7.1	6.8
Trondheim	91.4	33.4	58.0	63.2	25.1	38.1	28.2	8.3	19.9
Stavanger	34.5	19.0	15.5	26.7	16.1	10.5	7.8	2.9	4.9
Kristiansand	44.9	23.8	21.1	35.6	20.4	15.2	9.3	3.4	5.8
Drammen	17.5	16.9	0.6	13.0	12.7	0.3	4.5	4.3	0.2
Tromsø	36.0	29.7	6.3	5.4	4.9	0.6	30.6	24.8	5.8
In total	**513.2**	**382.1**	**131.1**	**378.3**	**294.1**	**84.2**	**134.9**	**88.0**	**46.9**

Data availability

The data that has been used is confidential.

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