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Use of GPS-data to improve transport solutions in a cost and environmental perspective

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ABSTRACT

In this paper we have utilised GPS data as a base to track truck movements and analyse transport activities. Combined with a Decision Support Tool we have investigated how different transport solutions affect the transport cost and CO_2 emissions. The information gained from GPS-data helps firms such as a fruit and vegetables wholesaler to gain better insights into their transport solution and operations from a cost and environmental perspective. This also means that the current analysis remains useful for the transporting company in making strategic decisions as to when and where they should engage in other transport assignments to improve the load factors on their trucks.

This paper presents that the picture the decision-makers had prior to GPS data being used was different from the real situation, and the insights gained lead to new knowledge and actions. As a result, this would contribute to greener and more cost-efficient solutions.

Background

The transport costs and CO_2 emissions are directly affected by the efficiency of the given transport arrangement and are some of the largest controllable costs in the supply chain (Bergmann et al., 1998). A traditional view of transportation cost is that it is mostly a cost burden, and common practice in terms of cost estimation is often vague and experience-based with few calculations at the root of the estimation (Bø and Baxter, 2016). CO_2 emissions from road transportation are a direct result of diesel consumption, and reducing emissions is typically a part of any effective transport solution. In this paper we have analysed the cost and emission trade-offs caused by return loads in backloading by using the example of a leading fruit and vegetable wholesaling company. Such returns result in additional distance and time, and the service offered due to time windows, frequencies and order sizes has a huge impact on the transportation cost. The result is that the criteria for reducing costs on the return trip are different from to the criteria for reducing CO_2 emissions. You need more pallets on the return trip to be cost effective as compared to how many pallets you need to be more environmentally friendly. This paper presents a detailed analysis of the impact on transportation costs and CO_2 emissions of return loads and customer service.

In this paper we have utilised Global Positioning System (GPS) data as a base to track truck movements and analyse transport activities such as stop times, loading and unloading times, driving distances and speed. Through this we have investigated the consequences of how different transport solutions affect the transport cost and CO_2 emissions based on information from the GPS data. The result is different from the picture the decision-makers had prior to GPS data being used, and the insights gained are valuable as they lead to new knowledge and changes in the transport system. Further, we have developed a decision support tool (DST) model to calculate the transport cost and CO_2 emissions from transport in a more exact way based on this new information. Looking to the future, the new information in this paper will enable the optimization of the transport plan. The vehicle velocity and CO_2 emissions are dependent on traffic flows and density, and there exists several models to calculate the effect of this. (Smirnova et al., 2020; Zhang et al., 2018) . In our paper we analyse observed velocity and CO_2 emissions based on reported data from the vehicles. Traffic flows will influence on the data reported and then be included in the calculations.

The Research question is; (See Fig. 1).

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How can the use of GPS-data give a better insight into the transport solution from a cost and environmental perspective?

This paper opens with a review of the relevant literature, the research methodology and an analysis of the transport system of a Norwegian fruit and vegetable wholesaler company. The paper concludes with an analysis of how backloading, order sizes and loading times affect costs and provides a guideline as to how to organize transport more efficiently in the future.

Literature review and theoretical background

Customer service refers to the ability to meet customers' requirements and expectations in terms of time, flexibility, frequency and time windows. High customer service has a huge impact on transportation cost and the environmental footprint (Holter et al., 2008). Increased competition in the market has led to increased customer service, and the questions are whether this service is necessary and how it affects transportation cost and CO_2 emissions (He et al., 2019). The goal is to achieve the right level of customer satisfaction at the lowest possible cost and with the lowest environmental impact.

This paper analyses how a transparent perspective, through a newly developed DST model with real time information from GPS-data, can contribute to a better understanding of the cost structure and environmental effects caused by different services. There is existing research based on transport calculations and the development of DTS models such as (Bø and Hammervoll, 2010; Bø and Baxter, 2016). Bø and Hammervoll developed a DST model to calculate the right transport price for a food wholesaling company and Bø and Baxter used a similar model to calculate the transport cost of collecting WEEE (Waste from Electrical and Electronic Equipment). In both studies, they based all the time processes in the arrangement on random field observation studies. The time processes have a huge impact on the transport cost, and this method is not exact. Despite it being both time consuming and costly to observe the time processes, which must be measured continuously, the values produced are nonetheless uncertain. By using real time information from the GPS system, is it possible to obtain far more accurate results (Ta et al., 2016).

Customer service elements such as delivery time, time windows and delivery frequency have a huge impact on the transport productivity (Dolya and Galkin, 2013; Lin and Tsai, 2014)). For truck transport, the frequency can be calculated by reference to the order size and the load size on the return trip. In some systems, companies have rules as to the minimum order size and minimum load to pick up. The key way to reduce the transport cost is by increasing the truck load factor on the main trips, however this tends to be more difficult to achieve when providing a high level of customer service (Santén, 2017). Another important factor is increasing the load factor on the return trips, also known as backloading (Santén, 2017). A third important element of reducing the transport cost is to utilize the trucks as much as possible during the year and in this way reducing the amount of time during which the trucks are non-productive. In sum, there are three key elements that can increase transport productivity and reduce costs;

1 Increase the truck load factor on the main trip
2 Increase the truck load factor on the return trip (backloading)
3 Increased utilization of the trucks during the year

Increased load factor leads to reduced ton cost according to the following formula;

$$\left(\frac{FixedCost}{Hour}+\frac{Wage}{Hour}\right)*Timeused+Distance*\frac{Variablecost}{KM}=Trip\ price$$

$$\frac{Tripprice}{Maximumload*Loadfactor}=Tonprice$$

Increased transport productivity also leads to reduced CO_2 emissions due to less fuel usage per transported ton of goods (Sun et al., 2019).

In order to understand the effects of the three elements of productivity, a transparent transport calculation model, a DST-model, is necessary. There are two reasons to use a DST model; (1) to calculate the cost and compare the cost with the price and (2) to analyse the transport arrangement and find ways to increase productivity. One hypothesis is that increased transparency leads to increased productivity (Bø and Baxter, 2020). In transport negotiations, the focus is predominantly on the final price, such as price per ton or price per trip. This is sort of a "blind" operation which lacks the understanding of costs. By using a transparent cost picture, the factors affecting costs become more apparent and one can more easily consider different solutions from a cost perspective (Hoyt and Huq, 2000).

In addition, simulations and sensitivity analysis can be used to see the effects of different transport arrangements and to analyse the effects of different levels of customer services. The total cost increases with increased time and distance, but the cost per ton decreases when the load factor increases. While it is true that the greater the total amount of goods, the greater the productivity and the lower the ton cost, delivering or picking up small amounts of goods can be very costly. Thus, at some point the cost becomes greater than the earnings.

With respect to increasing the load factor on the return trip by making additional pickups, the pickup may be along the existing route of the return trip or it may be necessary to drive an additional distance to pick up the goods. Realistically, it will usually be necessary to drive an additional distance. The question then becomes how much extra distance is acceptable when considering the cost trade-off between the extra distance and the increased load factor. Another question relates to the volume on the return trip. There is always a fixed stop time

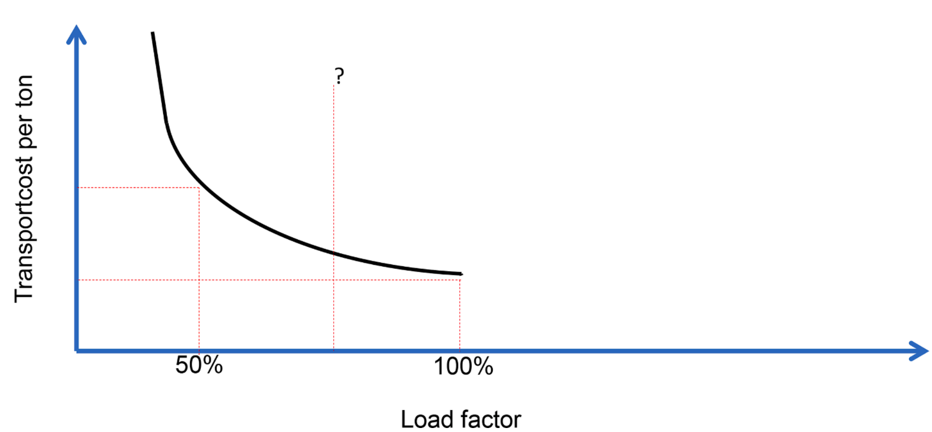

Fig. 1. How ton price is influenced by the load factor.

connected to each stop, and this means that the lower the volume is, the higher the cost is per item picked up. Again, we face a trade-off between increased load factor, extra distance and load picked up. By using GPS-data it is possible to track the real extra distances and stop times in order to optimize transport costs. Instead of having to rely on rules of thumb to estimate the minimum load to pick up, it becomes possible to calculate the necessary minimum pick up load based on exact additional costs. Considering also environmental effects, another question relates to the ways in which fuel use and CO_2 are affected by the extra distance and time, and if the cost trade-off is similar to the CO_2 trade off?

While GPS is far from a new technology and has its roots in the 1960s, it continues to evolve and find new uses (Theiss et al., 2005). The possible benefits of GPS for land transportation have been a topic for much previous research (Mintsis et al., 2004) including how GPS technology may contribute to improved information for transport operations. Popovic and Habjan found that the use of GPS as a source of more information improved transport service planning, vehicle routing and transport control, resulting in improved customer service, better vehicle utilization, reduced transport costs and time, among other things (Popovic and Habjan, 2012).

The current study expands existing literature by demonstrating how GPS data from trucks might help firms improve their transport operations. This is done using an empirical real world case study translating data into implications for cost, time use, distances, fuel consumption and CO_2 emissions. In turn, the insights gathered can be used to steer transport companies' and transport buyers' decision-making towards greener and more cost-efficient solutions.

The case study

The case used in this article is Norway's largest fruit and vegetable wholesale company and is a supplier to approx. 2/3 of Norwegian grocery stores. Further, 2/3 of all their fruits and vegetables are imported and the rest is purchased from Norwegian suppliers. The company has a central warehouse in the capital city, Oslo, and most of the fruits and vegetables are transported to this warehouse for further distribution to local warehouses, both those owned by the company and those owned by the food retailers themselves. 220 000 tons are distributed from the Oslo central warehouse and 70 000 tons are transported in from the Norwegian suppliers on a yearly basis. The majority of the transport is outsourced to a transport provider, partly owned by the case company. Their outgoing transport from the central warehouse is strictly regulated by delivery times and time windows set using timetables. They transport pre-packaged fruits and vegetables on their main trip to the warehouses, normally in full-loads, and try to pick up as much as possible on their returns from local producers (fruit and vegetable farmers and packaging departments).

In this work we have focused on the company's distribution and return trip activities in the South-eastern part of Norway. Fig. 2 shows the locations of the central warehouse (black), the regional warehouses (blue) and the producers (green). There are daily routes with scheduled departure times from the central warehouse to five of the regional warehouses. The figure shows the route destinations from A-E.

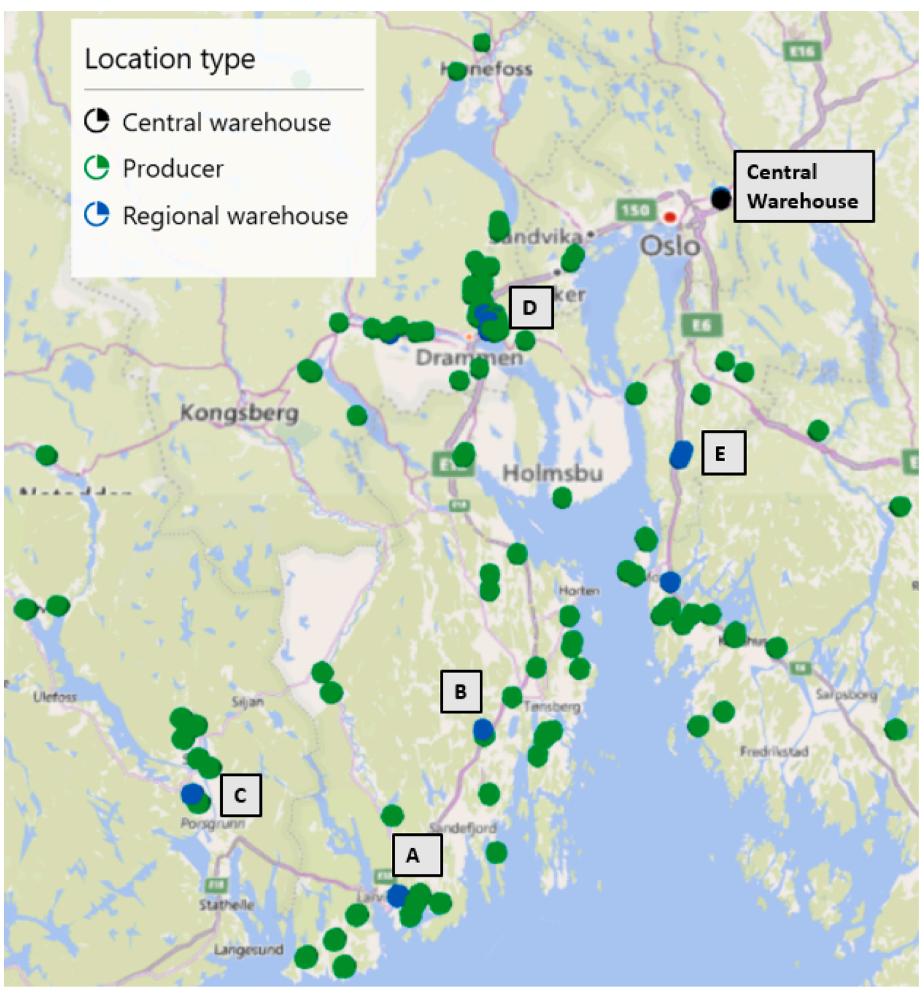

Fig. 2. Locations and route destinations for the company's distribution in the South-eastern part of Norway.

Data and methodology

In this paper we utilise data from trucks' fleet management systems (FMS) to obtain insights into the cost drivers of transport solutions, as influenced by different levels of customer service. Based on this information we have developed a decision support tool, a DST model, to calculate the transport costs, fuel consumption and CO_2 emissions more accurately. The data is based on a single case study.

Using GPS-data to map freight vehicle movements and measure loading/unloading stop times

Data collection

Through cooperation with private firms in the LIMCO project we have been able to track a vast number of trucks, receiving information on vehicle movements, fuel consumption, driving distances, as well as different driving behavioural parameters. We can gain such information from virtually all trucks produced after 2013 because the leading European truck manufacturers (such as MAN, Volvo, Scania and Mercedes) all equip their trucks with the necessary hardware and software to enable such data gathering. However, in order to realize this data potential, the truck owner must usually subscribe for specific data packages that provide data with a sufficient level of detail, as well as software that enables data analysis. This software usually offers reports of driving distances, fuel consumption and driving behavioural parameters for the trucks, but lacks information on vehicle movement patterns and operations such as loading/unloading activities, which is crucial for understanding the cost drivers of transport. Hence, to analyse this information we have converted raw truck GPS-data to give information about trips, driving activities, loading/unloading operations, route choices etc.

Data processing and cleaning

The process of linking the GPS position data together, calculating time intervals and determining whether the vehicle is in movement or has come to a stop is rather straightforward and follows the suggested methodology from the existing literature (Flaskou et al., 2015; Laranjeiro et al., 2019; Thakur et al., 2015; Yang et al., 2014) . The distance between GPS observations is estimated using the Haversine formula which calculates the distance (d) between two coordinates on the surface of the earth:

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

where Φ represents latitude coordinates, λ represents longitude coordinates, and r is the radius of the earth (≈6 371 km) (Chopde and Nichat, 2013).

The calculated speed is then a function of time and distance between each GPS observation. The actual vehicle distance and speed will be underestimated whenever the vehicle does not move in a straight line between two GPS observations. This problem will decrease with increased frequency between GPS observations, and is not relevant when measuring loading/unloading stop times. To make the aggregated driving distances more precise, we have added a flat 7.5 per cent to the calculated trip distances, a factor decided upon after comparing GPS calculations with precise road map distances on the relevant routes.

Some data cleaning was necessary to avoid errors in the raw data influencing the analysis. This included the removal of observations where the time stamp was identical to the previous observation, making it impossible to calculate the speed between them. For other observations the GPS-data was clearly wrong, for instance in cases where a vehicle moves across a great distance in an implausibly short period of time. To exclude such observations, we introduced a speed limitation of 110 km/h which corresponds to the maximum allowed speed on the Norwegian highways. Thus, observations with a higher speed were excluded from the calculations.

Identify loading/unlading activities

The calculated speed between GPS observations is used to identify truck stops and to measure loading/unloading times. A threshold value of maximum 8 km/h is used to identify the first stop observation. The cumulative time for all following GPS observations below this threshold is then calculated to estimate the total stop time. Following the method of (Gingerich et al., 2016) we are able to avoid breaks in the calculated total stop time due to GPS inaccuracy or vehicle positioning on the loading/unloading site. This is done by accumulating the total stop time during the time in which the vehicle is situated inside a 250-metre radius from the first stop observation.

For stops with a duration of less than ten minutes, the stop time is defined as part of the driving activity. For stops with a duration between ten minutes and two hours the GPS location of the stop is matched against a dataset of the company's locations for identification. Unmatched stops in this time interval are classified as "other stops" and will include service stops (for instance at petrol stations or resting/parking areas) and stops related to transport assignments for other customers.

Trip generation and route assignment

A new trip is generated whenever the vehicle arrives at one of the shipping company's warehouses, or whenever there is an observed stop with a duration of 2 h or more at another location. The trips are then assigned to routes based on a matching of the observed stop locations and the 5 route destinations as outlined in Fig. 2. The trips are separated into main trips from the central warehouse to regional warehouses and return trips back to the warehouse, including potential backloading. In addition, our definition of "trip" has resulted in a number of trips with other origins and/or destinations than the routes between the central warehouse and regional warehouses. Examples of this include trips where the vehicle is repositioning for overnight parking or doing a single pickup from a producer for delivery to a regional warehouse. While these trips have been identified, and also play a role in the total transport activity, they are not part of the further analysis presented in this paper which is limited to the main trips and the return trips on the 5 routes.

We collected a total of 3.4 million GPS observations for the company's vehicles during 2019. By using the method described above, we were able to extract nearly 5 000 trips with over 16 000 unloading/loading stops on the five routes of interest. 70% of these stops were identified as stops at the company's own locations, either warehouses or producers, and these are marked as the company's unloading/loading stops in Table 1. Stops that were not identified as at the company's locations are marked as "other stops", and these include service stops and stops related to other transport assignments.

Decision support tool

To develop a DST model, you need all the costs related to the truck itself and all the time processes related to the driver's salary cost. These calculations are complex and consist of several stages. The company and their service provider had to collect all the necessary cost data for the

Table 1
Sample of routes, trips and stops generated by GPS-data.

Route	Trips	Unloading/loading stops		
		In total	The company	Other stops
A	1 756	6 020	4 008	2 012
B	223	901	601	300
C	629	3 197	2 165	1 032
D	410	1 162	853	309
E	1 953	5 352	4 102	1 250
In total	4 971	16 632	11 729	4 903

calculation, such as investments in equipment, insurance, administration, fuel and MRO[1] and salary cost per hour. These costs are divided into three groups: fixed costs and distance independent costs, variable and distance dependent costs and salary costs. The first group is the fixed costs, such as depreciation, interest rate, administration, insurance and taxes, and these can be affected by the third element of productivity. The second group is the variable costs; diesel, maintenance, tires. Finally, the third group is the truck drivers' salary. Prior to the start of this project, the company used to estimate the time processes. However, the GPS system has now enabled them to obtain real time data with the exact distances and stop times. A trip price and a ton or unit price can be calculated by combining the three costs discussed above. Elements one and two of transport productivity are essential here.

CO_2 emissions are calculated based on diesel consumption and one litre of diesel equals 2,66[2] kilo CO_2. Total fuel consumption is calculated based on the driving distance and the measured average diesel consumption per km for the vehicle in operation, from the FMS data. In order to take the load weight into account when calculating diesel consumption, we have studied FMS fuel usage data. Table 2 shows the average, median and percentiles for the average fuel usage per day for the relevant the company's vehicles.

The vehicles have an almost identical fuel consumption, so the observed differences are mainly due to different average daily load weights. Based on this we estimate the diesel consumption to be 0,25 L per km when the vehicle is empty running without pallets and then an addition of 0,09 L per km for each additional pallet loaded, resulting in a diesel computation of 0,55 L per km when the vehicle is fully loaded (34 pallets). Fuel consumption during loading/unloading is also based on data from the FMS. The vehicles are set to be idle 24 % of the loading/unloading time and the fuel usage is set to 2,9 L per hour of idling.

Transport analyses based on GPS-data

Cost elements of backloading

Economies of scale are of course a part of the transport economy. Small volumes are typically more expensive to collect per ton as compared to large volumes. While the company's daily routes are planned with full loads from the central warehouse to the regional warehouses, the potential for backloading differs between the routes. For instance, while there are a lot of producers along the way on the return trip on routes A and B, on route E trucks would have to drive further south in order to reach many of the producers before returning to the central warehouse. Due to strict time restrictions, it is a challenge to manage both deliveries and pickups on the same trip. Fig. 3 shows the distribution of the number of pallets per pickup on return trips for the company's vehicles.

Table 2
Distribution of average fuel usage per day. Mean, median and percentiles (l/km).

Stat. measure	Fuel usage (l/km)
Mean	0,39
P10	0,30
P25	0,33
Median	0,38
P75	0,44
P90	0,50

.The distribution implies that the company offers a high degree of service, often collecting small numbers of pallets from the producers. The average number of pallets per pickup is eight. As a general rule, the company has set a minimum pick up number of four pallets from the producers and even pays the transport company for five pallets per stop despite the lower quantities. Nevertheless, in practice several pickups include fewer pallets. Order data from 2019 shows that 27% of the pickups were for less than four pallets and in total 36% of pickups were for less than five pallets. Surprisingly, a rather large number of pickups consisted of only 1 or 2 pallets. Based on this information the company pays for 52% more pallets than they actually pick up due to the minimum pick up size. However, if the producer actually delivers the number of pallets stated in the agreement, they could reduce the number of pickups by 15%.

There is a cost to this high level of service. To investigate how the number of pallets loaded, loading time and driving distances affect the costs of backloading we have analysed truck stop times at the producers' locations based on the GPS-data. The loading time is dependent on a variety factors, the most important being the number of pallets loaded, as well as how efficiently the loading process is performed at the locations. Typically, the loading time per pallet decreases when the number of pallets increases because the stop time includes a fixed time that occurs independently of the number of pallets that have to be picked up. Examples are the positioning of the vehicle, load preparations, communication between the driver and the farmer, signing of papers etc. The average total stop time (fixed stop time and loading time) across all observations at the producers' locations was estimated to be 35 min with a standard deviation of 20 min. The distribution includes a long tail with stop time observations between one and two hours. This could be the result of cases where the observation of the loading includes other activities, such as the driver taking a break or doing time-consuming administrative duties that are performed at the site. Hence, the median value across all stop observations was lower at 30 min for the 2019 dataset. Fig. 4 shows the distribution in time intervals of ten minutes.

To get an insight into how the total stop time is dependent on the fixed stop time and the number of pallets loaded we have studied average stop times and average numbers of pallets loaded per order for the different producers. Fig. 5 shows the results of a simple linear regression of the average stop time as a dependent of the average number of pallets.

The R^2 shows that the model explains 50% of the variation in the data. A significant regression equation was found ($F(1,49) = 49{,}7$, $p < 0{,}000$). The coefficients are strongly significant, and the equation gives the following relationship between the stop time and the number of pallets loaded:

$$\text{Stop time (min)} = 21{,}1 + 1{,}16 * (\text{number of pallets loaded})$$

This gives an estimate of the fixed stop time of 21 min and then an additional 1,16 min per pallet loaded.

In addition to the stop time at the producers' location, another cost component is the additional driving time and distance to and from the pickup location. This is dependent on which route the vehicle is driving on the main trip, and how far the producer locations are situated from the specific route. By using the DST model, we have calculated how the different cost elements affect the cost per pallet transported. As a result, Fig. 6 shows the relationship between cost per pallet and the extra driving distance to collect goods for backloading. The graph lines show this relationship for the different number of pallets per pick up from 1 to 5.

Fig. 7 shows that the cost per pallet transported is considerably higher for pickups with only one pallet, ranging from 200 to 1100 NOK per pallet depending on the detour the truck has to take to collect the pallet. The cost per pallet is strongly reduced when there is an increased

[1] Maintenance, repair and operations.
[2] Based on Nederlandse norm (2012). NEN-EN 16258. Methodology for calculation and declaration of energy consumption and GHG emissions of transport services (freight and passengers).

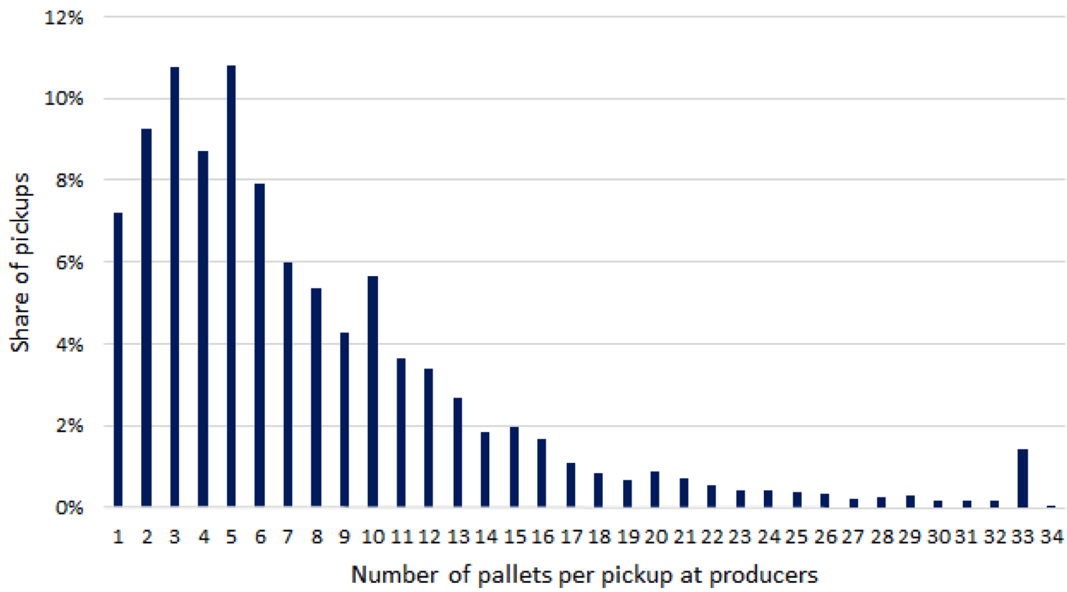

Fig. 3. Number of pallets per pick up on return trips.

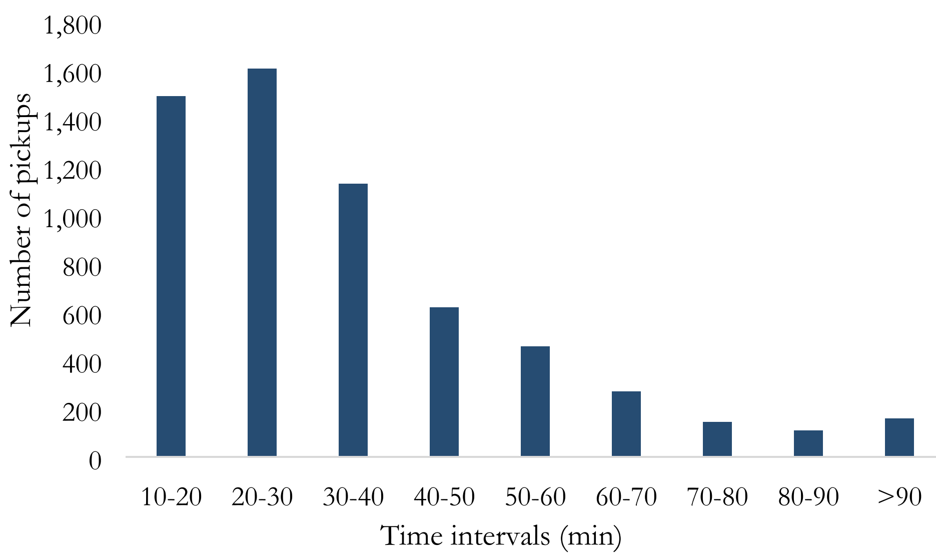

Fig. 4. Distribution of pick-up times intervals at the company's producers. 2019.

number of pallets per pickup. If the pickup includes 5 pallets the cost per pallet ranges from around 50 to 200 NOK depending on the extra distance required to collect the goods.

How unloading time at two warehouses affects the transport cost

By utilising the GPS-data the effect of stop time at two of the company's largest regional warehouses has been analysed. Both warehouses are situated in Vestby (the destination of route E). Based on observations from 2019 the average volume per delivery to Warehouse A was 14,1 pallets and to Warehouse B 12,5. The average time per delivery was 49 min for Warehouse A and 29 for Warehouse B; which equals 3,5 and 2,3 min per pallet, respectively. The difference in the stop time of 1,2 min per pallet amounts to 560 h per year of possible time saved if Warehouse A was as efficient in the unloading process as Warehouse B. The root cause of the difference in efficiency was identified as different operational routines, and this is an issue that is possible to solve. The potential cost reductions were estimated to be 280 000 NOK per year. In addition, by reducing the unloading time it may also be possible to reduce the number of trucks in operation, which may increase the cost benefits of a more efficient operation. Identifying bottlenecks such as Warehouse A and calculating the exact cost of the situation has proven valuable for the company's operational planning and their work on continuously improving their transport operations.

How backloading affects total transport cost and CO_2 emissions

Backloading affects the total transport costs and CO_2 emissions. However, whether a given transport solution is the most cost efficient and environmentally friendly alternative depends on the additional time and distances that are included in the processes, as well as the volumes that need to be picked up.

Table 3 shows the number of stops, distances and time spent on the return trips back to the central warehouse for the company's five routes

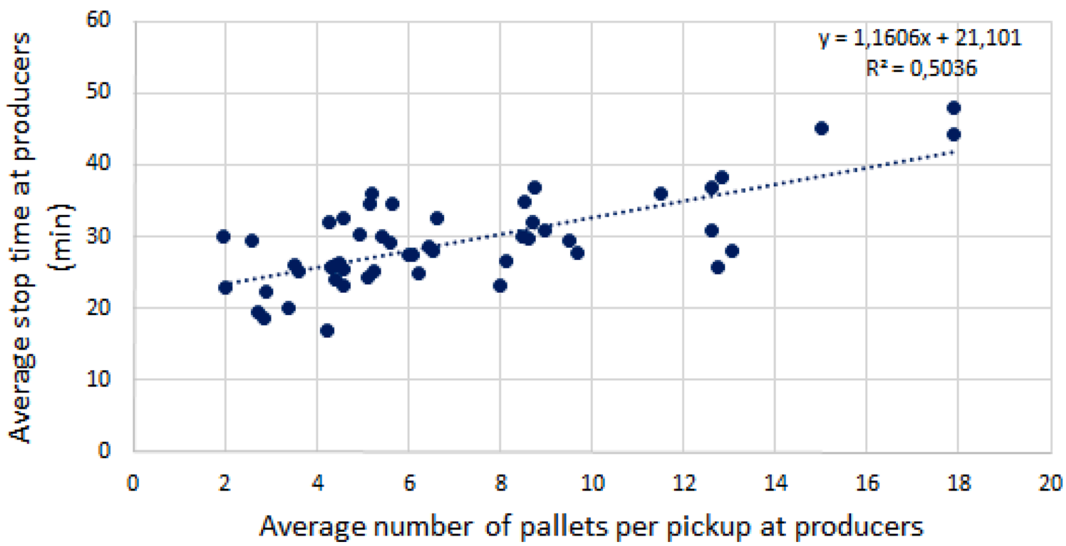

Fig. 5. Interrelation between average time stop time and number of pallets per pickup.

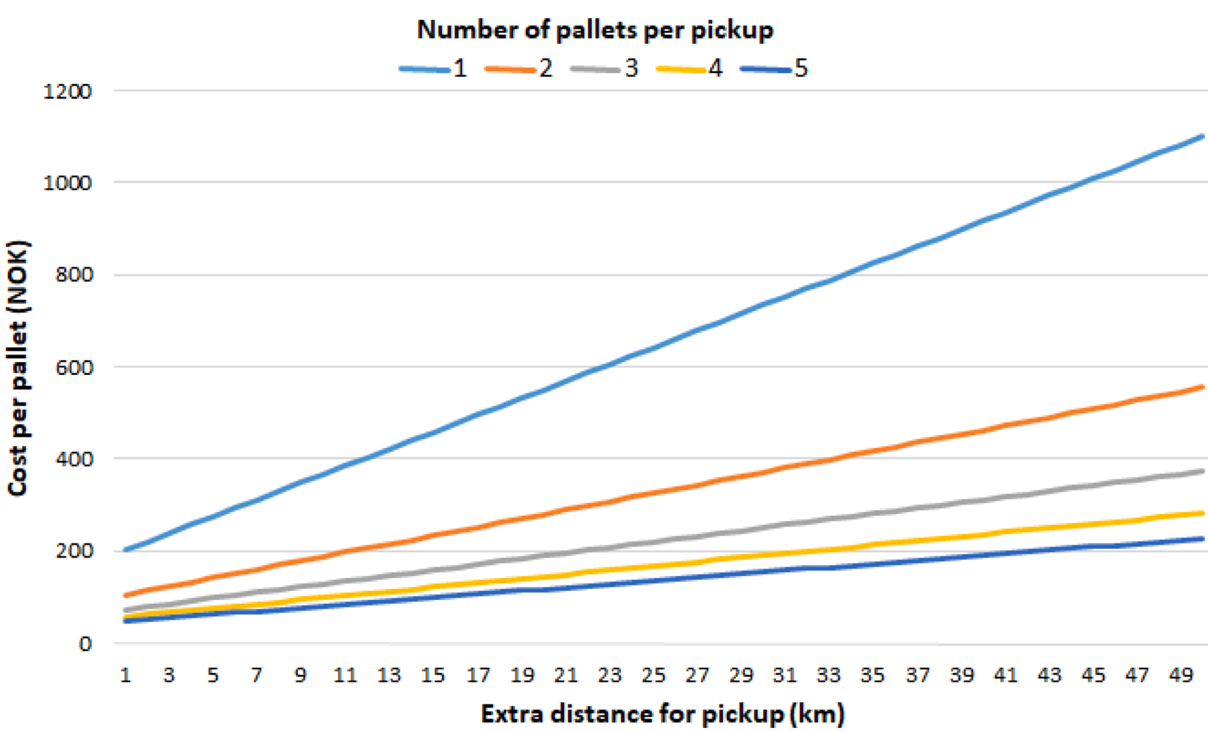

Fig. 6. The cost effect of increased load and distance per pickup on return trips (1 NOK ≅ 0,1 Euro).

based on the 2019 GPS-data. These results have been compared to a typical trip without backloading where the vehicles return directly to the central warehouse after the distribution route. This gives us estimates as to how much additional driving time and distance is required during the backloading processes. The number of pallets per pickup on the routes is estimated based on the order data, where the average number of pallets picked up from the different producers is calculated and then assigned to the routes based on their location. The estimated vehicle load rate is then a function of the number of stops for pickups per trip from the GPS data and the average number of pallets picked up at the relevant locations from the order data.

Table 4 shows that even though the distances and time spent on return trips along the different routes vary a lot, the additional distance and time per stop are more comparable between routes. The additional distance per stop for pickups varies between 19 and 28 km for the different routes, while the extra driving time per stop varies between 22 and 31 min. The available return volumes differ between the routes. Trucks on route B stop at an average of 3,4 different locations on the return and pick up almost 10 pallets on each of these stops, resulting in a near 100 percent estimated load rate on the return for this route. On the other hand, on route E trucks perform fewer stops and there are less goods to be picked up, resulting in an estimated load rate of 41% for trucks on this route. According to the timetable, the number of trips per year differs considerably between the routes. Route E has over 40% of the total number of trips per year and therefore has a negative influence on the total load rate for the area which is calculated to be just below 60% based on the sample of GPS generated trips. This weighted total return load rate for the 5 routes is in line with the company's own

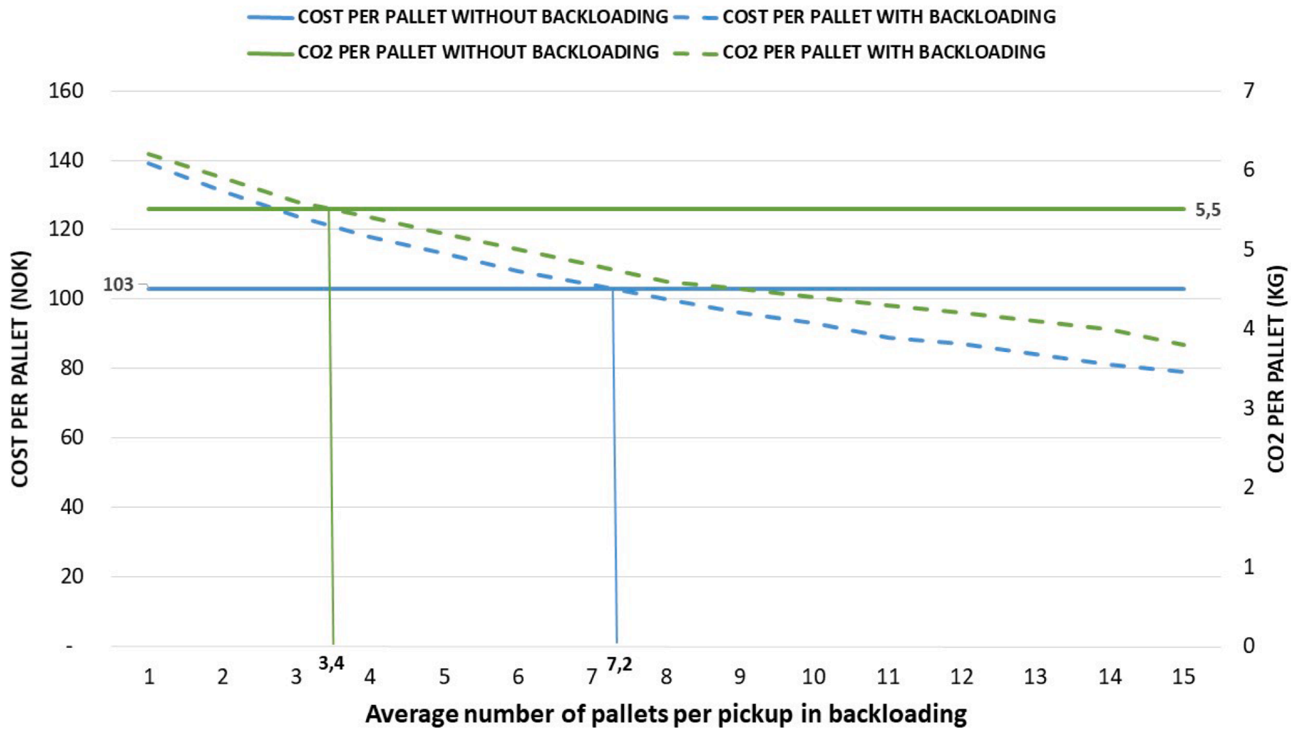

Fig. 7. Breaking point for cost and CO_2 depending on the number of pallets per pickup in the company's backloading.

Table 3
An overview of distances and time on return trips, with and without backloading.

	Return trip without backloading		Return trip with backloading							
Route	Distance (km)	Driving time (h)	Distance (km)	Driving time (h)	# of stops	Add. distance per stop (km)	Add. driving time per stop (min)	Pallets per pickup	Stop time per pickup (min)	Estimated load rate on return trip
A	147	2,0	191	3,0	2,3	19,1	24,3	9,5	33	65 %
B	119	1,7	200	3,2	3,4	24,0	27,3	9,9	37	99 %
C	167	2,5	256	4,2	3,2	27,6	31,2	9,4	34	89 %
D	48	0,8	88	1,6	2,0	20,1	24,4	10,0	38	59 %
E	45	0,8	90	1,6	2,2	20,6	21,9	6,3	26	41 %

Table 4
Round trip cost and CO_2 emissions in total and per pallet for each route with and without backloading.

Route	Round trip cost and CO_2 emissions without backloading				Round trip cost and CO_2 emissions with backloading			
	Trip cost (NOK)	Cost per pallet (NOK)	Trip CO_2 emissions (KG)	CO_2 per pallet (KG)	Trip cost (NOK)	Cost per pallet (NOK)	Trip CO_2 emissions (KG)	CO_2 per pallet (KG)
A	5 039	148	314	9,2	7 436	132	375	6,7
B	4 140	122	254	7,5	7 676	114	379	5,6
C	6 034	177	358	10,5	9 569	149	503	7,8
D	2 376	70	103	3,0	4 334	80	145	2,7
E	2 375	70	99	2,9	4 137	87	139	2,9

estimates for the area, suggesting that the sample and method based on GPS and order data gives a good estimation of the backloading process.

The estimation of cost driver values in the company's transportation system is a valuable input to the decision support tool and gives decision-makers an empirical base.

We have studied the costs and CO_2 emissions of the five routes, both with and without backloading, in order to decide which alternative is the most cost efficient and environmentally friendly.

When comparing the cost per pallet for the round trip for the two alternatives we have arrived at different conclusions for the different routes. For routes A, B and C the cost per pallet is the lowest when the trucks backload. For routes D and E, the cost per pallet is the lowest when the trucks do not backload, indicating that the trucks should return directly to the central warehouse. The results for CO_2 emissions are different. With respect to CO_2 -reductions, none of the routes would benefit from not backloading, although it should be noted that for route E the CO_2 emission per pallet is equal for the two alternatives.

Fig. 6 shows the breaking points for cost and CO_2 depending on the average number of pallets per pickup in the backloading. The average estimated values for all five routes are weighted based on the number of trips in the timetable for each route.

Backloading affects the total transport cost and CO_2 emissions of the transportation. Decisions and calculations pertaining to whether the company should backload on return trips are a function of the cost elements of backloading and the levels of service and have in this study been indirectly measured by the average number of pallets that are collected per stop. With respect to the company's distribution activities in the South-eastern part of Norway, given today's stop patterns, we find that the average number of pallets per pickup from producers on the return trips must be at least 7,2 to benefit from backloading from a cost perspective. For 2019 the actual average number of pallets picked up was 8, making backloading beneficial from a cost perspective. In terms of CO_2 emissions, the breaking point for backloading is considerably lower. As long as the average number of pallets per pickup is higher than 3,4, the firm would benefit from backloading for environmental reasons.

Conclusion and discussions

In this paper we have utilised GPS data as a base to track truck movements and analyse transport activities. Combined with a Decision Support Tool we have investigated how different transport solutions affect the transport cost and CO_2 emissions by using Norway's leading fruit and vegetable wholesale company as a case. While the distribution of goods from the company's central warehouse to 5 regional warehouses is carefully planned and consists of fully loaded trucks that operate along fixed weekly routes, the backloading of goods from the company's own suppliers on the way back to the central warehouse is far more complex and often performed on an ad hoc basis.

The current backloading is characterised by a high level of service; for instance, 36% of the pickups consist of fewer than five pallets and a considerable number of pickups only consist of 1 or 2 pallets, contributing to an average number of pallets per pickup of 8 and a load factor below 60% in 2019. To investigate the cost consequences and environmental footprint of this level of service we have studied the detour distances, loading and unloading times and number of pickups in the backloading process on the five different routes. Based on this, we have established the cost and CO_2 emissions with or without backloading in order to decide the most cost efficient and environmentally friendly of the two alternatives. When comparing the cost per pallet for the round trip for the two alternatives we arrive at different conclusions for the different routes, depending on the detour distances and the average pickup volumes. In terms of costs, for three of the routes backloading is preferable, while for two of the routes the trucks should instead return directly to the central warehouse without backloading. In terms of CO_2 emissions, none of the routes would benefit from not backloading.

For the company's distribution activities in the South-eastern part of Norway and given today's stop patterns, we have found that the average number of pallets per pickup from producers on the return trips must be at least 7,2 to benefit from backloading for cost reasons, while this number is only 3,4 when measured in terms of CO_2 emissions. The reason for this difference is that the CO_2 emissions are largely related to the transport distance, while the cost is also affected by time, which constitutes the largest cost-component of backloading.

By understanding the cost drivers and emissions related to the backloading process, companies are in better position to make strategic and operational decisions that would facilitate greener and more cost-efficient transport solutions. In our case study, one solution might be to reduce the level of service and to enforce the rule of a minimum of 4 pallets per pick up from the producers more strictly. Another strategic measure would be to introduce HUBs to consolidate volumes from producers with small quantities and through that contribute to higher load factors on return trips. Furthermore, a new route structure in the area may increase the potential return volumes on return trips, and therefore improve the load factors on some of the routes. On this note, it is interesting to learn that the company, dependent of this work, actually made adjustments to the route structure in 2020. Now, trucks more frequently traffic routes E and D in a triangular pattern, and this raises the potential return volumes and truck load factors for these routes.

In this work we have only considered return volumes for the company's own producers. The transporting company is also allowed to do transport assignments for other customers as long as they adhere to the company's contract. The GPS data indicated that this was taking place, defining a number of stops as "other stops" because they could not be matched with the register of the company's locations. An inclusion of this transportation as a part of the transport solution may show a different picture from the perspective of deciding whether or not to backload. Nevertheless, the core of the transporting company's operations is to serve outgoing and ingoing volumes to the company's central warehouse, and any additional transport has to fit into this operation. This means that the current analysis remains useful also for the transporting company in making strategic decisions as to when and where they should engage in other transport assignments to improve the load factors on their trucks.

The vehicle velocity, costs and CO_2 emissions are dependent on traffic flows and density on the roads, but in the current work we analyse observed velocity and CO_2 emissions based on reported GPS data from the firm's own vehicles. The quality of the decision making could be further improved by including other sources to traffic flows, for instance gathered from traffic sensors, google maps or other data sources.

The method used in this paper is relevant in many businesses. Lack of transparency is a common challenge, and increased transparency often leads to increased productivity (Bø, 2020). The information gained from GPS-data helps firms to gain better insights into the transport solution and operations from a cost and environmental perspective. An interesting observation is that the picture the decision-makers had prior to GPS data being used was different from the real situation, and the insights gained are valuable as they lead to new knowledge and actions. It is important to understand that the decisions are dependent upon the focus on costs or emissions. For example, due to backloading; the extra distance acceptable for backloading in a cost perspective is shorter than in an environmental perspective. Contract elements like minimum load to pick up and minimum payment to the transport company are common practice. By using GPS data, it is possible to measure the scale factor by increased load and use this to design a more precise contract. By understanding the cost drivers and emissions related to the transport arrangement, and the cost of different service levels, companies are in better position to make strategic and operational decisions that would facilitate greener and more cost-efficient transport solutions.

CRediT authorship contribution statement

Eirill Bø: Conceptualization, Software, Data curation, Methodology, Validation, Formal analysis, Investigation, Writing – original draft, Writing – review & editing. **Christian Mjøsund:** Software, Data curation, Methodology, Validation, Formal analysis, Investigation, Writing – original draft, Writing – review & editing.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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