The computation of carbon emissions due to the net payload on a truck

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Abstract

Many green logistics studies try to minimize the carbon emissions and in the process alter the load on the vehicle. Then, there is often a trade-off between the distance driven and the load on the vehicle and in order to determine which decisions lead to the most substantial emission savings, it is necessary to compute the carbon emissions of these decisions. Current studies are only able to determine this for very specific conditions, such as a given vehicle under given driving conditions, and they may require many input parameters. Therefore, this paper presents a simple and broadly applicable emission computation tool.

We determine the share of the carbon emissions of fully loaded vehicles due to the weight of the load on the vehicle, i.e. the load-based emission percentage (LBEP). We conduct a review study on papers that report on carbon emissions or fuel consumption for different load factors. Using regression analysis on these results, we find that on average the LBEP increases by about 0.5% per additional ton vehicle mass, starting from about 18% for a 5 ton vehicle. However, the variation around this average is large due to factors such as differences in driving conditions. Such LBEP values can then be used to evaluate the carbon emission savings of many decisions related to the load on the vehicle, e.g., the decision to drive less frequently but with more load on the vehicle.

1. Introduction

Many recent studies aim to minimize the fuel consumption and carbon emissions from road freight transportation. Road freight transportation is an important source of emissions of greenhouse gases which are generally believed to be the main cause of global warming (Lashof et al., 1990). Road freight transportation is responsible for about 7% of these emissions in the United Kingdom (McKinnon, 2007). In addition to the negative environmental impact, the fuel consumption of a vehicle can constitute a significant part of transportation costs, ranging from between 13 to 20% of the operating cost of the vehicles in the US (Barnes et al. 2013) but up to 60% reported in a case study from Turkey (Sahin et al., 2009). Since the carbon emissions and the fuel consumption of a given road transportation haul are arguably proportional to each other, these can be minimized simultaneously.

One way to reduce carbon emissions from road freight transportation is to find a way to carry out a given demand for transportation with fewer vehicle kilometers: Léonardi et al. (2008) call this an increase in logistics efficiency.

This requires that the degree of vehicle utilization is increased. Some figures suggest that considerable improvements could be achieved, as within the EU, about 24% of all transport hauls are with empty vehicles and the average utilization of the vehicle lies around 30% (McKinnon et al., 2015). In a literature review Santén et al. (2014) describe measures to improve the degree of vehicle utilization. Some of these measures require optimization with quantitative approaches, such as decisions on the number of warehouses and their location, the order and delivery frequency, transport operations (e.g., consolidation). Other measures are the standardization of packaging and loading, information sharing and IT, and regulations. There are many optimization approaches that aim to improve the degree of vehicle utilization to reduce the carbon emissions: We summarize the most important papers below.

One way to improve the utilization of the vehicle is through setting *order quantities*, i.e., by determining how much should be shipped (ordered). It is assumed that the longer the time between deliveries by truck is, the better the vehicle is filled up and the lower the emissions per item are, until the vehicle's capacity is exceeded and a larger vehicle is needed. This is also called consolidation of shipments. There is a trade-off if the costs of holding inventories makes the full utilization of the vehicle costly. Bouchery et al. (2011) present a version of the Economic Order Quantity (EOQ) approach where a decision maker can determine the shipment size to minimize the costs of the resulting transport and inventory levels or the expected carbon emissions or a combination of both. Li (2015) discusses the carbon emissions from different delivery strategies of a distributor to retailers. Hua et al. (2011) consider an EOQ-type inventory system where a cap is set on carbon emissions.

Several models evaluate the *number of warehouses* and their locations. Xifeng et al. (2012) present a model where emissions depend on the driven distance and the load on the vehicle. Harris et al. (2011) present a warehouse location problem with emission computations: The utilization of the vehicle determines carbon emissions from transport.

The impact of the load on the vehicle can also be important if the *routing efficiency* us increased, where the routing efficiency of road transportation is, according to Léonardi et al. (2008), the amount of fuel or carbon needed for visiting a given group of locations. This is optimized in so-called *green (vehicle) routing* approaches. Green routing approaches solve variants of the Vehicle Routing Problem (VRP), which is the problem of determining the set of routes with minimum total cost, driving time, or distance, see e.g., Toth et al. (2014). However, these objectives do not always correspond to minimization of fuel consumption or carbon emissions. As fuel consumption and carbon emissions are partially due the load on the vehicle, it may be sensible to minimize the average load on the vehicle in addition to the total distance, for example, by visiting big customers first on a route: If one can reduce the load and keep the driving distance more or less the same, carbon emission reductions are achieved, see e.g., Bektas et al. (2011). In Wøhlk et al. (2014) an approach is presented for minimizing the number of average load, meaning that emissions can be saved if the load on the vehicle is reduced. Ubeda et al. (2011) consider a routing problem where the vehicle utilization can be increased by adding reverse flows to the depots to the vehicle. Often, the load on the vehicle is combined with other factors such as the speed of the vehicle and the time of the day of the transportation on a road, see e.g., Demir et al. (2014) and Franceschetti et al. (2013).

Thus, many quantitative approaches try to find solutions where, among others, the load on the vehicle is adjusted to minimize or limit carbon emissions or fuel consumption. A key ingredient in these decisions is the computation of carbon emissions. In principle, this should be done for every decision under consideration. For example, if one minimizes carbon emissions through setting a vehicle speed and the load on the vehicle, there should be reliable carbon measurements for each selected vehicle speed and vehicle mass or load factor. Some of the mentioned optimization studies compute realistic carbon emissions (or fuel consumption), whereas some other studies, such as Bouchery et al. (2011) use artificial values. Some studies such as Ubeda et al. (2001) and Harris et al. (2011) use existing (*direct*) carbon emission or fuel measurements for given vehicles, typically from environmental and transport ministries in order to obtain realistic carbon emission estimates. Other studies such as Bektas and Laporte (2011) use so-called *engine emission models*, which are models for computing carbon emissions from the characteristics of the vehicle and the driving conditions (e.g., the speed of the vehicle). We argue that these currently used computation methods are insufficiently applicable for general conclusions because of the following problems.

The usage of direct measurements has the disadvantage that the resulting carbon emissions are specific to a single vehicle. For example, Harris et al. (2011) use results on a 5 ton (t) vehicle which if 60% loaded uses 0.228 l. of fuel per km and if 90% loaded uses 0.245 l. However, it is not reported under which conditions these results have been obtained and whether the driving conditions are representative for the situation to be modeled. Nor can the results be extrapolated to, say, a 6 or 8 t vehicle. Finally, the observations may be outdated and old measurements or models may no longer be applicable to currently used vehicles.

The usage of engine emission models has the further disadvantage that such models require many input factors, such as the speed of the vehicle, the driving conditions, the type of road, see e.g., Barth et al. (2005). This makes the results very specific to the vehicle and driving situation under consideration. A challenge identified in Turkensteen (2016) is that in particular driving conditions are hard to estimate and are often replaced by a fixed speed, which can lead to incorrect and biased emission results.

The consequence is that if we wish to argue that a new approach can lead to emission savings of a certain size, we can only do so for the very specific situation addressed in the study. If a study reports that 5% emission savings are achieved through routing or inventory decisions, we do not know in how far this is due to specific properties of the vehicle (van, truck) or the distribution situation (urban area, mountainous terrain, fixed speeds). If a different vehicle or distribution situation is considered in practice, this requires a data collection exercise that is not addressed in the papers discussed here. Therefore, we introduce a simple and approximate way to compute carbon emissions that can be applied in many decision situations.

This measure is as follows. Many transportation science studies agree (e.g., Barth et al. 2005; Walnum et al. 2015) that there is a linear relationship between the weight of the load on the vehicle and the resulting carbon emissions. This means that we can compare the carbon emissions of different decisions without knowing the exact emissions. Take decision A where an on average 50% loaded vehicle drives 50 km and decision B where an on average 70% loaded vehicle drives 40 km. If the load of a fully loaded vehicle causes 20% of the vehicle's carbon emissions (say f), we have that emissions from decision A are $(0.8+0.5\times0.2)\times50f =45f$ (where

(0.8+0.5×0.2)f are the emissions per km of a 50% loaded vehicle*)* and the emissions from decision B are *(0.8+0.7×0.2) ×40f=37.6.* Thus, the emissions of decision B would be 16.4% lower than those of A. In order to determine the relative carbon impact of the decisions in the example above, we only need the share of emissions of a fully loaded vehicle relative to the total emissions of that vehicle; we call this the *load-based emission percentage (LBEP)*.

In this paper, we determine the range of LBEP values for different vehicle types, where the key characteristic of the vehicle is its weight when fully loaded, the gross vehicle weight (GVW). To that end, we conduct a survey study of papers about carbon emissions and fuel consumption of vehicles with different loads, from which LBEP values can be computed. We use these results in regression analyses to determine the likely values of the LBEP for vehicles with given GVWs. In addition, we determine whether factors such as the usage of engine emission models, the age of the used carbon emission measurement, or the recorded driving conditions have a significant impact on the LBEP value.

This contribution is relevant for two reasons. Firstly, the LBEP can be a useful tool for comparing the carbon emissions between decisions that involve different distances and degrees of vehicle utilization. Secondly, we can make a comparison of the currently used observation methods. For example, if the results of some direct observations or engine emission models give LBEP values that are not in line with the values that can be expected for the considered vehicles, it may not be advisable to use these results.

The paper is set up as follows. In Section 2 of this survey paper, we discuss the vehicles used in freight transportation and the main terminology related to such vehicles. In Section 3, we provide a survey of papers that compute or measure the emissions caused by the load on the vehicle. Section 4 contains an analysis of these results, where the share of emissions due to the load are related to several important factors, such as the GVW, the driving conditions, and the type of measurement. Finally, Section 5 contains the conclusions and the directions of future research.

2. Vehicles and utilization: Terminology

This section introduces the main terminology used in this article and discusses different measures of and terms for vehicles and their degree of utilization. The different types of vehicles in road freight transportation are presented, as well as their capacity (the maximum percentage load of the vehicle's weight). After that, measures of vehicle utilization are discussed.

A main determinant of the type of vehicle is its g*ross vehicle weight (GVW)*, the maximum weight that a vehicle can have including load. In transportation literature (e.g., Ligterink et al., 2012), the weight of a vehicle is divided into the *kerb weight (or curb weight)*, i.e. the weight of an unloaded vehicle, and the *net payload* on the vehicle, i.e. the weight of the load on the vehicle. The maximum net payload on the vehicle is known as the vehicle's *payload capacity*.

Classifications of vehicles are often based on the GVW. To describe vehicles for commercial purposes, the term 'Duty Vehicles' is used. Such vehicles are often divided into Light Duty Vehicles (LDVs), Medium Duty Vehicles

(MDVs) and Heavy Duty Vehicle (HDVs). When vehicles are used for freight transport, the term ‘Goods Vehicle’ is used: e.g., a Heavy Goods Vehicle (HGV). Duty Vehicles (which include buses) are divided into 8 categories in the US according to their GVW, see also Campbell (1996). The table below, adapted from the National Academy of Sciences (2010), shows the weight class of each vehicle type, kerb weight, and the typical maximum payload.

Table 1: Vehicle classes and characteristics according to National Academy of Sciences (2010), adapted.

Vehicle class	*GVW, range in pounds*	*Kerb weight in pounds*	*Max payload, pounds*	*Capacity % of empty vehicle*	*Examples of vehicle usage*
3	10001-14000 (5 – 7t)	7650-8750	5250	60%	Vans
4	14001-16000 (7 – 8 t)	7650-8750	7250	80%	City/ parcel delivery
5	16001-19500 (8 – 9.75 t)	9500-10000	8700	80%	City/ parcel delivery
6	19501-26000 (9.75 – 13 t)	11500-14500	11500	80%	City/ parcel delivery
7	26001-33000 (13 - 16.5 t)	11500-14500	18500	125%	Furniture, refrigerated
8	33001-80000 (16.5 – 40 t)	20000-26000	54000	200%	Tractor trailer

A similar classification has been used in Campbell (1995). The omitted classes 1 and 2 are for vehicles such as cars, minivans, SUVs, pick-ups which are usually not used for goods transportation.

One can distinguish whether a goods vehicle have a joint. If so, they are called *articulated vehicles*; if not, they are called *rigid vehicles*. Articulated vehicles also include combinations with semi-trailers. The ARTEMIS classification of HDVs, from Rexeis et al. (2005), distinguishes between rigid truck classes with GVW less than 7.5, 12, 14, 20, 26, 28, and 32 t and larger than 32 t, and truck trailers and articulate trucks up to 28, 34, 40, 50, and 60 t.

A further classification of vehicles is the EURO classification on the pollution standards of vehicles in the European order, running from EURO I to EURO VI, see e.g., Hausberger et al. (2005). This classification mainly focusses on emissions of local pollutants, such as particulate matter, and has little relevance for the carbon emissions due to the load on the vehicle.

The *degree of vehicle utlization* measures how well a given vehicle is utilized. Many terms are used to denote the degree of vehicle utilization, such as load factor, vehicle utilization, loading factor, and fill rate (Santén et al., 2014). In this paper, we use the *load factor* for the degree of vehicle utilization.

The load factor should measure the share of the total vehicle capacity utilized (in this paper!) by a given net payload on a given transportation haul. Moreover, both the maximum capacity of the vehicle and the net payload are measured in weight units. Then, the most suitable measure of the load factor is the weight-based lading factor, see McKinnon (2015), which is the actual number of ton-kilometers divided by the potential numbers of ton-kilometers on a haul if the truck is fully loaded during that haul. The number of *ton-kilometers (tkm)* measures the load of the vehicle in tons times the distance traveled in kilometers. For example, if a vehicle with a load capacity of 10 ton travels 50 km but with 6 ton on it, it utilizes 300 tkm out of the 500 tkm that could have been used if the vehicle were fully loaded during the entire haul. Hence, the weight-based lading factor equals *(300/500) × 100%=60%*.

In some cases, the volume of the load determines the capacity of the vehicle, so that the maximum capacity in terms of weight cannot be attained, such as parcels or groceries, see Figure 11.2 and 11.5 in McKinnon (2015). It is easy to extend the computations to such cases. If the volume limits the weight of the load on the vehicle to $\alpha\%$ $(0<\alpha<100)$ of the maximum payload capacity, the LBEP is $\alpha\%$ of that of the same vehicle with the full payload capacity.

It can be expected that the LBEP value increases with the maximum payload capacity of the vehicle. We can see in Table 1 indicate that the payload capacity of the vehicle increases with the GVW and therefore, an increase in the load factor should have the largest relative impact in emissions for vehicles with large GVW. In the next section, we give an overview of studies that determine carbon emissions due to the load on the vehicle.

3. Review on carbon emissions due to the load on the vehicle

This section contains a review on studies that report the carbon emissions or fuel consumption due to the load on the vehicle. The search is limited to the following sources: 1) the source should be a research article or a publicly accessible source in English, 2) the source specifies the GVW of the reported vehicle and its payload capacity, and 3) the source should specify the fuel consumption or carbon emission levels of at least two data points for a given vehicle so that we can determine the levels for the empty and fully loaded vehicle. Finally, the the GVW of the reported vehicle should lie within 5 and 48 t.

Searches have been conducted in leading journals in the field of green logistics, such as the European Journal of Operational Research, Transportation Research (all parts), and International Journal of Production Economics, with keywords such as ‘emissions’, ‘load factor’, ‘empty vehicle’, ‘fuel consumption’, and ‘vehicle utilization’, and combinations of these. In addition, searches have been conducted on Google Scholar for these terms in combination with terms such as ‘vehicle’, ’truck’, and ‘van’.

One may expect that there should be many of such results. However, it is quite complicated to provide the carbon emissions or fuel consumption of vehicles with different load factors, as these differences should only be due to the load on the vehicle and not to differences in driving circumstances. For instance, it is conceivable that heavily loaded vehicles are driven during rush hour, whereas empty vehicles return to depots in free-flowing traffic conditions. If this is the case, the lower emissions of the empty vehicle may be caused in part by the quieter driving conditions and cannot be attributed solely to the lower net payload.

In our review, we distinguish between reported measurements on vehicles with different load factors that are extrapolated to empty and fully loaded vehicles, and computations performed with engine emission models. Since it can be argued that fuel consumption and emissions are proportional to each other (typically around 2.6-2.9 kg of carbon emissions per kg of fuel, see e.g., Kellner and Otto (2012), Piecyk (2015)), we also report studies quantifying the relationship between the load factor and the fuel consumption.

Thus, in our studies, we report the fuel consumption or carbon emissions of empty and fully loaded vehicles, denoted by *e* and *f*, respectively. These are used to determine the LBEP values, as follows: $LBEP = [(f - e) / e] \times 100\%$.

3.1 Overview of studies using actual measurements: direct observations

First, we review papers which report measurements for vehicles with different load factors. If a study does not report the results for a fully loaded or empty vehicle but only for two or more intermediate load factors, the results are extrapolated to obtain those of the fully loaded and empty vehicle. We list the results in Table 2.

Table 2: Overview of direct measurements of fuel consumption and carbon emissions from empty and fully loaded vehicles and LBEP values

Source	Type	Empty veh.	Fully loaded	Unit	LBEP	Load cap.	GVW (t)
Piecyk / DEFRA	33 t artic.	0.71	1.17	CO_2 kg/km	39.63%	66.67%	33
Ubeda	Eroski (undeclared)	0.77	1.02	CO_2 kg/km	24.07%	?	?
Harris based on NAEI	5 t	0.16	0.27	l/km	41.75%	60.00%	5
RR5 Coyle	26 t tipper	0.07	0.13	gallon/mile	43.33%	61.54%	26
"	32 t tipper	0.09	0.17	gallon/mile	48.83%	62.50%	32
"	44 t tipper	0.10	0.20	gallon/mile	47.62%	63.64%	44
"	38 t artic.	0.09	0.13	gallon/mile	28.31%	57.89%	38
"	44 t artic.	0.09	0.15	gallon/mile	37.77%	63.64%	44
Volvo Mårtensson	14 t gross weight	22.50	27.50	l/100 km	18.18%	60.71%	14
"	24 t gross weight	27.50	35.00	l/100 km	21.43%	58.33%	24
"	40 t gross weight	24.50	33.50	l/100 km	26.87%	65.00%	40
"	60 t gross weight	30.50	50.00	l/100 km	39.00%	66.67%	60

Coyle et al. (2007), from the British Department for Transport (DfT), measure fuel consumption levels of three tipper vehicles and two articulated vehicles with different payloads through a mixture of laboratory driving conditions. For each vehicle and each net payload, several test runs are performed. The relation between the mass of the vehicle and the miles per gallon (mpg) driven is determined through linear regression. We report the mpg for fully and empty vehicles.

Piecyk (2015) presents carbon emissions (in kg CO_2e) of a 33 t. vehicle with different degrees of vehicle utilization in the United Kingdom (originally from a report from Defra (2013) with four different load factors, namely 0%, 50%, the reported average UK load factor of 62%, and 100%. Fuel consumption of the 0% loaded vehicle is 0.71 kg/km and of the 100% loaded vehicle 1.17 kg/km.

Mårtensson (2003) provides fuel consumption ranges from four different Volvo trucks varying in GVW from 14 to 60 ton. The GVW of each type of vehicle varies, for example from 20 to 25 t. We take the middle value in these ranges. The results have been used in Arvidsson (2013) to discuss the impact of the load factor in urban routing.

The paper by Harris et al. (2011) uses measurements for two types of vehicles with GVWs of 5 t and 40 t. The report by DfT (2004) on the 5 t vehicle could not be retrieved. The results for the 40 t vehicle, according to Kohn (2005), have been computed using a model and are reported in the next subsection.

The paper by Ubeda et al. (2011) reports the fuel consumption levels of a vehicle with multiple load factors for a case company called Eroski. It is, however, not clear what type of vehicle has been used or how the measurements have been taken.

Some reported measurements lie outside our range of vehicles with GVW between 5 t and 45 t. The paper by Kara et al. (2007) uses measurements by the tire company Goodyear. Lajunen (2014) considers heavy combinations weighing between 40 and 90 t on Finnish roads. On the other side of the range, Joumard et al. (2014) measure carbon emissions of LDVs in France for light vans (2.5 t and 3.5 t).

3.2 Overview of studies using engine emission models: computed observations

So-called *engine emission models* to compute fuel consumption or carbon emissions are based on emission measurements, (sometimes taken under laboratory conditions and sometimes from actual transport hauls, for different values of relevant input factors, such as the speed of the vehicle, the slope of the road, and vehicle characteristics.

The usage of engine emission models is quite popular in logistics studies, in particular in green routing¸ see the overview papers by Demir et al. (2011) and Demir et al. (2013). Such models allow the decision maker to consider decisions such as the load on the vehicle and the speed of the vehicle simultaneously, which cannot be done if one solely relies on direct observations. The simplest of engine emission models are average speed models, such as COPERT or MEET, that have the vehicle's average speed as their main input factor, see e.g., Demir et al. (2011). The more detailed instantaneous emission models are very detailed but compute the emissions on an instant-by-instant basis, typically per second. Prominent instantaneous engine emission models are the CMEM from Barth et al. (2005), the PHEM from Boulter (2009), the HBEFA by Hausberger et al. (2009), and the ICFM by Bowyer (1985).

We report studies that use engine emissions models and provide either the carbon emissions and fuel consumption levels of fully loaded and empty vehicles, or a sufficiently detailed parameter description from which these values can be determined. We list the results in Table 4. We only report fuel consumption or carbon emission levels for the vehicles considered in the studies; the comparison of engine emission models in general is beyond the scope of this paper.

The Finnish national HDV emission database, LIPASTO (2015), reports fuel consumption levels in gram per km for three types of driving conditions: highway, urban, delivery, for the following vehicle types: a van (GVW of 2.7 t), a small truck (6 t), a medium truck (15 t), and a large truck (40 t). These measurements have been used in Liimatainen et al. (2010, 2014) and in Arvidsson (2013), where the latter paper contains a description of the model used to compute fuel consumption.

In the paper by Madre et al (2010), the so-called COPERT4 approach to compute the fuel consumption per km of 50% and 100% loaded vehicles, can be extrapolated to compute emissions of empty vehicles. The speed profile in the computations follow the so-called Artemis driving cycles which aim to emulate realistic driving conditions when the vehicle has an average of, e.g., 20 km/h. Rizet et al. (2012) use these computations to show that a fully loaded HDV emits 2.1 kg of CO_2 per km and an empty one 1.2 kg.

In some cases, the original results are used in a sequence of papers. Xifeng et al. (2012) report 0.772 kg/km for an empty vehicle and 1.096 for a fully loaded one with a gross weight of 25 t. Pan et al. (2013) use the same data and refer to the original paper where the MEET model (on which these results are based) is presented, namely Hickman et al. (1999). The already mentioned paper by Kohn (2005) reports fuel usage in liters of a 40 t vehicle with load factors of 70% and 79%, taken from the NTM (2005), which in turn bases its results on the engine emissions model HBEFA.

Amiri (2014) determines fuel consumption levels for three vehicles with GVW between 30.3 and 47.1 ton using a combination of engine emission models and secondary data.

In some green vehicle routing studies, instantaneous engine emission models are used under the assumption that the vehicle travels at fixed speeds (e.g., Franceschetti et al., 2014; Demir et al, 2014; Koc et al, 2015; Soysal et al., 2015). Some of these studies present a sufficiently detailed parameter specification of the used model, the CMEM, so that the fuel consumption of full and empty trucks can be determined. The paper by Franceschetti et al. (2014) uses the CMEM to compute emissions for given payloads and speeds for a 12.25 t vehicle (6 t kerb weight and 6.25 t load capacity). The specification of the parameter values in the paper can be used to compute the fuel consumption of an empty and fully loaded vehicle. Using a similar model, Koc et al. (2015) consider three vehicles with GVW (load capacity) of 7.5 t (4 t load), 18 t (12.5 t load), and 40 t (26 t load). A challenge is that these models require a fixed speed as an input in order to determine the percentage emissions due to the load. In our study, as in Madre et al. (2010), we select three fixed speeds for all vehicles: 20 km/h, 50 km/h, and 80 km/h.

Table 3: Overview of reported computed fuel consumption and carbon emissions of empty and fully loaded vehicles (MD: Conditions according to driving cycles; MF: Fixed speed)

Source	Type	Empty veh.	Fully loaded	Unit	PLBE	Load cap.	GVW (t)	Model type
Franceschetti using CMEM	80 km/h fixed	0.17	0.22	l/km	23.08%	48.98%	12.25	MF
"	50 km/h fixed	0.15	0.20	l/km	24.78%	48.98%	12.25	MF
"	20 km/h fixed	0.24	0.29	l/km	17.36%	48.98%	12.25	MF
Madre et al. using ARTEMIS	Rigid 7.5-12, 20 km/h	21.30	26.10	l/100 km	18.39%	50.00%	10	MD
"	Same, 60 km/h	13.50	16.90	l/100 km	20.12%	50.00%	10	MD
"	Same, 80 km/h	15.20	17.20	l/100 km	11.63%	50.00%	10	MD
"	Rigid 14-20, 20 km/h	29.80	37.40	l/100 km	20.32%	49.41%	17	MD
"	Same, 60 km/h	16.90	21.70	l/100 km	22.12%	49.41%	17	MD
"	Same, 80 km/h	17.50	20.30	l/100 km	13.79%	49.41%	17	MD
"	Artic. 34-40 t.20 km/h	39.60	62.60	l/100 km	36.74%	66.76%	37	MD
"	60 km/h	21.90	35.90	l/100 km	39.00%	66.76%	37	MD
"	80 km/h	20.90	30.30	l/100 km	31.02%	66.76%	37	MD
Pan, Xifing using MEET	Large veh.	0.77	1.10	kg CO2/km	29.56%	66.67%	40	MD
Koc using CMEM	80 km/h fixed	0.13	0.16	kg/km	20.65%	61.11%	9	MF
"	50 km/h fixed	0.10	0.14	kg/km	25.21%	61.11%	9	MF
"	20 km/h fixed	0.15	0.18	kg/km	18.70%	61.11%	9	MF
"	80 km/h fixed	0.19	0.26	kg/km	29.42%	69.44%	18	MF
"	50 km/h fixed	0.15	0.23	kg/km	34.10%	69.44%	18	MF
"	20 km/h fixed	0.23	0.30	kg/km	25.44%	69.44%	18	MF
"	80 km/h fixed	0.33	0.49	kg/km	33.03%	65.00%	40	MF
"	50 km/h fixed	0.27	0.43	kg/km	37.70%	65.00%	40	MF
"	20 km/h fixed	0.38	0.54	kg/km	29.72%	65.00%	40	MF
Kohn 2005 (Table 11)	NTM (2005)	0.27	0.38	l/km	28.95%	65.00%	40	MD
Amiri 14	Model	0.23	0.45	l/km	48.89%	51.82%	30.3	MD
"	Model	0.29	0.55	l/km	47.27%	52.70%	36.6	MD
"	Model	0.42	0.71	l/km	40.85%	58.98%	47.1	MD
LIPASTO	Highway	71.00	78.00	g/km	8.97%	44.44%	2.7	MD
LIPASTO	Highway	95.00	109.00	g/km	12.84%	58.33%	6	MD
LIPASTO	Highway	152.00	186.00	g/km	18.28%	60.00%	15	MD
LIPASTO	Highway	257.00	349.00	g/km	26.36%	62.50%	40	MD
LIPASTO	Urban	82.00	98.00	g/km	16.33%	44.44%	2.7	MD
LIPASTO	Urban	101.00	133.00	g/km	24.06%	58.33%	6	MD
LIPASTO	Urban	157.00	233.00	g/km	32.62%	60.00%	15	MD
LIPASTO	Urban	398.00	584.00	g/km	31.85%	62.50%	40	MD
LIPASTO	Delivery	79.00	92.00	g/km	14.13%	44.44%	2.7	MD
LIPASTO	Delivery	101.00	133.00	g/km	24.06%	58.33%	6	MD
LIPASTO	Delivery	155.00	219.00	g/km	29.22%	60.00%	15	MD

Table 3 lists the fuel consumption and carbon emission levels as well as the resulting LBEPs. Note that the LIPASTO observations on the 2.7 t vehicle and the Mårtensson observations on the 60 t vehicle are not used in the statistical analyses, as these lie outside our range of GVWs.

3.3 Summary of the review

Our review has yielded 48 observations for which we can determine the fuel consumption of the fully loaded and empty vehicle, the LBEP values, the GVW, and the payload capacity. Given the importance of the degree of vehicle utilization, it may be surprising that there are so few measurements in Table 3 and 4. One reason is that we consider the optimization of logistics decisions for a single vehicle, whereas many studies in transportation science report average results over classes of vehicles. Raw measurements on single vehicles, if obtained, are not presented and interesting measurements vanish in an aggregation process. Ligterink et al. (2012) argue that there is too little attention in transportation science to the impact of the payload on emissions. The number of actual measurements in Table 3 of fuel consumption and carbon emission levels for vehicles with different load is quite small, possibly because of the challenging nature of performing experiments to measure these levels addressed in the beginning of the section.

It may also be surprising that there are so few model-based results in the green logistics literature, in view of the large number of recent publications in this area. One reason for this is that not all publications take the load into account. For example, Figliozzi (2011) presents a model on transportation with a van in an urban setting where the load on the vehicle is not a relevant decision variable. Moreover, the determination of emissions of a full and an empty vehicle requires a very detailed specification of the used engine emission model, which some papers do not provide. Finally, some papers, such as Bouchery et al. (2011) and Hua et al. (2011), choose to focus on the presentation of their optimization approaches instead of the determination of realistic emission factors.

An interesting recent development is that vehicles have been equipped with devices that can provide large quantities of data. These data form the input for regression-based models that link actual fuel consumption levels or carbon emissions to properties of the vehicle, such as its load, and driving conditions, see e.g., Walnum et al. (2015). An interesting study is the one by Ligterink et al. (2012), where, based on a large set of measurements under actual traffic conditions, the power usage of vehicles with different average speeds, payloads, and GVWs can be computed. Unfortunately, it is not directly clear how the power usage should be transformed into fuel consumption and carbon emissions, as these are not directly proportional to each other, see e.g., the CMEM formulation in Barth et al. (2005). However, it can be expected that these online measurements will enrich and improve engine emission models in the future.

4. Analysis of carbon emissions due to the load

The results in Section 3 describe the LBEP values derived from the results in existing studies. In this section, we perform statistical analyses on these results to determine what LBEP values can be expected for any given vehicle with GVW between 5 and 48 t. The observed LBEP values lie between 13% and 49% and appear to be increasing the GVW and the maximum payload capacity. We also consider possible further explanatory factors, namely:

- The type of observation: is it computed using a model or is it a direct observation?
- The age of the observation: do we observe an additional effect of the original year of the observation?
- The driving conditions under which the observations have been taken.

The purpose is to provide estimates of LBEP values that can be used to model the impact of green logistics decisions, as is illustrated in a numerical example at the end of this section.

The LBEP values of all observations and the corresponding GVWs are plotted in Figure 3. We distinguish between the origins of the observation: a direct observation (Table 1), a model-based observation based on driving conditions (MD), or a model-based observation based on fixed speeds (MF). Finally, the observation for the 5 t vehicle reported in Harris et al. (2011), marked with a triangle, appears to be an outlier. We remove this observation from further analysis, also because the original source of this observation could not be retrieved. The results in Figure 1 indicate that there is a positive relation between the GVW and the LBEP.

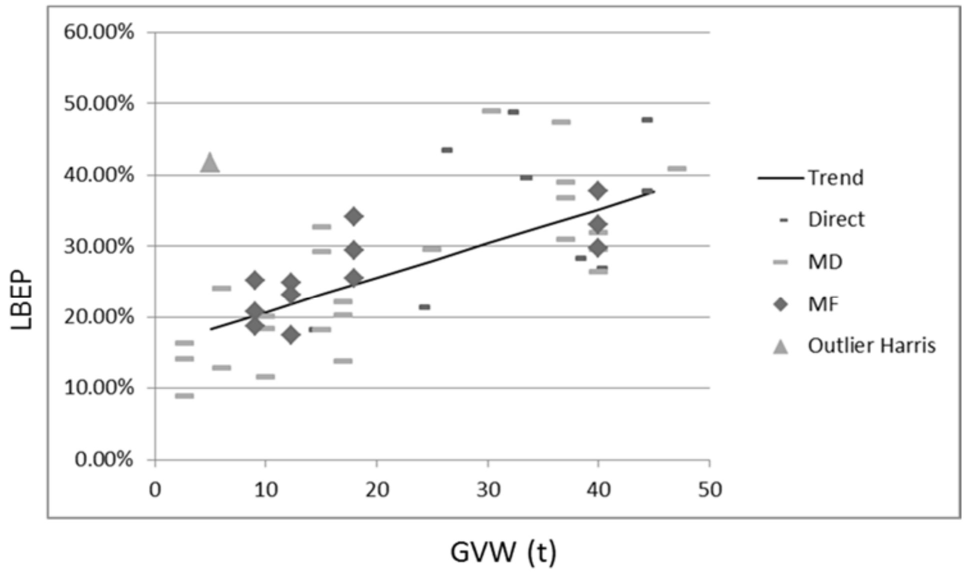

Figure 1: The observations with their LBEP and GVW values and linear regression line, divided into direct observations, models with driving conditions (MD), models with fixed speeds (MF), and the outlier from Harris.

Ordinary least squares regression has been performed on the remaining data, giving a trend line where the LBEP increases by about 0.5% for every additional ton GVW, see Eq. (1).

$$LBEP = (0.164+0.0050 \times GVW) \times 100\% \qquad (1)$$

The R^2 value of this regression analysis is 0.467, indicating more than half of the total variation is ot explained by the trend line. Regression with the square root of the GVW as the explanatory variable insufficient improvement in R^2 value to justify working with such a relationship.

One explanation for the positive relationship between the LBEP and the GVW is that the percentage maximum payload capacity increases with the vehicle's GVW, see also Table 1. Thus, relatively less energy is used to displace the vehicle's mass. The LBEP values can also be explained by the maximum payload capacity of the vehicle: the larger the capacity of the vehicle, the higher the LBEP value should be. However, we find that the relation between the LBEP and the vehicle's maximum payload capacity is less strong and (with a lower R^2 value of 0.165) than the relation with the GVW. The usage of both the GVW and the payload capacity has a worse adjusted R^2 value than the regression with only the GVW as independent variable.

One possible explanation of this is that the payload capacity reported in the observations do not appear to increase strongly as a function of the GVW, see Figure 2. In particular with the results from Table 1, denoted by NAS maximum payload capacity line, it turns out that the observations with low GVW have higher payload capacity percentages and those with high GVW have lower percentages. On the high end are the fixed speed observations by Koc et al. (2015), highlighted in the figure.

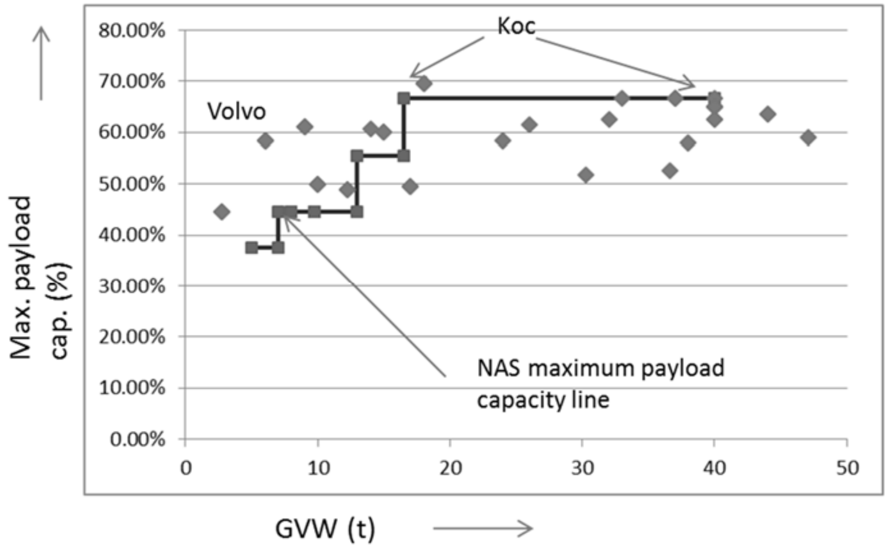

Figure 2: The observed maximum payload capacity as a function of the GVW (points) and the level from the National Academy of Sciences (NAS) from Table 1. Interesting observations are highlighted.

A potential explanation for the variation in LBEP values from the regression line is that the observations are in fact drawn from different populations. It could be that model-based observations with fixed or driving cycle speeds, and direct observations give in fact significantly distinct regression results. Therefore, we test the following:

Hypothesis: There is a significant difference between the LBEP values from direct observations and from observations computed using engine emission models.

We operationalize this first with the hypothesis that the regression coefficient of one class of observations, e.g., the model-based ones, is different from that of all observations. Chow (1960) introduces a version of the F-test to determine whether two series of observations have the same regression coefficients, see Appendix A. When applying this test to our data, we find that the result of this test is insignificant, implying that there is very little evidence that the regression coefficients of the model-based observations are different from the direct observations. A similar result is obtained when the model-based observations with fixed speeds are taken as a separate group. Interestingly, relatively high payload capacities are used in fixed speed models such as the ones by Koc et al. (2015). This could be one of the explanations why fixed speed models obtain LBEP values in line with or slightly higher than those from direct observations.

Another way to test the hypothesis is by adding a dummy variable for the observed measurements (1) and for the model-based ones (0) in the regression. The addition of this variable hardly increases the R^2 value (from 0.454

to 0.478). The regression coefficient of the dummy variable is -0.002, i.e., the expected LBEP value for model-based observations is 0.2% lower, but this coefficient is statistically insignificant (P-value of 0.4).

The age of an observation can influence LBEP values as well: the older the model or the measurement is, the larger the impact of the mass may become due to increased effectiveness of the vehicle itself. Therefore, we test the following:

Hypothesis: the age of the observation has a significant effect on the LBEP.

We perform a regression with the age of the observations as an explanatory variable in addition to the GVW, i.e., the number of years in the past since the result has been determined. We find that there is a weak but significant negative effect (P-value of 0.045), so the LBEP decreases by 0.5 percentage points with each additional year that forms the age of the observation.

A third possible cause of the observed variation in LBEP values is formed by the driving conditions. Since the driving conditions are difficult to classify precisely, we cannot statistically test the impact of driving conditions. Instead, we graphically analyze studies where there are several results for the same vehicle under different driving conditions, namely the fixed speed model results from Koc et al. (2015) and Franceschetti et al. (2013), and the realistic driving conditions model results from LIPASTO and from Madre et al. (2010). We highlight these observations in Figure 4.

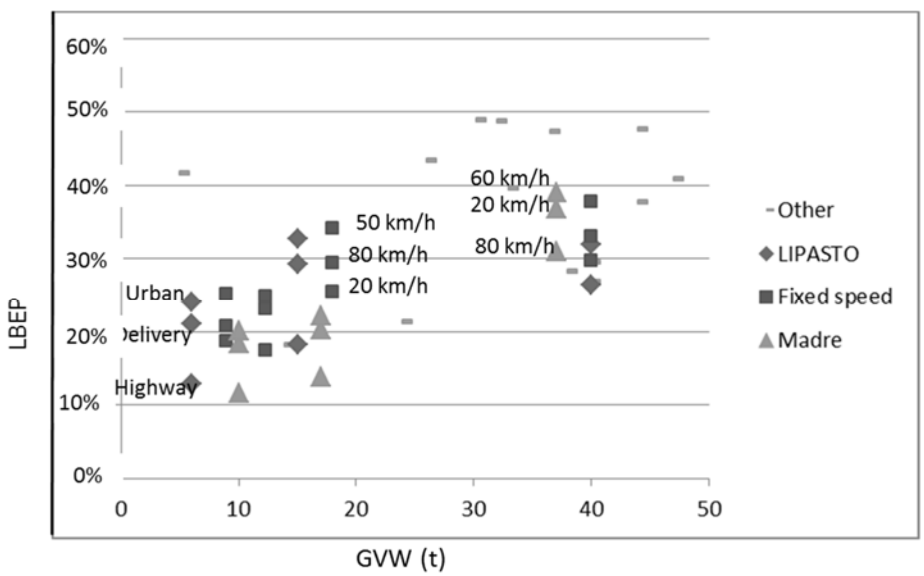

Figure 4: The effect of driving conditions on the LBEP for fixed speed models and driving conditions according to LIPASTO and Madre et al.

The results in Figure 4 show that for the vehicles up to 20 t, the range in LBEP values due to differences in driving conditions coincides with the range of all results. For heavy vehicles, such observations are all located below those of the other observations, which could be caused by inadequate speed profiles for these vehicles. We cannot identify precisely which driving conditions corresponds to which part of the range of LBEP values for a given GVW. The fixed speed models attribute the highest LBEP value to the driving conditions with an average speed of 50 km/h and the lowest to those with an average speed of 20 km/h, whereas the lowest LBEP value among the LIPASTO results are attained under urban conditions.

The LBEP values can also be affected by the type of vehicles observed. For example, Amiri (2014) considers vehicles in the construction sector and Coyle (2007) considers tipper vehicles. However, there are too few observations to determine whether the type of vehicle has an effect.

Given the variation in the observed results and given that it is difficult to attribute this variation to unique factors, it may be better to work with a range of likely outcomes for the LBEP for a given GVW rather than with a single estimate. Therefore, we ask the following:

Question: What is the range of LBEPs for any given GVW?

Assuming a normal distribution of observations, the regression line belonging to any quantile can be determined using *quantile regression*, introduced in Koenker et al. (1978). Quantile regression can be performed using packages such as R. In order to determine the regression line for quantile Θ, $0 \leq \Theta \leq 1$, the regression slope $b1$ and intercept $b0$ should be set in such a way that the following weighted sum of errors is minimize. If the observed percentage load-based emission is less than the level computed with $b0$, b1 and the GVW, this is a shortfall weighted with Θ; if it is larger than the computed level, the excess is weighted with 1-Θ. We take the sum of the weighted excesses and shortfalls over all observations. More details on quantile regression are given in Appendix A.

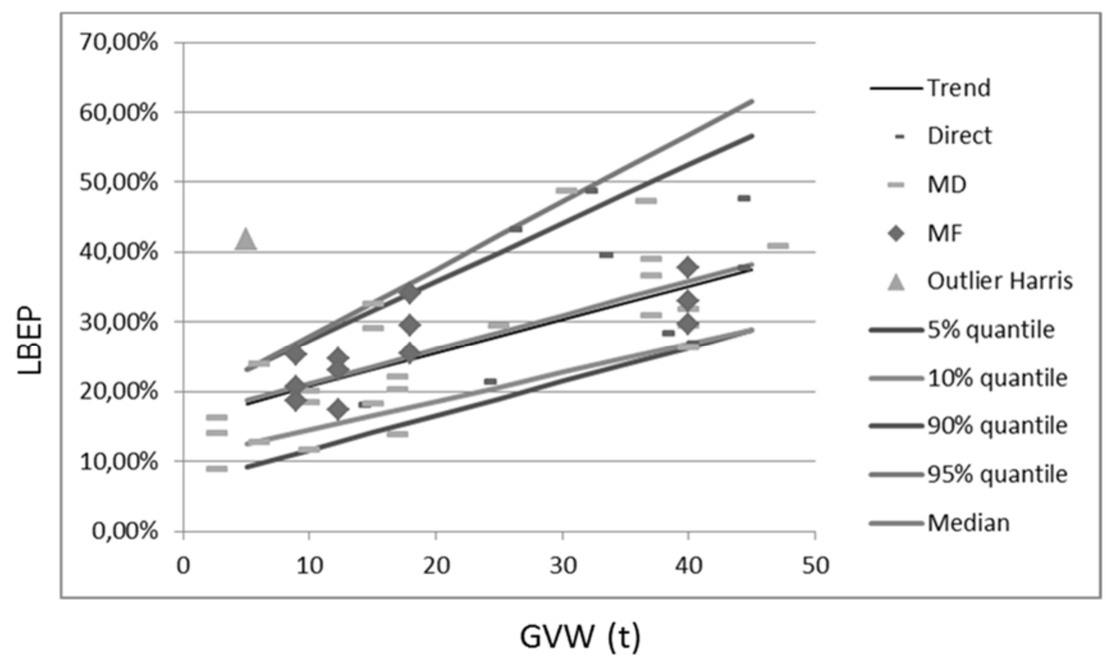

Figure 5: Quantile regression results, the linear regression results ('Trend') and the observations.

We perform quantile regression for the following quantiles: 5%, 10%, 50% (the median), 90%, and 95% and present the results in Figure 5. Based on Figure 5, the range of results appears to be best represented through the 10% and 90% quantiles. The 95% quantile appears to strongly overestimate the LBEP for vehicles with GVW larger than 35 t and the maximum measured LBEP appears to flatten out beyond a GVW of 35 t where it achieves a value of just below 50%, see Figure 5. The 90% quantile suffers to a lesser degree from this.

Table 4 presents the computed 10%, median (50%) and 90% quantiles of the LBEP for different GVWs. It can be observed that the median and the average results are close, which indicates that the observations are not skewed. The regression coefficients for the average, the median, and the 10% quantile LBEP (all in the row 'Per t') are close as well. The coefficient of the 90% quantile is quite high due to the strong increase in the largest observed LBEPs between 10 and 35 t GVW. It may be better to limit the maximum LBEP to 50%, the largest value observed.

Table 4: LBEP values predicted by different regression results for considered GVWs

GVW (t)	10%	Median	Average	90%
5	12.4%	18.7%	18.9%	23.2%
10	14.5%	21.1%	21.4%	27.4%
15	16.6%	23.6%	23.9%	31.6%
20	18.6%	26.0%	26.5%	35.8%
25	20.7%	28.5%	29.0%	39.9%
30	22.7%	30.9%	31.5%	44.1%
35	24.8%	33.4%	34.0%	48.3%
40	26.9%	35.8%	36.5%	52.5%
45	28.9%	38.3%	39.0%	56.7%
Per ton	0.412%	0.489%	0.504%	0.836%

To summarize the analyses in this section, the LBEP increases with the GVW, about 0.5% per ton, but the large amount of variation makes it sensible to consider a range of values, for example, indicated by the 10% and the 90% quantile of the observations, see Table 4. We find no significant effect of the type of observations (model-based or direct), but the age of the observations appears to have an impact.

It is also possible to relate the absolute fuel consumption levels of empty and fully loaded vehicles to the GVW, but this causes some challenges. Firstly, the results in Section 3 are reported in different units: kg of CO2 equivalents, kg fuel used, liter fuel used, and the number of gallon. These can be converted into each other using conversion factors, but in particular the conversion factor from fuel consumption to carbon emissions varies between different sources. For example, Palmer (2007) reports 5 different conversion factors from kg of fuel to kg of carbon emissions (CO2 eq.) varying from 2.52 to 2.85.

Using conversion factors of 0.85 kg of diesel per liter and 2.91 kg CO_2 life cycle carbon emissions per kg of diesel (Zadek and Schultz, 2010), we find that the fuel consumption of vehicles with different GVWs, both fully loaded and empty. The linear regression results for the fully loaded vehicle indicates that the fuel consumption per km increases by about 0.01 l per ton of GVW from an intercept of around 0.1 l per km with an R^2 value of 73%. The fuel consumption of an empty increases by about 0.0056 l per t of GVW with an R^2 value of 71% from the more or less same intercept. The type of observations have a strong negative effect on absolute fuel consumption levels. The computations based on fixed speed models are higher than other results at a 5% significance level and the general model-based results are higher at a 10% significance level.

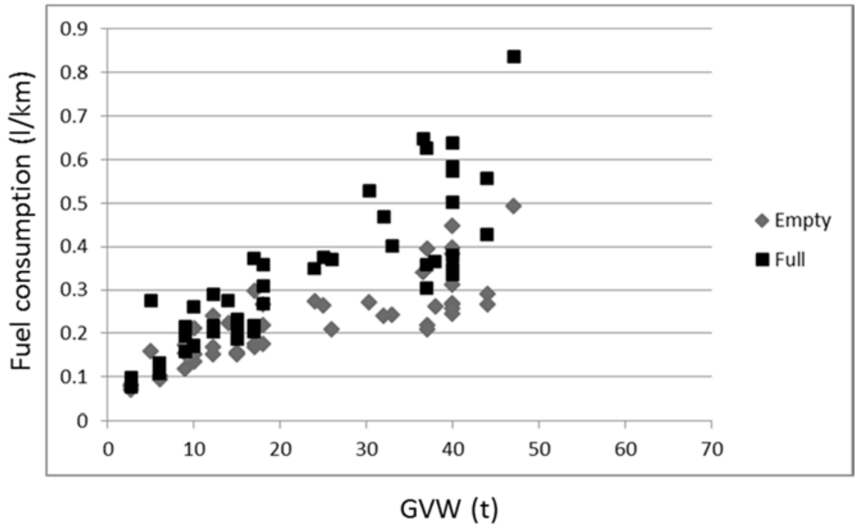

Figure 4: Fuel consumption per km of fully loaded and empty vehicles with GVWs

From these results, however, it is difficult to determine the fuel consumptions or carbon emissions of a given vehicle with a given payload, so per tkm. We find that the fuel consumption per additional ton-kilometer varies between 0.0035 liter (the 80 km/h driving from Madre et al., 2001) and 0.0095 l per km (the 28 t tipper vehicle from Coyle, 2007). So, even if one can determine the fuel consumption of a fully loaded or an empty vehicle accurately, it is difficult to measure the effect of adding load to the vehicle due to the large variation in fuel consumption per tkm.

Using a small numerical example, we illustrate the usage and the limitations of LBEP values in green logistics decisions. Take the example from the introduction where a vehicle drives 100 km and has a load factor of 50%. If we have a vehicle with GVW of 10 t, the 10% and 90% quantile range of the LBEP lies between 14.6% and 27.4%, see Table 4. If the average load factor is 50% and the driven distance 100 km, the 90% quantile emissions are *(0.80+ 0274×0.50) ×100 =93.7* units, where each unit corresponds to the emissions of a fully loaded vehicle driving 1 km. Likewise, the 10% quantile emissions are then *(0.80+0.146×0.50) ×100=87.3*. If absolute carbon emission levels are necessary, these can be obtained by multiplying these numbers with the emissions of a fully loaded 10 t vehicle, which is on average about 0.2 l per km (see Figure 4) multiplied with a conversion factor to obtain the emissions in kg. Note that the computations can be performed in a similar way for any vehicle with GVW between 5 t and 45 t.

5. Conclusions and future research

Many studies on green logistics decisions require that the carbon emissions are computed for different payloads on the vehicle. In general, it is it is in general quite difficult to determine the absolute carbon emissions or fuel consumption of a vehicle with a given load. Instead, we determine the share of emissions of a fully loaded vehicle resulting from the load, the load-based emission percentage (LBEP). We provide several examples in green logistics modeling where that the LBEP offers an easy and broadly applicable way to compute carbon emissions.

We survey studies that report or allow for the computation of the fuel consumption or carbon emissions of fully loaded and empty vehicles, which allows us to determine LBEP values. We find that the LBEP depends positively on the gross vehicle weight (GVW) and increases by about 0.5% per additional ton GVW, starting from about 18% for a 5 ton vehicle. However, since there is a large degree of variation that is difficult to attribute to certain circumstances, we present the range of possible LBEPs for different vehicles in Table 4 by the 10% and 90% quantiles.

As a results of our analysis, we compare different types of measurements. We find that there is no significant difference in LBEP values between direct and model-based computations (but there is a significant difference when absolute fuel consumption levels are taken). However, the age of the observation does have a slight significant effect, as the newer the observations, the larger the share of emissions due to the load on the vehicle.

We illustrate how the obtained LBEP values can be used to evaluate the carbon emission impact of logistics decisions. A limitation in the usage of the LBEP is that carbon emissions are rough approximates obtained from many observations and therefore may match specific vehicles badly. Obviously, if one knows the carbon emissions for different load factors of the given vehicle, this is preferable. However, there are too few of such observations for a broad application, e.g., in order to analyze in general in how far carbon emissions can be reduced by decreasing a delivery frequency. A second limitation in the usage of the LBEP is that it does not distinguish between differences in driving conditions and speeds. However, our analysis in Section 4 indicates that it may be difficult to determine the precise impact of having certain driving conditions, e.g. slow driving in an urban environment.

This research gives rise to future research directions. In our review, we have found relatively few reported load-based carbon emission or fuel consumption levels. Moreover, it holds that the age of the observation seems to have a significant impact. Thus, the results should be updated regularly in order to ensure that a logistics modeler has access to recent and accurate LBEP values. If, as Ligterink et al. (2012) argue, large amounts of emission and fuel consumption data from measurements become available, these data can be used to improve the estimates for the LBEP over time and to determine the effect of having different driving conditions (e.g., urban and rural roads) and distribution situations (e.g. the construction sector or the usage of tipper vehicles).

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Appendix A: Used statistical methods

Let *x* be the observations of the independent variable(s) (e.g., the GVW) and *y* the observations of the dependent variable (percentage load-based emissions).

Chow's test for equality between coefficients in linear regressions of groups of observations:

Let x_1, y_1 be the *m* actual observations and x_2, y_2 the *n* model-based observations. Let b_1 be the regression coefficient of the actual observations and b_2 of the model-based ones. Moreover, let *b* be the regression coefficient of all observations. Moreover, *p* denotes the number of explanatory variables. In our case, $p=1$.

Then we have the following F-statistic indicating the likelihood that the two groups have the same regression coefficients, i.e., H_0: $b_1=b_2$ (Chow, 1960):

$F(m,n-1) = (\|x_1b_1 - x_1b\|^2+\|y_2-x_2b\|^2/\|y_1-b_1x_1\|^2)\times((n-p)/m)$.

This statistic follows a F-distribution with $(m,n-p)$ degrees of freedom.

Quantile regression

Given the explanatory variables *x* (the vehicle's GVW) and the dependent variable *y* (the observed LBEP) and given quantile $0<\Theta<1$, set b_0, $b_1 \geq 0$ such as to minimize the following (Koenker et al., 1978):

$Min\ \Sigma_{t\in T}\Theta|(y_t - (b_0+b_1)x_t| + (1-\Theta)|(b_0+b_1)\ x_t - y_t)|$

where *T* denotes the set of observations.