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Exploring the impact of traffic congestion on CO_2 emissions in freight distribution networks

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Abstract This research quantifies the impact that regular road traffic congestion has on the CO_2 emissions of a real-world distribution network, and it studies the consequences when the number of distribution centers changes. For this purpose, this study makes use of a network model allowing for a detailed representation of all relevant transport operations, including production flows between factories and distribution centers, line haul shipments between distribution centers and customers, and round/delivery trips between transshipment points and retailer locations for the last mile. The processed trip and traffic information does not rely on standard traffic data collection approaches, such as interviews, in situ technologies, or floating car data, but the road traffic data are retrieved from an online navigation service, such as Bing Maps, Google Maps, Inrix, Here, and TomTom. This study proves that online navigation services may considerably contribute to future research projects analyzing CO_2 sensitivities and greenhouse gas cutting opportunities in logistics networks.

Keywords Distribution network · CO_2 emissions · Road freight transportation · Traffic congestion · Online navigation service

1 Introduction

Greenhouse gas (GHG) emissions make a significant contribution to atmospheric changes and climate disruptions, which are harmful to the natural and built environments and which pose a threat to human health and welfare. Different anthropogenic GHG contribute to global warming; however, in the transport sector, they are dominated by CO_2 emissions from burning fossil fuels [1].

As almost all CO_2 emissions from freight transport operations are energy related, the most accurate way of calculating these emissions is to record energy consumption, e.g., in terms of liters of fuel, and to employ standard emission factors to convert energy values into CO_2 [2]. The amount of fuel consumed by a vehicle, in turn, depends on a variety of vehicle-, environment-, operations-, and traffic-related parameters, such as vehicle characteristics, length of haul, travel speed, payload, road gradient, driving behavior, traffic conditions, fleet size, fleet mix, and empty running [3–5]. While some of these factors, such as transportation technologies and fuels, have improved over the years, traffic congestion has not diminished, but is forecast to further increase in many countries, such as France, Germany, the UK, and the USA [6, 7].

This article is concerned with distribution logistics. It studies the impact that traffic congestion has on the CO_2 emissions of a whole distribution network covering the factories, the distribution centers (DCs), transshipment points (TSPs), and the retailers. The starting point of this research is the idea that, if GHG emission targets are set, it is important to understand the effects of all GHG determining factors of freight transportation. Studying the impact of traffic congestion on the CO_2 emissions of a major logistic system, such as a distribution network, is particularly motivating because this allows an area-wide

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assessment and comparison of congestion effects on different types of transport activities.

The focus of this study is on 'regular traffic congestion,' which means that there are periodically traffic conditions on the various road segments that differ from those in the free-flow situation, i.e., there are periodically higher numbers of vehicles and other impediments, such as traffic light circuits, which causes lower average travel speeds and, eventually, changed itineraries for given origin–destination pairs caused by re-routing decisions. The goal is to get insights into the 'average,' typical exposure of a logistics network to traffic congestion and the related effects on CO_2 emissions. Unusual events, such as accidents and road works, are neglected.

To gain insights into the effect of regular road traffic congestion on the volume of CO_2 emissions of a distribution network, this research analyzes the distribution network of an existing manufacturer of fast-moving consumer goods (FMCG). In doing so, it contributes to the literature by presenting a comprehensive approach to determine the CO_2 footprint of a given distribution network. The presented approach allows for an accurate estimation of CO_2 emissions as all relevant transportation flows are represented in a detailed manner. Furthermore, concerning the approximation of the CO_2 volumes emitted during the transport operations and in contrast to several previous studies, the number of factors that determine vehicle fuel consumption and that are taken into account is extensive; it includes the fleet mix, vehicle characteristics, length of haul, load factors, empty running, travel speed, and traffic conditions. In addition, this research shows that online navigation services are a valuable source of traffic information, which may be used in lots of forthcoming research projects analyzing CO_2 sensitivities and GHG cutting opportunities in logistics networks. Recent research recommended further work on the provision of reliable and detailed speed data as travel speed is a highly determining factor for CO_2 emissions and as most effort is usually dedicated to the measurement and modelling of GHG emissions, while the quality of the necessary traffic data is rarely considered [4, 8]. This paper presents a valuable data source. Finally, this research provides insights into the extent to which regular traffic congestion affects the transport-related CO_2 emissions of a distribution network and it investigates to what extent the CO_2 volume caused by traffic congestion changes when the network structure, in terms of the number and the geographical locations of the DCs, is modified.

The results are beneficial for the designers and the operators of logistics networks who require an understanding of traffic congestion impacts on logistics operations, for instance, when searching for the reasons behind differences in the CO_2 efficiency of different transport activities in different geographical areas. Furthermore, the designers of the system need to accurately quantify the problem in order to assess the effectiveness of measures intended to relieve impairments of traffic congestion; for instance, on a strategic level, when deciding whether to install additional logistics facilities, or, on a tactical level, when deciding to postpone certain transport operations. The approach presented supports better decision making as it allows evaluating a priori the extent to which traffic congestion will affect road freight transport operations in alternative network configurations. And, as will be shown, it is important to consider the traffic congestion effect on GHG emissions as it contributes to a significant percentage of the total emissions in a distribution network. Finally, the network model and the data source may be combined in future research in order to study additional GHG sensitivities of logistics networks (e.g., fleet mix, load factors, travel time variability, postponement of departure times).

2 Literature review

Demir et al. [4] give an overview of recent research on green road freight transportation. They review factors affecting fuel consumption and conclude that vehicle speed is most important. This finding is in line with research outcomes presented by Boulter and McCrae [8], which highlights the importance of considering the effect of congestion on the CO_2 emissions in logistics networks because traffic congestion affects travel speed [9]. van Woensel et al. [10] show that neglecting the congestion effect leads to an underestimation of traffic flow GHG emissions as the latter depend largely on the number of vehicles and the speed of these vehicles.

2.1 Effects of traffic congestion on road freight transport operations

Traffic congestion affects freight transport operations as it increases the average travel time and the transit time variability [11, 12]. Prior research focused on one of these aspects or studied the consequences of both effects by explicitly differentiating between 'recurring daily traffic delay' or 'regular congestion' and 'non-recurring traffic delay' or 'major congestion incidents.' Regular congestion occurs as vehicle speeds are reduced due to a high volume/capacity ratio on specific corridors at specific times. Non-recurring traffic delays occur when there are incidents such as collisions, medical emergencies, and vehicle breakdowns [12, 13]. The focus of this study is on regular congestion, i.e., the typical road-, weekday-, and time of day-specific exposure of the transport operations throughout the distribution network to traffic congestion.

McKinnon et al. [14] present results from a survey intended to assess the impact of congestion-related unreliability on logistics activities across many industry sectors. Among others, they performed traffic data analyses that confirmed the view expressed by the logistics managers surveyed that most congestion is regular and predictable. Falcocchio and Levinson [13] report research results indicating that recurring bottlenecks are the most common cause of recurring traffic delays, besides poor traffic signal timing.

This research reports the effects of traffic congestion on the CO_2 emissions of the analyzed distribution network that are due to weekday- and time of day-typical changes in travel speeds on the various road segments travelled throughout the distribution network. In addition, it considers the fact that the vehicle drivers may change the itinerary to avoid congested roads. Golob and Regan [15], for instance, report results from a study that indicates that carriers place a high value on real-time traffic information to minimize the impact of traffic congestion on their transport operations. And McKinnon et al. [14] present interview findings confirming that commercial vehicle drivers engaged in delivery operations build up a detailed awareness of traffic conditions and routing options because they visit the same region regularly. Both effects, changes in travel speeds and re-routing decisions, will affect the characteristics of the transport operations (e.g., average travel speeds, kilometers travelled, load factors, and the number of transport operations), which, in turn, change the CO_2 emissions of the distribution network.

2.2 Traffic congestion and green road freight transportation

Maden et al. [16] present empirical research using real-world traffic data to quantify the effect of traffic congestion on CO_2 emissions from freight transport operations. In their case study, they analyze the CO_2 effects of using traffic information (time-varying travel speeds) compared with routing and scheduling where this information is not available. They use the factor speed in a fuel consumption model similar to the one used in this research. However, the level of detail of their CO_2 analysis is limited as, for instance, no attempt has been made to modify the functions for the weight of goods carried at each stage of the routes or to consider different vehicle types. The influence of the vehicle load weight factor and the vehicle class on the CO_2 efficiency of road freight transportations is, however, important and should be considered in GHG analyses, as research showed [17, 18]. The same is for the research presented by Figliozzi [19], who used travel time data from an archive of freeway sensors and time-dependent vehicle routing algorithms to analyze CO_2 emissions for different levels of congestion and time-definitive customer demands

in urban freight distribution networks. Vehicle loading or different types of vehicles are not considered in his research. Barth and Boriboonsomsin [20] examined the impact of congestion on CO_2 emissions by evaluating typical traffic conditions in a traffic corridor in Southern California. And Schrank et al. [21] present research about the extent to which urban congestion has an impact on wasted fuel and CO_2 emissions. While their traffic data source corresponds to that used in this study, they concentrate on the urban area level and their observations are therefore limited to vehicle movements in some urban corridors.

This research advances the understanding of the effect of traffic congestion on the CO_2 emissions from road freight transportation as it is not limited to only a fraction of the transport operations executed to move the finished goods from the factories to the customers. It explicitly allows for the comparison of the congestion effect on CO_2 emissions of different transport activities and geographical areas. Furthermore, in this research, the number of factors determining fuel consumption that is taken into account is extensive and the analyses are based on a traffic data source that allows for an area-wide observation of representative trip characteristics.

2.3 Road traffic data sources

Boulter and McCrae [8] review scientific studies that highlight the crucial role of the provision of accurate, reliable, and detailed speed data as an accurate and detailed knowledge of actual driving speeds is fundamental for emission estimations. They recommend further work on the provision of reliable and detailed speed data as most effort is usually dedicated to the measurement and modelling of emissions, while the quality of the necessary traffic data is rarely considered. And McKinnon and Piecyk [22] present experiences in the UK that highlight the difficulty of compiling an accurate and consistent set of emissions data for trucking. This research contributes to overcome that problem.

2.3.1 Conventional data sources

The 'conventional' road traffic data sources used for logistics system analyses are interviews/surveys [23], traffic information provided by private and/or public authorities using 'in situ' technologies, such as detectors located along the roadside or vehicle counts [24], and floating car data/fleet management systems [25]. In the latter case, GPS or mobile phone devices are inside the moving vehicles recording spatially and temporally the itinerary. Recently, Kellner [26] listed problems that will arise when measuring congestion effects in large-scale logistics systems, such as a distribution network, by means

of the conventional data sources: Concerning in situ technologies, traffic sensors are expensive to install and maintain and they are therefore not widespread [25]. A nationwide observation of traffic conditions and CO_2 emissions, covering the whole distribution network, is not possible when relying only on traffic information collected by the means of in situ technologies. The typical concerns arising from interviews/surveys and floating car data are a lack of consistency in the measurements and a lack in representativeness of the processed data. Consistency in the measurements is a concern in logistics systems consisting of several parties, such as shippers and carriers [23]. All of them have to collect trip/traffic information in a consistent, complete, correct, and unbiased way. The risk of processing erroneous or biased numbers is particularly high when the trip/traffic information is collected by the parties themselves and/or when the study is based on rough estimates. Furthermore, the use of GPS devices to collect trip data is typically limited to one company, for technological and behavioral reasons [27]. The representativeness of the gathered and processed information becomes a concern when the number of traffic observations on the different trip segments is low. Boulter and McCrae [8] recommend that the use of short-term traffic data, observed in traffic studies over 2 or 3 days/weeks, should be avoided where possible when analyzing GHG emissions in transport networks as it may reflect specific and/or exceptional traffic conditions.

2.3.2 Navigation service data

To overcome these problems, this study makes use of traffic data provided by an online navigation and traffic information service, such as Bing Maps, Google Maps, Inrix, Here, and TomTom. The traffic information offered by these services is valuable for at least four reasons [26]: (1) As there are concerns about the accuracy of installed detectors and floating car data [25, 28], some navigation service providers use complementary solutions combining different data sources in order to improve the reliability and accuracy of the delivered trip/traffic information (e.g., historic data records, GPS measurements, local experts' knowledge, camera imagery, road sensors) [29, 30]. (2) In contrast to in situ technologies, navigation data allow for an area-wide observation of traffic conditions as it processes data from in situ technologies and floating car data. (3) While the consistency in the measurements is a concern when using interviews/surveys and floating car data, data provided by navigation services are gathered in an objective and consistent way. The trip/traffic data collection method is the same across all parties involved, and there are no possibilities for the parties to report erroneous or biased numbers. Navigation services allow the retrieval of

anonymized and unbiased information with no limitation to a certain institution or regional area. (4) In general, the traffic data retrieved from online navigation services will have a higher level of representativeness than the traffic information collected by means of interviews/surveys and floating car studies. This is true as some online navigation services allow the retrieval of averaged/smoothed trip information, i.e., time-typical travel times and delays, for a given moment in time. Such data have been prepared using different traffic observation technologies and a large data history of floating car data [29, 30]. Fleischmann et al. [31] explain statistical techniques used by navigation service providers to estimate time-typical trip data (trip length, travel time, speed) with high accuracy. In addition, it is possible to capture the fact that the vehicle drivers occasionally use alternate routes to avoid congested road sections as the time-minimal route changes depending on the traffic conditions.

3 Methodology

To explore the impact of regular road traffic congestion on the CO_2 emissions of a distribution network, the totality of transport operations for one calendar year of a real-world distribution network is observed under two conditions, the 'free-flow' and the 'normal' traffic situation. This approach allows isolating the impact of traffic congestion on GHG emissions. To avoid the results of this study being excessively company specific due to the locations of the facilities and to understand how a reconfiguration of the logistics network affects the CO_2 impact of traffic congestion on the transportation flows, the number of DCs is experimentally increased from one to four.

The case company, the dataset, and the distribution network model that are used in this research have recently been introduced by Kellner [26], who analyzed the effects of traffic congestion on distribution network characteristics in terms of transit times, delays, kilometers travelled, vehicle operating costs, stock-in-transit, cost per customer, and the number of transport operations by the means of navigation service data. This research extends the network analyses of Kellner [26] by studying the effects of traffic congestion on the CO_2 emissions from transportation. In detail, it makes use of the network model and the trip data that have been requested by Kellner [26] from an online navigation service and combines them with the COPERT functions [32] to evaluate all transport operations with CO_2 emissions. The following sections summarize the network model and the traffic data acquisition with focus on the aspects that are relevant for the GHG network analysis. Furthermore, they explain the translation of the freight transport operations into CO_2.

3.1 Case company

The case company is a major German manufacturer of FMCG/groceries, classified in Standard Industrial Classification (SIC) Group 20 'Food and Kindred Products.' The FMCG/grocery industry is a useful case because these products are convenience goods and distributed nationwide. Therefore, the analysis is not restricted to a certain geographical area.

The focal company operates six factories. These factories are located in Germany and process the products destined for the German market. The finished products are moved by trucks from the factories to one DC and then onward to the company's customers, i.e., food/FMCG retailers, mainly supermarket chains. The food and kindred products are distributed palletized to supply virtually any store/supermarket in Germany. Customer locations are either points-of-sale or retailer DCs.

This company provided a comprehensive dataset with information on its real-world distribution activities over one calendar year. The shipment dataset alone contains details about 20,000 DC inbound and 105,000 DC outbound shipments, with information about the delivery days, the origin–destination pairs, shipment sizes, and cost information. A total of 4640 distinct customer locations have been supplied with a total of 340,000 tons of FMCG. This dataset has been used to set up a distribution network model that reflects all transportation flows for the calendar year being considered.

3.2 Distribution network model

In the distribution network model, all transport operations are modelled on a daily basis, all locations are on street number level, and the network flows are those experienced by the case company. The analysis considers the exact calendar day when the single shipments have been moved because the typical traffic conditions vary according to the weekday and the number of shipments is not the same on each day. In addition, the exact tonnages and the number of low-volume shipments determine the transport operations on a daily basis, i.e., the number of consolidated shipments and the delivery trips. The transport operations have been classified into four transportation flows: production flows (DC inbound shipments), DC-direct shipments, DC-consol shipments, and delivery trips (Fig. 1).

1. Production flows: These are high-volume shipments with 17 tons per shipment on average. The production flows are transported directly from the six factories to the DC (DC inbound).

2. DC-direct shipments: These are DC outbound shipments with a tonnage above 5000 kg. DC-direct shipments are transported directly from the DC to the customers, i.e., there is no transshipment in between.

3. DC-consol shipments: DC outbound shipments with a tonnage below 5000 kg are consolidated at the DC and forwarded as consolidated shipments via transshipment points. The TSP locations correspond to the 29 TSP sites operated by a major German logistics service provider specializing in the FMCG segment. The shipments are always transported to the TSP that is nearest to the customer destination. The consolidation is modelled taking into consideration exact shipment days and TSP locations. The typical vehicle capacity utilization of the DC-consol shipments is 14 tons. In the distribution network model, this tonnage is assumed for all DC-consol shipments.

4. Delivery trips: The goods that are transported with DC-consol shipments to the transshipment points are
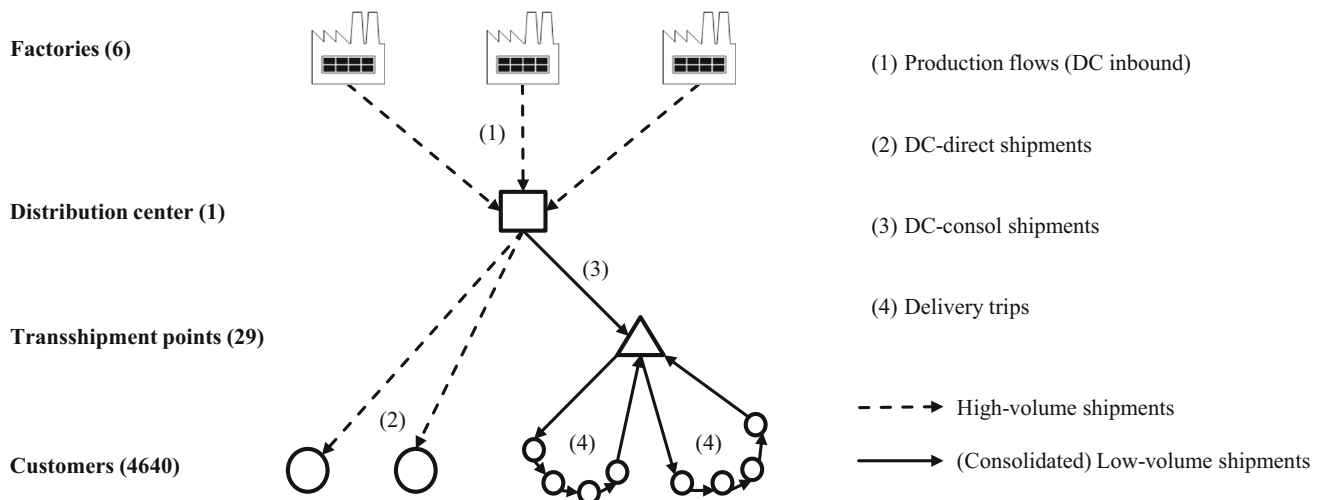

Fig. 1 Distribution network model

forwarded in delivery trips to the retailers. The spatial allocations of demand points to transshipment points make up the TSP service areas.

For the modelling and the analysis of the traffic effect on the transport operations, the four transportation flows are classified into two trip types, namely line haul shipments and round trips.

3.2.1 Line haul shipments

Line haul shipments consist of one trip segment, from the origin to the destination location. The production flows, the DC-direct shipments, and the DC-consol shipments are in this class. The trip information that is needed to environmentally evaluate these shipments is requested from the navigation service by indicating the trips' starting and ending points. Typically, articulated heavy goods vehicles (HGVs) with a maximum payload capacity of 25 tons are used to move the line haul shipments (Articulated 34–40 tons).

3.2.2 Round trips

Round trips consist of several trip segments linking the first and the last tour stop with the TSP and linking the single tour stops with each other. The delivery trips are in this class.

In the network model of Kellner [26], a two-step methodology is used to model the round/delivery trips. First, the TSP service areas are clustered into subregions, called 'delivery zones.' This makes sure that the delivery trips created are realistic as they serve a separate group of customer destinations lying relatively close to each other. Simultaneously, a centroid is determined for each delivery zone. The centroids serve to identify 'reference customers.' The reference customer of a delivery zone is the customer that is located nearest to the centroid. Second, Fleischmann's 'ring model' [33] is used to approximate on a daily basis the delivery trips that supply the customers. The ring model assumes that the distances between customers in a certain round trip and the TSP are the same and that all customers are supplied with the same tonnage on average. This allows the estimation of the number of customers in a certain round trip (n), which is the minimum of the number of customers that can be served due to vehicle capacity restrictions, and the number of customers that can be served due to time restrictions:

$$n = \min\left\{ \frac{\text{Capa}}{\text{tn}}; \frac{H - \left(\frac{d_A}{v_A} + \frac{d_R}{v_R}\right) + \frac{d_L}{v_L}}{s + \frac{d_L}{v_L}} \right\} \quad (1)$$

In Eq. (1), Capa is the maximum weight-based vehicle capacity utilization. It is determined by taking into

consideration the average tonnage per pallet for DC outbound shipments and comes with a weight-based load factor of 55 %. tn is the average tonnage demanded by customers taking part in the considered round trip. This parameter is determined individually for each round trip and takes into account all shipments that are delivered to the customers served on a certain delivery day and in a certain delivery zone. H is the number of daily working hours spent on the delivery trips, which is 8.5. s is the average unloading time at the customers, which is 15 min. d_A is the distance of the approach from the TSP to the first customer, d_R is the distance of the return leg from the last customer back to the TSP, and d_L is the local, average distance between the customers. v_A, v_R, and v_L are the average travelling speeds on the corresponding legs.

Once the number of customers in a tour is known, Eqs. (2)–(3) can be used to determine the length l and the travel time t of the round trip.

$$l = d_A + d_R + (n - 1) \times d_L \quad (2)$$

$$t = \frac{d_A}{v_A} + \frac{d_R}{v_R} + n \times s + (n - 1) \times \frac{d_L}{v_L} \quad (3)$$

For the CO_2 analysis, it is important to consider the type of vehicle that is used to carry out the delivery trips as the volume of CO_2 emissions per kilometer may differ considerably for short-distance round trip vehicles (see below). Typically, two vehicle types are available: a 'Rigid 7.5–12 tons' with a maximum payload capacity of 6 tons (Capa = 3.3 tons) and a 'Rigid 20–26 tons' with a maximum payload capacity of 12 tons (Capa = 6.6 tons). In order to determine the vehicle that has carried out the round trip, first, the round trip is estimated for the 'Rigid 20–26 tons.' If the same round trip could also be run with a 'Rigid 7.5–12 tons,' then the 'Rigid 7.5–12 tons' is used, otherwise the 'Rigid 20–26 tons.'

3.2.3 Changing the number of distribution centers

The number of DCs is changed by determining the cost-minimal 1-, 2-, 3-, and 4-DC configurations. A p-median model is used to locate the DCs and to allocate the customers in such a way that the overall transportation costs are minimized. Once the locations of the DCs are identified, it is possible to request trip data for all origin–destination pairs that are run in the hypothetic networks [26].

3.3 Translating freight transport operations into CO_2 emissions

As stated above, the most accurate way of calculating emissions from freight transport operations is to record fuel consumption and to employ standard emission factors to

Table 1 Fuel consumption model: regression parameters [32]

Vehicle type	Rigid 7.5–12 tons (Euro VI) (max. payload: 6 tons)			Rigid 20–26 tons (Euro VI) (max. payload: 12 tons)			Articulated 34–40 tons (Euro VI) (max. payload: 25 tons)		
Load factor	0 %	50 %	100 %	0 %	50 %	100 %	0 %	50 %	100 %
a	912.81	884.21	892.07	318.82	−465.38	−1580.66	−56.05	−2077.80	−221.75
b	11.62	10.87	10.46	26.87	155.18	440.59	85.84	593.30	67.97
c	−0.17	−0.17	−0.17	2.16	5.93	12.59	3.49	14.73	1.17
d	−439.58	−459.96	−514.30	1103.88	1888.82	3097.33	1637.92	3781.48	262.81
e	1	1	1	1	1	1	1	1	0
f	0.32	0.26	0.23	−0.09	−0.22	−0.28	−0.15	−0.28	−0.00
g	−0.00	−0.00	−0.00	0.02	0.05	0.09	0.03	0.10	0.01

convert the amount of combusted fuel into CO_2. When energy values are not available—for instance, when planning or evaluating future/alternative transport scenarios—fuel consumption models may be used, which estimate fuel consumption of transport operations based on a variety of vehicle-, environment-, and traffic-related parameters, such as vehicle speed, load factors, road gradients, and acceleration [3, 4, 34]. This research adopts the fuel consumption model 'COPERT 4,' as described by the European Environment Agency (EEA) [32]. COPERT has been chosen because it is a European-wide accepted methodology to calculate fuel consumption and GHG emissions from road freight transport. It integrates methods and results from other accepted scientific projects (e.g., ARTEMIS, COST 319, HBEFA, and MEET), and the methodology proposed by COPERT is used in other emission models [4, 8, 35]. Furthermore, COPERT has been widely used in different studies and proved its adequacy in research on green road freight transportation [4, 35].

COPERT uses regression functions to estimate the fuel consumption of HGVs. The independent variable is the average travel speed on the trip. There are specific functions depending on the vehicle type, the European emission standard, road slope, and vehicle load, resulting in almost 12,000 regression models [32]. The various regression functions have been derived from large-scale real-life experiments [3, 8]. Equation (4) is the generic function, which is the same across all combinations of vehicle types, emission standards, road slopes, and load factors that are relevant in this research.

$$FC = \left(a + b \times v + c \times v^2 + d/v\right)/\left(e + f \times v + g \times v^2\right) \tag{4}$$

FC is the diesel fuel consumption in g/km, and v is the average travel speed in km/h. Table 1 summarizes the regression coefficients a, b, c, d, e, f, and g.

It should be noted that EEA [32] presents regression functions for three load factors: 0, 50, and 100 %. Because

the effect of vehicle loading on CO_2 emissions is linear with load according to the ARTEMIS data, fuel consumption can be linearly interpolated between the relevant functions [36]. Furthermore, the functions used in this research come with a road slope of 0 % as no data were available for the road gradient. Once the fuel consumption of the transport operation is known, CO_2 emissions may be calculated by multiplying the fuel consumption FC with an emission conversion factor. DEFRA [37] proposes 3.1643 (g CO_2)/(g diesel), and it is this emission conversion factor that is used.

Figure 2 shows the effect of travel speed on CO_2 emissions for the three vehicle types and three load factors. For low speed values, fuel consumption is high because of inefficiencies in the usage of fuel that decrease as speed
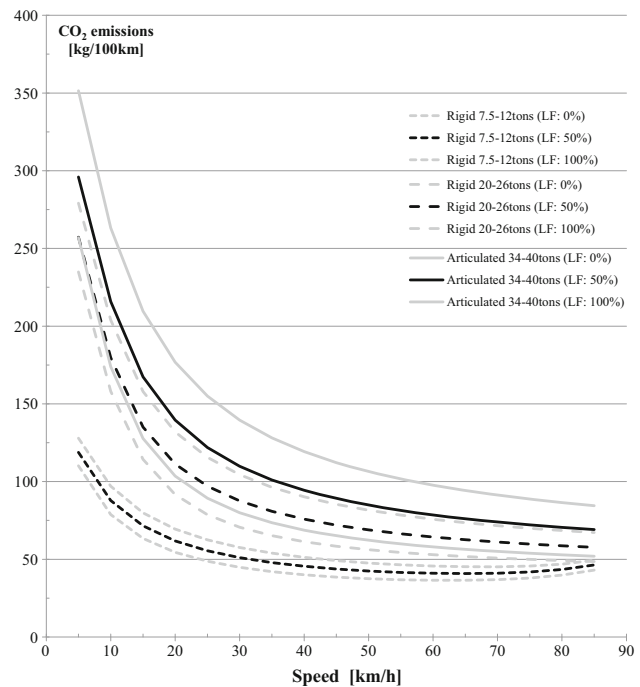
Fig. 2 Vehicle speed and CO_2 emissions

increases [3, 20, 38]. For the 'Rigid 7.5–12 tons' vehicle, there is a CO_2 minimal speed at about 65 km/h. Higher speed raises CO_2 emissions per kilometer due to the aerodynamic drag. According to Eq. (4), for the medium- and high-volume vehicles, the inefficiencies in the usage of fuel that result from low speeds remain constantly more important than the inefficiencies of a higher aerodynamic drag at higher speeds. Note that the shapes of the CO_2 emission curves depend on the fuel consumption model used and the vehicle characteristics assumed. Hill et al. [39], for example, show truck speed–fuel efficiency curves that differ (at the higher speeds) from those presented in Fig. 2. While the curves presented by Hill et al. [39] are similar to the COPERT curves up to 60 km/h, they start climbing on a rising scale at about 60 km/h to reach their maximum at 120 km/h. Certainly, the replacement of the COPERT model by the fuel consumption model used by Hill et al. [39] will affect the numeric results of the example case presented below. However, the differences in the results should be minor because the very high speeds do not represent the typical daily usage of heavy goods vehicles, for instance, because of speed limits. This has been stated by Hill et al. [39] and is in line with the findings of this research.

Equation (4) is used to evaluate all transport operations with CO_2 emissions. The latter depend on the vehicle type, the average travel speed, trip length, and the load factor. Therefore, the fact is taken into account that different vehicle types are used for the different transportation flows. The trip lengths and average travel speeds are requested/derived from the data delivered by the navigation service for each trip segment run in the distribution network. Note that there is one trip segment for the line haul shipments and $(n + 1)$ trip segments for the round trips. The load factors of the production flows and DC-consol shipments are 68 and 56 %, respectively. The load factors of the DC-direct shipments vary depending on the shipment size (the average is 48 %). The load factors on the trips connecting the TSPs and the reference customer are $(n \times tn)/(vehicle payload capacity)$ (on average 42 %), the load factors on the trips connecting the customers in the round trips are $((n \times tn)/2)/(vehicle payload capacity)$ (on average 21 %), and the load factors on the trips connecting the reference customers and the TSPs are 0 %. Concerning the delivery trips, the total CO_2 emissions of a certain tour are allocated equally among all shipments that are part of this tour. This is plausible as the shipments are homogenous in terms of the distance to the transshipment point and the tonnage.

Clearly, the fact that COPERT bases its CO_2 estimations on the average speed travelled on the single legs may be seen as a rough estimation of the impact of vehicle speed on CO_2 emissions, especially in the case of stop-and-go situations [20]. A more precise estimation may be realized when the exact speed profiles, i.e., the speed or energy consumption per second, of the vehicles that have carried out the single transport operations are known. In that case, micro-level emission models may be used, which are based on instantaneous vehicle kinematic variables, such as speed and acceleration, or on more aggregated modal variables, such as time spent in each traffic mode, cruise, and acceleration [4]. However, such detailed information is hard to procure for an ex post analysis of several thousand transport operations and not available ex ante, when evaluating alternative/future transport scenarios. Therefore, macro-level average-speed emission models have been developed, which are important tools in a wide-area emission assessment and which are often used in green supply chain management studies [4]. According to Barlow and Boulter [34], who present research that determined the accuracy of the predictions of different fuel consumption models, average-speed approaches provide in many scenarios a reasonably accurate characterization of total emissions from road transport.

3.4 Traffic data acquisition

The trip and traffic information, in terms of tour lengths and travel times, that is needed as an input for the COPERT models is retrieved from one of the above-mentioned online navigation service providers via the available application programming interface.[1] Some online navigation service providers offer the possibility to retrieve trip information for the desired origin–destination pairs for the moment of the request or, alternatively, for a specific weekday and time of day. In the latter case, the response contains averaged/smoothed data corresponding to the typical situation for the selected weekday and time of day, without exceptional conditions. In order to ensure the representativeness of the delivered day- and time-typical travel information, navigation service providers use different statistical techniques [31]. All analyses presented in this paper are based on day- and time-typical trip information as this is in line with this research's understanding of regular traffic congestion.

3.4.1 Free-flow situation

As the selected navigation service provider does not offer free-flow information, the typical situation for a departure at 10:30 p.m. is used. This departure time led to the minimum travel time over the day in almost each case in a sample of 2000 randomly requested origin–destination pairs. Palmer and Piecyk [40] also found that typically, the

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[1] The traffic data used in this study are the same as Kellner [26] used for his analyses.

best start times for delivery operations occur just before midnight or during the early hours of the morning, when the goal is to minimize the travel time.

3.4.2 Normal traffic situation

The travel time and trip distance information for the normal traffic situation is requested from the online navigation service for the weekday when the shipment was actually moved and for the departure time when the different transport operations typically start.

Concerning the production flows and DC-direct shipments, a great share of these transport operations starts with vehicle loading activities in the morning. Then, the trips start. For each transport operation, the assumed departure time is 8:00 a.m.

Concerning the DC-consol shipments, the normal traffic situation corresponds to a departure time of 5:00 p.m. because less-than-truckload shipments are consolidated for a certain delivery region and typically collected by the carrier in the late afternoon or early evening hours. In overnight trunking operations, the consolidated cargo is moved to the respective transshipment points. There, the single shipments are prepared for the delivery trips, which start in the morning hours.

Concerning the delivery trips, first, the number of customers and the average tonnage per customer are determined for each calendar day and delivery zone. Then the trip lengths and the travel times are requested for a departure time of 8:00 a.m. for the legs between the TSPs and the reference customers. In doing so, the actual weekday is considered. The same values are requested for a departure time of 4:00 p.m. for the return legs from the reference customers to the TSPs. Concerning the local trips, trip lengths and travel times are requested for a sample of customer–customer trips in the considered delivery zone and on the considered weekday for a departure time between 10:00 a.m. and 2:00 p.m. and, then, the average is established. This is also done for the same legs for a departure time of 10:30 p.m. (free-flow). Finally, Eqs. (1)–(3) are used to create the delivery trips for the normal and the hypothetic free-flow situation.

3.4.3 Estimating HGV travel times

As the selected navigation service provider only offers trip information for passenger cars but not for HGVs, HGV travel times t_{HGV} (in seconds) are approximated using trip length l (in meters) and passenger car travel time t_{Car} (in seconds), as proposed by Kellner [26]:

$$t_{HGV} = 54.57(\text{s}) + 0.02 \times l + 1.09 \times t_{Car} \tag{5}$$

4 Understanding the effect of regular traffic congestion on CO_2 emissions

Regular traffic congestion means that there are periodically, depending on the weekday and the time of day, different traffic conditions on the various segments of the road network to that of the free-flow situation. This affects average travel speeds and, eventually, causes altered routes connecting the origin–destination pairs as the time-minimal itinerary changes. Figure 3 shows the effect on the CO_2 emissions of the line haul shipments and the round trips when the average travel speed is increased from the normal to the free-flow situation.

The following subsections explain the development of CO_2 relevant characteristics of the line haul shipments and round trips with increasing/decreasing average travel speeds. These explanations are generally applicable; however, the orders of magnitude of the effects (cf. vertical axis in Fig. 3) depend on the specific trip parameters. In the interests of simplification, the following explanations ignore the fact that the routes/trip distances may change due to bypasses of congested regions.

4.1 Effects of average travel speed changes on the line haul shipments

Figure 3a shows that within a reasonable range of speed increases (decreases), CO_2 emissions from line haul shipments decrease (increase) approximately linearly. The lines reproducing the CO_2 emissions of an articulated HGV 34–40 tons in Fig. 2 support this finding: If, for any load factor and trip length, any (free-flow) speed is reduced within a reasonable range, then the effect on CO_2 emissions is approximately linear. Even if the average free-flow speed on a trip is reduced from 85 to 28 km/h (reduction factor 3), the curve in Fig. 2 comes still with an R^2 value of 0.91. This finding suggests that the overall effect of travel time increases due to traffic congestion on the CO_2 emissions of the distribution network may be linearly extrapolated (see below).

4.2 Effects of average travel speed changes on the round trips

Figure 3b shows CO_2 relevant effects of changing average travel speeds for the round trips. In the round trip case, three situations may occur [26]:

1. Under free-flow and normal conditions, the number of customers is determined by the vehicle capacity. This case can be observed when there are mainly high-volume shipments or when the customers served are
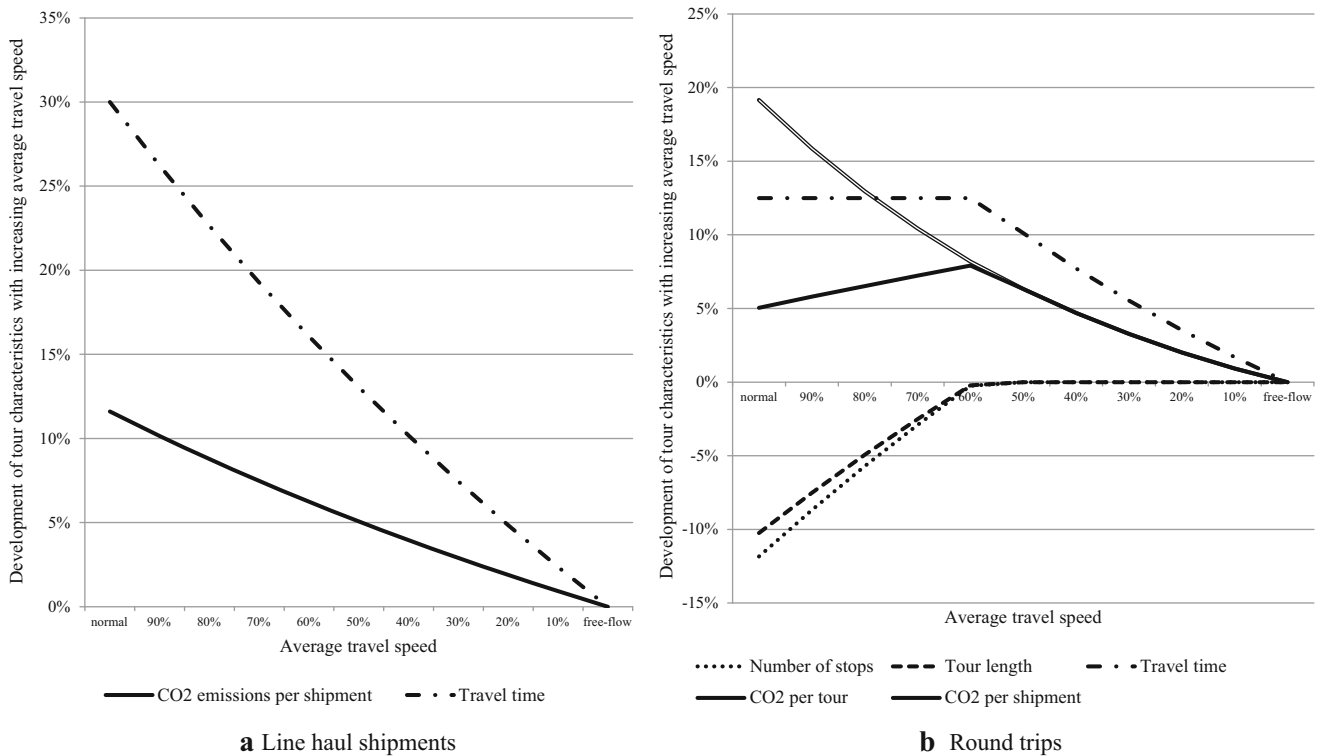
Fig. 3 Effects of average travel speed changes on the line haul shipments and the round trips

located near to each other, like in city regions. In this case, the number of tour stops and the itinerary (tour length) are independent of travel time. Traffic congestion increases the tour travel time and decreases the average travel speed, as in the case of the line haul shipments. This development corresponds in Fig. 3b to the section between '60 %' and 'free-flow' and is equivalent to the development in the line haul shipment case.

2. Under free-flow and normal conditions, the number of tour stops is determined by the time restriction. This case can be observed when there are mainly low-volume shipments and/or when the delivery zones are broad, like in rural regions. The development of the characteristics of these tours is reproduced in Fig. 3b, section between 'normal' and '60 %.'

    Three effects are relevant for the volume of CO_2 emissions when the number of tour stops is determined by the time restriction: (A) On the one hand, there will be a reduction of the CO_2 emissions on the single tour legs when the average travel speed increases as the emissions per kilometer decrease (cf. Fig. 2). (B) On the other hand, when the travel times on the single legs are reduced as a result of average travel speed increases and the number of customers served in the trip is still determined by the time constraint, more customers will be inserted in the trip. When the number of customers increases due to travel

time decreases, the tour length will also increase (cf. Eq. 2). This will boost the volume of CO_2 emissions of the tour. (C) When there are more customers served per tour, the load factor is increased, which will also increase the CO_2 emission of the round trip. When these three effects are combined, the volume of CO_2 per trip may rise or fall when the average travel speed increases.

However, when there are more customers in a delivery round, less delivery trips are necessary to serve all customers and the average CO_2 emissions per tour stop will drop. Various parameter configurations for Capa, tn, s, d_A, d_R, d_L, v_A, v_R, v_L, and the vehicle type have been tested to find situations where the volume of CO_2 per customer does not decrease with rising average travel speeds. There are very few instances with extreme parameter configurations that lead to an increase in the CO_2 per tour stop when the average travel speed increases. Most of them are less relevant for the following analyses as they do not represent the 'typical' round trip. Thus, for the major part of the round trips, CO_2 emissions per customer will drop when travel speed increases, as it is shown in Fig. 3b.

3. Due to traffic congestion, the number of tour stops is no longer limited by vehicle capacity, but the time restriction becomes decisive. Figure 3b visualizes this situation (starting from the 60 % mark, the travel time becomes the limiting factor).

5 Results for the example case

5.1 Overall results of the company case study

For each transport operation, the CO_2 emissions and other indicators have been calculated for the normal and the free-flow traffic situation, to be finally aggregated. Table 2 shows the increase in CO_2 emissions and in distance travelled and the changes in the average travel speed for the normal compared to the free-flow situation for the whole distribution network.

The CO_2 emissions that arise for the distribution of the 340,000 tons of FMCG are for the normal traffic situation between 10,566 and 12,535 tons, depending on the number of DCs. The CO_2 volume decreases with a rising number of DCs as the sum of all kilometers travelled to distribute the goods decreases [41], here from 15.7 to 13.2 mio kilometers.

In the networks with more than one distribution center, regular traffic congestion increases the total CO_2 emissions by about 2.5 %, regardless of the number and locations of DCs. This indicates a stable effect. This, in turn, implicates that the absolute effect is lower in a multi-DC structure compared to a single-DC network as CO_2 emissions are typically lower when there are more DCs [42]. The high increase in CO_2 emissions and distance travelled for the production flows in the 1-DC network stems from the fact that the transport operations originating at the factory with the highest output take relatively long detours in the morning hours to avoid congested roads. This also explains why the average travel speed is even higher in the normal than in the free-flow situation: More kilometers are travelled to avoid the congested areas, and these detours allow higher average speeds compared to the free-flow trip. In light of this, the impact of traffic congestion on the CO_2 emissions is relatively homogenous. The CO_2 increase is highest for the delivery trips (+4.2 %), which takes into account detours of congested roads, the reduction of customers served per tour, and additional delivery trips needed. This observation may be explained by the fact that the delivery trips experience with a minus of six percent the highest decrease in average travel speed. This, in turn, is plausible as there are many customer–customer legs in city regions, where traffic congestion is especially hurting the efficiency of the transport operations, whereas the long-distance line haul operations often use motorways and primary roads. Note that, in the case of the delivery trips, the CO_2 increase is the same for all network configurations because changing the number of DCs only changes the production flows, the DC-direct shipments, and the DC-consol shipments; however, this does not alter the delivery trips [26]. Even if there are some TSPs that are supplied by more than one distribution center because the different retailers in these TSP service areas are assigned to different DCs, the delivery trips will not alter because each customer is supplied on a given delivery day via the nearest TSP.

Table 2 Aggregated effects of regular traffic congestion on the CO_2 emissions, on the kilometers travelled, and on the average travel speed of the transportation flows

Indicator	Transportation flows	1 DC	2 DCs	3 DCs	4 DCs
CO_2 emissions	Production flows (%)	13.1	3.2	2.5	2.4
	DC-direct shipments (%)	2.0	2.1	2.0	2.0
	DC-consol shipments (%)	1.3	1.5	1.4	1.5
	Delivery trips (%)	4.2	4.2	4.2	4.2
	Total (%)	4.5	2.6	2.4	2.4
	Total: normal situation (tons)	12,535	11,395	10,719	10,566
	Increase free-flow to normal (tons)	535	288	253	248
Km travelled	Production flows (%)	15.2	0.7	0.2	0.3
	DC-direct shipments (%)	0.0	0.1	0.1	0.1
	DC-consol shipments (%)	0.0	0.1	0.1	0.1
	Delivery trips (%)	2.4	2.4	2.4	2.4
	Total (%)	3.2	0.7	0.7	0.7
	Total: normal situation (km)	15.7×10^6	14.3×10^6	13.4×10^6	13.2×10^6
	Increase free-flow to normal (km)	488×10^3	99×10^3	87×10^3	85×10^3
Avg. travel speed	Production flows (%)	7.3	−5.8	−5.1	−4.9
	DC-direct shipments (%)	−4.9	−5.4	−4.8	−5.0
	DC-consol shipments (%)	−3.4	−4.0	−3.6	−4.0
	Delivery trips (%)	−6.0	−6.0	−6.0	−6.0

5.2 Delivery trips

The relatively high impact of traffic congestion on the CO_2 efficiency of the delivery trips may also be explained with the traffic effect on the total kilometers travelled. On the one hand, traffic congestion causes additional kilometers travelled because of detours avoiding congested regions. On the other hand, additional delivery trips are occasionally needed to supply the customers (76 extra tours are only due to traffic congestion). The average number of customers served per trip is 6.73 in the free-flow and 6.45 in the normal situation (-4.2 %). And the share of the delivery tours limited by the time constraint increases from 51.2 to 53.3 % [26].

The change in CO_2 emissions on a single shipment basis is between -37.8 and $+54.8$ %. The average is $+4.2$ %. For 1.85 % of the round trip shipments, traffic congestion leads to a reduction of the CO_2 volume emitted and for 98.15 % to an increase. CO_2 reductions of about 30 % are observed when a 'Rigid 20–26 tons' vehicle is used in the free-flow situation with a low load factor and, due to a reduction of the number of customers in the round trip as a consequence of travel time increases, a 'Rigid 7.5–12 tons' vehicle is used under normal conditions. This observation indicates the major importance of choosing the right vehicle to move the shipments. Moreover, there are slight CO_2 reductions (below 1 %) for about 0.13 % of all delivery shipments because for these shipments the itinerary is shorter in the normal situation where congested roads are avoided than in the free-flow case.

5.3 Line haul shipments

For the line haul shipments, the CO_2 increase on a single shipment basis is for the 1-, 2-, 3-, and 4-DC configurations at maximum 43.4, 23.4, 41.4, and 41.4 %. The average is about 2.5 %. For about 0.5 % of all line haul shipments, the CO_2 emissions are reduced as a result of traffic congestion. These are shipments for which the routes have been changed to avoid the congested roads and the changed itinerary is shorter than the one in the free-flow situation. The emissions are reduced when the CO_2 savings that come with saved distance travelled are greater than the CO_2 emissions caused by the travel speed reductions.

Overall, the effect of traffic congestion on distance travelled is relatively low in percentage values (Table 2). Bypassing congested roads causes a slight increase in kilometers travelled [26].

Furthermore, the results prove that the time of departure of the transport operations significantly affects the average travel speed and the CO_2 volume.[2] DC-consol shipments are less affected by traffic congestion because these transport operations are carried out during the nighttime.

The CO_2 increase that is due to regular traffic congestion is about 50 % higher in the case of the production flows and the DC-direct shipments when compared to the DC-consol operations. This means that the amount of CO_2 of the distribution network may be reduced when transport operations are shifted to the nighttime hours. Whereas this measure is difficult to implement for the DC-direct shipments—these deliveries depend on the opening hours of the retailers—shifting (at least a share of) the production flows from the day- to the nighttime is less problematical.

5.4 Effects of further travel time increases

This section summarizes the results of a linear regression analysis intended to extrapolate the impact of further increases of traffic delays on the CO_2 emissions from transportation. In this analysis, it is assumed that the effect of increasing/decreasing traffic delays on the CO_2 emissions of the distribution networks is (approximately) linear. Traffic delays are defined as the normal travel time minus the free-flow time.

The traffic delays have been separately measured on the different tour segments that are driven throughout the distribution network because there are different levels of traffic congestion on the single transport legs. Then, for all tour segments, the individual delays are increased by a constant factor δ from 1.0 up to 3.0 with step size 0.1. This is done for the 1-, 2-, 3-, and 4-DC configuration, which leads to 84 observations. These 84 observations serve as the data input for the regression analysis: The CO_2 emissions are the dependent variable, and the values for δ and the (inverted) number of DCs are the independent variables. Equation (6) presents the model. Total CO_2 are the total CO_2 emissions (in tons), δ is the factor by which the delays are increased, and (1/Number of DCs) is the inverted number of DCs.

$$\text{Total}\,CO_2 = 9600(\text{tons}) + 260 \times \delta + 2770 \\ \times \frac{1}{\text{Number of DCs}} \qquad (6)$$

The regression analysis indicates that the total CO_2 volume may be explained to a good extent by the linear model: $R^2 = 98.7$ %, MAPE = 0.7 %, the maximum deviation of the estimated from the observed CO_2 emissions is 1.3 %, and all coefficients have p values below 0.001. According to Eq. (6), a doubling of the delays on the single legs will boost the CO_2 emissions by 260 tons—regardless of the number of DCs. This means that the CO_2 increase in percentage values is higher in networks with more distribution centers and that the CO_2 advantage of a

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[2] This finding is in line with the research results presented by Palmer and Piecyk [40].

multi-DC network compared to a 1-DC structure declines with rising delays. On average, a doubling of the delays on all legs increases the total CO_2 emissions by about 2.3 %. This effect may be linearly extrapolated, which means that an increase of the delays by 20 % will boost the total CO_2 emissions by 0.46 %, for instance.

5.5 CO_2 mitigating opportunities

Apart from observing the effect of a rising number of DCs on the CO_2 emissions from traffic congestion, the presented network model and data source enable the designers and the operators of the logistics network to evaluate additional strategies aimed at reducing the CO_2 intensity of the distribution activities. In an analogous manner to the analysis of the effect of rising numbers of DCs, the effects of changing the network structure by altering the number of TSPs could be analyzed.

For the actual 1-DC configuration, two sensitivities are studied: First, the effect of shifting 30 % of the shipments starting at the factory with the highest output to 10:30 p.m. departure times is observed. Second, the effect of only using 'Rigid 20–26 tons' vehicles—instead of a mix of 'Rigid 7.5–12 tons' and 'Rigid 20–26 tons'—for carrying out the delivery trips is calculated. The first option leads to a reduction of 2.9 % of CO_2 emissions for the production flows. The second option leads to a plus of 10.2 % in CO_2 emissions of the delivery shipments, indicating the major importance of selecting the right vehicle to carry out the round trips.

6 Conclusion

6.1 Summary of the findings

This research presented an approach to quantify the effect of regular traffic congestion on the CO_2 emissions of a typical FMCG distribution network. In the example case, regular traffic congestion causes about 2.5 % of the total CO_2 emissions. The number of DCs affects this percentage to a minor degree. However, the traffic effect on CO_2 volumes in absolute values declines when the number of DCs increases. The outcomes of the regression analysis indicate that within a certain range, the impact of increasing traffic delays on total CO_2 emissions may be approximated with a linear model. That means that when all traffic delays will rise by 10 %, the CO_2 emissions are expected to rise by 0.25 %. For some line haul shipments and round trip shipments, CO_2 increases of more than 40 and 50 % have been observed. However, the average increases are below 5 %. Whereas the effect of traffic congestion on the CO_2 emissions of the line haul shipments are—apart from some detour kilometers—essentially due to lower average travel speeds, which cause inefficiencies in the usage of fuel, the characteristics of the round trips—in terms of kilometers travelled, number of customers served, total trips needed, load factors—may change completely due to lower average travel speeds, which affects the CO_2 footprint of the distribution network. The volume of CO_2 emissions may be reduced, for instance, by shifting transport operations to the nighttime hours or by choosing the right vehicle for carrying out the delivery trips.

This study demonstrates that using traffic data provided by online navigation services allows monitoring the effect of regular traffic congestion on the CO_2 performance of a whole distribution network. Independent of the GHG aspect, this article shows that using this data source allows basing logistics system analyses on area-wide representative trip data, taking time-typical traffic conditions and their consequences (travel time changes, re-routing decisions) into account. Considering the discussion of the different road traffic data sources in Sect. 2.3, it becomes obvious that the use of one of the conventional traffic data sources would have posed problems in the fields of representativeness, area-wide geographical coverage, and/or in the consistency and completeness of measurements.

6.2 Generalizability of the results

Of course, the generalizability of the results requires confirmation through the analysis of more cases because the example case certainly does not represent the situation of all SIC-20 manufacturers. The fact alone that the positions of the different facilities affect the degree to which the firm is exposed to traffic congestion causes generalizability concerns.

Concerning the case company, however, it is recognized as a representative SIC-20 firm in terms of the customers served, its product portfolio, the shipment sizes and delivery frequencies, and the flow of materials. Generally, the studied case allows for a good representation of FMCG distribution in Germany because the analyzed shipment data include a great share of the German retailer locations; this allows for a nationwide observation of traffic conditions. In addition, the impact of traffic congestion has been observed for the cost-minimal 1-, 2-, 3-, and 4-DC configurations. Thus, in principle, four distinct network structures have been investigated. And, as has been demonstrated, the impact of traffic congestion did not differ a lot in relative values across the four networks. Moreover, the results for the delivery trips do not depend on the facility locations of the manufacturer, but on the positions of the TSPs and the retailers. Both are independent of the manufacturer and part of many supply chains [26].

6.3 Further research

Future research may analyze more logistics networks in order to generalize the results. Furthermore, the network model and the data source may be combined to observe the effects of travel time variability and/or for a continuous monitoring of the transport system in order to learn how GHG emissions develop over a longer period. In addition, future research may use navigation service data to analyze additional CO_2 cutting opportunities more in detail. These might include green route planning taking time-typical travel times into account, the analysis of the CO_2 effect of postponing vehicle departure times, changing the delivery day, or the analysis of region-specific differences in travel times and CO_2 emissions.

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