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Article

Grocery Delivery or Customer Pickup - Influences on Energy Consumption and CO_2 Emissions in Munich

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Abstract: The number of supermarkets offering a grocery delivery has been increasing during the last years**.** Many studies deduce CO_2 emission savings using this concept. Since the delivery of groceries also consumes energy and produces emissions, break-even points can be calculated, from where the delivery has environmental advantages compared to the customer pickup. In this paper, influences of differing vehicle use on break-even points for savings of energy and CO_2 emissions are analyzed for the case of Haidhausen Süd, a city district of Munich in Germany. Internal combustion engine and electric vehicles are investigated to depict current as well as future trends. After an introduction to the used methodology, the potential to save energy and CO_2 emissions related to the delivery of groceries in the chosen district of Munich is evaluated. Afterwards, influences on the break even points are presented and discussed. As the results show, a delivery of groceries leads to energy and carbon dioxide savings in a wide range of private vehicle use for grocery shopping trips. Nevertheless, if the complete customer vehicle fleet is electrified, the use of delivery vehicles with an internal combustion engine can cause an additional environmental impact at the current modal split for shopping trips in Germany.

Keywords: Grocery Delivery, Energy-Savings, CO_2 -Savings, Munich, Break-Even Point, Electric Delivery Vehicle, Customer Pickup, Modal Shift

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1. Introduction

Nowadays, cities are confronted with traffic problems, resulting in an increasing environmental impact. Looking at the traffic volume of the motorized private transport in Germany in 2017, 17.5 % [1] is attributed to shopping trips. After leisure trips (35.4 %) and rides in relation to the job (20.0 %), this purpose stands on the third position of the official statistic [1]. Since a part of all shopping trips is related to the supply with foodstuffs, the delivery of groceries instead of an individual customer pickup offers a chance to reduce the traffic in cities. Thereby, delivery vehicles can substitute the customer shopping trips. At the same time, this scenario offers the opportunity to save energy and carbon dioxide.

In many studies, the delivery of goods is compared to the customer pickup. Siikavirta et al. [2] analyze this scenario in a case study for a grocery shop in Finland. There, the substitution of shopping trips by delivery vehicles would lead to a reduction of CO_2 emissions in the range from 18 % to 87 %. Similar results were presented by Halldórsson et al. [3]. The authors investigated the specific CO_2 emissions for delivery and customer pickup, by averaging various statistical data. While a delivery would lead to emissions of 181 gCO_2 per drop, the customer pickup scenario would emit around 4,274 gCO_2. They also examined the influence of the success rate of first delivery on the specific emissions. If the first delivery is not successful, the emissions are clearly increased.

Since the delivery of groceries can be seen as a case of deliveries on the last mile of city logistics, many scientific papers deal with this part of the supply chain. Thereby, the energy efficiency on this last part of a delivery chain is often discussed [4]. In general, the last mile is seen as the least efficient part of a supply chain [5], because of customer requirements, such as fast and reliable delivery, many

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delivery vehicles are used with a low vehicle utilization. This leads to a low average utilization of delivery vehicles [6]. Hence, different optimization approaches were developed in order to reduce the environmental impact of deliveries in this part of the supply chain. Bányai [7] for example presents a real-time optimization model in order to increase the energy efficiency. Since the delivery vehicle's drivetrain affects energy consumption and emissions, the use of electric delivery vehicles is seen as an alternative for internal combustion engine vehicles [8]. Because of the high costs, the use of battery electric vehicles is not yet profitable today, but might become an option in the next years [9][10]. Oliveira et al. [11] did a systematic literature review on different delivery vehicles on the last mile, which offer the opportunity to increase the sustainability. In addition to electric delivery vehicles, they reviewed the use of bicycles and tricycles as well as smaller commercial vehicles as alternative. Moreover, autonomous delivery vehicles are developed, but the legal situation still has to be clarified for a future productive use [12]. In general, the use of intermodal transportation or a shift to other transportation modes offer a chance to influence the environmental aspects of deliveries [13]. Göçmen et al. [14] for example use ecologic, economic as well as social impact factors to optimize the intermodal transportation network of a logistics company in Turkey.

Looking back at the delivery of groceries, the approach of a modal shift in order to reduce environmental impacts can also be identified. By applying a delivery, the transportation of groceries is shifted from individual shopping trips to tours of delivery vans. As the delivery of foodstuffs also consumes energy and emits CO_2, it also forms a possible ecological risk. Hence, break-even points need to be analyzed, from which the delivery of groceries is ecological more useful than individual shopping trips. In other words, as the motorized public transport is mainly responsible for energy consumption and emissions of individual shopping trips [15], minimum shares of private vehicle use in order to avoid additional energy consumption and CO_2 emissions caused by the delivery must be evaluated.

The aim of this paper is to identify and analyze those break-even points for energy consumption and CO_2 emissions in the case of Haidhausen Süd, a district in the center of the city of Munich. For this purpose, the general potential to save energy and carbon dioxide emissions by a delivery of groceries is analyzed, first. Since the use of freight electric vehicles for deliveries in city logistics becomes more and more popular, the evaluations address Internal Combustion Engine Freight Vehicles (ICEFV) as well as Electric Freight Vehicles (FEV). In relation to the goals of the German government to reduce the environmental impact of the transportation sector [16], the use of electric vehicles in the field of the motorized private transport is also named. Hence, the influence of a complete electrification of the German private vehicle fleet on break-even points is integrated in the analyses of this paper.

Brown et al. also analyzed break-even points in their study [17]. They just focused on the use of diesel-powered delivery vans. Through this paper the following points are discussed:

- The use of electric vehicles for the delivery of groceries are adressed
- An assessment methodology for the investigation of energy and CO_2 savings as well as break-even points based on real-world geodata and Monte Carlo Simulations is presented
- Impact evaluation of an electric and combustion-engined private vehicle fleet for customer pickup tours on possible savings
- Results analysis for a district of Munich, Germany

After the introduction, section 2 presents the used materials and methodology. There, the calculation of the distances the delivery vehicles as well as the customers must drive is described, first. For this purpose, geodata from OpenStreetMap [18] in combination with a Monte-Carlo-Simulation is used. Afterwards, the approach to calculate energy consumption and emissions of delivery vans and private vehicles is introduced. In section 3, results are presented and discussed. There, the potential to save energy and CO_2 -emissions by a delivery of groceries in Haidhausen Süd using ICEFV and FEV is analyzed and discussed. To that, the modal split of customer shopping trips in Germany is used. Subsequently, the break-even points, influenced by the already named parameters, are analyzed. Section 4 concludes the results and gives an outlook.

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2. Materials and Methods

Fig 1. shows the structure of the methodology. Based on characterizing data of the investigated region (section 2.1), the average distance per shopping trip as well as the average distance driven by the delivery vehicles is calculated (see section 2.2). Knowing the certain distances, energy consumption and carbon dioxide emissions are calculated using specific values (section 2.3). With those energy consumptions and CO_2 emissions, the break-even points can be calculated, afterwards. By varying parameters of the private vehicle fleet as well as of the delivery vehicles, influences on the break-even points can be analyzed. In the following, the methodology is described in detail.

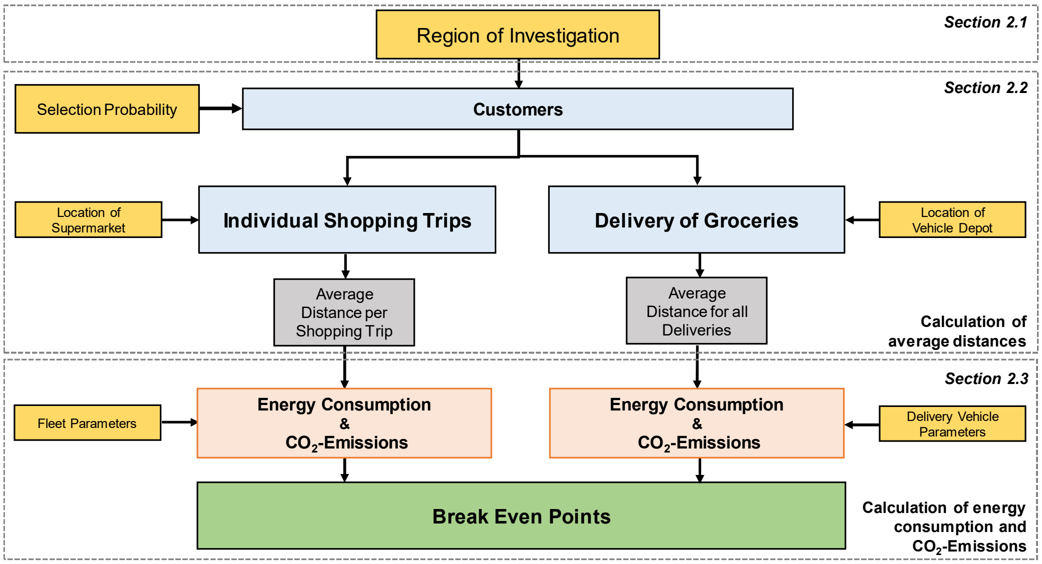

Figure 1. Methodology of the study.

2.1. Region of Investigation

As a representative for Munich, Haidhausen Süd, a part of the city district Au/Haidhausen, is used as region of investigation in this paper. In 2016, this region counted around 14,400 inhabitants and approximately 7,600 apartments respectively households. With an area of around 0.795 km^2, this leads to an inhabitant density of around 18,100 inhabitants/km^2 respectively ca. 9,560 apartments or households per square kilometer [19]. With an average number of 12.5 households per building, Haidhausen Süd can be seen as an urban structure. One grocery store is selected to be the main purchasing point for the customers. This market is located near to the center of Haidhausen Süd at Pariser Platz. The depot, from where the delivery vehicles start and return to in order to delivery groceries in the evaluations of this paper, is assumed to be at the southeastern city boundary of Munich. Hence, the delivery vehicles have to drive approximately 7 km to reach Haidhausen Süd. The supply of the supermarket with goods is not taken into account and balanced, respectively. **Fig.2** gives a brief overview of the region of investigation. The red marker represents the position of the supermarket.

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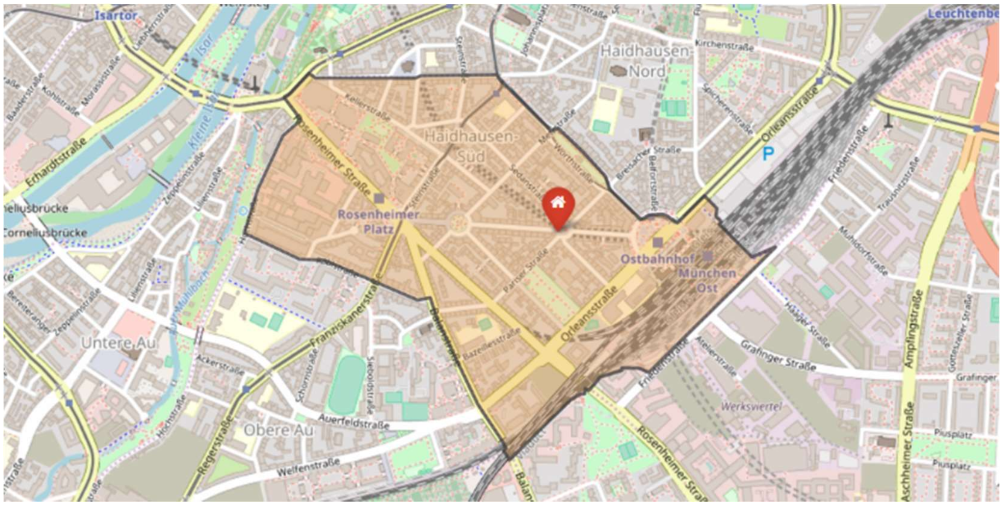

Figure 2. Overview of Haidhausen Süd (Map: [18]).

2.2. Calculation of Average Distances

Fig. 3 shows schematically the differences between delivery and customer pickup.In order to calculate the average distances, customer trips (**Fig. 3 (a)**) as well as delivery tours (**Fig. 3 (b)**) must be planned. Since the spatial distribution of the customers respectively the spatial properties of the delivery areas affect the distances, different sets of delivered customers in the defined region need to be investigated in order to estimate the average distances. Therefore, a set of households is picked randomly using a selection probability. This set represents the amount of customers, who decided to receive their groceries by delivery instead of driving to the supermarket on their own. Investigating and evaluating a sufficient high amount of single sets of delivered customers, an average value of the distances can be estimated, therefore. Compared to the random selection of points within a certain radius around the depot presented in [17] and [20], the calculation in this paper is based on data from OpenStreetMap [18]. For that purpose, all buildings within the borders of Haidhausen Süd are extracted and a street graph is created to calculate the full distance matrix of the region.

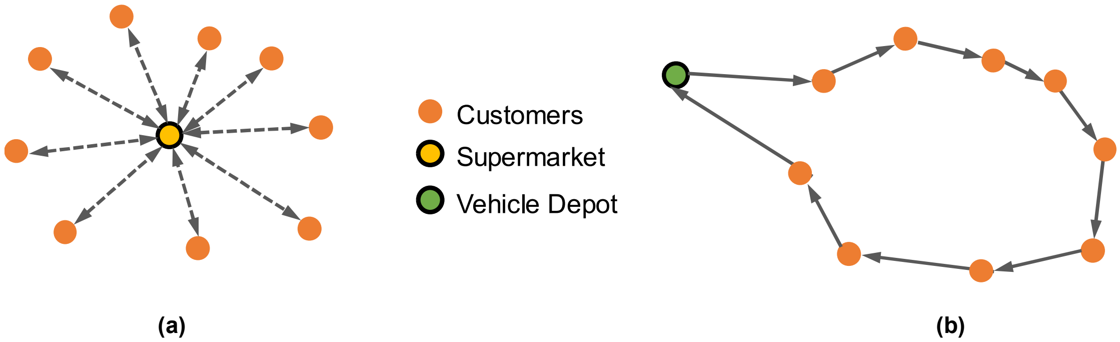

Figure 3. Customer Trips to the Supermarket (a) and Delivery Vehicle Circle Tour (b).

2.2.1. Creation of Delivery Samples

In order to create sets of customers for the estimation of the distances, a decision procedure for the selection of households has to be developed. For this purpose, the delivery probability p_D is used. It can be defined as the probability that a household from the amount of all households in the region of investigation is ordering groceries instead of driving to the supermarket. As equation (2) shows, the Bernoulli-Experiment of the decision procedure can be written with a random variable $X_h(\omega)$,

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where ω is a uniformly distributed random number in the interval [0;1) Within this paper p_D is defined, such that one of ten or two of ten supermarket customers use the delivery instead of driving to the supermarket. Hence, the delivery probabilities are 10 % and 20 % respectively.

$$X_h(\omega) = \begin{cases} \text{Delivery}\,, & if\ \omega \leq p_D \\ \text{No Delivery}, & if\ \omega > p_D \end{cases} \tag{2}$$

Since the delivery probability is defined for a household, the mapping of households to buildings in the examined region must be known. Because the data of OpenStreetMap does not include this information, an assignment approach using the average base area per household a_h is applied. Using this approach instead of employing accurate data (i.e. official data on inhabitants per building, building height, number of floors etc.) makes the methodology stay more flexible for future investigations in other regions. Considering the sum of the base area per building $a_{B,b}$ of all buildings B in the examination region as well as the absolute number of households h, a_h can be written as

$$a_h = \sum a_{B,b}/h \quad \forall b \in B \tag{3}$$

Applying equation (4) to each building, it is possible to estimate the number of households per building h_B. Buildings with huge base areas (industrial buildings, buildings of the tertiary sector) are excluded to minimize the errors of this approach.

$$h_B = \lceil a_b/a_h \rceil \tag{4}$$

As delivery services usually apply delivery areas for the serving of the customers, the examination region is divided into clusters with an equal number of households. Considering the probability a household will be delivered, the number of households per delivery area h_D can be expressed as shown in (5). C_V represents the number of households a vehicle can serve. C_V is assumed to be constant due to constraints such as vehicle size, maximum load mass and daily duration of delivery. Hence, the amount of households per delivery area is decreasing with an ascending delivery probability.

$$h_D = \lceil C_V/p_D \rceil \tag{5}$$

Assuming that a delivery area is served by just one delivery vehicle, it is possible to calculate the number of deployed delivery vehicles K in the examination region for a certain delivery probability, using equation (6).

$$K = \lceil h/h_d \rceil \tag{6}$$

The clustering of households into delivery areas is done using a Same-size k-Means-Algorithm [21]. Applying the already introduced random experiment to all households of one delivery area, a delivery sample is created. In addition to the creation of a random distribution of delivered customers in the delivery areas, this approach also depicts different amounts of served customers and thus integrates different counts of applied delivery vehicles as well as customer shopping trips in the analyses.

2.2.2. Tours of Delivery Vehicles

As the order of the appearance of the single households in the randomly created delivery sample is not representing a reasonable delivery tour, a vehicle routing algorithm is applied to minimize the tour length d_D and create a feasible journey. Hence, it is assumed that the delivery vehicles use optimized routes. Without the use of delivery areas, the routing problem can be described as a Capacitated Vehicle Routing Problem (CVRP) with K vehicles [22]. The degree of freedom is limited using the delivery areas, so the CVRP decomposes to K Traveling Salesman Problems (TSP) [22]. The full distance matrix of the region was considered as base of the routing algorithm in order to include one-way streets. As the average length of the delivery tour is just depending on the vehicle capacity and not on the drive technology of the vehicle, the same delivery tours at certain delivery

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probabilities are used for ICEFVs and FEVs. In order to solve the TSP, the routing engine of Google Optimization Tools is involved [23].

To calculate the average distance a delivery vehicle has to drive, many delivery sample have to be taken into account in order to depict different spatial distributions of possible customers. Considering the distance of the delivery tour for a certain delivery sample as a function of the delivery probability p_D and spatial distribution of households S, the calculation of the average distance $\overline{d_\mathrm{D}}$ a delivery vehicle hast to drive in order serve the customers respectively the expected value of d_D can be expressed using the Monte Carlo Estimator [24]

$$\overline{d_D} = \frac{1}{m}\sum_{i=1}^{m} f(p_D, S) \tag{7}$$

There, m is the total number of investigated delivery samples. Described by the Strong Law of Large Numbers [25], m has to be sufficiently high in order to get a convergence of the Monte Carlo Simulation [26]. Multiplying the estimated average distance per delivery vehicle with the number of applied vehicles respectively the number of delivery areas, the total average driven distance of all delivery vehicles in order to serve the region can be calculated.

For the following examinations in Haidhausen Süd, it is assumed that the delivery vehicles have a total capacity of 200 deliveries. Hence, at a delivery probability of 10 % the region is divided into five delivery areas, while at 20 % nine delivery areas are used. **Fig.4.** shows the success for the estimation of d_D using the introduced methodology for a delivery probability of 10 %. For this evaluation, 1,000 delivery samples were created, while taking into account that each delivery area is used for the same number of created delivery samples. It can be seen, that the average distance a delivery vehicle has to drive to serve the customers converges to stable values of around 18.4 km, while the standard deviation converges to values of around 0.9 km. As the standard deviation is relatively low compared to the average distance, it is neglected for the following analyses.

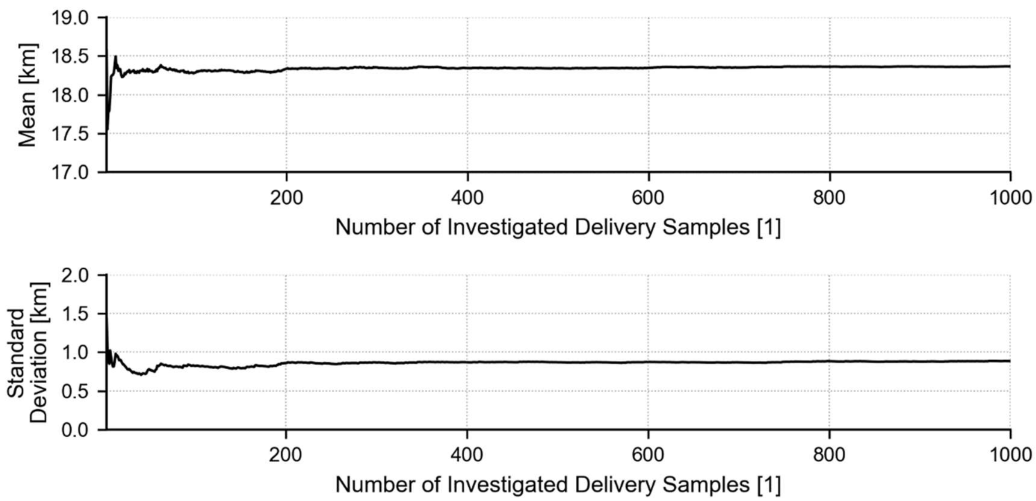

Figure 4. Convergence of the Monte Carlo Simulation for the Estimation of the Average Distance of a Delivery Vehicle (Delivery Probability 10 %).

Table 1. summarizes the calculated average distances per delivery vehicle and in total for a delivery probability of 10 % as well as 20 %. Since the distance between two vehicle stops for the delivery of goods is decreasing with an increasing delivery probability, the total distance per vehicle is reduced. In addition to that, the size of the delivery areas is reduced, so that the vehicle has to drive shorter distances to serve all customers. At the same time, as the number of delivery areas is ascending, the distance of all delivery vehicles to serve Haidhausen Süd is increasing in total.

Table 1. Characteristics of Grocery Delivery Tours in Haidhausen Süd.

Characteristics	Unit	Delivery Probability	
		10 %	20 %
Number Applied Vehicles	[1]	5	9
Average Distance per Vehicle	[km]	18.4	16.6
Total Distance	[km]	91.8	149.8

2.2.3. Customers Shopping Trips

As the customers do not drive a circle tour, the trips must not be optimized. Assuming that the customer tours always start and end at the household's location, the distance can be expressed as

$$d_C = d(Home, Supermarket) + d(Supermarket, Home), \tag{8}$$

where $d(a, b)$ describes the distance to drive from a to b. Using the full distance matrix of the region of investigation, d_C can be calculated.
Since the location of the household in the region of investigation affects the distance of the shopping trip to the supermarket, the average distance $\overline{d_C}$ of one trip is calculated considering all single trips of served customers in the delivery samples. However, the average distance is independent from the delivery probability; it is just influenced by the spatial properties of the region of investigation, respectively. **Table 2.** concludes the calculated average distances per customer grocery shopping trip and in total for a delivery probability of 10 % as well as 20 %. Since the doubling of the delivery probability forces a selection of in average twice the number of customers, the total distance of customers' shopping trips is also approximately doubled.

Table 2. Characteristics of Customer Grocery Shopping Trips in Haidhausen Süd.

Characteristics	Unit	Delivery Probability	
		10 %	20 %
Number of Customer Trips	[1]	832	1664
Average Distance	[km]	1.0	1.0
Total Distance	[km]	834.4	1667.2

2.3. Energy Consumption and Emission Factors

Knowing the typical distances of the delivery vehicles as well as of the customer vehicles, the energy consumption E_V and resulting CO_2-Emissions EM can be calculated

$$E_V = e_V \cdot d_V \tag{9}$$

$$EM = E_V \cdot em_{EC} \tag{10}$$

There, e_v is the distance-specific energy consumption and d_v is the driven distance. em_{ec} are the energy-specific CO_2 emissions of a certain energy carrier.

2.3.1. Delivery Vehicle Fleet

Since the vehicle fleet of delivery services often consists not of one specific vehicle type, datasheets of different vehicle manufacturers with a maximum total mass up to 3.5 t were evaluated in order to research the specific energy consumption. A volume of the cargo bay in the range of 5 m^3 to 9 m^3, which is in the middle range of all investigated vehicles, was assumed to have the already named vehicle capacity of 200 deliveries. The maximum total weight was selected with the requirement, that the delivery vehicles can be used with the regular driving license for motor cars in Germany. As vehicles with electric as well as combustion engine drive are investigated, the stated specific energy consumptions in the datasheets of the certain drive types were averaged to create typical FEVs as well as ICEFVs. This leads to average specific energy consumptions of 19.9 kWh/100km for FEVs and 60.6 kWh/100km for ICEFVs. As those specific energy consumptions

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are derived during test procedures, namely in the New European Driving Cycle (NEDC), a simple vehicle model based on driving resistances and efficiencies is used to get values that are more realistic. With the assumption of flat roads, the power at the wheels in dependency of current velocity $v_v(t)$and acceleration $a_v(t)$ can be written as

$$P_{Wheels}(t) = \left(0.5\rho_{Air}c_W A \cdot v_v^2(t) + m_V g f_R + \lambda m_V \cdot a(t)\right) \cdot v(t) \tag{11}$$

There, the total mass of the vehicle m_V can be split up into two components, where

- m_E represents the empty mass of the vehicle, including the driver and all necessary components for operating the vehicle (for example fuel, lubricants etc.)
- m_L reflects the load mass of the vehicle, i.e. the mass of the delivered groceries.

To simplify the model, the load mass is set to constant instead of time-dependent, resulting in a non-decreasing vehicle mass during the delivery tour. To reproduce the vehicle mass reduction due to delivered groceries, m_L is set to the half of the resulting load mass when considering the whole vehicle capacity. Hence, this advancement can be seen as the calculation of the vehicle with an average load mass. Recognizing an average mass per delivered household of 2.5 kg, the total mass of the delivery vehicle can be written as

$$m_V = m_E + 0.5 \cdot C_V \cdot 2.5\,kg \tag{12}$$

Since some additional vehicle characteristics must be known for the calculation of the power at the wheels, supplementary values of the vehicle manufacturer datasheets were averaged, resulting in typical empty mass m_E, cross sectional area A and maximum engine power $P_{E,Max}$ for FEV and ICEFV. While air density ρ_{Air} and gravity acceleration g are given by physics, drag coefficient c_W, rolling resistance coefficient f_R as well as rotating mass impact factor λ are supposed to have typical values. **Table 3.** shows the values used for the calculation of the power at the wheels.

Table 3. Parameters for the Delivery Vehicle Energy Calculation

Parameter	Symbol	FEV	ICEFV
Empty Mass	m_E	1695 kg	1854 kg
Total Mass (Using eq. (12))	m_V	1945 kg	2104 kg
Max. Engine Power	$P_{M,Max}$	48 kW	92 kW
Cross Sectional Area	A	3.92 m^2	3.25 m^2
Drag Coefficient	c_W	0.33	
Air Density	ρ_{Air}	1.204 kg/m^3	
Gravity Acceleration	g	9.81 m/s^2	
Rolling Resistance Coefficient	f_R	0.01	
Rotating Mass Impact Factor	λ	1.1	

As the characteristics of the drive profile of the vehicle, i.e. curve of velocity and acceleration against time, have a high influence on the energy consumption, it is necessary to use values reflecting the characteristics of delivery vehicles. Thus, the NREL Baltimore Parcel Delivery [27] (BPDC) cycle was used for the energy demand simulations. In contrast to other drive cycles, BPDC shows a total of 41 stops with a huge number of acceleration and breaking procedures over a distance of around 33 km. For the application of this cycle in the following examinations, it is expected:

- BPDC is representative for delivery vehicles in Haidhausen Süd
- Velocity and acceleration are not affected by different drive technologies of the vehicles, i.e. values of acceleration and deceleration are equal for all investigated vehicles.

In order to calculate the final energy demand $E_{F,V}$ of the delivery vehicles, the engine efficiency η_{En} must be considered in addition the efficiency of components like for example gear and drive train, bundled in η_{Comp}

$$E_{F,V} = \int_t \frac{P_{Whe}\quad(t)}{\eta_{En} \cdot \eta_{Comp}} dt = \sum_t \frac{P_{Whe}\quad(t)}{\eta_{En} \cdot \eta_{Comp}} \cdot \Delta t \tag{13}$$

Due to the high number of stops, the engine of a delivery vehicle is working frequently at different points of utilization. For this case, the application of a constant efficiency would lead to errors in the calculation. Hence, an efficiency model for electric and internal combustion engines based on the current utilization from Brooker et al. [28] was integrated. There, the engine efficiency η_{En} can be derived applying the calculated power at the engine shaft as well as the maximum motor power $P_{E,Max}$. In contrast, the efficiency of remaining components η_{Comp} is set to constant. The possibility of regenerative braking for electric vehicles is also considered using the approach of Brooker et al. [28]. Auxiliary consumers are not taken into account in evaluations of this paper. Applying (14), the specific final energy consumption can be calculated

$$e_v = E_{F,V}/d_{Cycle}, \tag{14}$$

where d_{Cycle} is the distance covered by the driving cycle.

In order to validate and calibrate the implemented vehicle model, the averages of the stated energy consumptions were compared to the simulation results. Therefore, the energy consumption was simulated in the NEDC, which was the underlying test cycle. At this stage, only the empty mass m_E of the vehicle was taken into account. By varying the component efficiency, the model was calibrated to the average stated consumptions in NEDC. Using the calibrated model, the specific energy consumption in the BPDC was calculated. **Table 4. s**ummarizes the results. The simulated specific energy consumption in BPDC shows an increase of 7.5 % compared to the stated value for FEVs. In the case of ICEFVs, the simulation results depict 21.5 % ascent compared to the average manufacturer data in NEDC. As no real-life energy consumptions of delivery vehicles in Munich could have been researched, the simulated values must be seen as representative for the delivery of groceries in this region of investigation. Although a simple model was used for the calculation, the derived specific energy consumptions have a higher precision compared to the stated values, because a characteristic velocity and acceleration profile of delivery vehicles is used for the calculations. This leads to a higher rating of the following analyses.

Table 4. Simulation Results for the Energy Consumption of Delivery Vehicles

Parameter	Unit[1]	FEV	ICEFV
NEDC (Average Stated Value, empty mass)	kWh/100km	19.9	60.6
NEDC (Simulation, empty mass)	kWh/100km	20.3	60.4
Deviation	kWh/100km	0.4	-0.2
Relative Deviation	%	2.0	-0.3
BPDC (empty mass)	kWh/100km	19.8	67.3
BPDC (loaded)	kWh/100km	21.4	73.6
Increase to NEDC (Average Stated Value)	%	7.5	21.5

[1] Tank2Wheel

As all evaluated vehicles in the category ICEFV use diesel engines, the specific emissions of diesel fuel in Germany of 266.4 gCO_2/kWh [29] are used for such vehicles. Since the use of electric vehicles produces CO_2 emissions at the power plants, the average specific emissions of 489 gCO_2/kWh [30] for the German electricity mix in 2017 are used to map this behavior in the case of FEVs.

2.3.2. Customer Vehicle Fleet

Neglecting the low share of alternative drive technologies, the German private vehicle fleet can be divided into diesel and petrol engine vehicles, embraced as Internal Combustion Engine Customer Vehicles (ICECV). Using the shares of the two engines [1] as well as the average fuel consumption of private cars in Germany [1], an average weighted specific energy consumption of 65.8 kWh/100km can be calculated. The specific emissions of petrol in Germany at 263.2 gCO_2/kWh [29] as well as the already name value of diesel fuel lead to average weighted specific CO_2 emissions of 264.2 gCO_2/kWh of the German ICECV fleet. In order to investigate the influence of a complete electrification of the German private vehicle fleet, a typical specific energy consumption of Electric Customer Vehicles (ECV) is assumed to be 15.0 kWh/100km. In the case of ECVs it can be expected, that the charging electricity mix is not differing to FEVs, which leads to equal specific emissions.

The specific energy consumptions and CO_2 emissions, necessary for the calculation of the absolute values of all investigated vehicles in this paper, are summarized in **Table 5**.

Table 5. Specific Energy Consumption and Emissions of Investigated Vehicles

Vehicle	Drive	Type	Spec. Energy Consumption[1]	Specific Emissions
FEV	Electric	Delivery	21.4 kWh/100km	489 gCO_2/kWh [2]
ICEFV	Combustion (Diesel)	Delivery	73.6 kWh/100km	266.4 gCO_2/kWh
ECV	Electric	Customer	15.0 kWh/100km	489 gCO_2/kWh [2]
ICECV	Combustion (Mix)	Customer	65.8 kWh/100km	264.2 gCO_2/kWh

[1] Tank2Wheel [2] Emissions of German electricity mix related to energy consumption at place of use.

2.3.3 Calculation of Break-Even-Points

Using the data of **Table 5**, the energy consumption E_C and resulting CO2-Emissions EM_C of individual shopping trips using private vehicles can be written as

$$E_C = x_V \cdot n_C e_{CV} d_{CST} \tag{15}$$

$$EM_C = E_C \cdot em_{C,EC} = x_V \cdot n_D e_{CV} d_{CST} \cdot em_{C,EC} \tag{16}$$

where n_C is the total number of customer trips, d_{CST} is the average distance per trip and x_V is the percentage of private vehicle use for shopping trips. e_{CV} and $em_{C,EC}$ are the specific energy consumption and specific CO_2 emissions of the customer vehicles, respectively. In the same way, energy consumption and carbon dioxide emissions of the delivery vehicles can be expressed as

$$E_D = d_D e_{DV} \tag{17}$$

$$EM_D = E_D \cdot em_{D,EC} = d_D e_{DV} \cdot em_{D,EC} \tag{18}$$

where d_D is the driven distance of all delivery vehicles, e_{DV} is the specific energy consumption of the investigated delivery vehicle and $em_{D,EC}$ are the specific CO_2 emissions of the delivery vehicle looking at a certain energy carrier EC.

Neglecting other modes with environmental impact, the minimum shares of private vehicle use for grocery shopping trips in order to avoid additional energy consumption $x_{V,En}$ and CO_2 emissions $x_{V,Em}$ caused by the delivery or the break-even points can be calculated:

$$E_C \geq E_D \;\Rightarrow x_{V,En} \geq \frac{d_D e_D}{n_D e_{CV} d_{CST}} \tag{19}$$

$$EM_C \geq EM_D \;\Rightarrow x_{V,Em} \geq \frac{d_D e_D em_{D,EC}}{n_D e_{CV} d_{CST} em_{C,EC}} \tag{20}$$

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In order to visualize savings at different shares of private vehicle use in the range from 0 % to 100 %, the relative savings s caused by the delivery of the groceries instead of individual shopping trips shown in (19) are used. There e is either energy consumption or carbon dioxide emissions.

$$s = (e_{Customers} - e_{Delivery})/e_{Customers} \tag{21}$$

3. Results and Discussion

3.1. Potential for Saving of Energy and CO_2 at Current Share of Private Vehicles Use for Shopping Trips

It is a well-known fact, that not all customer shopping trips for groceries are executed with private vehicles. In order to identify the potential of a delivery of groceries to save energy and CO_2, the modal split for shopping trips has to be considered.

Fig 5. shows the modal split for shopping trips in Germany in dependency of the community size [15]. The visualized values are valid for people who have permanent access to motorized private vehicles. Just ways with the aim of shopping are observed. With an increasing amount of inhabitants in a community, the use of motorized private transport is clearly decreasing. Combining the shares of driver and co-driver, in communities with less than 20,000 inhabitants, a share of 72 % [15] uses private vehicles for the shopping of groceries. Looking at cities with more than 500,000 inhabitants, just around 46.5 % [15] use this mode. Since this percentage is decreasing, other modes become more popular. Due to reduced distances to the next shopping facility, a higher share of people is doing their shopping as pedestrian or using the bicycle. Equally, a higher share uses public transportation for this application. This fact can be traced back to a higher availability of this mode as well as to a higher serving rate of public transportation. The availability of parking lots as well as the traffic flow in cities can also be seen as drivers for the reduced percentage of the motorized private transport for shopping trips. [15]

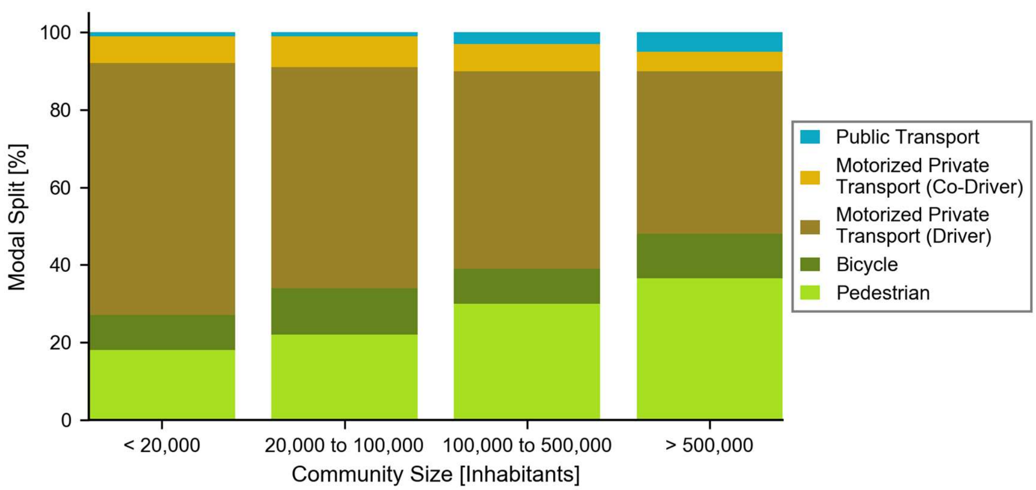

Figure 5. Modal Split for Shopping Trips in Germany depending on the community size (Data derived from [15])

As Haidhausen Süd is a part of the city of Munich, which has around 1.45 Mio. [19] inhabitants, the modal split for communities with more than 500,000 inhabitants is used for further investigations. Hence, **Table 6.** summarizes the distribution of the shopping trips to the different traffic modes for a delivery probability of 10 % and 20 % in Haidhausen Süd. There, the shares of the motorized private transport or simplified the use of private vehicle, are the major drivers for energy consumption and carbon dioxide emissions caused by private shopping trips. Neglecting the low percentage of public transportation and looking at the fact, that bicycles or shopping trips as pedestrian are not consuming energy or producing carbon dioxide emissions, this statement can be approved.

Table 6. Modal Split of Customer Grocery Shopping Trips in Haidhausen Süd

Characteristics	Delivery Probability			
	10 %		20 %	
	Count [1]	Distance [km]	Count [1]	Distance [km]
All Customer Trips	832	834.4	1664	1667.2
Pedestrian	304	305	607	609
Bicycle	100	100	200	200
Motorized Private Transport (Driver)	345	346	691	692
Motorized Private Transport (Co-Driver)	42	42	83	83
Public Transportation	42	42	83	83

Using the data from Table 6., at a delivery probability of 10 % a total distance of approx. 388 km is covered by private vehicles. Doubling the amount of delivered customers, a total 775 km is driven by this mode. With those distances, the potential to save energy at the current share of private vehicle use can be evaluated. **Fig 6.** compares the energy demand of ICECVs at the current share of private vehicle use for grocery shopping (46.5 %) with the energy consumption of FEVs and ICEFVs. At both investigated delivery probabilities, a grocery delivery would lead to energy savings. Due to the higher efficiency respectively lower specific energy consumption of FEVs, the absolute as well as relative savings show higher values when applying those vehicles. As the doubling of the amount of delivered customers leads not to a doubling of the energy use of the delivery vehicles, the energy savings are not constant at different delivery probabilities.

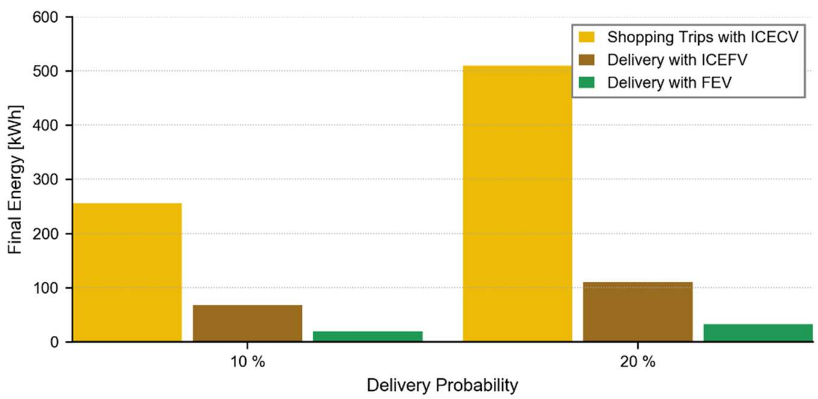

Figure 6. Potential to save energy by the delivery of groceries in Haidhausen Süd for different drive types of delivery vehicles (Customer Vehicles: ICECV, Share of private vehicles use for shopping trips 46.5 %)

Table 5 gives an overview of absolute and relative savings. Even at the share of private vehicle use of 46.5 %, the delivery of groceries with ICEFVs would lead to energy savings of around 73.6 % and 78.4 % compared to individual shopping trips with ICECVs at a delivery probability of 10% and 20 % respectively. The energetic advantages of FEVs lead to savings of 92.3 % and 93.7 %.

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Table 5. Absolute and Relative Energy Savings

Vehicle	Unit	Delivery Probability	
		10%	**20%**
ICECVs	**kWh**	**255.7**	**510.1**
ICEFVs	**kWh**	**67.6**	**110.2**
Savings (Absolute)	kWh	188.1	399.9
Savings (Relative)	%	73.6	78.4
FEVs	**kWh**	**19.7**	**32.0**
Savings (Absolute)	kWh	236.0	478.1
Savings (Relative)	%	92.3	93.7

Looking at the CO_2 emissions (**Fig. 7**), the delivery instead of customer pickup would also lead to savings. There, the relative CO_2 savings in the case of a delivery with ICEFVs show almost the same values compared to the energy savings, because the emission factors of ICEFVs and ICECVs are more or less equal. Applying FEVs for the delivery of groceries, the CO_2 savings are decreased, compared to energy savings. This fact can be drawn back to the clear higher specific emissions of the electricity mix compared to the German private vehicle fleet. With a view on **Table 6**, relative as well as absolute savings can be concretized. At a delivery probability of 10 %, the use of ICEFVs instead of customer shopping trips would lead to CO_2 savings of around 49.5 kgCO_2 per delivery tour or 73.3 %. Using FEVs, the absolute savings increase to a value of approximately 58 kgCO_2 or 85.8 %.

Combining the results, the delivery of groceries in this district of the city of Munich would offer the opportunity to save energy and CO_2.

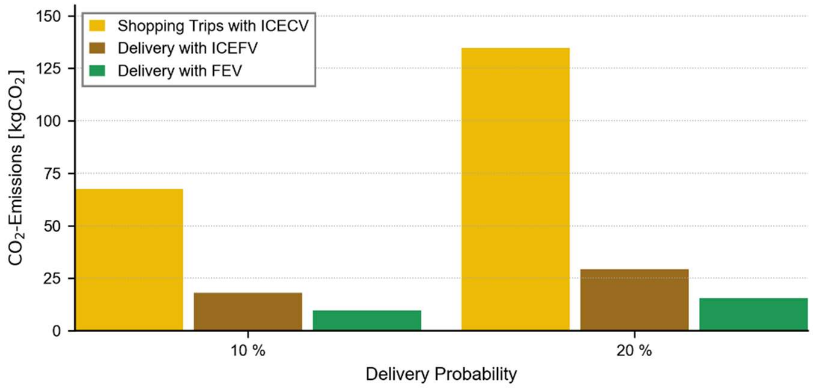

Figure 7. Potential to save CO_2 emissions by the delivery of groceries in Haidhausen Süd for different investigated drive types of delivery vehicles (Customer Vehicles: ICECV, Share of private vehicles use for shopping trips 46.5 %)

Table 6. Absolute and Relative CO_2 Savings

Vehicle	Unit	Delivery Probability	
		10%	**20%**
ICECVs	**kgCO_2**	**67.5**	**134.8**
ICEFVs	**kgCO_2**	**18.0**	**29.4**
Savings (Absolute)	kgCO_2	49.5	105.4
Savings (Relative)	%	73.3	78.2
FEVs	**kgCO_2**	**9.6**	**15.7**
Savings (Absolute)	kgCO_2	57.9	119.1
Savings (Relative)	%	85.8	88.4

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3.2. Analysis of Break-Even Points for Energy Consumption

Fig. 8 shows the resulting energy savings at a delivery probability of 10 % for shares of private vehicle use in the range from 0 % to 100 %. Neglecting the public transport again, the minimum share of private vehicle use to generate energy savings or the break-even point is visualized as the cutting point of the saving-curves with the axis of private vehicle share.

Looking at the curve of customer and delivery vehicles with combustion engines (ICEFV+ICECV), a delivery would offer the chance to save energy at shares greater than 12.3 %. Since the FEVs consume less energy than ICEFVs, this minimum share is reduced to 3.6 % (FEV+ICECV). As ECVs show a lower energy consumption than ICECVs, the minimum share of customer trips for energy savings is increased in general, when looking at an electrified customer vehicle fleet. The view on FEVs and ECVs (FEV+ECV) lead to a minimum share of 15.7%. In the case of a delivery with ICEFVs, ECVs would lead to a cutting-point of 53.9 % (ICEFV+ECV). Assuming a constant modal split for future developments, this scenario would lead to an additional energy consumption respectively no savings caused by the delivery, as the current share of private vehicle use is 46.5 %. Since all other named scenarios show cutting-points below this share, this leads to the statement that an electrification of the customer vehicle fleet has to force the electrification of delivery vehicles in order to save energy.

In contrast to the break-even points, a share of 100 % reflects the fact, that all customers use private vehicles for shopping trips. There, the use of FEVs and a customer vehicle fleet consisting of ICECVs leads to the highest savings. The use of ICEFVs in combination with ECVs would offer the chance to save around 45 % of energy. In general, the relative savings increase with an ascending share of private vehicle use. Additional to the shifting of the cutting-point, a decreasing specific energy consumption of the private vehicle fleet is damping the curve of the savings.

The doubling of the amount of served customers leads to a left-shift of the savings-curves (**Fig. 9**), resulting in lowered cutting-points and higher savings at a share of 100 %. The course of the savings is affected by the increase of the energy consumption of the delivery vehicles. At a delivery probability of 20 %, the use of ICEFVs compared to a fleet of ECVs would offer the opportunity to save energy at the current share of private vehicle use for shopping trips. In general, the left-shift can be drawn back to the increased absolute number of substituted shopping trips.

Except the investigation of ICEFV+ECV at a delivery probability of 10 %, all depicted scenarios would lead to energy savings at the current share of private vehicle use for grocery shopping.

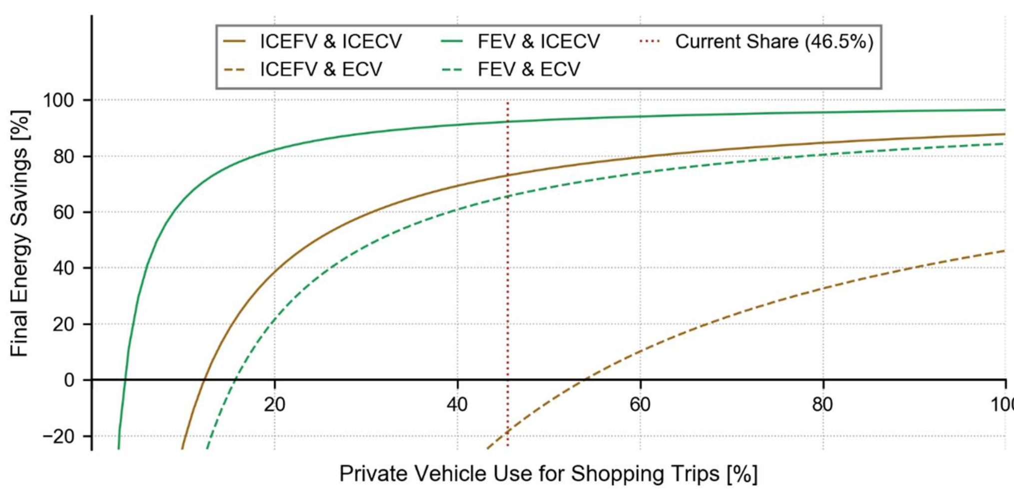

Figure 8. Final Energy Savings caused by a delivery of groceries as a function of the percentage of vehicle use for individual shopping trips (Delivery Probability 10%)

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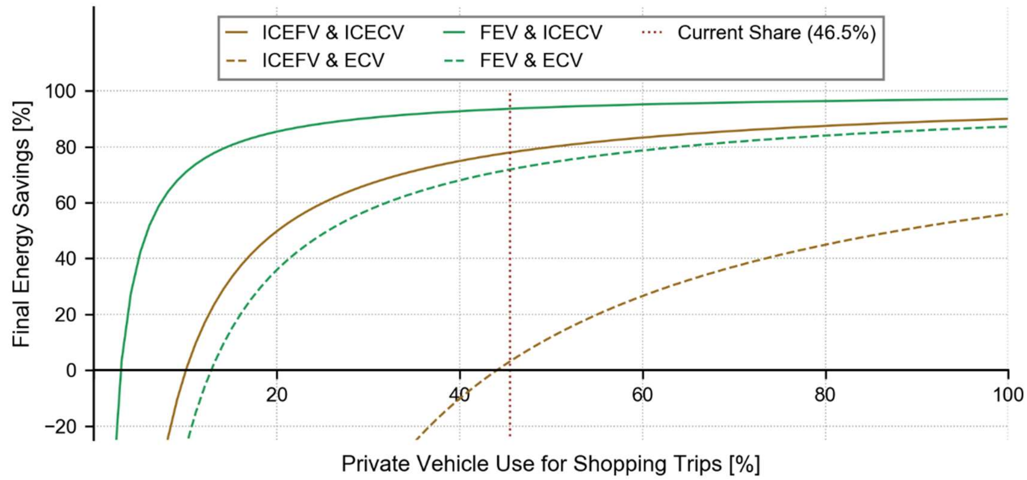

Figure 9. Final Energy Savings caused by a delivery of groceries as a function of the percentage of vehicle use for individual shopping trips (Delivery Probability 20%)

3.3. Analysis of Break-Even Points for CO_2 Emissions

Compared to the energy savings, the break-even of carbon dioxide savings are clearly different in some scenarios. **Fig. 10** and **Fig. 11** show the results for a delivery probability of 10 % and 20 %, respectively.

The use of ICEFVs for the delivery of groceries instead of individual shopping trips by an ECV-fleet would already offer the opportunity to save CO_2-emissions at shares greater than 29.4 % at a delivery probability of 10 %. The distinct lowering of the break-even point compared to energy savings (53.9 %) in this case can be drawn back to the high difference between the specific CO_2-emissions of electricity and diesel fuel. Decreasing specific emissions of the charging electricity mix, would result in higher minimal shares of private vehicle use in order to generate savings. As the reduction of specific emissions of the electricity mix is a declared goal for future development, the statement derived at the analysis of energy savings for this scenario is supported. Assuming a constant modal split for shopping trips in future, a complete electrification of the private vehicle fleet must presuppose the use of FEVs for the delivery of groceries in order to save CO_2, simultaneously.

This behavior is depicted in the scenario FEV+ECV. There, the minimum shares of private vehicle use are equal to the ones derived at the analysis of energy savings for both examined delivery probabilities. This can be drawn back to the equal specific emissions of the charging electricity mix.

Looking at the use of ICEFVs in contrast to an ICECV-Fleet, the break-even point also is almost constant compared to energy savings. Since the specific emissions of those vehicle types are more or less the same, the share is almost not changed. While the share to save energy is at 12.3 %, it marginally increased to 12.4 %, when looking at the CO_2 savings at a delivery probability of 10 %.

Last, the view on FEVs and ICECVs leads to increased break even points of emissions compared to the energy savings. At delivery probability of 10 %, a minimum of approximately 6.6 % of all shopping trips must be accomplished by private vehicles in order to save carbon dioxide. This behavior again can be lead back to the difference between the specific emissions.

With a view to the doubling of customers using the delivery of groceries, the same tendency as already described for the break-even points of CO_2 emissions can be observed. In contrast to energy savings, all depicted scenarios would lead to CO_2 savings at the current share of private vehicle use for grocery shopping, considering the current specific emissions. **Table 6** puts together the results for the break-even points in order to save energy and carbon dioxide in Haidhausen Süd by a delivery of groceries.

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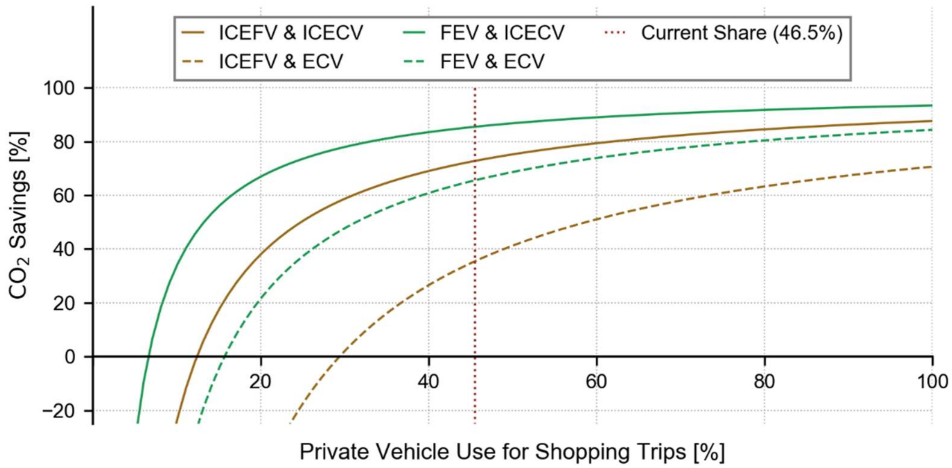

Figure 10. CO_2 - Savings caused by a delivery of groceries as a function of the percentage of vehicle use for individual shopping trips (Delivery Probability 10%)

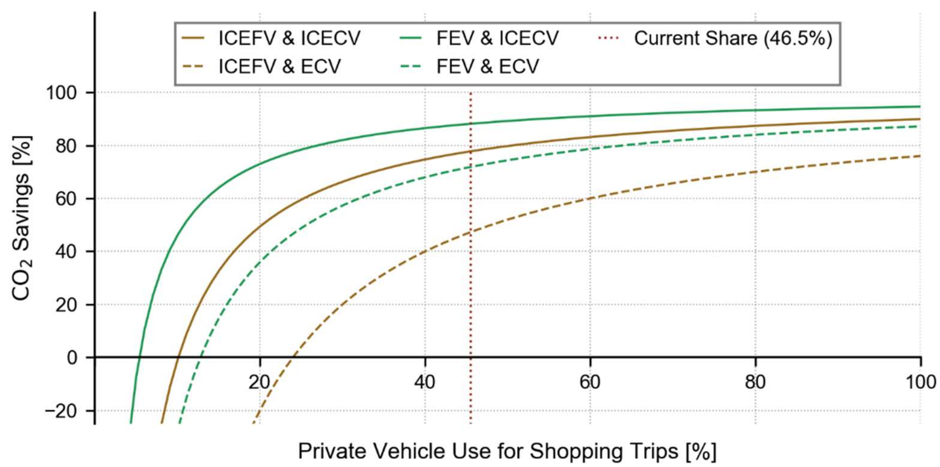

Figure 11. CO_2 - Savings caused by a delivery of groceries as a function of the percentage of vehicle use for individual shopping trips (Delivery Probability 20%)

Table 6. Minimum Shares for Private Vehicle Use in Shopping Trips to Save Energy and Emissions

Delivery Vehicles	Customer Vehicles	Energy Savings Delivery Probability 10 %	Energy Savings Delivery Probability 20 %	Emission Savings Delivery Probability 10 %	Emission Savings Delivery Probability 20 %
ICEFV	ICECV	12.3 %	10.0 %	12.4 %	10.1 %
	ECV	53.9 %	44.1 %	29.4 %	24.0 %
FEV	ICECV	3.6 %	2.9 %	6.6 %	5.4 %
	ECV	15.7 %	12.8 %	15.7 %	12.8 %

4. Conclusions and Outlook

The results of this paper show, that the delivery of groceries in Haidhausen Süd as district of the city of Munich has the potential to save energy and CO_2 compared to individual shopping trips. A distinctive finding is that not only combustion-engined, but also electric delivery vehicles, show the potential to save energy and CO_2. Another finding is, that the substitution of customer shopping trips employing FEVs leads to higher relative CO_2 savings than the use of ICEFVS, which can be drawn back to the higher efficiency of electric vehicles, although the specific emissions of the German electricity mix clearly are higher compared to diesel fuel. Hence, the use of FEVs for the delivery of groceries is one option to decrease the environmental impact once again compared to customer pickup.

As the analyses of the break-even points for energy and CO_2 savings in this paper for the case of Haidhausen Süd showed, the delivery of groceries leads to savings in a wide range of private vehicle use for shopping trips. Hence, even if a huge share of customers shifts to environmentally friendly modes for the shopping of groceries, a delivery would offer opportunities to save energy and CO_2. This statement is also valid, if the average distance of one customer pickup increases, because, for example, the supermarket is located at the borders of the region of investigation. Therefore, the delivery would show benefits even at lower shares of private vehicle use. Consequently, the length of a customer shopping trips has a huge effect on the break-even points respectively savings. On the other hand, if the depot of the delivery vehicles is located further away from the region of investigation, the savings may be reduced. Additionally, the amount of avoided customer shopping trips affects the savings. As the number of substitutions increases, more delivery vehicles must be employed. Hence, the results indicate higher energy use and CO_2 emissions of the delivery vehicles. The results of this paper can be summarized in the following:

- Specific energy consumption and specific CO_2 emissions of private as well as delivery vehicles clearly affect the position of break-even points
- Break-even points for energy and carbon dioxide emissions have to be evaluated independent of each other, because the results can differ
- When internal combustion engine delivery vehicles are used, a complete electrification of the private vehicle fleet can cause additional energy consumption at the current share of private vehicle use for shopping trips in Germany
- In this case, a reduction of the specific CO_2 emissions of the electricity mix could also lead to additional emissions caused by the delivery
- At the current share of private vehicle use, an electrification of the private vehicle fleet enforces the use of electric delivery vehicles in order to save energy and emissions in future

Since different new concepts for urban mobility have been developed in recent years, the share of private vehicle use might change in future. The methodology presented in this paper can be used for future evaluations of break-even points and energy and emissions savings potentials.

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