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Using a Route-based and Vehicle Type specific Range Constraint for Improving Vehicle Routing Problems with Electric Vehicles

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Abstract

In this research project, we implement a vehicle type dependent range constraint into a Vehicle Routing Problem (VRP) to consider the limited range of electric vehicles in urban freight transport planning due to the its restricted battery capacity and energy consumption. We apply this VRP in the route optimization jsprit which is linked to the microscopic agent-based simulation MATSim. In the framework of a case study focusing on food retail distribution in Berlin, Germany, we operationalize the range constraint and demonstrate the functionality and the effectiveness of this constraint using the distance from routing in a transport simulation network. Based on the simulation results, we analyze and discuss the impacts of the limitations of Battery Electric Vehicles (BEVs) on freight transport demand, road mileage performed and the resulting transport costs and greenhouse gas (GHG) emissions.

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Keywords: freight transport; electrification; vehicle routing problem; agent-based modelling; MATSim; range limitation; battery electric vehicle

1. Motivation and research objectives

Reducing greenhouse gas (GHG) emissions is one major objective to limit the global warming to below 2°C above pre-industrial level and go towards a (more) sustainable future (United Nations, 2015). At the European level, the European Commission agreed on the "European Green Deal" in 2019 which includes decoupling of the economic growth from resource usage and having zero net GHG-emissions by 2050 (Europäische Kommission, 2019). Besides this, at national level, different countries defined their own plans for climate protection, e.g. the German "Climate Action Plan 2050" (BMUB, 2016). 35% of CO_2 emissions in the transportation sector are currently emitted by road freight transport (BMUB, 2018). This German action plan foresees to reduce the GHG-emissions of the transport sector by 40% until 2030, compared to 1990. The European Commission aims to reduce the transport emissions by 90% until 2050. To achieve this goal, electrifying the transportation sector could be a suitable solution. Hence, the current internal combustion engine vehicles (ICEVs) have to be replaced by battery electric vehicles (BEVs).

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The range of BEVs is currently restricted and recharging is still much more time consuming in comparison to refueling of ICEVs. As a consequence, route planning is so far too optimistic and (some of) the routes planned are too long and cannot be carried out by BEVs (Liimatainen et al., 2019; Martins-Turner et al., 2020).

This issue could be avoided if route planning considers the limitations concerning the battery capacity and energy consumption of BEVs. As a consequence, the adjusted distance of the routes planned could be performed by BEVs.

For this reason, our research objective is to integrate the limited range of BEVs in existing Vehicle Routing Problem (VRP) solution algorithm to generate more realistic routes carried by BEVs. In this publication, we will investigate the impacts of the limitations of BEVs on freight transport demand, road mileage performed and the resulting transport costs and GHG-emissions. Due to the limitations of these vehicles we expect that more BEVs are necessary in comparison to ICEVs to fulfill the orders of the clients. In the following, we will present the methodology developed to consider the limited range of BEVs. First, we will describe the implementation of the range constraint in the route planning algorithm. For generating the routes, the route optimization *jsprit* is used to solve the VRP which is linked to the microscopic Multi-Agent Transport Simulation (MATSim). Afterwards, the extended algorithm will be applied to a case study focusing on food retail distribution in Berlin, Germany. Based on the simulation results, we will finally show and discuss the impacts of BEVs on the freight transport demand in food retailing.

2. Methodology

VRPs are used to "determine a set of vehicle routes to perform [...] transportation requests with the given vehicle fleet at minimum costs" (Irnich et al., 2014). In our study, VRPs have to be solved to generate tours in urban freight transport. We use *jsprit*, an open source VRP-solver (jsprit, 2018), which can be linked to the open source transport simulation software MATSim (Horni et al., 2016). To generate realistic tours for BEVs in urban freight transport, we consider a *range restriction* of these vehicles. We implement this constraint as an extension of the VRP. In the following, we will describe the methodological procedure to implement this extension. The aim is to generate only routes which consider the maximum range of the respective vehicle type.

We assume that conventionally diesel vehicles can perform an infinite range, as they can refuel as often as they want to continue the route without any significant loss of time. If electric vehicles are used, it is assumed that they start their tour fully charged and must handle their route without recharging. A scenario in which the vehicles can be recharged is currently not integrated and is also not trivial to implement. In a real network where there is hardly any charging infrastructure, this would also require major investments. We assume that a charging infrastructure for recharging during the route is not necessary since the mileage performed within the investigated urban area and within a business day can be carried out by an electric-driven vehicle without recharging. Hence, charging infrastructure is only necessary at the vehicle depot.

Figure 1 shows the functionality of the introduced range constraint. *Fulfilled* means that inserting the job into the tour is allowed. In contrast to this, *not fulfilled* defines that an insertion of this job is not possible. The program code of the range constraint is available online (see `https://github.com/matsim-org/matsim-libs` repository).

The improved range constraint is integrated in the VRP solving algorithm. The tour range of each vehicle type depends on the battery and the specific consumption. Based on this, it is not possible to generate a route which is longer than the maximum range of each vehicle type. The first step to insert the constraint is to collect the consumption and the battery capacity for each electric vehicle type. Thereby, we enable to set the maximum range for each vehicle type separately. In order to implement the range restriction, a prerequisite is to integrate the distance calculation in the VRP solving process. The conventional cost matrix used for jsprit only contains the costs for one route with a specific departure time between two locations of each vehicle type, since the costs are usually used as the decisive criterion. Therefore, the network-based distances are added to this matrix. Now, we get the distance between every location pair in the network. This distance is calculated as the sum of the links lengths.

Using the range constraint for a VRP, the constraint is checked at each part of changing the route. These changes could be the *usage of a different vehicle type* or *adding a new job to the tour*. Therefore, the method of the constraint is called which verifies whether all conditions for the route of the corresponding vehicle type are still fulfilled for the change made. If this is not the case, the examined change in the route is rejected. By this method, all suitable investigations for the range restriction of the electric vehicles are integrated.

The functionality illustrated in Figure 1 shows that the range restriction applies to vehicles with a certain energy capacity. If a fuel capacity is also set for an ICEV, the constraint also works for the conventional vehicle. We assume that when a new pickup element should be added to the tour, the related delivery element is also included. In this context, the algorithm searches the minimal additional distance for each possible position of the delivery in the tour. Therefore, when accepting a pickup, this minimum distance is taken into account.

In conclusion, we can include several vehicle types with different ranges in one scenario. Besides BEVs, vehicles without range limitations can also be integrated to make the VRP solvable if some of the locations are out of the range of BEVs. Each vehicle type has different costs. These input parameters are the basis for the objective function of jsprit which aims for minimizing the total costs of one VRP.

After jsprit selects the most cost-effective variant according to the specified number of iterations, the route planning is completed, and the problem is solved. Afterwards, MATSim is started and executed.

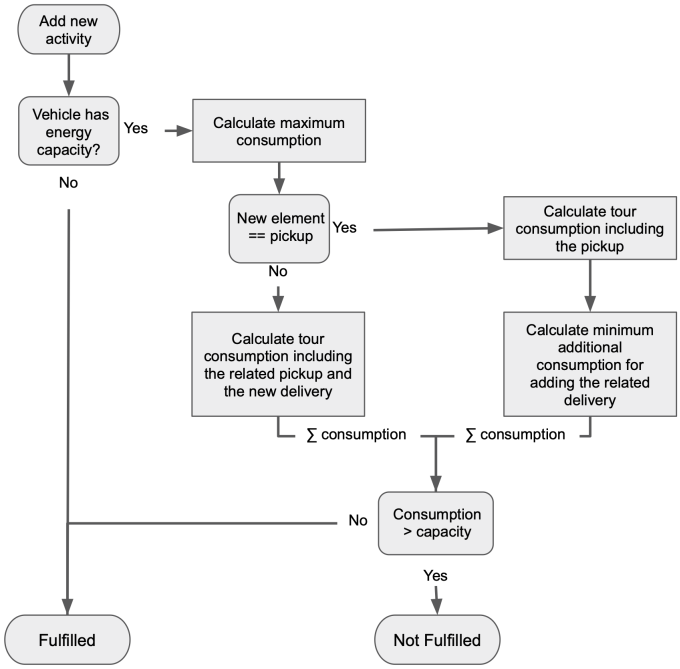

Fig. 1. Functionality of the range constraint.

3. Case study: Urban food distribution

In the framework of this case study, we investigate the food retail distribution in Berlin, Germany. This study was developed with by Gabler et al. (2013); Schröder and Liedtke (2014) and is modified for the present study.

In the baseline scenario, we focus on the traditional freight transport in urban food retail distribution carried out by diesel vehicles. In further scenarios, the baseline scenario is extended by including electric trucks with specific vehicle characteristics. The expected effects are the changed fleet composition and possibly the increased number of trips and mileage performed and as a result increased power consumption, transport costs and GHG-emissions. To apply the newly introduced functionality, MATSim (Horni et al., 2016) and the linked route optimization *jsprit* (jsprit, 2018) are used for modelling and simulating these scenarios.

The present study uses the road network of the MATSim Open Berlin Scenario (`https://github.com/matsim-scenarios/matsim-berlin`) (Ziemke et al., 2019). For our simulation we dispense with the passenger transport, since we only investigate the changes regarding the generated freight transport in food retailing sector. For generating adequate routes and travel times also in the tour planning, we are using a time-dependent network (Rieser et al., 2016) which uses the link travel times from the simulation output of the MATSim Open Berlin Scenario.

3.1. Baseline scenario: Food distribution by diesel-driven trucks

In the baseline scenario, deliveries to the food retail branches are carried out by **diesel trucks with a permissible total weight (ptw) of 7.5t, 18t, 26t and 40t**. The 17 locations of the distribution centers and the 1,040 locations of the branches of the food retail chains are collected and georeferenced. A distinction is made between nine different German retail chains. These retailers could be also differentiated into supermarkets, discounters and self-service stores. Based on this, there are 15 carrier types determined in the observed system. The locations of each retail chain are assigned to the associated distribution centers. Furthermore, the freight demand per branch for an average business day is derived. The various products are aggregated into the following three groups: (i) fresh, (ii) frozen and (iii) dry goods. As a result, in total 45 carriers are modelled independently. Estimating the daily quantity demanded by the retail branches is based on a retailer's annual sales. As a result, the freight demand for each retail branch for Berlin is derived (Gabler et al., 2013). Determining the delivery time window for each branch we assume that frozen and dry goods are delivered within the time window between 9:00 a.m. to 7:00 p.m. and fresh products between 4:00 to 9:00 a.m. (Martins-Turner and Nagel, 2019).

In this case, each retailer is his own logistics service provider and their distribution centers are also the vehicles' depots. Each distribution center is equipped with its own fleet consisting of the various truck types with their corresponding vehicle characteristics (including ptw, vehicle capacity, transport costs, fuel consumption; see Table 1). The vehicle capacity of the vehicles used to deliver fresh and dry goods is measured on the max. number of euro pallets that fit on the loading area of each truck type. In contrast, the measurement unit freezer box is used for the vehicle capacity for the distribution of frozen goods. We assume that three minutes for each stop (constant stop time) and additionally one minute for the concrete delivery or pickup of the single pallet to/from the branch (variable stop time) is needed.

By means of a transport cost calculation (TCC), we can derive the variable (distance-dependent), the fixed and the personnel (time-dependent) costs. For the TCC, we use the parameter values prepared by Martins-Turner et al. (2020) which are based on the German Bundesverkehrswegeplan (BVWP, Federal Transport Plan, BMVI, 2016). Since the BVWP has a national economic perspective, taxes and insurances are not included in the cost calculation (PTV et al., 2016). For calculating the time-dependent transport costs, data, driver wages for representative vehicle types are also given in Planco et al. (2015). In contrast, taxes except the sales tax (VAT) and insurances are relevant for the carrier. For this reason, we have to consider these costs components in our TCC. Therefore, we use the data provided by Eurotransport (2017).

As a basis for route optimization, it can be determined whether the logistics service provider has a fixed number of trucks or he independently determines the need for vehicles as part of route optimization. Here, we assume that he has an infinite fleet and uses the optimal number of vehicles to distribute the goods. Therefore, the fleet composition is a result of the VRP (Schröder and Liedtke, 2014; Gabler et al., 2013). The food retailers transmit to the logistics service provider both their freight demand to be delivered and the time window at which they should be delivered. The retail branches are supplied from their distribution centers. If more than one distribution center is available, a multi-depot VRP is solved. One vehicle can perform several tours per day (Martins-Turner and Nagel, 2019). Table 1 shows an overview of the parameter values used in the baseline scenario. These values are based on Gabler et al. (2013); Martins-Turner and Nagel (2019); Martins-Turner et al. (2020); Planco et al. (2015).

3.2. Scenario: Food distribution by electrified trucks

In this scenario, we use exactly the same input data as for the baseline scenario. In addition, we introduce BEVs. Hence, deliveries to the food retail branches can also be carried out by **electric-driven trucks with a ptw of 7.5t, 18t, 26t and 40t**. In this context, we point out that a larger ptw is allowed within the European Union when using a clean propulsion system (PARLIAMENT and UNION, 29.04.2015). We assume that the battery size is designed in a way that both BEVs and ICEVs have the same payload capacity. We determine that only 70% of the theoretical (gross) battery capacity is used as (net) capacity for the tour planning to ensure an adequate battery lifetime and to maintain a reserve for unexpected energy consumption.

With regard to the transport costs calculation of BEVs, Martins-Turner et al. (2020) provide two different cost schemes which only differ in the chassis costs: i) based on a market analysis assuming that the chassis prices of BEVs are 1.6 times as high as those of ICEVs and ii) based on Fuessel (2017) assuming that the chassis prices of BEVs will correspond to those of ICEVs from the moment mass production will start. For our case study, we will use the more future related assumption, using the cost values for equal chassis prices for BEV and ICEV (BEV100 in Martins-Turner et al. (2020)). Table 1 shows the resulting costs.

As already discussed, an additional *tax on GHG-emissions for ICEVs* is suitable to supports the change from ICEVs to BEVs. By such a tax the variable costs per distance for the ICEVs increases and thereby, the BEVs become more attractive. This tax should internalize the external costs for emitting GHG-emissions. Assuming a well-to-wheel production of $3.17 kgCO_2$/liter diesel (DIN EN 16258:2012, 2013), 1 € tax per ton of CO_2 leads to additional costs of 0.00317 €/liter diesel. If the (high) value of 300 €/ton is set as an end point for a rapid change towards a greener transport system, the additional costs are 0.951€/liter diesel.

The newly implemented range constraint is now applied for the BEVs. The ICEVs are not restricted in their range for tour planning. As a consequence, each carrier gets its own fleet composition with BEVs and/or ICEVs as a result of the tour planning algorithm. Since the algorithm is cost-oriented, the fleet composition depends on the different cost structures of the vehicle types provided.

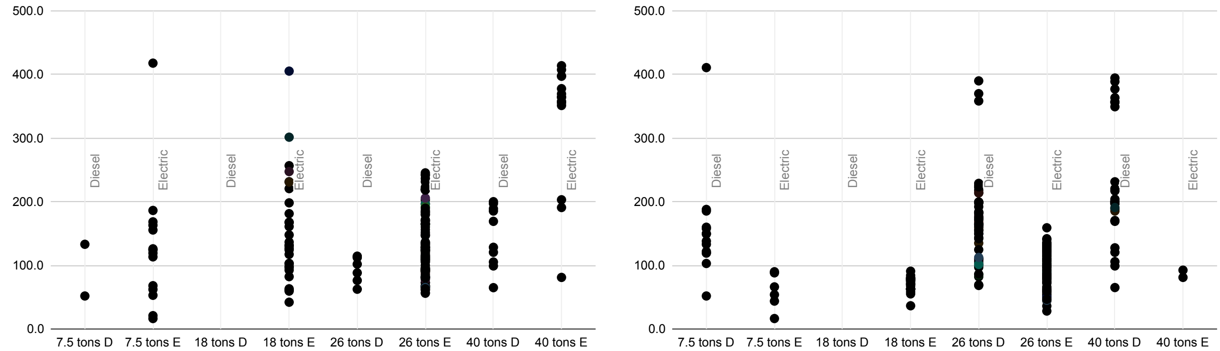

Fig. 2. Observed distances driven by each vehicle type in the BEV scenario with 300 €/t tax on CO_2-emissions for the ICEVs: Without (left) and with (right) usage of improved algorithm.

Table 1. Describing the scenarios: Characteristics of the ICEVs and BEVs.

Vehicle types	**ICEVs**	**BEVs**	
Trucks 7.5 t ptw to deliver fresh and dry (frozen) goods			
Vehicle capacity	10 (70)	10 (70)	P/T (B/T)
Fixed costs	63.49	74.76	€/day
Variable costs	0.00040	0.00046	€/m
Time-dependent costs	0.00490	0.00490	€/s
Diesel consumption	0.0001357		l/m
Energy consumption		0.00061	kWh/m
Battery capacity gross (net)		87 (60.9)	kWh
Trucks 18 t ptw to deliver dry goods			
Vehicle capacity	16	16	P/T
Fixed costs	80.47	92.26	€/day
Variable costs	0.00065	0.00055	€/m
Time-dependent costs	0.00490	0.00490	€/s
Diesel consumption	0.0003319		l/m
Energy consumption		0.00106	kWh/m
Battery capacity gross (net)		122 (85.4)	kWh
Trucks 26 t ptw to deliver fresh and dry (frozen) goods			
Vehicle capacity	24 (160)	24 (160)	P/T (B/T)
Fixed costs	82.60	111.90	€/day
Variable costs	0.00067	0.00072	€/m
Time-dependent costs	0.00490	0.00490	€/s
Diesel consumption	0.0003319		l/m
Energy consumption		0.00150	kWh/m
Battery capacity gross (net)		286 (200.2)	kWh
Trucks 40 t ptw to deliver dry goods			
Vehicle capacity	33	33	P/T
Fixed costs	126.58	183.93	€/day
Variable costs	0.00069	0.00078	€/m
Time-dependent costs	0.00559	0.00559	€/s
Diesel consumption	0.0003754		l/m
Energy consumption		0.00180	kWh/m
Battery capacity gross (net)		443 (310.1)	kWh

Legend: P=palettes, B=boxes, T=trips, l=liter, kWh=kilowatt hours

In Table 1 we present the resulting cost structure. It should be noted that the transport costs of BEVs are higher in comparison to these of ICEVs with the same ptw due to the additional battery costs. We combine this scenario with different variable costs per distance for the ICEVs to investigate the effects of the GHG-emissions tax.

4. Results

In the following, we show the results of the simulation. We compare the baseline scenario (only ICEVs) with the BEV scenarios using the improved algorithm concerning fleet composition, mileage performed and GHG-emissions. For supplying the remaining stores in the BEV scenarios, ICEVs are allowed as well. With an increasing amount of **taxes** on GHG-emissions for ICEVs, the probability for choosing BEVs instead of ICEVs increases. Furthermore, we will present the BEV scenario without the improved algorithm to show the effectiveness of the range constraint.

Effectiveness of the improved algorithm. Figure 2 shows the tour distances driven for each vehicle type of the BEV scenarios. We illustrate the results without (left side) and with (right side) the range constraint for the BEV trucks. As expected, the observed tour distances of the BEV trucks are shorter when using the constraint in comparison to the distances without using the limitation.

Applying the range constraint leads to an increased usage of ICEVs, because the maximum tour length is not suitable to reach all shops. Since vehicles are allowed to reload goods during their tour and some depots are further away from their shops, there are some trucks driving even longer tours than the rest. This leads to a gap in the observed tour length.

As in reality, the vehicles may choose other routes between their stops within the traffic simulation, compared to the tour planning. Therefore, we observe for some tours slightly longer distances than allowed by the (net) battery

Table 2. Results of usage per vehicle type depending on GHG-tax for ICEVs — number of vehicles per day.

scenario	tax	add. costs	7.5 tons		18 tons		26 tons		40tons		total	
	[€/ton CO_2]	[€/liter]	ICEV	BEV	ICEV	BEV	ICEV	BEV	ICEV	BEV	ICEV	BEV
base	0	-	17	-	15	-	223	-	40	-	**295**	**-**
BEV and ICEV with range constraint	0	-	15	1	4	5	200	37	27	0	**246**	**43**
	25	0.079	16	2	4	7	176	56	27	0	**223**	**65**
	50	0.159	18	1	2	8	170	59	27	0	**217**	**68**
	100	0.317	14	4	2	12	140	87	26	2	**182**	**105**
	150	0.476	18	3	2	17	127	109	26	2	**173**	**131**
	200	0.634	15	5	1	20	108	123	26	2	**150**	**150**
	250	0.793	18	6	0	25	86	141	26	2	**130**	**174**
	300	0.951	14	6	0	23	56	183	26	2	**96**	**214**

Table 3. Results of usage per vehicle type depending on GHG-tax for ICEVs — kilometers driven per day.

scenario	tax	add. costs	7.5 tons		18 tons		26 tons		40tons		total	
	[€/ton CO_2]	[€/liter]	ICEV	BEV	ICEV	BEV	ICEV	BEV	ICEV	BEV	ICEV	BEV
base	0	-	1 800	-	2 099	-	26 863	-	5 994	-	**36 755**	**-**
BEV and ICEV with range constraint	0	-	1 642	16	559	383	26 201	2 877	5 992	0	**34 393**	**3 277**
	25	0.079	1 883	96	442	519	24 482	4 447	5 995	0	**32 802**	**5 062**
	50	0.159	2 092	16	210	588	23 916	4 668	5 991	0	**32 209**	**5 272**
	100	0.317	1 635	156	292	895	20 769	7 231	5 919	174	**28 616**	**8 455**
	150	0.476	2 514	116	271	1 231	17 828	9 302	5 919	174	**26 530**	**10 823**
	200	0.634	2 206	247	201	1 462	15 867	11 116	5 884	174	**24 158**	**12 998**
	250	0.793	2 579	264	0	1 808	13 360	12 965	5 880	174	**21 819**	**15 210**
	300	0.951	2 189	359	0	1 619	9 421	17 230	5 879	174	**17 488**	**19 382**

capacity. 98% of the measured tours are within the calculated range or exceed it by max. 5%. Only two of 214 tours exceed the plan-able range by >10 %. The most deviating tour is 19% longer. This is still feasible, because the VRP algorithm gets a plan-able (net) battery capacity for the vehicle type which is only 70% of the (gross) battery capacity (see Sec. 2), leading to an available reserve to exceed the plan-able range by ≈ 43%. Furthermore, some of the tours planned with ICEVs are capable to be driven with BEVs.

Fleet composition, distances driven and influence of the CO_2-tax for diesel-driven trucks. In our study, the fleet composition is a result of the tour planning. While 295 ICEVs are necessary to serve the demand in the baseline scenario, the number of vehicles used per day in the BEV scenario depends on the amount of the CO_2-tax for the ICEVs (see Table 2). Without any tax on GHG-emissions, 246 ICEVs and 43 BEVs are used. A tax of 300 €/t CO_2 will result in a fleet of 96 ICEVs and 214 BEVs. This drastic change results from the higher fuel price and therefore higher variable costs per distance for the ICEVs as well as the cost-based objective function of the VRP algorithm. Due to the limited range of the BEVs, an increased usage of BEVs leads to more vehicles needed in total. Again, there are ICEV tours which could be driven one-by-one with BEVs of the same ptw.

Table 3 shows the results on the kilometers driven. In all BEV scenarios in total more vehicle kilometers are measured than in the baseline scenario. Due to the limited range of the BEVs, the observed shift from ICEVs to BEVs regarding the kilometers driven is not as strong as the shift with regard to the number of vehicles used.

Well-to-Wheel GHG emissions. We apply the Well-to-Wheel (WTW) methodology according to JRC et al. (2014) to analyze the environmental impact of the simulated scenarios. The WTW-methodology includes the GHG-emissions from the production of diesel and electricity as well as from their use in the vehicles. Based on the observed distance travelled from the transport simulation (see Table 3), vehicle type specific energy consumption and the specific CO_2-emissions factor per energy unit, we calculate the Well-to-Wheel GHG-emissions. The vehicle type specific fuel consumption is assumed for the ICEVs between 13.57 l diesel/100 km (7.5 tons truck) and 37.45 l diesel/100km (40 tons truck). The electricity consumption of the BEVs is between 61 and 180 kWh/100km (see Table 1).

We assume 250 business days per year (Planco et al., 2015) and a factor of 3 170 g CO_2/liter diesel (DIN EN 16258:2012, 2013). For showing the influence of the electricity production, three different emission factors are identified in the state of the art: 518 gCO2eq/kWh for the electricity production in 2018 (Icha and Kuhs, 2019), 347 gCO2eq/kWh in 2030 and 25 gCO2eq/kWh for renewable energies (Wietschel et al., 2019). The values per year for the different scenarios are shown in Figure 3.

As a consequence of the shift from ICEVs to BEVs due to the increasing GHG-tax, the total W2W-GHG-emissions decrease. The usage of clean(er) electric energy has a huge impact in the BEV scenarios. The annual GHG-emissions decrease from ≈ 9 600 tons in the baseline scenario to ≈ 4 600 tons (- 5 000 tons) when promoting the change to use BEVs (tax = 300) and using only renewable electricity. Assuming the German electricity mix from 2018, the GHG-emissions would be ≈ 8 100 tons/year (- 1 500 tons).

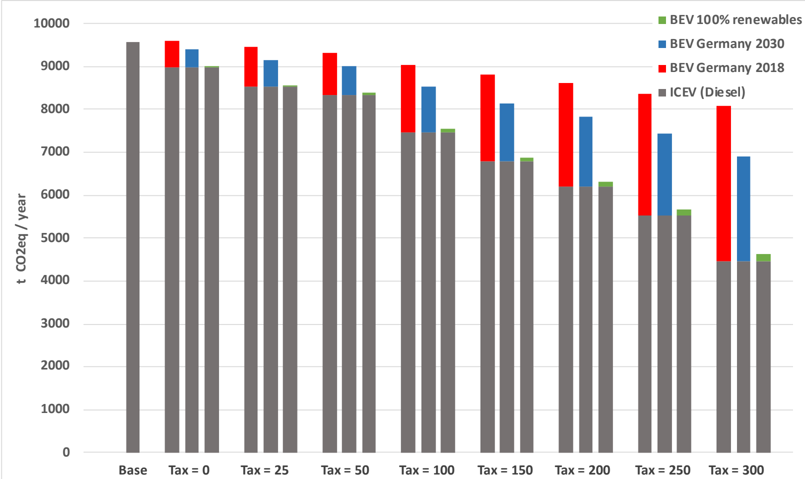

Fig. 3. Calculated CO_2-emissions per year for the baseline and the BEV scenarios (tax on CO_2-emissions on ICEVs from 0 to 300 €/t) with range constraint. The emissions of the BEVs are shown for three different energy sources: energy mix for Germany 2018 (red), for Germany 2030 (blue), renewable only (green). The emissions from the ICEVs are marked in gray.

5. Conclusion and Outlook

We present the methodological procedure to implement a constraint for a vehicle routing algorithm which restricts the planned tour distance. By the new vehicle type specific method, energy consumption and energy capacity for each vehicle type can be independently defined. The new algorithm was applied to an existing case study focusing on food retail distribution in Berlin, Germany. The solution includes that the carriers can choose between different vehicle types. For each maximum payload one diesel-driven and one electric driven is provided. We assumed that only the BEVs have a limited range due to their battery capacity. ICEVs can be used as fallback solutions if BEVs are not sufficient.

We showed that the algorithm works as expected. A small number of observed tours in the traffic simulation are exceeding the plan-able range. But even the tour with the largest divergence needs less than the half of the included tolerance. We increased the (variable) costs for the ICEVs by introducing taxes on GHG-emissions in the framework of the BEV scenarios. Thereby, we observed an increasing switch from the usage of ICEVs to BEVs. In addition, due to the limited range of the BEVs, a slight increase of the total number of vehicles used and kilometers driven can be determined in comparison to the baseline scenario with only ICEVs. For the corresponding Well-to-Wheel GHG-emissions we assumed different electricity mixes. We can state that GHG-emissions decrease by more than 50% from approx. 9 600 to 4 600 tons/year when using renewable electricity. Assuming the emissions based on the energy production in Germany in 2018 the decrease in the same scenario would be 15% (−1500 tons). In contrast to ICEVs, the BEVs have the potential to become more environmentally friendly, without additional investments into the vehicle fleet, just by using an energy mix with increasing the proportion of renewable energy. Furthermore, there is either a need for a strong regulation toward the usage of BEVs or for promoting the change by market reactions and making the usage of BEVs cheaper than the usage of ICEVs. Besides e.g. subsidizing the purchase costs of BEVs, this could be easily implemented by introducing a significant GHG-emissions tax on ICEVs.

The results also show that there are some tours planned with ICEVs, even when the same-sized BEVs would be able to carry out it. It seems that the VRP algorithm does not find the best suitable fleet composition. This is probably due to the objective function, which is only cost-oriented, and due to a missing strategy to replace vehicle types. The provided improvement of the algorithm does not include any recharging during the tour, neither at the shops nor during loading goods at the depot. Due to the stop times we can assume that an installation of charging infrastructure at some longer stops and at the depots for recharging during reloading goods would be possible. Including recharging at (defined) locations would allow to drive longer distances with the electric-driven trucks without or with only less extra time. As a consequence, the usage of BEVs would become more efficient. In this context, further research questions could be, where such recharging infrastructure could be located. Another improvement would be to include a more detailed energy consumption calculation model which takes into account e.g. road gradients or congestion. Further research studies should investigate the limits of electrification, e.g. by running scenarios with BEVs with a higher battery capacity, even if this results in less payload due the higher weight. This could be extended by running the electrification scenarios with electric trucks with different battery capacity for each vehicle type.

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