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Electrification of Urban Freight Transport - a Case Study of the Food Retailing Industry

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Abstract

Decarbonisation is a major challenge for the coming decades,for all industries, including the transport sector. Here, battery electric vehicles are a potential solution for the transport sector to reduce its carbon impact. Asides from the question whether there is sufficient supply of electric vehicles for freight transport, it is also unclear whether battery-powered trucks meet the practical requirements, especially in terms of their driving range. To investigate this, tours were generated by solving a Vehicle Routing Problem (VRP). This also generates the fleet size and composition depending on a set of different vehicle types. The network with underling traffic conditions comes from an publically-available transport model. The generated tours are simulated with an open-source transport simulation (MATSim), for both diesel and battery electric vehicles (BEVs). In a sensitivity study, two different purchase prices were considered for calculating vehicle costs. The case study uses a model of the food retailing industry for the city of Berlin. 56 % of the tours can be driven without recharging. When recharged one time, 90 % of the tours are suitable for BEVs. The costs for transporting the goods will increase by 17 to 23 % depending on the assumption for the purchase prices for the BEVs.

Keywords: freight transport; decarbonisation, electrification; agent-based modelling; MATSim; vehicle routing problem

1. Introduction

Reducing greenhouse gas emissions to limit global warming and climate change with all its consequences is one of the major global challenges of the 21st century. As a response to this challenge, the European Commission agreed on the ”European Green Deal”, which includes having net zero emissions of greenhouse gases by 2050 and decoupling of the economic growth from resource use [5]. To achieve this goal, ”a 90% reduction in transport emissions is needed by 2050” [5]. Currently 35 % of CO_2 emissions in Germany are emitted by trucks [2]. Beside reducing the transport system’s impact on global climate, bans on diesel vehicles are being discussed in various cities to protect the population from harmful emissions[24, 26]. In this paper, we investigate if and to what extent the current requirements

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for urban freight transport can be fulfilled when replacing the current internal combustion engine vehicles (ICEVs) by battery electric vehicles (BEVs).

Goods for a city typically arrive at distribution centres ("hubs") at the periphery of the city. From these hubs, they are distributed throughout the city. Generating tours for a fleet to perform this distribution task can be done by solving the Vehicle Routing Problem (VRP). An open source toolkit for solving VRPs is jsprit [14], which can be used stand alone as well as in conjunction with the agent-based transport planning software MATSim [28].

Vehicle Routing Problem (VRP). For transport companies, creating optimal vehicle routes depends on various factors. These factors can be internal and external. The internal factors include the location of depot(s) and the available fleet at the depot(s). Each vehicle type in a fleet has a set of given properties, e.g. carrying capacity and fixed and variable costs [14]. The most important external specifications are customer requests: quantity and type of goods, location and time window to deliver goods. Other external constraints the carrier must consider are the road network and (expected) traffic situations, tolls and driving restrictions [3]. Consideration of congestion is usually not part of urban tour planning [4].

A VRP can be defined as follows: finding a plan to "determine a set of vehicle routes to perform [...] transportation requests with the given vehicle fleet at minimum costs"[13]. Solving a VRP answers two main sub-problems for the carrier: (i) assigning requests to tours (clustering) and (ii) determining the optimal sequence in which the requests are served within a tour (routing)[18, 22]. More information regarding different types of vehicle routing problems can found e.g. in [25], [22] or [14].

jsprit. For solving VRPs, several toolkits are available. One of these is the open-source toolkit jsprit [14]. Jsprit optimizes the solution iteratively by ruining parts of the solution and recreating them. The objective function is to reduce the costs for the carriers. Inputs are e.g. fixed costs for the vehicle including depreciation, insurance, maintenance and so on, variable cost for covered distance and travel time, and other costs such as tolls and penalties for missed time windows[14].

Each VRP has a carrier with a certain fleet and list of requests. The fleet is located at the depot(s) and can be defined either with concrete vehicle amounts or with an infinite fleet of specified vehicle types. When using the infinite fleet size, the the fleet composition is also part of the solution. The requests (demand) can be defined using one location (the other one is the depot) or explicitly by defining pickup and delivery location. Defining only one location opens the possibility to solve multi-depot VRP (MDVRP), while defining both pickup and delivery locations allows the vehicle to reload goods during the tour. Further information about both kinds of defining the requests can be found in [15].

2. Methodology

This study uses the open source software Multi-Agent Transport Simulation (MATSim, `https://matsim.org`, `https://github.com/matsim-org/matsim`). It is an activity-based, extendable framework that is designed for agent-based transport simulations of large-scale scenarios. Several optional extensions are available (`https://matsim.org/extensions`) as well as open-access scenarios (`https://github.com/matsim-scenarios`) [11].

Investigating the effects of measures is a three-step approach: (1) Building a model of the base case, (2) building a model of the investigation case(s) and (3) comparing the results, e.g. costs and benefits.

The model of the base case is distributing goods to the food retailing shops with ICEVs, in this case diesel powered trucks. For this, a model of the daily demand is needed as well as a method to generate plausible vehicle tours serving that demand. With some modifications, the demand based off of earlier studies (see section 3). The vehicle tour for each vehicle starts at a depot, going back and forth between depot and delivery locations (shops) and finally returns to the the depot. These tours need to be generated in advance of the traffic simulation, because the agents (persons, drivers) in the traffic simulation have to follow the tour plan [28]. For generating the tour plan we are using the open source software jsprit [14] as heuristic Vehicle Routing Problem (VRP) solver. It is integrated into MATSim using the MATSim freight contrib [28]. Because of this integration we are, in contrast to [4], able to consider traffic congestion in our model (see 3).

For the investigation cases, equal demand is assumed. However, only battery electric vehicles (BEVs) are available to transport the goods. Running the scenario means that we solve the VRP using jsprit with 10 000 iterations and afterwards run a single MATSim iteration. From the output events, we can calculate the travel times and distances for each vehicle. In an ex-post analysis, we analyse the effects on the carriers in terms of fleet compositions and costs. We also evaluate the tours of the vehicles to see under which conditions it is possible to use battery electric trucks as replacement for diesel trucks.

3. Case Study

This case study is located in Berlin, the capital and largest city of Germany. It deals with transporting goods to the shops of the food retailing industry. It is based on the case study of Schröder and Liedtke [23].

Road Network. The previously generated demand model was transferred into the network of the MATSim Open Berlin scenario (`https://github.com/matsim-scenarios/matsim-berlin`), which is available publicly and free of charge [27]. Since we are only interested in the effects of changing the truck fleet from ICEVs to BEVs, we do not run a simulation that includes passenger transport. The time dependent travel times in the network were generated accordingly to the observed traffic in the simulation output of the MATSim Open Berlin Scenario, using so called NetworkChangeEvents [21].

Demand. For this scenario we use the demand model of Schröder and Liedtke [23], which was modified by [15]. The main modification is enabling vehicles to run more than one delivery tour from the depot. This includes that loading vehicles with goods at the depot becomes part of the VRP. We assume the same average loading time of three minutes per pallet at the depot as it is assumed by [23] for unloading one pallet. In total, the demand of 15 retailing companies in Berlin with 17 distribution centres located in and around Berlin is modelled. These companies serve 1057 food retailing shops with 1928 demand requests. The shops' demand is the demand of an average day.

Each shop has a variety of heterogeneous products they offer to their consumers. Schröder and Liedtke aggregated the different products a shop offers to their consumers into three different groups: fresh, frozen, and dry. These groups require different transport conditions and thus were transported by different carriers in the model [23]. This leads to $15\,companies \cdot 3\frac{groups}{company} = 45\,carriers$ in the model.

Since the vehicles can run several (sub-)tours that include reloading goods during a day, the original time-window constraint of the model by [23] was modified. The vehicles availability as well as the delivering time-windows for dry and frozen goods is set to [9am – 7pm]. The time window for fresh goods remains unmodified [4am – 9am]. [15]

Each carrier plans its tours based on its own fleet available at the depots. The available vehicle types in the fleet of a carrier depend on the type of goods and the business type of the company.

Vehicle types and costs calculation. In the scenario of Schröder and Liedtke, some assumptions about the available vehicle types were taken. In total, they define four different vehicle types with the size of the vehicles as distinguishing criterion: light 7.5 tons, medium 18 tons, heavy 26 tons and heavy 40 tons. All vehicles are ICEVs. All vehicles are located at a depot, but not all vehicle types are available for each carrier [23, 8]. The number of vehicles of the different available types are not limited for each carrier. Therefore, the fleet composition is a result of the VRP.

The cost calculation of this study has been updated to have consistent costs for the different vehicle types over all scenarios. The used methodology and many values for the calculation are based on the German Bundesverkehrswegeplan (BVWP, Federal Transport Plan [1]). The purchase cost of the vehicles is depreciated half by time and half by driven distance. Because the BVWP models from national economics perspective, taxes and insurance premiums are not included in the cost calculation of BVWP [19]. However, insurances premiums and other taxes except the sales tax (VAT) are relevant for the carrier and should therefore be included in the costs for tour planning. Therefore, missing values for insurances and taxes were taken from [6]. Data for representing vehicle types are given in [17]. We use the following vehicle types as represents for the following permissible gross vehicle weight (GVW) classes in the base scenario (ICEVs):

- **light - 7.5 tons**: Mercedes Atego 818L / MAN TGL 12.220 BL
- **medium - 18 tons**: MAN TGX 18.440 XLX
- **heavy - 26 tons**: Mercedes Actros 2544 LL
- **heavy - 40 tons**: MAN TGM 18.340 BL + Trailer 7.75m

Table 1. Cost parameters for the different vehicle types

vehicle type	cost type	Base: ICEV	A: BEV 160	B: BEV 100
7.5 tons	fixed [€]	63.49	81.04	74.76
	variable per distance [€/m]	0.00040	0.00051	0.00046
	variable per time [€/s]	0.00490	0.00490	0.00490
18 tons	fixed [€]	80.47	107.43	96.26
	variable per distance [€/m]	0.00065	0.00061	0.00055
	variable per time [€/s]	0.00490	0.00490	0.00490
26 tons	fixed [€]	82.60	107.43	111.90
	variable per distance [€/m]	0.00067	0.00076	0.00072
	variable per time [€/s]	0.00490	0.00490	0.00490
40 tons	fixed [€]	126.58	192.80	183.93
	variable per distance [€/m]	0.00069	0.00080	0.00078
	variable per time [€/s]	0.00559	0.00559	0.00559

Battery Electric Trucks (BEV). For this study, the battery size of the electric trucks is selected in a way, that the maximum payload equal for the ICEVs and BEVs. It has to be taken into account, that according to [16] within the European Union an additional ton GVW is allowed for medium and heavy trucks and up to two additional tons for heavy trucks with a trailer when using a clean propulsion system. We assume, that 70% of the theoretical battery capacity is used in order to ensure an adequate battery life. According to current publications on battery management such as [20], this is a rather conservative choice. To calculate the possible ranges, consumption data for electric trucks currently available on the market are chosen. This leads to consumption specifications of 61 kWh/100km for the light, 106 kWh/100km for the medium, 150 kWh/100km for the heavy and 180 kWh/100km for the heavy truck with trailer. These specifications are supported by findings of current publications such as [9]. With these specifications set, we calculate possible driving distance of 100 km for the 7.5 tons truck, 80 km (18 tons), 133 km (26 tons) and 172 km (40 tons).

The costs for electric vehicles are majorly driven by the battery. Therefore we consider the prices for the chassis and for the battery separately. For the chassis, market analysis shows, that currently electric chassis are about 1.6 times more expensive than ICEV chassis. According to [7], the prices for BEV chassis will approach the prices for ICEV as soon as mass production picks up pace. Therefore we will consider the current situation with a 60% price increase from ICEV to BEV chassis (case A: BEV 160) and the possible future situation with equal chassis prices as a sensitivity analysis (case B: BEV 100).

The cost for commercial vehicle batteries is significantly higher than batteries for private vehicles [12]. According to [12] and our own analysis of the current market for commercial BEVs we choose a battery price of 600 €/kWh. Furthermore we set the possible charging cycles to 4000 and specific energy density to 0.15 kWh/kg on pack level according to [10]. Due to the possible charging cycles, no battery change is required in the presumed use phase of of the vehicles, even with an average of more than one charging event per day.

The resulting costs structure for all vehicle types used as input for the VRP is summarized in table 1.

4. Results

In terms of total costs for the carriers, we observe an increase by 23.5% when using BEVs compared to ICEVs in the case that the chassis prices of the BEV will be by 60% higher as they are for ICEVs (A). In the sensitivity case (B) with equal chassis prices, the cost for the carrier will increase by 16.9%.

Distance and time travelled increases by 1.5 to 2.7 %. This could be related to the small reduction of the fleet size. The decreasing fleet size sounds reasonable since higher costs for the BEVs compared to the ICEVs forces jsprit to a more efficient solution regarding the vehicle usage. Table 2 shows some results of the simulation for a typical workday.

Figure 1 shows the distance of the tours driven in the network for the three cases. The distances in both investigation cases seems with few exceptions comparable to the distances observed in the base case. 56 % of all tours can be driven without recharging during the day. Assuming one recharging during the tour and therefore doubling the vehicles range will result in 90 % possible tours with BEVs (see Table 3). As introduced in section 3, we calculate the range with 70% of the theoretical battery capacity.

Table 2. Results of the simulation for a typical workday

		Base: ICEV	A: A: BEV 160	B: BEV 100
Costs [€]		67 288	83 087	78 659
	total	283	275	279
	light 7.5 tons	17	20	21
vehicles used	medium 18 tons	16	24	27
	heavy 26 tons	223	207	207
	heavy 40 tons	27	24	24
Distance travelled [km]		36783	37 368	37 761
Time travelled [h]		1 054	1 074	1 070

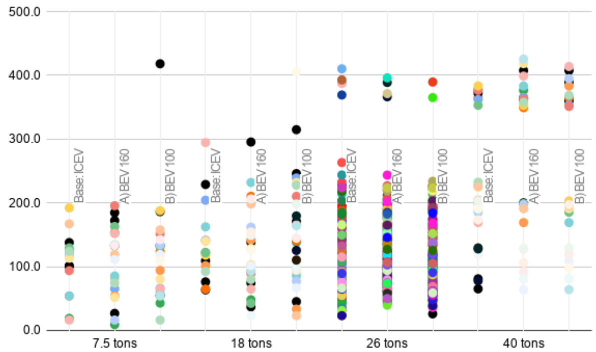

Fig. 1. Total tour distances [km] driven per vehicle type and case

5. Conclusion and Outlook

In this paper, we analysed whether electrification is suitable for the urban last mile supply of shops based on a case study in the city of Berlin. The BEVs were designed to have the same payload as ICEVs in the same weight class. In the selected scenarios we could show with an ex-post analysis that 56 % percent of the resulting tours can be driven with battery electric trucks without recharging during the tour, another 34% with recharging one time.

In terms of costs, the change from ICEVs to BEVs will result in increasing costs by 23% if the chassis of the BEVs are 60% more expensive as the chassis of the ICEVs (case A). In the sensitivity case (B) with equal chassis cost, the total transportation costs will increase by 17%. These costs include the costs for the battery as well as the costs for diesel respectively electric energy. Regarding the fleet size and composition, no significant change is observed.

In this paper we evaluate the feasibility of using BEVs with an ex-post analysis. Including a vehicle type specific distance constraint into the VRP can force respecting this limitation already in the tour generation. Based on this, including (re-)charging into the VRP solving may be a useful further development as well as a more logistic network planning, introducing hubs between the depots and the shops. Providing additional variants of vehicles with larger battery capacity seems to be another option, even though this leads to a reduction of the allowed payload. Regardless of these improvement potentials for our method, we were able to show, that even without major changes in the carriers operating strategies, a significant amount of urban freight delivery tours can be electrified with current technology.

Table 3. Proportion of tours that can be driven with BEVs according to i) single and ii) doubled range

	i: without recharging					ii: with one-time recharging: range doubled				
vehicle Type	range	A: BEV 160		B: BEV 100		range	A: BEV 160		B: BEV 100	
7.5 tons	100 km	9 / 20	45 %	9 / 21	43 %	200 km	20 / 20	100 %	20 / 21	95 %
18 tons	80 km	7 / 24	29 %	5 / 27	19 %	160 km	18 / 24	75 %	15 / 27	56 %
26 tons	133 km	131 / 207	63 %	137 / 207	66 %	266 km	202 / 207	98 %	203 / 207	98 %
40 tons	172 km	7 / 24	29 %	7 / 24	29 %	374 km	11 / 24	46 %	13 / 24	54 %
total		**154 / 275**	**56 %**	**158 / 279**	**57 %**		**251 / 275**	**91 %**	**251 / 279**	**90 %**

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