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INCREASING THE MILEAGE OF BATTERY ELECTRIC MEDIUM-DUTY VEHICLES: A RECIPE FOR COMPETITIVENESS?

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Increasing the Mileage of Battery Electric Medium-Duty Vehicles: A Recipe for Competitiveness?

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Abstract
Battery electric freight vehicles have the potential to mitigate the local urban road freight transport emissions, but their numbers are still insignificant. Logistics companies often consider electric vehicles as too costly compared to vehicles powered by combustion engines. The current literature suggests that increasing the mileage can maximize the competitiveness of electric freight vehicles. In this manuscript we develop a generic model to determine the cost-optimal balance between a high utilization of electric freight vehicles – which often have low operational costs – and their required expensive battery replacements. Our work relies on empirical findings of the real-world energy consumption from a large German field test with vehicles of 7.5 and 12 tons, respectively. Our results suggest that increasing the range to the technical maximum by intermediate (quick) charging and multi-shift usage is not the most cost-efficient strategy in every case. A low daily mileage is more cost-efficient at high energy prices or consumptions, relative to the diesel prices or consumptions, or if the battery is not safeguarded by a long battery warranty. In practical applications our model may help companies to choose the most suitable electric vehicle for the application purpose, or the optimal trip length from a given set of options. For policymakers, our analysis provides insights on the relevant parameters that may either reduce the cost-gap at lower daily mileages, or increase the utilization of electric urban freight vehicles, in order to abate the negative impact of urban road freight transport on the environment.

1 Introduction

Electric freight vehicles have been proposed as a measure to reduce the air pollutant emissions from transport and achieve a carbon dioxide-free city logistics by 2030, as envisioned by the European Commission (2011). However, the numbers of battery electric vehicles operated by logistics companies remain marginal, despite the recent bans for combustion vehicles in Asian and European cities due to overstepped air pollutant limit values and growing corporate environmental responsibility activities in the transport sector. One of the main barriers for the companies are the higher costs of electric vehicles, compared to conventional vehicles with an internal combustion engine (Kley et al., 2011; Amburg and Pitkanen, 2012; Taefi et al., 2015).

Total cost of ownership (TCO) calculations suggest that a key variable to determine the competitiveness of electric freight vehicles is their utilization (Feng and Figliozzi, 2013; Lee et al., 2013; Lebeau et al., 2015b).
Vehicle costs are also analyzed in research on vehicle routing problems (VRP) with electric vehicles (EVRP). VRP model the optimal route planning in order to minimize, e.g., the total mileage, the number of vehicles required or operational costs, subject to a minimum customer service requirement. EVRP models integrate additional restrictions and constraints, for instance range limitation of the electric vehicles or intermediate recharging. Research on EVRP has derived the same conclusion, that a high mileage of electric trucks is one of the key factors to achieve a more competitive operation, e.g., Davis and Figliozzi (2013) and Lebeau et al. (2015a).

A possible option to achieve a high mileage is to operate the electric freight vehicles in multi-shift operation, which would, on the downside, lead to more frequent battery replacements. Hence, the time and number of battery replacements have to be considered as they can impair the competitiveness of the electric freight vehicle (Feng and Figliozzi, 2013; Lebeau et al., 2015b; Lee et al., 2013). However, those authors do not provide a conclusion on the optimal balancing between electric vehicle (EV) utilization and the necessary battery replacements.

Further, previous research furthermore calls for integrating a more detailed understanding of the energy model of EV into TCO and EVRP (Afroditi et al., 2014; Conti et al., 2015; De Cauwer et al., 2015; Lebeau et al., 2015a). While first energy models exist in EVRP, scientific evidence on the realistic energy consumption of medium-duty electric vehicles is scarce, cf. section 2. Hence, the aim of the present work is to fill in the described gaps and deliver a generic vehicle-centered cost-optimization model, based on the vehicle's energy availability, consumption and charging profile, in short, its operational profile. By applying the model to certain external conditions and vehicles, we aim to answer the questions:

- Which average daily mileage is the most cost-efficient for a certain EV model compared to a similar diesel model?
- What are the main parameters that influence the cost-efficiency?

Our work may provide the basis for enhancing utilized energy models of existing TCO and EVRP calculations. Furthermore, our model may help practitioners in deciding on a suitable freight EV model or finding the most competitive operational profile for their existing freight EV. Finally, our results indicate which parameters are most relevant for policymakers, to either subsidize the purchase, or the operation of electric freight vehicles.

The remainder of this manuscript is structured as follows: Section 2 presents the related literature and details the research gaps and available knowledge in the related scientific disciplines. Section 3 provides information on the analyzed real-world test and describes the TCO calculation model. The results of the real world-test are detailed and discussed in section 4. Subsequently, the results are included in the TCO calculation which is presented and discussed in section 5. Finally, section 6 derives implications of the work.

2 Background

In order to detect the most cost-efficient mileage of an EV, the TCO at various driven mileages up to the possible maximum have to be determined and compared to those of a conventional vehicle. In TCO calculations, usually a fixed daily mileage within the range of an EV is assumed and subsequently varied in a local sensitivity or elasticity analysis. The energy (or fuel) consumption is a sensitive parameter in TCO calculations (Lee et al., 2013; Feng and Figliozzi, 2013), but is approximated differently throughout TCO studies. Parameter values are usually taken from manufacturer's data sheets or calculated by applying real-world travel speed profiles or drive cycles.

Feng and Figliozzi (2013) compare the TCO of an EV to the TCO of a conventional medium-duty vehicle and analyze the fleet replacement in six scenarios. They set the energy consumption of the EV to a value of 0.8 kWh/km without further elaboration and conclude that the EV needs a high utilization of at least 80 miles/day (129 km/day) to become competitive in three of six calculated scenarios. An additionally considered battery replacement significantly reduces the competitiveness and impacts the break-even points of the EV. Macharis et al. (2013) compare the TCO of eight battery electric and five conventional diesel vehicles. Their calculation integrates the cost of battery replacement once the battery warranty expires, but they do not spell out which energy consumption their calculations are based upon. The authors find that while electric quadricycles and small vans can become competitive, the medium-duty EV does not. In a later work, the same authors focus their research on light commercial vehicles and calculate the TCO for operations in Belgium (Lebeau et al., 2015b). According to the authors, the values for energy consumption reflect the "urban consumption". However, a sample comparison with the manufacturers' data sheets of the Renault Kangoo Z.E and the Nissan e-NV 200 shows that specific values for urban consumption had not been utilized in the publication, but the combined energy consumptions were in fact according to the UN/EC Regulation 101 (Nissan, 2015), based on the New European Drive Cycle (NEDC). The sensitivity analysis of Lebeau et al. (2015b) confirms the findings of Feng and Figliozzi (2013) that the electric vehicles become more competitive with an increased utilization. Their sensitivity analysis suggests that the cost-efficiency of the light commercial vehicles decreases with each battery replacement, concluding that an electric vehicle's battery should only be replaced if it is intended to operate the vehicle until the end-of-life of the next battery pack. However, the study leaves open how a battery replacement affects the competitiveness of the electric vehicles compared to conventional vehicles.

Field-tests suggest that the realistic energy consumption of electric freight vehicles can deviate from the values reported by the vehicles' manufacturers, as utilized in the TCO calculations above, but scientific evidence is scarce. A real-world test in the US with a total of 530 electric vehicles of two types delivers an average energy consumption of 0.52 kWh/km (5.5 ton Navistar eStar) and 1.15 kWh/km (7.5 to 12 ton Smith Electric Newton) (Prohaska et al., 2015). However, the authors indicate in the supplementary material that these figures cover multiple vehicle configurations, in multiple environments, topologies, and load profiles and hence are an average that cannot be used to predict the efficiency of any particular vehicle. A better comparability between the values given by the manufacturer and realistic energy consumption can be drawn if a specific vehicle is tested according to a standard test procedure. In Europe and China, the energy consumption of any passenger car (EV or conventional) is measured by a dynamometer test defined in UN ECE-R101 based on the NEDC drive profile. Commercial freight vehicles (EV or conventional) are tested on the road according to German standard DIN 70030-2. The study of De Cauwer et al. (2015) in Belgium finds that the real-world energy consumption of a small electric delivery van, the Renault Kangoo ZE, deviates by 48% from the energy consumption according to the NEDC. This result is similar to the outcome of a field test evaluating 200 electric passenger cars over a two-year period in Denmark (Fetene et al., 2016), where the EV consumed on average 46.6% more energy than indicated by the manufacturer's data sheets. Wang et al. (2015) compare the energy consumption of different passenger car types in a real-world test according to the NEDC values, suggesting that the traffic conditions of Beijing are comparatively favorable for electric vehicles: their average energy consumption is only 3.1% higher than the NEDC results, while conventional vehicles consume 38.8% more energy in the real-world than indicated by the NEDC. An even greater difference of 45% between the measured fuel consumption according to the NEDC and real-world data was reported for commercially used conventional passenger cars in Europe for year 2013 (Mock et al., 2014). The first models have been developed to describe the energy consumption of electric passenger cars and an overview on the past studies is provided for example by Zhang and Yao (2015). Electric freight vehicles differ from electric passenger cars, since the amount of loaded cargo is an additional factor influencing the energy consumption. Hence, additional empirical evidence on the realistic consumption of medium-duty electric vehicles is required.

The TCO calculation of Lee et al. (2013) approximates the realistic energy consumption of urban freight transport by implementing urban and suburban drive cycles, such as the New York City Cycle to calculate the TCO for medium-duty electric vehicles in the USA. They vary the daily range between 48 to 96 km/day and assume that the vehicle retires when the total mileage reaches 240,000 km.

Their study finds that – over an array of possible conditions – the EV TCO becomes more competitive in urban drive cycles with frequent stops and low average speeds, if the achievable lifetime vehicle distance traveled is high and at the same time no expensive battery replacement or quick-charging equipment are necessary. However, the authors do not discuss whether it is technically possible to achieve the highest daily mileage considered (96 km) at the end of the battery's life. At this point, the battery can only achieve 80% of its initial capacity and has to be replaced (Narula et al., 2011). Hence, the state of health (SOH) of the battery limits the maximal electric capacity and thus the range of an EV. Davis and Figliozzi (2013) integrate models to calculate the power consumption, to include routing constraints, and to describe the real-world travel speed profiles, in order to examine the competitiveness of a medium-duty EV. Their study finds that the medium-duty EV becomes more competitive in scenarios with a high vehicle utilization and where vehicles with an internal combustion engine operate inefficiently – for example, during deliveries with frequent stops and idling motor, or in congested urban traffic. The authors additionally research the effects of a single battery replacement after 150,000 miles (241,402 km). When including this battery replacement, the EV TCO increases and only in a few of the researched scenarios does the vehicle become more cost-competitive than a conventional vehicle. While the authors explicitly implement different energy consumption levels, they do not account for a reduced battery capacity and thus reduced range, due to the reduced battery SOH during its life-time.

None of the TCO calculations in the literature consider recharging the EV battery during its operation, in order to prolong the range. In EVRP, Goeke and Schneider (2015) and Schneider et al. (2014) consider the necessary time to recharge the EV depending on the remaining battery charge. Similar to the EVRP with time windows and recharging by Hiermann et al. (2016), they assume the time for fully recharging the battery to be a linear function. Since in reality the servicing time by the customer might not allow a complete recharge of the battery, Keskin and Catay (2015) develop an EVRP with partial battery recharging. The EVRP of Felipe et al. (2014) additionally allows partial recharges with various charging standards. Both consider the time for recharging a battery to be a linear function. However, research on lithium-based batteries – the most common EV batteries – shows that their performance is non-linear and time-variant (Marra et al., 2010), especially when charging at higher C-rates (Kim et al., 2011). Figure 1 depicts a typical charging characteristic of a lithium-ion battery at a charging rate of 1C based on Panasonic (2012), applying the widely-used constant current/ constant voltage charging methodology (Zgheib et al., 2016).

The C-rate indicates at which current relative to the battery's capacity the battery is charged or discharged. At 1C, the energy available in a battery, or equivalently its SOC, increases linearly with the charging time by up to about 75% SOC. Up to this limit, the battery is charged by a constant current (CC-phase). When the maximum cell voltage is reached at about 75% SOC, the charging method is switched to constant voltage (CV-phase) (Marra et al., 2012) in order to protect the battery from overcharging (Moon et al., 2011). If the C-rate is reduced, the linear CC-phase is extended (Moon et al., 2011), i.e. to 90% SOC at 0.5 C, for the battery researched by Marra et al. (2012). A full charge of

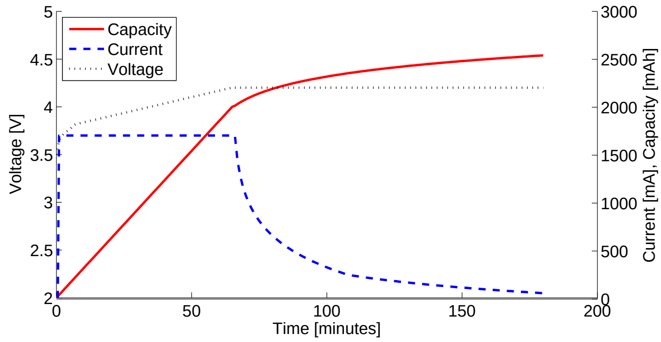


Fig. 1: Charging characteristic of an exemplary EV lithium-ion battery

this battery at 0.5 C takes about three times longer than charging it to only from 10 to 70% SOC (ibidem). This characteristic can be utilized to reduce the time needed for recharging, by only recharging within the CC-phase to add a certain mileage to the vehicle's range. Not fully recharging the battery might also limit the increased energy consumption, when starting a trip with a full battery, as observed – but not further explained –in the study of Fetene et al. (2016).

Research in EVRP already implements the first realistic observations of energy consumption and some TCO models utilize drive cycles or energy models to simulate realistic energy consumption. However, field data on the realistic energy consumption of electric freight vehicles are still scarce and not yet incorporated in TCO calculations. At the same time, the process of battery recharging has received some but far less attention in EVRP and none in TCO calculations. Moreover, neither of the cited publications have considered the findings from battery research regarding the battery's SOH, which influences the available energy in an EV, and thus range at high mileage scenarios. The current study will fill these gaps in order to analyze the most cost-efficient mileage of an EV compared to a conventional vehicle.

3 Model formulation and methodology

We base our analysis of the most cost-efficient mileage of electric freight vehicles on the TCO evaluation methodology (section 3.1). We implement the findings of the literature review into an energy model. The model considers the energy availability depending on the battery's state of health; energy recharging based on the lithium ion battery's linear charging characteristics between 10 and 70% SOC and realistic energy consumptions (section 3.2). The latter are obtained from a German real-world field test (section 3.3). A numeric simulation is carried out for three medium-duty electric and comparable diesel vehicles (section 3.4), calculating the differential TCO up to the theoretically possible maximal average daily mileage. We obtain this maximal mileage by deriving a range-optimized usage profile (section 3.5).

3.1 Calculation of the ΔTCO

In order to assess whether an electric freight vehicle is more cost-efficient than a conventional counterpart, the TCO of electric and diesel models are calculated and compared. The ΔTCO in equation 1 delivers a negative result if the cumulative cost of the EV is lower than the cumulative cost of the diesel vehicle at the end of the TCO calculation.

$$\Delta TCO = TCO_{EV} - TCO_{Diesel} \tag{1}$$

with

$$TCO = \sum_{m=0}^{M} X_m \cdot (1+r)^{-m} + \sum_{m=1}^{M} Y_m \cdot m \cdot (1+r)^{-m} + \sum_{m=1}^{M} \sum_{s=1}^{K} Z_s \cdot s \cdot (1+r)^{-m} \tag{2}$$

The TCO of the vehicles' TCO_{Diesel} and TCO_{EV} are each equal to the sum of three components, compare equation 2: i) One-time investments X_m, such as the costs for purchasing the vehicle, for battery replacement, and the costs for scrapping or revenue from reselling the vehicle or batteries; ii) annual "fixed" costs Y_m, such as the circulation tax or costs for emission testing, which reoccur in the first month of each year and are zero in the other months; iii) kilometer-dependent costs Z_s, which grow by the distance (km) s traveled, for example costs for energy or diesel respectively, or maintenance and service. The limits M and K denote the maximal values for the month or monthly driven kilometers, respectively. As usual in TCO calculations, the discount factor r delivers the discount rate $(1+r)^{-m}$ to represent the time value for money in each of the three components. We calculate the TCO for steps of one km up to the maximal mileage per day with the software package Matlab on a desktop computer. Subsequently, in a one-at-a-time empirical sensitivity analysis, we vary the input factors and calculate the relative difference of the observed output parameter – the cost-difference, based on the methodology described by Hamby (1994) and Karnavas et al. (1993). The analysis is performed in order to reduce the output uncertainty and to understand which parameters contribute most to the variability of the results.

3.2 Model formulation

With the observations from the literature review in section 2, we derive equation 3 for calculating the realistic EV range R^{Real}:

$$R^{Real} = \sum_{s=1}^{K} \frac{E \cdot SOH_s \cdot SOC_{s,c}}{C^{Real}} \tag{3}$$

subject to:

$$SOH_k = 1 - 0.2 \cdot \frac{s}{K} \tag{4a}$$

$$s = v \cdot t \tag{4b}$$

$$K = \begin{cases} K^{Wrnt} & \text{if number of kilometers is warranted} \\ \dfrac{0.9 \cdot E \cdot N^{Wrnt}}{C^{Real}} & \text{if number of cycles is warranted} \end{cases} \tag{4c}$$

$$SOC_{s,c} = \begin{cases} SOC^{Init} - \dfrac{k \cdot C^{Real}}{E} & \text{if the EV is driving} \\ SOC^{Init} + \frac{c}{T} & \text{if the EV is charging} \end{cases} \tag{4d}$$

$$T = \begin{cases} 0.33 \cdot T^{0\text{-}100\%} & \text{if given charge time T is from 0\% to 100\%} \\ T^{20\text{-}80\%} & \text{if given charge time T is from 20\% to 80\%} \end{cases} \tag{4e}$$

Further parameters and variables:

E	the maximal energy available in fresh EV battery (kWh)
C^{Real}	the realistic energy consumption of EV (kWh/km)
v	the average speed of the vehicles (km/h)
K^{Wrnt}	the kilometers warranted before the battery's end-of-life (km)
N^{Wrnt}	the number of cycles warranted before the battery's end-of-life
$T^{0\text{-}100\%}$	the time to charge the battery 0% to 100% (min)
$T^{20\text{-}80\%}$	the time stated to charge the battery 20% to 80% (min)
SOC^{Init}	the initial state of charge before charging or driving (%)
c	duration of recharging the EV (min)
t	duration of driving the EV (min)

Equation 4a describes the state of health of a battery. A fresh battery has a SOH of 100% which degrades with calendar life and usage. Once the battery reaches 80% of the initial capacity (80% SOH) the battery has reached its end-of-life as EV battery (Marra et al., 2010; Narula et al., 2011). The battery degradation due to the usage mainly depends on four factors, i) the number of cycles, ii) the charge/discharge current rates, iii) the depth of discharge and iv) the ambient temperatures (Marra et al., 2010; Conti et al., 2015). In practical applications, the SOH can be derived by measuring the internal resistance of a battery and comparing it to the battery's initial resistance (Marra et al., 2010). Nevertheless, in practice, battery manufacturers base their warranties on a guaranteed number of charging cycles N^{Wrnt} or kilometers K^{Wrnt}, sometimes in combination with calendar life. The distance s driven with the current battery is calculated by multiplying the average vehicle speed v by the time t spent driving in equation 4b.

We derive the mileage K, at which the batteries need to be replaced (equation 4c), by considering the warranted number of kilometers and warranted cycles. We assume that the battery reaches its end-of-life, once the battery manufacturer's warranty expires. This is given when the driven distance s is equal to the total number of kilometers warranted K^{Wrnt}. In the case where the manufacturer warrants a certain amount of battery cycles instead of the number of kilometers, the warranted battery cycles need to be translated into the kilometers driven. In order to be able to do this, first the "cycle" needs to be defined, since manufacturers sometimes do not exactly specify on what to count as a cycle in their data sheets. This raises questions with respect to partial charging. In the current study, we follow the common definition that full cycles in percent are counted: for example, charging twice from 0% to 50% and discharging twice from 50% to 0% is counted as one full cycle. To derive an approximation for the number of total number of kilometers K covered by the warranty, the initial (realistic) battery range at the average 90% SOH is multiplied with the number of guaranteed cycles N^{Wrnt}.

Equation 4d denotes how much of the possible energy E is available at a certain point in time. The value depends on the initial SOC^{Init} and decreases when the EV is driven or increases when the EV is charged. For driving, the model utilizes a realistic average vehicle speed v and energy consumption C^{Real}, based on several drivers, several topographies, loads, stops, auxiliary usage and ambient temperatures, compare section 3.3. For this reason, we can assume a linear decrease of the SOC per kilometer driven. If an EV offers different charging levels, our model selects the highest charging speed. Since we aim to minimize the charging time and thus maximize the time available for driving, we keep the SOC between 10% and 70%, where it can be charged linearly in about a third of the time needed for a full charge $T^{0\text{-}100\%}$ at 0.5 C (Marra et al., 2012). In case where the manufacturers state the time needed to charge the battery from 20% to 80%, this value ($T^{20\text{-}80\%}$) is applied. Accordingly, SOC^{Init} is set to 70% for the first calculation, and the model assures that the final charge of the day only recharges the battery up to this level, in order to provide a similar starting point for each day of the range and TCO calculation.

3.3 Energy consumption of medium-duty EV in the real-world Elmo test

In order to present scientific evidence with regard to the realistic energy consumption of electric freight vehicles, we analyze data from the project "Elektromobile Urbane Wirtschaftsverkehre" (acronym: "Elmo"). The German project title translates as "Electrified commercial transport in urban areas". The project was co-financed by the German Federal Ministry of Transport and Digital Infrastructure and led by the Fraunhofer Institute for Material Flow and Logistics, IML, for the time period between September 2011 and June 2015[1].

In June 2012, the German Federal Government ranked Elmo as a "lighthouse project" for the successful demonstration of electric vehicles in commercial transport (BMWI, 2012). The project conducted one of the largest field tests with medium-duty electric vehicles in Germany at that time. During the project's run-time, ten medium-duty electric vehicles of three companies covered over 130,000 km in about two years. All deliveries were carried out in the German federal state of North Rhine-Westphalia. Four different types of electric vehicles were deployed: three types of up to 7.49 tons and one of up to 11.99 tons, either utilized for deliveries to third parties (business or end customers) or transport on-own-account. An overview of the vehicles' specifications and utilization is

[1] Further information about the project is available at http://www.iml.fraunhofer.de/de/themengebiete/verkehrslogistik/themen_transportverkehrlogistik/Elmo.html (in German)

provided in Table 1, based on information of the vehicle manufacturers within the project and publicly available information, such as data sheets. Due to confidentiality reasons, most of the information provided will be presented in an aggregated form or discussed in comparison to the average values of the German urban freight transportation segment.

EV Type	Manu- facturer	Transport task	Gross weight [t]	Battery energy [kWh]	Approx. price [€]	Charging time [h]	Range [km]
A	1	Third party delivery	7.49	61	65,000	8-10	80-100
B	1	Third party delivery	7.49	77	75,000	12	105-115
C	2	Third party delivery	7.49	80	110,000	≥8	110-160
D	3	On-own-account	11.99	160	200,000	4.5	200

Tab. 1: Overview of the medium-duty electric vehicles utilized in project Elmo

All utilized vehicles were converted from available diesel models. The EV type B is an experimental vehicle derived from type A, developed by the same manufacturer. It only differs in terms of battery capacity and weight. Purchase prices are confidential, hence our approximations are based on general information by the manufacturers. The specific final sale prices depend on the chosen configurations. For the experimental EV type B we estimated the price based on the information for type A plus the differential average battery costs, which amounted to €437/kWh in the year 2013 according to Nykvist and Nilsson (2015).

It can be observed that the EV manufacturers communicated an expected range of an EV, instead of a fix energy consumption according to a standard measurement procedure, i.e., DIN 70030-2. One of the manufacturers reasoned that the EV range and hence energy consumption depends largely on the ambient temperature, drive style, topography, number of stops, usage of auxiliary loads, etc. Hence, the manufacturers were hesitant to provide a misleading measurement value and rather indicated an expected range according to the intended customer's use case.

The main focus of the project Elmo was to assess whether battery electric vehicles meet the requirements for day-to-day operations for companies running corporate fleets. One guiding question was how these vehicles can be integrated into existing fleet and logistics operations. As a secondary goal, the project aimed to assess aspects related to traffic, operational processes, energy supply, and ecologic influences which arise during the integration of electric vehicles into the corporate fleet (Stütz et al., 2016). Our study reports the results related to the energy consumption of the vehicles in the field test.

The vehicles' data were logged manually by the drivers, since the use of data loggers was technically and legally restricted. Logged data were for example the time, date, duration, distance and number of stops per round trip, as well as the SOC at the beginning and the end of the trip. The data were manually enriched with additional information, such as the average temperature, and the average price of diesel based on the EU oil price bulletin (European Commission). Qualitative data from interviews (with drivers and operation managers) as well as field studies were used to validate the correctness of the manually recorded data. Moreover, this approach helped to shed some light on vehicle utilization as the data, besides daily round trips, also covered downtime and vehicle outages. Hence, the reasons which impeded continuous vehicle operation during the course of the project can also be analyzed using the Elmo database.

3.4 Vehicles compared in the TCO

We test our model and answer the research question by carrying out exemplary numeric simulations of medium-duty electric vehicles. Those vehicles are not yet mass produced, but are converted from existing diesel vehicles. Thus, the EV models chosen in this TCO calculation are technically identical to their conventional siblings, except for the drive-train: the 7.49 ton Toyota Dyna 200 is the basis for the 7.49 ton Dyna EV 200 converted by Emoss; the 5 ton Plantos by German E-Cars is based on a 5 ton Mercedes Sprinter; the 11.99 ton CM1260 is based on a MAN TGL and was also converted by Emoss. Both conversion companies, Emoss and German E-cars provided recent information about the prices and technical details of the electric vehicles in telephone interviews. Recent information of the Toyota Dyna 200 was gathered from the general European importer and information on the conventional MAN TGL was gathered from a local distributor. The configuration of the Mercedes Sprinter was chosen with the help of the Mercedes Online-configurator in February 2016, which indicated that the 5 ton 513 CDI with EURO VI Motor and automatic gearshift comes closest to the Plantos. Additional information about the Sprinter was taken from Mercedes data sheets for the variant with the ultra-high roof and long wheelbase (Mercedes Benz, 2015).

3.5 Range-maximized usage profile

The equations in section 3.2 deliver the maximal technically possible range of an EV, in case the usage profile is optimized. This means that the time for driving t and charging c are optimized in our model, at a given average energy consumption due to routing, topography, driver's behavior, etc. In this scenario, we assume that all loading and unloading of the cargo, drivers breaks and changes can take place while the vehicle charges.

The maximized exemplary usage profile for the calculation assumes that the vehicle starts to drive once the SOC reaches 70%. Hence, it remains within the linear area of the charging curve and reduces the time required for charging. Furthermore, the exemplary profile assumes that the vehicle stops in order to deliver freight and recharge, as soon as the SOC reaches 10%, in order to prevent the negative aspects of a deep battery discharge. The last charge and trip of the day are adjusted, so that after a 24 h period the EV attains the initial value of 70% SOC. Since the SOH of the battery degrades with the driven number of kilometers (see equation 4a), the range that can be achieved with the described usage profile is calculated on a daily basis in equation 3.

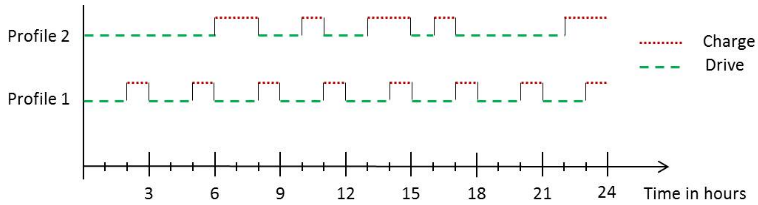


Fig. 2: Examples of user profiles delivering the same range

It is noteworthy that many other solutions exist which deliver a similar optimal range with different levels for the SOH. For instance, the EV could be driven on shorter trips and could be charged more frequently during shorter stops. Hence, the usage profile can be adapted to the user requirements. Exemplary profiles leading to the same maximal range are depicted in Figure 2.

4 Energy consumption in the Elmo real-world test

The data of the project Elmo are analyzed with regard to two aspects. First, we describe the usage profile and average energy consumption of the tested EV. Second, we discuss the energy consumption distribution over the months.

4.1 Usage profile and average energy consumption

The data in project Elmo were collected in the period from September 2012 to July 2014. During this period, the EV traveled a total of 131,018 km, performed 196,906 delivery stops and consumed 102,736 kWh of energy in total. Table 2 shows the aggregated mileage and plug-to-wheel energy consumption per EV type. The latter is compared to the given energy consumption, in utilizing equation 3 (with a new and fully charged battery; SOH= 100%, SOC = 100%, K=1) to convert the ranges given by the manufacturers in Table 1.

EV Type	Route profile	Mileage [km]		Energy consumption [kWh/km]	
		Average	Standard deviation	Given	Average
A	Urban, 200 stops	73.80	± 5%	0.61 to 0.76	0.74
B	Urban, 200 stops	77.25	± 7%	0.67 to 0.73	0.90
C	Urban, 30 stops	49.04	± 9%	0.75 to 1.09	0.90
D	Freeway and urban, 3-4 stops	92.92	± 12%	0.8	0.73

Tab. 2: Real-world energy consumption per EV type in project "Elmo"

According to Table 2, the average daily mileage of the two EV types A and B were relatively similar to each other and constant throughout the months of this study: type A traveled 73.80 ± 5% km/day (relative standard deviation), type

B traveled 77.25 $\pm$7% km/day. Both vehicle types were used to collect and distribute parcel shipments. A typical urban parcel delivery round trip in Germany, suitable for an EV, is characterized by picking up the parcels in the early morning at a distribution center, then driving a certain distance mostly on urban roads – sometimes also including a short passage on rural roads or freeways – to the delivery area. Here, up to 200 stops are performed in order to deliver the parcels throughout the day, with short driving distances in-between the stops in urban traffic conditions. The EV returns to the distribution center in the evening, where the vehicle is slow-charged overnight. This driving profile is very energy intensive, hence we expected high energy consumptions for these two vehicle types. Indeed, Table 2 shows that the actual energy consumption of the type A vehicles is at the upper margin of the expectations while the experimental type B did not meet the manufacturer's expectancy and consumed 23% more than maximally anticipated.

The type C EV transported goods for the companies on own account. The vehicles started from depots located close to the cities' borders on fixed tours of 49 km/day $\pm$9%. In the city, about 30 stops were performed, before returning to the depot and slow-charging overnight. The EV types B and C both have a similar gross weight and nearly similar battery size, but were converted by different companies. Their energy consumptions were nearly at par (although it has to be recognized that type B undertook six to seven times more delivery stops). The type C EV consumed 0.9 kWh/km on average, in the middle of the range specified by the manufacturer. This result was expectable: on the one hand, energy was conserved, as the cargo was unloaded during the tour, hence the EV was operated only partly loaded and the drivers were trained by the manufacturer to utilize an energy-conservative drive style. On the other hand, the vehicles were operated in urban traffic, which again raised the energy demand.

Of all electric vehicles in the field test, type D covered the longest average distance of 94.92 km/day $\pm$ 12%. The route profile of this EV type differed from the others, since it covered longer distances of constant speed between only three to four stops per day. The vehicles type received a full slow-charge over night. In order to increase the range, the company tested to the partial charging of the EV when it returned to the depot in-between the delivery stops by the faster level 2 DC charging. In certain test cases with intermediate charging, the type D traveled substantially more than 300 km/day. With a gross weight of 12 tons, type D was the heaviest vehicle in the fleet test and its battery was 160 kWh, which is about double the size of types B and C. The manufacturer reported the EV range to be 200 km, which translates to an energy consumption of 0.8 kWh/km. This is similar to the energy consumption of type C, although type C has a lower gross weight. Surprisingly, the realistic energy consumption of type D was, with 0.73 kWh/km, 8% below the manufacturers values and had the lowest energy consumption of all vehicles in the test.

We discuss the results of the real-world test in what follows:

- Interestingly, this study found that the heaviest vehicle (type D) had the lowest energy consumption in the field test. All vehicle types were deployed in the same federal state, with a roughly comparable climate, topography and payload profile. Assuming that all vehicle types were driven by trained drivers applying an energy-conservative driving-style and usage of auxiliaries, the main difference between the usage profiles was that type D undertook less stops and the tours contained longer stretches of freeway driving. This suggests that medium-duty EV energy demand increases with the number of delivery stops in urban traffic and reduces in more smooth traffic conditions, similar to conventional diesel vehicles. Whether the effect is attenuated compared to diesel vehicles, due to the recuperation of energy when braking, has not been assessed in this study.

- The comparison between the EV types A and B, which mainly differ in the battery size, offers an interesting finding: both electric vehicles are identically constructed and equipped with a similar battery type. Further, both electric vehicles are deployed by the same company, on similar route profiles and climate conditions, with comparable cargo loads. Assuming a comparable use of auxiliaries, the additional energy consumption of the EV type B (0.90 vs. 0.74 kWh/km) suggests that the larger and thus heavier battery potentially had a negative impact on the range gain. Deriving the range from the realistic energy consumption shows that the EV can only travel about 3 km more than type A, while costing approximately €10,000 more, due to the larger battery. Hence, this result suggests that equipping an EV with a larger battery might not automatically lead to a higher range, since the vehicle's gross weight and hence the energy consumption increases.

- The energy consumption deviated between -8 % and 24 % from the values given by the EV manufacturers. In the real-world tests of De Cauwer et al. (2015) and Fetene et al. (2016), the electric passenger car energy consumption is reported to be between 29 % and 64 % higher than stated in the data sheets according to the NEDC measurement. Hence, the freight EV manufacturers' information on the expected range and thus energy consumption gives a better estimation of the realistic consumption than the available information for passenger vehicles, which is usually based on NEDC measurements.

- All electric vehicles were charged with energy from renewable sources, which result in no plug-to-wheel emissions, and well-to-plug CO_2-equivalent emissions of 0.04 kg/kWh; diesel fuel has well-to-tank emissions of 0.57 kg/l and 2.67 kg/l tank-to-wheel (Umweltbundesamt, 2014). The real-world fuel consumptions of the comparable diesel vehicles in the project are company confidential, hence the overall savings of CO_2-equivalents in the test may only be estimated: assuming the consumption of the conventional fleet between 0.2 and 0.25 l/km, the ten electric vehicles saved 81 to 102 tons of CO_2-equivalents throughout the test. Naturally, this potential increases by up to 1.5% (i.e. zero well-to-plug emissions) when the respective vehicle owner makes use of local sources of renewable energy. In case of EV type D, over the course of the project time frame, on average 29% of the electricity required to charge the vehicles came from a large photo-voltaic array mounted on the roof of the distribution center. With respect to the confidentiality of fuel consumption data, we are able to report the following range of possible savings in CO2-equivalents: EV types A to C: 20 to 30 kg/day, EV type D: 90-100 kg/day. The substantial differences trace back to two different aspects: i) different average daily mileage: EV type D served up to two or three routes/day while A to C only had one; ii) higher fuel savings per km: EV type D replaced a heavier truck with a substantially higher fuel consumption per km than the ICEs replaced by EV types A to C.

4.2 Variation of the energy consumption throughout the calendar year

The energy consumption of the vehicles is assessed over the calendar year. Figure 3 shows the difference from the average energy consumption for each month per EV type and marks the largest deviation from the average.

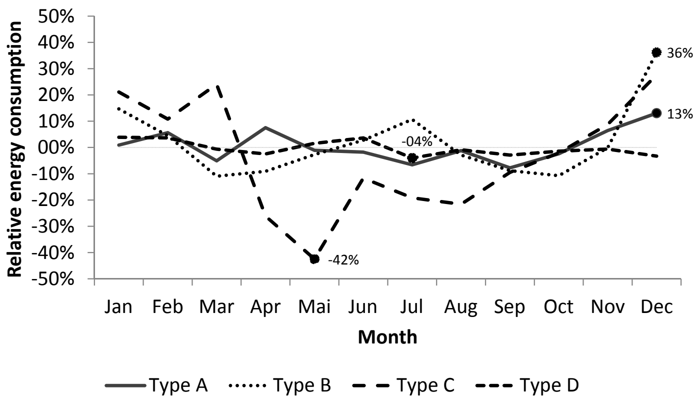


Fig. 3: Relative deviation of energy consumption per month from average

Interestingly, the energy consumption differences of the EV types vary. While type D shows a relative constant energy consumption throughout the year of ±4%, the deviation from the yearly average is especially large for type C (between -42% and +28%).

In order to interpret these results, we compare our results to exemplary findings in the literature: Fetene et al. (2016) found a 34% increase of the energy consumption in the five "winter" months (November to March) compared to the "summer" (all other months) in a real-world test with 200 electric passenger cars in Denmark. For the 3.5 ton parcel delivery vehicles of DHL, an increased energy demand of 30 to 60% was recorded in winter due to an increasing load by auxiliaries (Taefi et al., 2016). In the area of the Elmo field-test, the average temperature is the lowest (below 10 degrees Celsius) in the same five "winter" months (Wetterdienst, 2016). However, in our real-world test with medium-duty electric vehicles, the "winter" effect is only partly visible. The energy consumption in "winter" increases by 6%, 11%, 32%, and 2% compared to "summer", for the types A, B, C and D, respectively (Figure 4).

We assume the results are superimposed by other influencing factors, such as a higher stop-frequency; a different use of auxiliaries, such as heating; or different cargo weights in certain delivery seasons. These influences might also explain

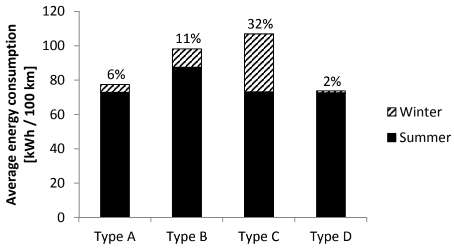


Fig. 4: Increase of average EV energy consumption in winter

the differences in the energy consumptions of the four types. Especially for type C, the use of the cabin heating could provide a possible reason for the increased power consumption in winter. It was the only vehicle type in which an electric heating spiral of 2 kW maximum power was actually an option for the driver. EV types A and B also feature a heating spiral of similar maximum power, but drivers were ordered not to use the cabin heating. These vehicles face, furthermore, an increased transport volume and stop frequency towards the end of the year compared to spring or summer. The root causes for an increased power consumptions are, therefore, expected to be rather endogenous than exogenous. EV type D was equipped with an independent heater (powered by a small combustion engine) so that any influence of the heating on electric power consumption can be ruled out. Having observed these effects, we suggest further research, in order to explain the empirically observed differences in the energy consumption of medium-duty electric vehicles and their influencing factors in more detail.

5 ΔTCO calculation and optimal mileage of electric vehicles

In applying the generic ΔTCO model presented in section 3 we compare the overall costs of medium-duty electric vehicles with their conventional siblings. For confidentiality reasons only one vehicle is similar to an EV type utilized in the Elmo test. Two further vehicle pairs with different technical characteristics are added, to put the results into perspective. The technical characteristics of the compared vehicles are described in Section 5.1. The calculation is placed within the reference scenario of Germany. Parameters, such as taxes, subsidies, city tolls, or the costs of goods and services for servicing and maintaining the vehicles differ from country to country; further, different projections on cost developments exist. Hence, section 5.2 describes the utilized cost projections and parameters. We describe the results of the TCO calculations in section 5.3, then carry out a sensitivity analysis in order to identify parameters that cause uncertainty and analyze their impact in section 5.4. Based on the calculation results we discuss the cost-optimal mileage of exemplary medium-duty electric vehicles in section 5.5.

5.1 Technical characteristics of the compared vehicles in the TCO

The TCO calculation is carried out for three vehicle pairs. We compare conventional diesel medium-duty vehicles to their electrical conversion model. Hence, the vehicles can be considered as technically identical, except for the power-train. The technical characteristics of the vehicles compared in this TCO are listed in Table 3.

Acronym	MAN Diesel	MAN-based EV	Dyna Diesel	Dyna-based EV	Sprinter Diesel	Sprinter-based EV
Model	TGL	CM1260	Dyna 200	Dyna EV 200	Sprinter CDI 513	Plantos
Manufacturer / Converter	MAN	Emoss	Toyota	Emoss	Mercedes	German E-Cars
Gross weight [t]	11.99	11.99	7.49	7.49	5	5
Purchase price[1] [€]	75,000	200,000	31,765	110,000	50,601	95,000
Power-train						
Power [kW]	133	150	110	120	95	85
Estimated realistic consumption of energy or fuel						
Diesel [l/km]	0.19	n/a	0.1	n/a	0.11	n/a
Energy [kWh/km]	n/a	0.73	n/a	0.75	n/a	0.464
Battery parameters						
Energy [kWh]	n/a	160	n/a	120	n/a	38.6
Range [km]	n/a	200	n/a	160	n/a	120
Battery warranty						
Cycles	n/a	2,000	n/a	n/a	n/a	2,000
Years	n/a	5 years	n/a	3 years	n/a	n/a
Kilometers	n/a	n/a	n/a	100,000	n/a	n/a
Charging time						
SAE AC Level 2 [h]	n/a	n/a	n/a	8	n/a	14
SAE DC Level 1 [h]	n/a	2[3]	n/a	n/a	n/a	2.5[2]

[1]excl. VAT [2] 20-80 % [3] 0 - 50%

Tab. 3: Technical characteristics of the vehicles compared in the TCO

The purchase prices of the vehicles are approximations – as stated by the manufacturers – since the final price depends on the specific configuration. The realistic fuel consumptions of the MAN is given with 18 - 20 l/100 km, of which we choose the average. The energy consumption of the MAN-based EV was measured in the real-world test. This vehicle charges from 0 to 50% SOC in 2 hours. Applying a linear extrapolation, which is possible in the CC-phase, this is equivalent to a time of 144 min when charging from 10 to 70% SOC. The consumption of the Dyna diesel and EV are both given by the manufacturers for the standard platform model without a box, hence they are comparable. The energy consumption of the standard model Mercedes Sprinter is 10.5 l/100 km in urban conditions with a commercial registration. This value was increased by 5% in order to account for our long wheelbase and ultra-high roof configuration. No additional correction of the fuel consumption is undertaken for the commercial vehicles, since their fuel consumption stated in the data sheets must be measured on the road according to DIN 70030-2. The values for the Sprinter EV, however, deviate from the standard road measurement: its energy consumption is measured by a dynamometer test, based on the NEDC. Hence, its consumption of 0.32 kWh/km is corrected by +45% according to the findings in the literature.

5.2 *Scenario and projections*

The TCO model in this study anticipates that the vehicles are purchased in the final days of the year 2015 ($m = 0$) and deployed from January 2016 ($m = 1$) onwards for six years or 72 month. The following parameters and projections are utilized:

- Purchase price subsidy: In Germany the purchase costs of electric vehicles were not subsidized in 2015, hence no cost reduction of EV price is incorporated into the TCO calculation.
- Vehicle tax: The vehicle taxes for the diesel vehicles are calculated according to the vehicle's technical specifications and included in the TCO calculation. Electric vehicles are exempt from the annual circulation tax for ten years.
- Emission testing: Electric vehicles are free of tailpipe emissions; hence costs for emission testing (€10 annually) only occur for the diesel vehicles in the TCO comparison.
- Battery price projection: The prices for replacing EV batteries are projected to decrease relatively sharply, but many different projections exist. We base our model calculation on the most recent and complete review and projection of battery prices by Nykvist and Nilsson (2015). The authors report that the average battery price was US $410 in 2014 and they project that it will decline with an annual learning rate of $14 \pm 6\%$ until 2017/2018. At that time the average price of US $230 will be level with the price of the market leaders and decline with a learning rate of about 8%.
- EV battery replacement: Modern lithium batteries have been used in EV applications only recently. Hence, most experiences regarding the battery lifetime are based on experiences under laboratory conditions. Due to the uncertainty of the battery lifetime in real-world applications, we assume that an EV battery will need to be replaced once the battery warranty expires.
- Battery resale value: The first modern EV batteries which reached their end-of-life just recently entered the secondhand market. Experts estimate that the batteries can be sold at about 50% of the current price for a new battery, and will be utilized in stationary applications (Narula et al., 2011). Following this evaluation, our TCO will incorporate a resale value of 50% of the current battery price at the end of the battery life.
- Vehicle resale value: The discounted residual value of the vehicle (without the battery) is calculated as a linear function: we assume that the vehicles cannot be resold and need to be scrapped in the theoretically achievable highest lifetime mileage scenario (over 500,000 km), but can retrieve a resale value of 50% of the purchase price without the batteries in the lowest mile scenario (below 3,000 km).
- Charging infrastructure: This calculation model excludes costs for the charging infrastructure for two reasons. Firstly, the installation costs vary

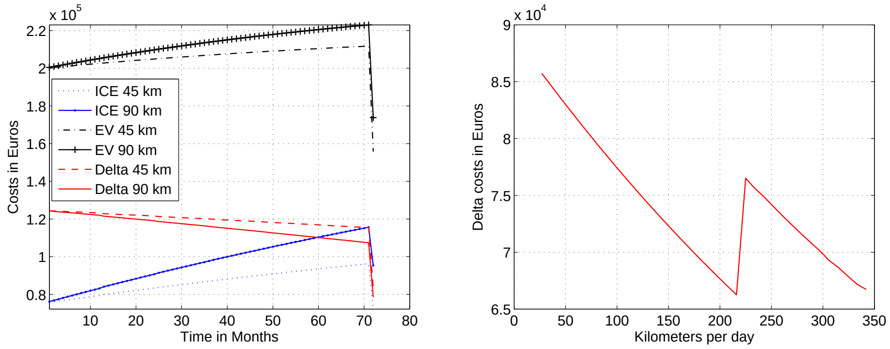
significantly based on the chosen technology and the prerequisites of the company's electrical installation. Secondly, the more expensive quick-charging infrastructure can be shared among several electric vehicles. Hence, infrastructure costs need to be assessed individually.

- Energy price projection: The energy price is based on a comprehensive study for the Federal Ministry of Economic Affairs and Energy (Schlesinger et al., 2014). The authors project that the energy price excluding VAT paid by industry customers will rise from €0.119/kWh to €0.159/kWh in 2020, and further to €0.177/kWh in 2025.
- Diesel price projection: We base the diesel price on a projection by Brokate et al. (2013). They have developed a scenario analysis for the German passenger car market until 2040 and based their projections of the diesel price on a projection provided by the International Energy Agency in 2012 in which the diesel price will increase from €1.14/l in 2010 to €1.21/l in 2020, and to €1.24/l in 2030 (excluding VAT).
- Feasibility of the energy and diesel price projections: We test the feasibility of the projections by linearly interpolating the value for the year 2014 and comparing it to the realistic average values without VAT in Germany in year 2014. The average diesel price paid by consumers was at €1.13/l, the average price of electrical energy for companies with a total energy consumption between 2,000 MWh to under 20,000 MWh was €0.135/kWh (Statistisches Bundesamt, 2015). Assuming linear price increases, the interpolated values from the diesel price forecast for 2014 are €1.17/l of diesel and €0.135/kWh of electrical energy. With errors between 2 and 3%, both prognoses can be accepted as sufficient for the basic TCO calculation. However, the recent decrease of crude oil and thus diesel price is not included in these projections and is discussed separately in the conclusions (section 6).
- Discount factor: The base interest rate in Germany hit a historical low with 1.8% in Germany in 2015, while the weighted average cost of capital sunk to 6.7% in the transport and leisure industry (KPMG, 2015). This study sets the discount factor to 5%.

This model generates the ΔTCO between vehicle pairs, hence costs which are similar for both vehicles, such as costs for scrapping, vehicle insurance, and road worthiness testing, can be neglected and are not included in the consideration.

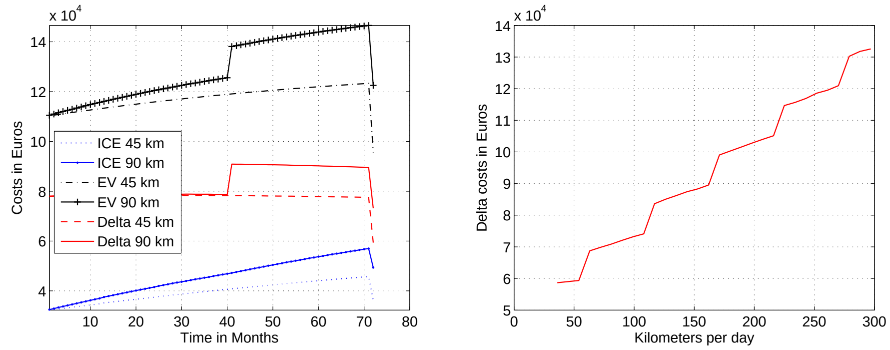
5.3 Results of the ΔTCO calculation

Based on the input values discussed in section 5.2 and 5.1, the monthly ΔTCO of the vehicle pairs are calculated according to equation 2. This equation delivers negative values for the cost-differences if the TCO of the EV is lower than the TCO of the compared diesel vehicle. Figure 5 depicts the results for the diesel and electric MAN-based vehicle, Figure 6 for the Dyna-based vehicles, and Figure 7 for the Sprinter-based vehicles.



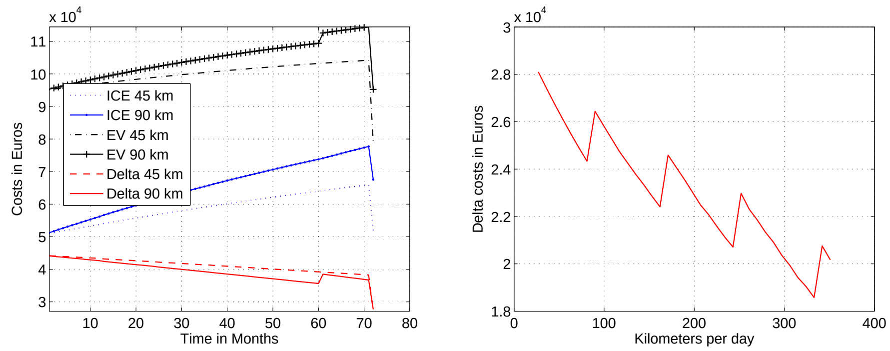
(a) ΔTCO over time (b) ΔTCO over mileage

Fig. 5: ΔTCO of electric and diesel 12 ton MAN-based vehicles



(a) ΔTCO over time (b) ΔTCO over mileage

Fig. 6: ΔTCO of electric and diesel 7.5 ton Dyna-based vehicles



(a) ΔTCO over time (b) ΔTCO over mileage

Fig. 7: ΔTCO of electric and diesel 5 ton Sprinter-based vehicles

We evaluate our model by plotting a commonly depicted TCO graph of the electric and diesel vehicles over time at an average mileage of 45 km/day and 90 km/day in Figures 5a, 6a, and 7a. Additionally, the resulting cost-differences are calculated according to equation 1 and are included in the graph. The graphs deliver four typical results which we anticipated from existing findings in the literature and thus verify that the model delivers appropriate results:

1. The operational costs of the electric vehicles are lower than the operational costs of the diesel vehicles, hence the TCO graphs of the diesel vehicles increase more steeply than the graphs of the electric vehicles.

2. The operational costs of electric vehicles at higher average mileages (90 km/day compared to 45 km/day) are relatively lower than for the diesel vehicles.

3. The battery replacements in the higher mileage scenario in Figures 7a and 6a impair the advantages of the EV operational costs.

4. None of the medium-duty electric vehicles are competitive compared to their conventional sibling. At a daily average of 90 km driven on 300 days for six years, the electric vehicles are between €27,700 (Sprinter-based) and €78,500 (MAN-based) more expensive than their conventional counterpart.

5. None of the medium-duty electric vehicles are competitive compared to their conventional sibling. At a daily average of 90 km driven on 300 days for six years, the electric vehicles are between €27,700 (Sprinter-based) and €78,500 (MAN-based) more expensive than their conventional counterpart.

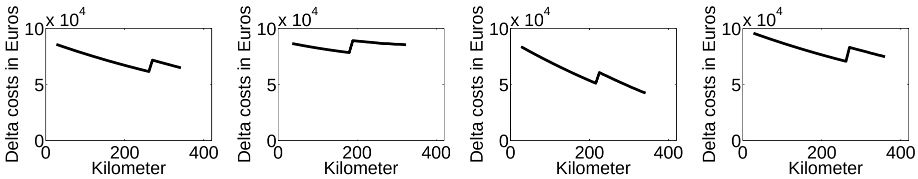
In order to analyze the most cost-efficient mileage, we slice the costs calculated in the last months of the TCO from the three-dimensional data and plot them over the numbers of kilometers in the Figures 5b, 6b, and 7b. The cost-difference of the MAN-based vehicles in Figure 5b behaves according to the expectations: with a higher mileage the EV becomes increasingly competitive. However, the cost-differences are not falling monotonically. Spikes occur if more frequent battery changes are required at higher mileages. As an example, the MAN-based EV is relatively more cost-efficient when driving between 120 and 215 km/day than at 230 km/day. The costs for the battery replacements are also the reason that the TCO of the Sprinter EV does not significantly decrease at higher mileages, despite lower operational costs, Figure 7b. Further, the hypothesis that all electric vehicles become more cost-efficient at higher mileages is disproved by the Dyna vehicles. The differential costs depicted in Figure 6b show that the Dyna EV becomes less cost-efficient the higher the number of kilometer driven.

The three-dimensional graphs of the three vehicle pairs are included in the Appendix as a reference. In order to analyze the reasons for the different cost progressions and to interpret the results, we carry out a sensitivity analysis.

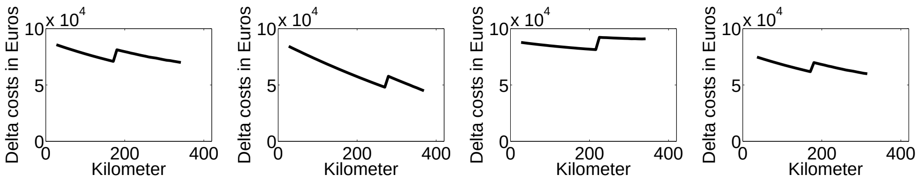
5.4 *Sensitivity analysis*

The parameters of the MAN-based vehicles are varied in a one-at-a-time sensitivity analysis. The goals of this analysis are two-fold: first, we aim to detect important parameters that have the highest impact on the competitiveness of the EV at lower daily mileages. Second, we pursue to understand which parameters are mainly responsible for the EV to become more (or less) competitive with an increasing mileage. Therefore, we vary the input parameters by ±20%.

Figure 8 depicts in an exemplary manner how the differential costs change when adapting the vehicle-related input parameters of battery warranty, energy consumption, diesel consumption and battery size. In order to achieve consistent results, a change of the parameters "battery price" and "battery size" also includes an adaptation of the purchase price.



(a) Warranty +20% (b) Energy +20% (c) Diesel +20% (d) Size +20%



(e) Warranty -20% (f) Energy -20% (g) Diesel -20% (h) Size -20%

Fig. 8: Sensitivity analysis of selected input parameters of MAN-based vehicles

In fitting a linear regression $L = a + b \cdot km$ to the results, we are able to apply the analysis over all average mileages (km) per day. The regression delivers the parameters a and b, of which a represents the intersection with the y-axis (cost-differences) and b the factor at which the graph is descending or ascending. We relate the output difference to the input difference. The resulting sensitivity indexes SI_a and SI_b indicate the importance of the respective parameter for the relative costs at lower mileages (SI_a) and with an increasing mileage (SI_b), compare Table 4. Positive values for SI_a indicate that varying the input parameter leads to a higher competitiveness of the EV. A positive value for SI_b shows that the TCO of the EV performs relatively better the more the vehicle is utilized.

It can be observed that the sensitivity indexes are not always symmetrical. The reason is that the variance of some parameters may have several influences, which have a different magnitude, depending on the calendar date when they occur. As an example, reducing the energy consumption leads to savings due to comparably lower operational costs per km. At the same time, this change influences the recharging profile; this again influences the time and number of required battery replacements. Since the projections for diesel fuel, electric energy and battery prices utilized in the model are not linear, compare section 5.2, the points in time when the energy and diesel are consumed, and the battery is replaced lead to different, non-symmetric results for the costs.

The sensitivity index SI_a in Table 4 shows that, of the tested parameters, the size of the battery is the most relevant parameter influencing the differential TCO at low average daily mileages ($SI_a = 0.62$). Reducing the battery size by 20% leads

	SI_b		SI_a	
Parameter	+20%	-20%	+20%	-20%
Vehicle characteristics				
Battery warranty	1.43	-1.78	-0.03	0.02
Energy consumption	-6.25	6.29	0.02	-0.01
Diesel consumption	7.36	-7.36	0.01	-0.01
Battery size	0.66	-0.69	-0.56	0.56
Scenario parameters				
Energy price	-4.38	4.38	-0.01	0.01
Diesel price	7.36	-7.36	0.01	-0.01
Discount value	0.10	-0.11	-0.14	0.15
Residual value vehicle	-1.42	1.42	0.29	-0.29
Resale value battery	1.25	-1.25	0.06	-0.06
Diesel road tax	0.00	0.00	0.01	-0.01
Purchase price battery	-2.62	2.62	-0.26	0.26
Maintenance EV	-0.72	0.72	0.00	0.00
Maintenance conventional vehicle	1.41	-1.41	0.00	0.00
Operational profile				
Operation days	2.96	-1.28	0.03	-0.05
Charging speed	-0.02	1.25	0.04	-0.01

Tab. 4: Sensitivity indexes of the MAN-based vehicles' TCO input parameters

to a reduction of the TCO gap of 14%, since the EV would have a lower purchase price with a smaller battery. However, reducing the battery size has a negative impact on the competitiveness of an EV at higher ranges ($SI_b = -0.69$), because due to the smaller battery more frequent battery changes are required, also compare Figures 8d and 8h. However, it has to be pointed out that the one-at-a-time sensitivity analysis does not reflect the potential need for further charging infrastructure to recharge the smaller battery during operations, which could outweigh the cost-savings for a smaller battery. In contrast, a smaller battery could lead to an increased energy efficiency of the EV (compare section 4.1, page 12), which could positively impact the EV TCO. An individual assessment, depending on the tour planning and recharging possibilities, is, therefore, required to analyze whether an EV might increase its competitiveness with a smaller battery.

Two further relevant factors at low average daily mileages are the residual value of the vehicle only (not the battery) and the purchase price of the battery. A 20% lower residual value for the vehicle has a relative higher negative impact on the TCO of the EV ($SI_a = -0.29$), since the initial purchase price of the EV is higher than of the diesel vehicle. However, with higher average daily mileages, the impact of the factor is slightly decreasing ($SI_b = 1.42$), since the TCO model assumes that the vehicles fetch a lower resale price with a higher mileage. A 20% lower battery purchase price obviously reduces SI_a (0.26) and also positively influences the TCO of the EV the higher the number of kilometers driven ($SI_b = 2.62$).

None of the factors that mostly influence the TCO at lower mileages are relevant when increasing the mileage. Index SI_b shows that with a higher utilization the most important factors are the variances of the diesel consumption and price. A decrease of the diesel price and consumption by 20% leads to an increase of the slope of the cost graphs (both -7.36), also compare Figure 8g. A reduction of the energy consumption ($SI_b = 6.29$) has a slightly lower effect compared to an equal increase of the diesel price, also compare Figures 8c and 8f. A reduction of the energy price has only about 60% the effect of an equal increase of the diesel price (4.38 vs. 7.36). Further parameters that impact the slope of the graph to a smaller extent are the purchase price of the battery and the battery warranty. These parameters mainly determine whether an EV becomes more competitive with a growing mileage.

5.5 Discussion

The results of the study indicate that none of the three exemplary calculated medium-duty electric vehicles are more profitable than comparable diesel vehicles. This finding supports the case study of Macharis et al. (2013), which also found a medium-duty EV calculation to be non-competitive. Our study researched the cost-optimal mileage in further detail. We find that a higher utilization of an EV can reduce the cost gap, but scenarios exist where this is not the case. Within the preconditions of our scenario, it is for example more advantageous to operate the 12 ton MAN-based EV at an average of 200 km/day than at 250 km/day; the costs of the 5 ton Sprinter-based EV only vary slightly over the number of kilometers driven; while the 7.49 ton Dyna EV becomes more costly with a higher mileage. Hence, our results partly contradict the hypothesis that is commonly derived in the literature via TCO and EVRP calculations, that electric vehicles become relatively more competitive compared to conventional diesel vehicles with an increasing mileage.

It is noteworthy that in order to reach very high average daily mileages, a multi-shift utilization with intermediate quick-charging of the battery would be necessary. The possible costs for the charging infrastructure have not been included in the model. A potential need for building up quick-charging infrastructure would shift the result in favor of the diesel vehicles. Further, achieving a very high mileage operational pattern might be rare in a practical application. Moreover, charging the EV battery with high charging rates was found to accelerate battery degradation (Lacey et al., 2013). Hence, a long battery warranty is important to reduce the risk of costly battery replacements, especially in high mileage scenarios which are only achievable with intermediate charging.

Our sensitivity analysis underlines the importance that companies clearly analyze the planned usage profile before choosing a suitable EV. A low energy consumption, high utilization and long battery warranty are the most important parameters that can lead to a competitive operation of the EV. However, the realistic diesel consumption and future diesel price estimations are even more relevant factors that determine whether an EV can be operated profitably compared to a diesel vehicle. If a company operates very fuel-efficient diesel vehicles, but the comparable EV model is not energy-efficient, an exchange with an EV might not be profitable. The example of the Dyna vehicles illustrates the impact of these factors at increasing mileages. In our model the energy and diesel prices as well as the days of operation are similar for all simulated vehicles. The manufacturers of the conventional Dyna vehicle indicated that the realistic diesel consumption of the vehicle is rather low, arguing that it was designed as a fuel-efficient vehicle. At the same time, the converted Dyna EV consumed nearly as much energy as the 12 ton MAN-based EV, as indicated by the conversion company. This, paired with a relatively short battery warranty of 100,000 km, leads to increasing costs of the Dyna EV with a growing mileage compared to the diesel model.

The reason for the differences between our findings and those in the body of literature is that existing sensitivity analyses researched the difference of the output (i.e., cost) based on changes for the input parameters (i.e., mileage) by varying a base parameter (i.e., 50 km). This so-called 'local' sensitivity analysis delivers results relative to the chosen setting of the base parameters, but not for the entire parameter distribution. The local findings may not be valid far from the base settings (Hamby, 1994). This is the case in our research. By expanding the mileage to the theoretical maximum, we include the so far under-researched effects of the reduced state of health of a battery and more frequent battery changes on the cost-efficiency of medium-duty electric vehicles. Our calculation thus expands the knowledge base on the competitiveness of electric vehicles at high average daily mileages. This understanding is relevant in practical applications, since the Elmo real-world test shows that companies undertake testing to raise the daily mileage significantly over 300 km, in order to increase the competitiveness of their electric vehicles.

Based on these results, we do not recommend a minimum period of time to achieve a cost-efficient medium-duty EV operation as noted by Davis and Figliozzi (2013), nor do we suggest to only sell an EV at the point in time where the battery has to be replaced, as recommended by Lebeau et al. (2015b) for light commercial electric vehicles. Instead, we suggest that for each vehicle, it is necessary to individually calculate the most cost-efficient mileage, based on the specific EV parameters, such as its energy consumption, charging rate, battery, size battery warranty; as well as the compared diesel vehicle's parameters; and the external factors, such as energy prices, subsidies and vehicle purchase prices in the markets.

6 Conclusion

This study analyzes the cost-optimal mileage of medium-duty electric vehicles compared to similar conventional vehicles. In order to reach this goal, this study fills gaps in the literature by adding evidence about the real-world energy consumption of medium-duty electric vehicles; applying a time-optimized EV charging strategy; and including battery degradation and replacement in a total cost of ownership calculation.

The results of our study suggest that in certain, but not in every scenario an EV will become more cost-efficient with an increasing mileage compared to a conventional vehicle. Hence, we recommend that practitioners should determine the necessary operational profile before purchasing an EV, in order to select a vehicle configuration which delivers the most cost-efficient TCO compared to the replaced diesel vehicle. This includes analyzing the traffic conditions in which the EV will be deployed, since our study indicates that – similar to conventional vehicles – the energy consumption of an EV in high-density urban traffic with many stops is higher than when the EV is driven on long stretches at constant speeds. In utilizing our calculation model, it is possible to analyze whether purchasing an EV with a smaller battery but intermediate quick-charging option might offer a more cost-efficient solution. An EV with a larger battery might not only be more expensive and hence less competitive; due to the higher battery weight, but the potentially reduced energy-efficiency of the EV might impair anticipated gains in the range of vehicles, as found in the Elmo real-world test.

As a limitation to our results, the TCO has been calculated with an oil price prognosis as input factor which does not reflect the recent price turbulence. The current oil price is about 30% below the projections assumed in the model, which are based on the International Energy Agency's projections of 2012. Our analysis shows that applying a 30% lower diesel price would lead to an increasing cost gap for all three exemplary simulated EV models.

This finding has interesting implications for policymakers. In 2016, the German government adopted a subsidy scheme of €4,000 when purchasing an EV. In the Netherlands, a maximal "environmental investment allowance" of 36% of the purchase price, up to €50,000 can be granted (Netherlands Enterprise Agency, 2015). While any of these subsidies would lower the TCO gap of an EV at very low mileages, the EV would become less competitive the more it is utilized, if the current diesel price prevails. This is counter-productive, since an EV only generates effective environmental advantages when it is utilized as much as possible and replaces a conventional vehicle. Hence, our findings suggest that subsidizing a high utilization of electric vehicles is a more successful and sustainable policy strategy. The real-world test presented in this study indicates that the ten medium-duty electric vehicles saved a significant amount of between 81 to 102 tons of CO_2-equivalents throughout the 131,018 km driven in the test. The most important cost-leverage to motivate companies to purchase and operate an EV at high mileages, is to raise the per-kilometer costs of diesel vehicles relative to electric vehicles. A potential measure, thus, is to increasing the price of diesel fuel, i.e., by abandoning the taxation subsidy of diesel fuel: since diesel fuel has an overall tax advantage of €0.219/l at filling stations, compared to petrol in Germany. Further policy options to raise the relative per-kilometer costs of diesel vehicles are to implement a kilometer-dependent city toll for conventional freight vehicles; to reduce the energy price taxation when charging electric vehicles; or to subsidize the setup of proprietary quick-charging infrastructure for companies.

Despite higher costs, medium-duty electric vehicles might pose an interesting option for multi-shift trips that include night delivery. Electric vehicles are more silent in operation, especially when accelerating or decelerating in urban traffic

(Cavar and Jolic, 2011). Our model proposes answers to the relevant question of how the competitiveness of electric vehicles develops in high-mileage or multi-shift utilization. Even though uncertainties exist with regard to the utilized input values, such as the future oil price or the resale value of batteries, the main results of our model are generalizable and the model is transferable to other markets and vehicles, by adapting the input values, such as external parameters and technical vehicle specifications. Moreover, the discussed factors can be utilized in future calculations that include an EV energy model, such as electric vehicle routing problems and life cycle analyses.

The following limitations of the current study offer opportunities for future research:

- Due to the lack of data, we estimated the costs for service and maintenance of medium-duty electric vehicles to be half the costs of conventional vehicles, similar to other TCO calculations in the literature (Feng and Figliozzi, 2013; Macharis et al., 2013; Lebeau et al., 2015b). Further real-world tests are needed to determine whether this estimation is valid, since our sensitivity analysis showed that the costs for maintenance and service have a mild but not negligible impact on the TCO calculation.
- Our study finds in accordance with Lee et al. (2013), that apart from the vehicle's mileage, the TCO is most sensitive to the diesel fuel efficiency or costs. While the efficiency of the electric vehicles was closely monitored in the Elmo field-tests, the fuel consumptions of comparable diesel vehicles were only estimated by the fleet managers. Real-world fuel consumptions of the medium-duty diesel vehicles, which are compared to electric vehicles in a TCO calculation, need to be monitored with a similar level of detail, in order to carry out an exact TCO calculation.
- The maximal possible daily range of the EV has been calculated by analyzing the charging characteristic of an exemplary lithium-ion battery. Hence, our results are valid for electric vehicles with a lithium-ion battery only, and still might deviate slightly, depending on the specific battery.

While this study emphasizes the importance that logistics companies understand the most cost-efficient operational profile of their medium-duty electric vehicles, it also highlights that most of these vehicles cannot financially compete under the current conditions in Germany. Subsidies and privileges are required in order to help logistics companies to bridge the TCO gap, if a substantially higher number of electric vehicles is desired to reduce the local air pollution as well as greenhouse gas and noise emissions in cities. As the current study suggests, such subsidies should preferably increase the utilization of electric vehicles in urban freight transport by increasing the advantage of the operational costs of electric vehicles.

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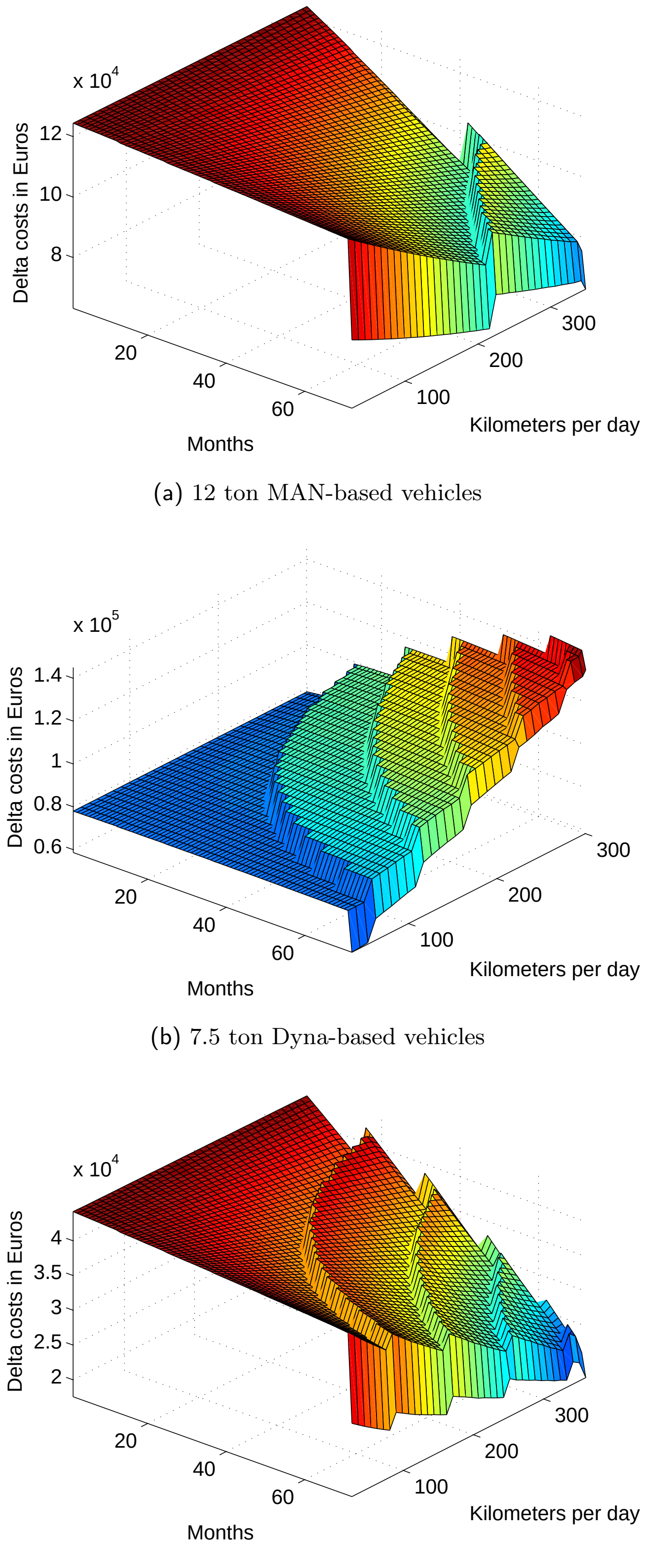
A Appendix



(a) 12 ton MAN-based vehicles

(b) 7.5 ton Dyna-based vehicles

(c) 5 ton Sprinter-based vehicles

Fig. 9: 3D-view of electric and diesel ΔTCO

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