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Today's technical feasibility of heavy-duty battery electric trucks for urban and regional delivery - A real-world case study.

Steffen Link[1,2,*], Patrick Plötz[1]

[1]*Fraunhofer Institute for Systems and Innovation Research ISI, Breslauer Str. 48, 76139 Karlsruhe, Germany*
[2]*Karlsruhe Institute of Technology, Kaiserstraße 12, 76131 Karlsruhe, Germany*
**corresponding author: steffen.link@isi.fraunhofer.de*

Executive Summary

Heavy-duty battery-electric trucks (BET) promise tremendous and immediate potential to reduce greenhouse gas emissions in road freight transport. However, their real-world application is still being questioned due to the limited electric range or insufficient charging infrastructure. Thus, our case study aims to assess the technical feasibility of urban and regional delivery in Germany based on real-world operational data. Our results demonstrate the importance of both vehicle and tour-specific analyses. With up to 600 kWh, we find nearly 40% of all transport performance and 60% of all trucks to be electrifiable, whereas intermediate charging, tour optimization, and adjusted truck-tour allocation can significantly increase both ratios.

1 Introduction

A broad consensus has been reached that cutting greenhouse gas (GHG) emissions rapidly and eventually reaching climate neutrality by 2050 is essential to comply with the Paris Climate Agreement, i.e., keep the global mean temperature below 1.5°C. Today and despite their rather minor significance in the total vehicle fleet, heavy-duty vehicles contribute about 8% of the total EU GHG emissions [1]. While several technological pathways for zero-emission trucks exist, battery-electric trucks (BET) benefit from the technological experience and recent battery innovations - i.e., costs, volumetric and gravimetric energy density, and fast charging capability [2–4] - and, thus, short-term large-scale availability [5]. The increasing manufacturer commitment toward BET further accentuates this shift [6].

While several studies imply a great potential for urban and regional delivery with a daily mileage lower than 400 km [3], most recent studies even see long-haul transport close to a threshold where BETs become feasible [3, 4, 7]. Despite this commitment and literature-proofed feasibility, truck fleet owners are still questioning the technical feasibility of BETs for their application in light of limited vehicle range, insufficient public charging infrastructure, and payload restrictions [8, 9]. This individual reservation demands a shift from generalized assessments based on synthetic operating schedules [10], fleet analyses [11, 12], or standardized driving profiles and generic use patterns [2–4, 7, 13].

Thus, we aim to evaluate the technical feasibility of BETs with a comprehensive case study by using real-world and per-vehicle operational data rather than generic driving patterns or synthetic operating schedules. We focus on urban and regional delivery in the German food retail sector. We examine four different truck classes and use vehicle- and tour-specific energy simulations while accounting for uncertainties. On top, we explore different potentials for increased truck fleet electrification by allowing for intermediate charging. We close with a discussion and appropriate recommendations.

2 Data and methods

2.1 Data

We use tour data from commercial tour scheduling software for two depots in the northeast region of Germany, within 220 km around Berlin. Our sample covers one month from 2021, roughly 9,500 commuting tours, 543 retail stores, around 1 million km, and 224 trucks. These are trucks with a gross vehicle weight (GVW) of 18 or 26 tons as solo refrigerated trucks, truck-trailer combinations, and tractor-semitrailer combinations. The data covers information on the temporal sequence, route, and payload. These 9,500 commuting tours are chained to more than 4,000 daily tours. While Depot1 primarily supplies Berlin and partially the metropolitan area, Depot2 additionally supplies the entire northeast region. ***Figure 1*** shows both depot locations within the northeast region associated with individual retail stores (left) and tours (right).

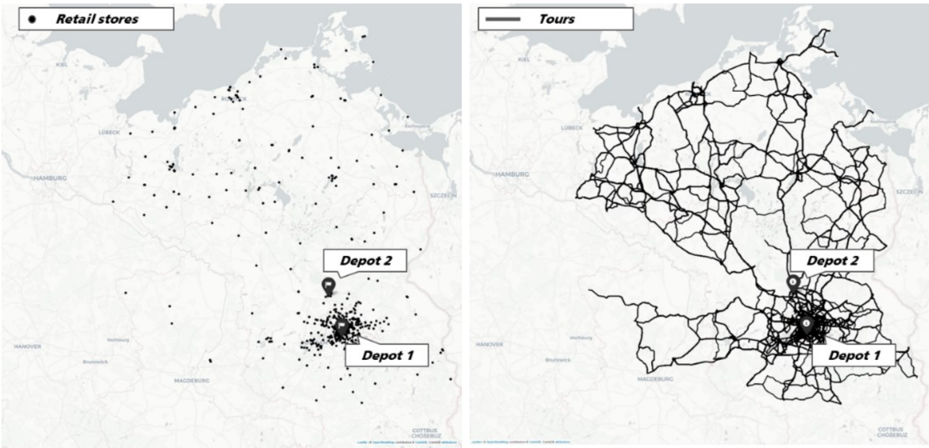

Figure 1: Data sample - Northeast Region: Customers (Left) and Tours (Right)

2.2 Methods

Energy simulation

The technical feasibility involves a tour-specific energy simulation for each truck. Since exact time- or distance-based vehicle speed profiles are missing, we use a simplified modeling approach rather than detailed component-based vehicle models, such as used by [2].

We use the mathematical-physical vehicle model proposed by [14], for instance, also adopted by [3, 13], as a base version to account for vehicle dynamics and energy losses related to aerodynamic drag forces, frictional forces, and inertial forces. On top, we incorporate energy demand from both accessories and commodity cooling, restriction to the depth of discharge (DoD), and minimum residual range requirements. While $\boldsymbol{Eq.1}$ shows the adjusted base version, $\boldsymbol{Eq.2}$ shows our full battery capacity model. $\boldsymbol{Eq.3}$ shows our vehicle weigh calculation. Parameter and values are shown in ***Table 1*** and ***Table 2***.

$$E_{Driving} = \left[\frac{\left(\frac{1}{2} \cdot \rho \cdot C_D \cdot A \cdot v_{rms}^3 + c_{rr} \cdot m_T \cdot g \cdot v_{av} + \partial_\alpha \cdot m_T \cdot g \cdot v_{av}\right)}{\eta_{bw}} + \partial_{Reku} \cdot m_T \cdot a_{av} \cdot v_{av} \cdot \left(\frac{1}{\eta_{btw}} - \eta_{btw} \cdot \eta_{brk}\right) \right] \cdot \frac{D}{v_{av}} \tag{1}$$

$$E_{total} = \frac{E_{Driving} + P_{Aux} \cdot t_{Driving} + P_{Cool} \cdot (t_{Driving} + t_{Stopp}) + E_{Residual}}{\eta_{DoD}} \quad (2)$$

$$m_T = m_{Curb\_D} - P_{Motor} \cdot (m_{Emot} - m_{ICE}) - m_{DPT} + E_{bat} \cdot \rho_{Bat} + m_{Trailer} + m_{Payload} \quad (3)$$

$E_{Driving}$ represents the net battery capacity [kWh] required to overcome all driving resistances. Major parameters are vehicle drag coefficient (C_D), vehicle frontal area (A), mean vehicle velocity (v_{av}), root-mean-square velocity (v_{rms}), mean vehicle acceleration (a_{av}), tire rolling resistance coefficient (c_{rr}), trip distance (D), and total vehicle mass (m_T). Parameter (∂_α) approximates the average road gradient per tour. η_{btw} denotes the battery-to-wheels efficiency and summarizes battery discharge efficiency (η_{dis}) and drivetrain efficiency (η_{btw}). The proportion of recoverable energy is specified via ∂_{Reku}. η_{brk} accounts for additional braking losses.

E_{Total} represents the gross battery capacity [kWh] required to complete any tour successfully. Additional per-vehicle energy demand from accessories (pneumatics, hydraulics, heating and air conditioning (HVAC), on-board power grid) is approximated using mean power consumption per driving time, following [15, 16]. Likewise, the energy demand for commodity cooling is calculated. The mean power consumption - generally highly dependent on the temperature delta, the cooling volume, and the frequency of opening and closing - is calculated based on the ATP/DIN 8959. The temperature difference is assumed to be 25°C.

m_T represents the total truck weight [kg]. We use a top-down approach starting from diesel truck values, suppose a common vehicle chassis, and then calculate the possible BET weight. Therefore, we subtract all major diesel powertrain-related components such as the ICE, gearbox, and fuel tank from the diesel curb weight (m_{Curb_D}). Afterward, we add major electric powertrain components such as motor and battery. For truck-trailers and tractor-trailers, we add the trailer curb weight. We close by including the tour-specific payload weight.

Main uncertainties result from the energy consumption formula based on simplifying assumptions, technical vehicle parameters, and real-world operating conditions. We follow [14] and cast all major parameters using individual PERT distributions instead of running sensitivity analysis of selected parameters afterward to account for these uncertainties and increase robustness. Minimum, most likely, and maximum values are specified based on empirical data, literature values, or assumed to spread ±20%. Finally, we perform a standard Monte Carlo simulation for each trip (n=100). Parameter spreads are indicated in the tables below.

Vehicle-specific specifications like vehicle aerodynamics, tire rolling resistance, and diesel chassis curb weight are aggregated per truck class (lower quantile (Q25), median (Q50), upper quantile(Q75)) [17]. Tour-specific parameters like payload, mean vehicle velocity, trip distance, or timestamps for driving and stopping are taken from the tour scheduling software. An averaged road gradient is calculated based on truck routing software [18]. This involves a piecewise linearization of the reconstructed tour (500m steps) and the calculation of distance-weighted quantiles (Q25 and Q75) as minimum and maximum value. We adopt the most likely value from [14]. The root-mean-square velocity is calculated using the Steiner-König-Huygens theorem, including crosswind influence. The mean vehicle acceleration is approximated by cycle-specific values based on 18 different American driving cycles [19]. Since urban driving usually features higher dynamics due to stop-and-go traffic, traffic lights, or planned stops per distance than regional deliveries, we distinguish between both use cases.

Table 1: Truck-class-specific simulation parameters. Ranges indicate the PERT distribution's minimum, most likely, and maximum values. Individual parameters are constant values.

Parameter		18t	26t	Truck-Trailer	Tractor-Trailer	Source
m_{Curb_D}	[kg]	5,761 -6,475 - 7,125	8,239 - 8,679 - 9,073	8,239 - 8,679 - 9,073	5,761 - 6,475 - 7,125	Q25-Q50-Q75 [17]
$m_{Trailer}$	[kg]	-	-	6,500 ± 20%	8,500 ± 20%	derived from [15]
$C_D \cdot A$	[m²]	5.559 -5.698 - 5.837	5.463 - 5.997 - 5.737	6.557 - 7.839 - 9.179	5.559 - 5.698 - 5.837	Q25-Q50-Q75 [17]
c_{rr}	[N/kN]	5.5 - 5.7 - 6.9	5.0 - 5.6 - 6.8	5.0 - 5.6 - 6.8	4.9 - 5.1 - 6.5	Q25-Q50-Q75 [17]
P_{Aux}	[kW]	2.97 ± 20%	3.39 ± 20%	4.32 ± 20%	4.11 ± 20%	[15, 16]
P_{Cool}	[kW]	3.11 ± 20%	3.11 ± 20%	5.90 ± 20%	5.14 ± 20%	ATP/DIN 8959
P_{Motor}	[kW]	200 - 228 - 265	265 - 323 -350	265 - 323 -350	331 - 355 - 368	Q25-Q50-Q75 [17]
v_{Std}	[m/s]	0.413	0.417	0.744	0.677	[-]

Table 2: Other simulation parameters. Ranges indicate the PERT distribution's minimum, most likely, and maximum values. Individual parameters are constant values.

Parameter		Value / Value range	Source
η_{DoD}	[%]	90% ± 5%	[13]
ρ_{Bat}	[Wh/kg]	150 - 175 - 225	[13, 14, 20]
∂_{Reku}	[%]	50% ± 10%	[14]
a_{av}	[m/s²]	Urban: 0.331 ± 20%, Regional: 0.160 ± 20%	Q25-Q75 [19]
η_{BTW}	[%]	$= \eta_{BTW}$ (95% ± 2.5%) · η_{PT} (90% ± 2.5%)	[13, 14]
η_{brk}	[%]	97%	[14]
v_{RMS}	[m/s]	$= \sqrt{v_{av}^2 + v_{std}^2} + v_{Wind}$ (3 ± 20%)	Modelled based on [14] and VECTO [21]
$E_{Residual}$	[kWh]	30	Own assumption
p	[kg/m³]	1.15 - 1.225 - 1.3	Own assumption
m_{Emot}	[kg/kW]	1.43	[22]
m_{DPT}	[kg]	$= m_{Gearbox}$ (300 kg) + m_{Tank} (108 kg) = 408 kg	Own calculation based on [2]
m_{ICE}	[kg/kW]	3.3	[23]
m_{PL}	[kg]	Base value from truck schedule (± 20%)	Own assumption
$P_{Charge,Dep}$	[kW]	$\in \{50,150,250,350,450,1000\}$	Own assumption based on common charging standards
$P_{Charge,CR}$	[kW]	150	Own assumption
r_{NCP}	[%]	75% ±10%	Own assumption
η_{NCP}	[%]	68.1% (184/270) - 82% (164/200) - 92.6 % (250/270)	[24]

For each truck, gross battery capacities between 100 and 800 kWh are simulated in 50 kWh increments and compared against the required battery capacity per tour. We include higher permitted GVW limits for BETs in Germany, i.e., up to 2 tons depending on truck class [25]. If the required battery capacity is lower than the simulated battery capacity minus DoD restrictions and the permitted GVW is not exceeded, this simulation run (note n = 100) per daily tour is labeled "technically feasible". If at least 90% of all simulations runs are labeled as "technically feasible", we label this daily tour as "technically feasible". If all daily tours per vehicle are labeled "technically feasible", we affirm the BET replacement for this truck and denote the simulated gross battery capacity. Note that this is very restrictive, as just one daily tour might negate BET replaceability.

Scenarios and premises:

There is no tour optimization, truck re-allocation, or adjusted scheduling for all calculations. Tours are presumed to be exactly as of February 2021 so that potential BET would mimic the existing diesel truck schedule. There is no opportunity to charge during mandatory driving breaks, as these coincide with the stops at customer retail stores. Thus, private charging infrastructures would be the only possibility to avoid time losses.

Our base scenario (S0) assumes that vehicles depart from the depot fully charged in the morning, and installed gross battery capacities must be sufficient throughout the day. Additionally, we investigate the effect of private destination charging to extend vehicle coverage. Thus, we integrate potential intermediate depot-charging within the depot premises (S1) that might happen directly at the cargo terminals during vehicle commodity loading ($t_{Loading}$). Additionally, we investigate the effect of charging opportunities at individual customer retail stores (S2), where the stopping time (t_{Stopp}) at the local cargo terminals might be used for charging. We still assume that vehicles depart from the depot fully charged in the morning. In both scenarios, vehicles recharge without time losses, and the tour schedule is maintained.

For both scenarios, we approximate the state of charge (SoC) evolution throughout any tour based on consumed energy (driving, accessories, and cooling) per traveled distance. For depot charging, we consider six different peak charging powers ($P_{Charge,Dep}$). For individual retail stores, we explore the effect of 150 kW peak charging power ($P_{Charge,CR}$) at any retail store. The latter might be in line with a joint passenger car charging infrastructure deployment at local customer parking lots. We use an average charging power across the whole SoC-corridor based on peak charging power, empirical findings on net charging power η_{NCP} from passenger cars, and a 2C charging rate limit. Parameters are included in ***Table 2***.

Result evaluation

We distinguish between 3 different aggregation levels for our evaluations. This allows us to better quantify different potentials. First, we examine the technical feasibility at the truck level. In contrast, we aggregate results on individual daily tours and, thus, exclude any truck allocation to explore and approximate a green-field-like vehicle scheduling. However, the daily trip chains are untouched. Last, we aggregate ton-kilometers (tkm) per daily tour as a common metric in transport statistics. The latter incorporates information about short and light-loaded tours versus long and heavily-loaded tours. All calculations are performed on a standard Lenovo notebook with i7-8565U @1.8 GHz and 16 GB RAM.

3 Results

Daily mileage and timestamps

The daily operating distance are visualized in ***Figure 2***. The visualization splits per truck class and depot location and involves individual values as scatter and boxplots. The daily operating distance typically ranges from 46 to 105 km (25% and 75% quantile) for Depot1 and from 143 to 384 km for Depot2. Across both depots, there are typically 1 to 5 commuting tours per day while serving 1 to 4 customer retail stores per commuting tour. Solo trucks focus on Berlin and the metropolitan area, while truck-trailer and tractor-semitrailer combinations also supply the entire northeast region. Daily mileages in the urban and metropolitan deliveries are usually less than 200 to 300 km, while up 500 to 700 km may be typical for regional deliveries. However, over 1,000 km are possible in multi-shift and cross-daily operations.

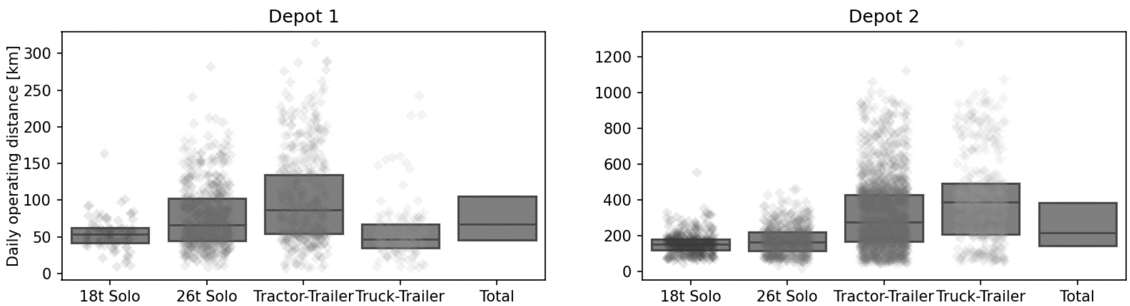

Figure 2: Evaluation of daily operating distances per truck class and per depot location. Sample points are scattered, whereas the boxplots indicate the lower quartile, median, and upper quartile. Own illustration.

Vehicle scheduling specifies four timestamps, from vehicle loading at the cargo terminals within the depots ($t_{Loading}$), driving time ($t_{Driving}$), stop time at customer retail stores (t_{Stopp}), and eventually vehicle unloading at the cargo terminals to complete one single commuting tour. An evaluation including single values and boxplot per category is shown in ***Figure 3***, combining both depots. While vehicle loading typically takes 70-105 minutes, customer stops last similar (71-114 minutes), yet unloading takes only 15-22 minutes. As mentioned earlier, additional breaks such as the mandatory 4.5h driving break are not scheduled as these are covered at customer stops.

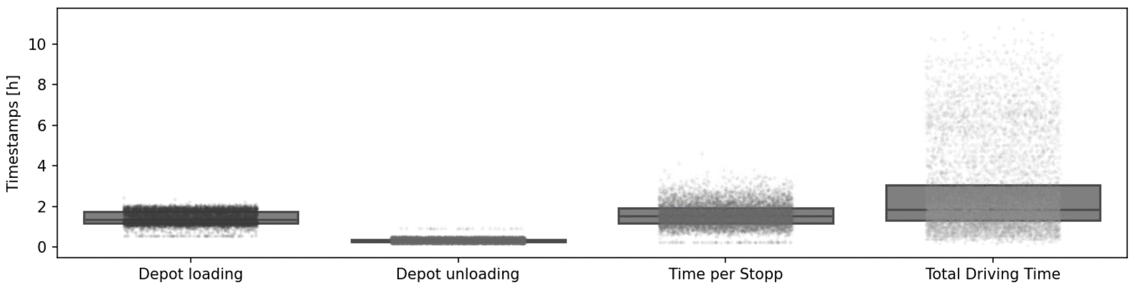

Figure 3: Evaluation of vehicle operating times across both depots. Sample points are scattered, whereas the boxplots indicate the lower quartile, median, and upper quartile. Own illustration.

Comparing timestamps from planning against actual data reveals certain deviations so that specified planned times for stops, vehicle loading, and vehicle unloading are usually undercut, whereby exceeding is also possible. This means that only 65% to 85% of the specified planned times are usually obtainable. We multiply all timestamps and reduce the possible charging time by this fraction (r_{NCP}) to gain high confidence for net charging time. We set 10 minutes as the minimum charging time. In total, we ensure practical implementation and approximate potential time losses for waiting, vehicle docking, or connecting to the charging station.

Specific energy consumption:

Figure 4 shows our simulation results as specific energy consumption per km. To illustrate the spread, the left side visualizes the energy consumption as a density plot per truck class over different battery capacities. Note that the density plots extrapolate beyond simulated battery capacities. The right side shows the sample-weighted boxplot per truck class, whereas fliers and whiskers are removed. All plots comprise only feasible tour-battery combinations. The sample-weighted median spans from 1.01 kWh/km median for the 18 t solo truck, 1.14 kWh/km for the 26 t solo truck, and 1.52 kWh/km for tractor-trailer, to 1.66 kWh/km for the truck-trailer combination. Depending on the truck class and driving time, around 0.1 to 0.4 kWh/km may be attributed to accessories and commodity cooling.

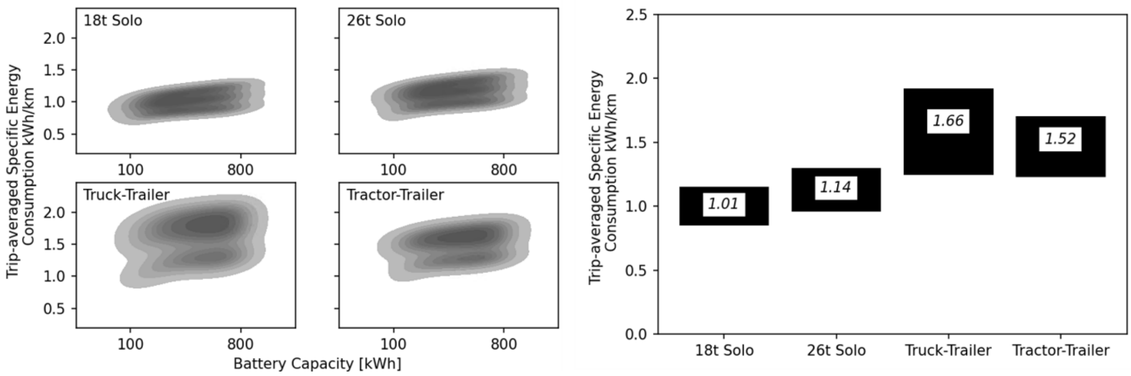

Figure 4: Specific energy consumption (kWh/km) per truck class. Left: Density plot over battery capacity. Right: Sample-weighted boxplot per truck class (median plotted, fliers and whiskers removed). Own illustration.

Base scenario S0 - Feasibility without additional charging:

The effect of different battery capacities on BET feasibility aggregated per truck class is visualized ***Figure 5.*** The y-axis (CDF - cumulative density function) indicates the share of vehicles that would cope with this or less battery capacity throughout each vehicle's numerous trips. Remark that we require all daily tours per vehicle to be technically feasible to affirm its BET replaceability.

For Depot1, battery capacities from 100 to 200 kWh for 18t solo trucks and 100 to 350 kWh for 26t solo trucks are sufficient to electrify all these vehicles. The truck-trailers (450 kWh) and tractor-trailers (550 kWh) require larger batteries than solo trucks. For the latter, the highest gains are between 300 and 500 kWh. Overall, around 600 kWh may be sufficient to affirm full fleet BET replaceability. These battery capacities are already available today. The drop at around 600 kWh for 26t solo trucks indicates the GVW exceeding. However, such large batteries are not needed for Depot1.

For Depot2, the feasibility is significantly lower, and larger batteries are required. This mainly affects truck-trailers and tractor-trailers. In total, well above 200 kWh are required in all classes. The vast majority (80%) of 18t solo trucks range between 200-350 kWh, while 200-600 kWh are required for 26t solo trucks. Around one-third of tractor-trailers and 15% of truck-trailers are technically feasible with around 600 kWh. The wide-stretched plateau for truck-trailers is striking. Overall, 29% of the total fleet can already be electrified with just 400 kWh, 51% with 600 kWh, and 64% with 800 kWh.

The aggregated assessment across both depots indicates 50% BET replaceability with 400 kWh, 60% with 600 kWh, and 66% with 800 kWh.

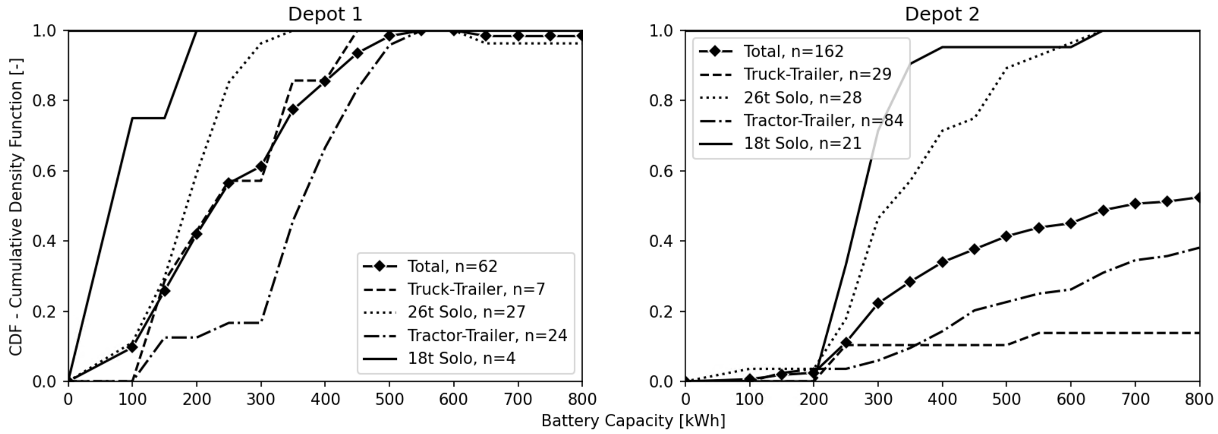

Figure 5: BET feasibility per truck class (on truck-level) Left: CDF over battery capacity for Depot 1. Right: CDF over battery capacity for Depot 2. Own illustration.

Figure 6 focuses on tours and ton-kilometers and, thus, neglects vehicle allocation. The y-axis indicates the share of feasible daily tours and electrifiable transport performance (tkm) with this or less battery capacity. For Depot1, battery capacities between 200 and 300 kWh are sufficient to electrify 80 to 90% of all tours. 400 kWh are sufficient to electrify almost all trips, though a few long and heavily loaded trips are omitted. As the previous analysis showed, around 600 kWh may be sufficient to affirm full BET replaceability. For Depot2, one-half of all tours can be electrified with about 400 kWh and up to 65% with 600 kWh. Nearly 80% may be possible with up to 800 kWh. The highest gains are between 150 and 250 kWh, decreasing towards 400 kWh. The high difference in transport performance shows that especially long or heavily-loaded tours are not feasible. Here, feasibility is around 20% for 400 kWh and around 35% for 600 kWh. The aggregated assessment across both depots indicates that 67% of all daily tours can already be electrified with just 400 kWh and 75% with 600 kWh. In contrast, this equals only 26 to 39% of all tkm.

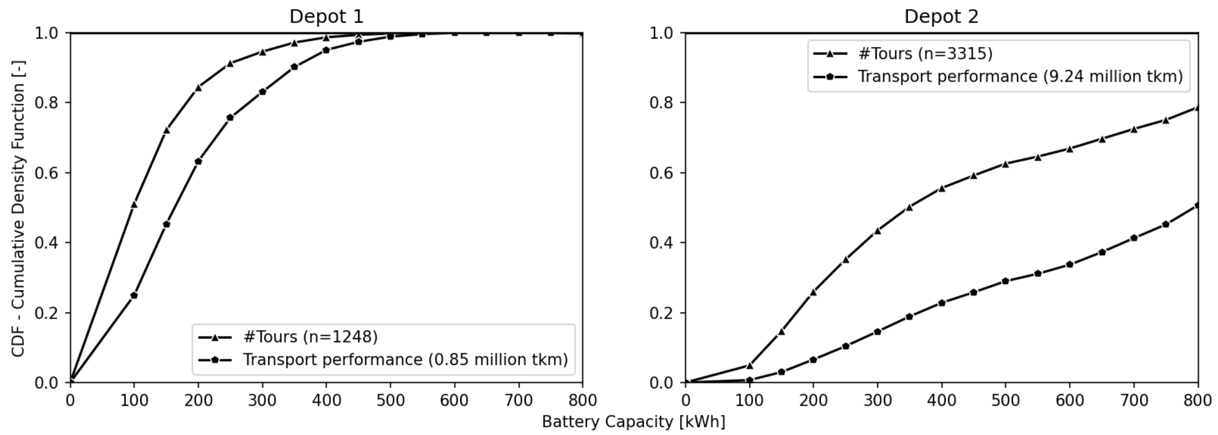

Figure 6: BET feasibility per depot on tour- and tkm-level Left: CDF over battery capacity for Depot 1. Right: CDF over battery capacity for Depot 2. Own illustration.

Our base scenario highlights three main findings: (1) There is no one battery capacity per truck class, even within one fleet. Thus, a vehicle-specific examination for the right battery capacity that ideally matches the vehicle's operating profile is crucial. This is in line with the modular battery capacities offered by the manufacturers to avoid unsuitable battery capacities. (2) If the vehicle allocation is neglected, the tour feasibility is significantly higher than on truck-level. Often, a few unfeasible tours are the crunch. This implies certain potential by re-allocating daily tours within the truck fleet. This might tend to mixed fleet considerations, where most tours are done with BETs, and minor shares remain for (already existing) diesel trucks. (3) Long and / or heavily-loaded tours are most challenging.

Scenario comparison S1 & S2 - The influence of intermediate charging:

For our scenario evaluation, we aggregate both depots. Results are visualized in ***Figure** 7*, where the color scale indicates technical feasibility. The median (50% threshold) is given in white. Results for 300 and 600 kWh once without depot-charging (0 kW) and once with depot-charging (350 kW) are highlighted per scenario. We limit to truck-level at the left-hand side and tkm-level at the right-hand side. The upper row corresponds to S1 and quantifies the effect of intermediate depot-charging only. Thus, the x-axis (i.e., 0 kW charging power) matches the base scenario. The lower row corresponds to S2 and includes intermediate charging at customer retail stores throughout any trip.

For S1, we find 33-67% of all trucks to be replaceable with currently available BET technology (up to 600 kWh and 350 kW depot-charging). This equals 20-48% of all tkm. For S2, we find up to 63-74% of all vehicles to be replaceable. In particular, the feasibility of lower battery capacities increases. At tkm-level, this equals 41-70%.

Overall, our scenarios highlight four main findings for currently available technology: (1) Higher charging power leads to higher feasibility with smaller batteries. However, this effect saturates beyond 350 kW. (2) Higher sensitivity towards installed battery capacity rather than charging power. (3) Intermediate charging options at retail stores enable an increase of roughly 20% of electrified tkm. (4) Full electrification fails in any scenario, indicating further actions such as tour optimization and adjusted scheduling (e.g., SoC-based). Note that daily trip chains are untouched. If the energy demand from commodity cooling were neglected in S2, results would have been higher by a single-digit percentage at tkm-level, and full fleet electrification would have been almost affirmable for standard trucks.

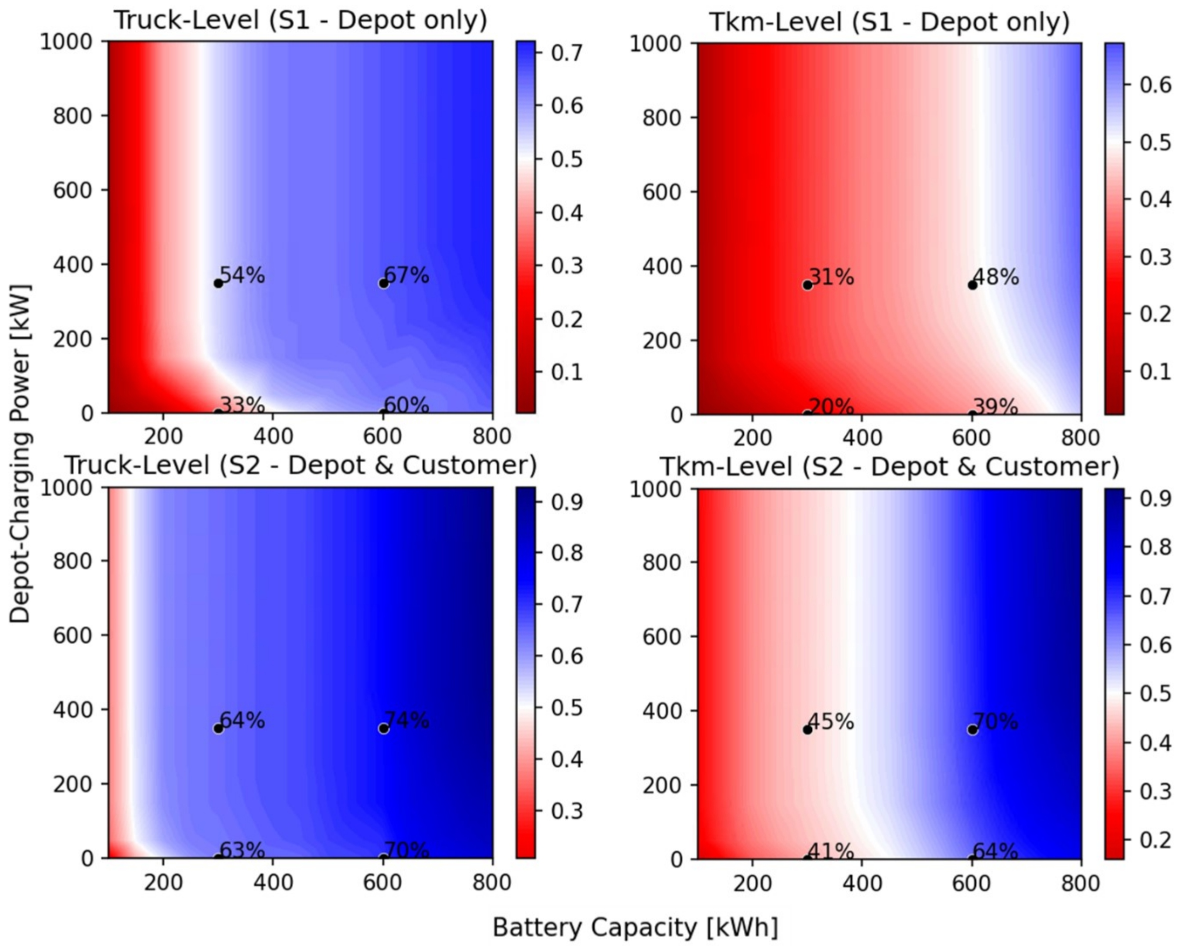

Figure 7: Scenario Analysis. Variations for battery capacity [kWh], depot-charging power [kW] and customer charging availability. Left-hand side: Vehicle-level. Right-hand side: tkm-level. Own illustration

4 Discussion

The following discussion includes tour data, representativeness, energy consumption modeling, charging assumptions, and battery aging.

(1) Tours and vehicle allocation are presumed to be exactly as of February 2021 so that potential BET would mimic the existing diesel truck schedule. While we assume that all trips must be technically feasible to classify one truck as technically feasible for our vehicle-level aggregation, we depart from this rather restrictive assumption for tour- and tkm-level. Nevertheless, daily trip chains are untouched and could be optimized.

(2) We acknowledge that our food-retail case study may not be representative for the entire German distribution logistics and road freight transport since each industry has its unique characteristic usage patterns and constraints. However, we analyzed four different truck classes covering about 87% of the German N3 truck stock [26]. Our calculated annual mileage is typically from 15,000 km to 124,000 km (10% and 90% quantile), with a mean value of 56,000 km and a median of 42,000 km. Our annual mileage is lower than official statistics [27] and driving data surveys [28]. However, pure long-haul transport is missing in our data but included in the others.

(3) Uncertainties for our simulated energy consumption result from the simplified simulation approach, no dynamics within one trip and, naturally, only catching certain variations and irregularities, no detailed component-based simulation, and the underlying generic vehicle specifications. Nevertheless, our results are consistent with other studies [2, 3, 7, 10] even though large-scale empirical real-world data from series BET is missing today. Since we define the SoC as a function of traveled distance, we ignore any fluctuations that may limit real-world feasibility.

(4) For convenience, we assume that charging is available at all retail stores. Plus, all cargo terminals for depot loading are equipped with charging infrastructure. Thus, we assume 100% availability at any time. While this mirrors a full rollout, it seems intuitive that charging infrastructure may not be built at all cargo terminals or cannot be built at all retail store locations due to different constraints (e.g., costs, available space, and grid connection). Different optimization approaches may be used to determine the relevant locations or the optimal number of equipped cargo terminals.

(5) We neglect battery aging effects (i.e., cyclic and calendar). Typically, the battery state-of-health (SoH) would decrease to 70-80% toward an ending truck service life. This impacts technical feasibility, assuming that the truck-tour allocation remains identical over the whole service life. In contrast, assuming more variable vehicle planning, newer trucks might master the more difficult daily tours given a typically ongoing truck fleet renewal, while older trucks perform on easier daily tours (i.e., SoH-based tour allocation). To approximate aging, one might chose the next higher battery increment when affirming the feasible battery capacity threshold per truck.

5 Conclusion

Our case study quantifies the technical feasibility of BET for urban and regional delivery in Germany, covering over 9,000 real-world tours, over 540 customers, and more than 200 heavy trucks from 4 different truck classes (all N3) operating within only 220 km around Berlin. We see 200-300 km as daily mileage in urban delivery, while 500-700 km are typical for regional deliveries.

We find high potential for BET feasibility even if we exactly mirror the existing operating schedule for diesel trucks. With up to 600 kWh and no additional charging infrastructure, we reach 39% of electrified tkm and may replace nearly 60% of all trucks. We find no one battery capacity per truck class but high heterogeneities, even within just one fleet. Thus, fleet owners and shippers should carefully evaluate the modular battery sizes offered by the manufacturers to find the most suitable capacity per truck. However, this also limits flexible and universal vehicle planning. Interim charging options at the depot (S1) or at individual retail stores (S2) boost feasibility and almost double the electrified tkm. Here, intermediate charging offers little added value for urban delivery and the effect is greater for regional deliveries. The individual effect of each measure is larger than the combined effect and, thus, should be balanced against each other. Holistically, one must optimize the installed battery capacity per truck and balance the overall truck fleet versus all potential charging stations from a techno-economic standpoint. However, there is an overall higher sensitivity to battery capacity given long individual journeys than additional depot charging. In any case, overnight charging at the depot is crucial.

While further fast-charging at public charging points (note: usually associated with off-site charging costs and time loss) might further increase these shares, tour optimization, truck re-allocation, and adjusted tour schedules embedded significant potential without additional structural measures and costs (note: neglecting planning costs). Many studies see mandatory driving breaks combined with public fast-charging points as one key to an all-electric future. However, the real-world potential for urban to regional deliveries may be limited since mandatory breaks coincide with stopping points, and the private development of fast-charging points (350 to 1000 kW) may be questionable.

Given our findings, representativeness, and the literature-proofed general feasibility, we recommend that all fleet owners and shippers start examining their transition to climate-friendly commercial vehicles. We emphasize the necessity of finding the right battery capacity per truck by analyzing its operational patterns, as well as the ad-hoc potential through tour optimization and variable truck-tour allocation (i.e., SoC- and SoH-based). Further research should focus on more case studies from other relevant industries, highlight custom pitfalls in daily operations, and enhance to economic evaluations.

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Authors

Steffen Link graduated in Industrial Engineering and Management from the Karlsruhe Institute of Technology (KIT). Since 2020 researcher in the Competence Center Energy Technology and Energy Systems at the Fraunhofer ISI. His research focuses on batteries and transport decarbonization. Currently pursues his Ph.D. degree at the KIT Institute of Electrical Engineering (ETI).

Patrick Plötz studied Physics in Greifswald, St. Petersburg and Göttingen. Doctorate degree in Theoretical Physics from the University of Heidelberg. Since 2011 researcher in the Competence Center Energy Technology and Energy Systems. Since March 2020 Coordinator of Business Unit Energy Economy. Since 2020 private lecturer at the Karlsruhe Institute of Technology (KIT).