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Quantifying the impact of fleet planning re-optimization on truck electrification in distribution logistics

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Electrifying heavy-duty truck fleets is critical for decarbonization, yet several cutting-edge approaches are based on historical diesel plans which do not account for electric truck characteristics. Such one-to-one replacement of diesel trucks without adapting operational plans may thus underestimate the technical and economic feasibility of battery electric trucks. To better understand the potential for fleet-level optimization, we compare a one-to-one replacement strategy against a holistic re-optimization approach that jointly solves for fleet composition, shipment-to-vehicle allocation, vehicle routing, and charge scheduling. Using real-world data from German grocery logistics (~38,000 shipments), we find that re-optimization unlocks significantly higher electrification potential and economic performance. It increases the electrifiable payload from 48% to 85% and doubles the fleet-level cost reduction (7.0% vs. 3.5%) compared to the optimized diesel baseline. These results demonstrate that maximizing electric fleet viability requires moving beyond simple hardware substitution to fundamentally restructuring operational logistics.

The transition to low-emission transport road freight is critical for achieving climate neutrality by 2050 and meeting the goals of the Paris Climate Agreement. Heavy-duty battery-electric trucks offer significant potential for reducing greenhouse gas emissions, but their adoption faces numerous barriers including technical, financial, and operational factors. Prominent challenges include high upfront capital costs, limited availability of charging infrastructure, and concerns regarding range and payload capacity[1–5].

Many studies have analyzed the feasibility and total cost of ownership (TCO) of electric trucks, with the majority of these studies having been conducted on a truck level rather than fleet level[1–8]. These truck-level TCO studies suggest that electric trucks can leverage their powertrains' superior energy efficiency to reduce variable costs. Thus, their economic feasibility depends on 1) achieving high utilization (i.e. in terms of high annual mileage) and 2) favorable energy costs in order to offset the substantial fixed costs of battery acquisition[9–11]. However, while such truck-level analyses provide a useful framework for understanding basic principles for achieving cost competitive electric truck operations, they may provide an incomplete and potentially misleading picture of fleet operations, a criticism which has been voiced by several logistics service providers[12]. Often, such studies are based on archetypal or averaged usage patterns, likely due to a scarcity of real-world truck driving data, which does not fully account for heterogeneous real-world usage patterns involving trip variations and infrequent long trips which are important for realistic results[13–15]. This heterogeneity has often been omitted in previous literature analyzing fleet-level electrification[11,14,16,17] despite being critical for understanding economic and operational feasibility[12].

A recent common approach to fleet-level electrification is to replace existing diesel trucks with electric trucks on a one-to-one basis, maintaining the original transport plan currently operated by diesel trucks where feasible. This approach involves analyzing real world data on individual diesel trucks' operational patterns to determine which ones, if any, are feasible to replace with electric trucks[9,18,19]. This approach has the advantage of accounting for heterogeneity in operating patterns within a fleet. Another advantage is its conceptual simplicity; it allows logistics companies to electrify their fleets while planning to continue their operations as usual with minimal changes. However, one-to-one replacement also has its disadvantages, largely due to its underlying assumption that previous logistics operations can, or should, remain unchanged despite the inherently different characteristics of electric trucks. In other words, one-to-one electrification does not account for the different cost structure and operational constraints of electric trucks, which may significantly affect optimal fleet composition and operations.

One-to-one replacement can be performed on both human dispatched and algorithmically optimized operational plans for diesel trucks. However, neither of these are guaranteed to be optimal for a mixed fleet including

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Table 1 | Achievable electrification rates for each scenario.

Scenario			Electrification Metrics			
Electrification Approach	**Objective**	**Charging Setup**	**Electric Trucks in Fleet**	**Electrifiable Payload**	**Electrifiable Mileage**	**Electrifiable Tonne-km**
Diesel Baseline	Cost Minimization	N/A	0/138 (0%)	0%	0%	0%
One-to-One Replacement	Electrification Maximization	Intershift (50 kW at depot)	43/138 (31%)	36%	20%	16%
		Intrashift (50 kW at depot + 150 kW at loading bay)	53/138 (38%)	48%	30%	25%
	Cost Minimization	Intershift (50 kW at depot)	43/138 (31%)	36%	20%	16%
		Intrashift (50 kW at depot + 150 kW at loading bay)	53/138 (38%)	48%	30%	25%
Re-Optimization	Electrification Maximization	Intershift (50 kW at depot)	150/185 (81%)	85%	55%	55%
		Intrashift (50 kW at depot + 150 kW at loading bay)	115/150 (77%)	85%	54%	55%
	Cost Minimization	Intershift (50 kW at depot)	108/145 (74%)	79%	49%	51%
		Intrashift (50 kW at depot + 150 kW at loading bay)	95/131 (73%)	80%	50%	53%

electric trucks. Several studies have thus highlighted the potential to go beyond one-to-one replacement and improve fleet electrification using route and charging optimization to design electrified fleets and plan their transport operations and charging[8,9,12,20,21]. Rather than replacing existing diesel trucks one-to-one without changing their operational plans, the fleet and its operations could be re-optimized based on actual transport demand and accounting for the specific characteristics of both diesel and electric trucks. Thus, this approach retains the benefits of operational heterogeneity while simultaneously adapting logistics operations to avoid introducing unnecessary inefficiencies. This approach of re-optimization could increase the achievable electrification rate and cost performance of the fleet by integrating route and charge planning at the fleet level. While highlighted as a promising avenue, the benefits of this optimization driven approach have not yet been evaluated for real world cases and thus its benefits have not been quantified.

This study compares two approaches for freight electrification using a large-scale case study with real-world data. The two approaches are 1) replacing individual vehicles in a diesel fleet one-to-one while maintaining the same operational planning (*one-to-one replacement*) and 2) holistically re-optimizing the fleet composition and its operational planning (*re-optimization*). The rate of electrification is measured across several different metrics: the share of electric trucks in the fleet, share of payload delivered by electric vehicles, share of kilometers driven by electric vehicles, and share of tonne-km performed by electric vehicles. The total cost impact of electrification is evaluated with fleet TCO including charging infrastructure. The study informs logistics companies how to assess their logistics operations when transitioning to electrified fleets. The study objective is thus to assess the difference between these two approaches with the following questions:

1. To what extent does re-optimization affect achievable electrification rates relative to one-to-one replacement?
2. To what extent does re-optimization affect the total cost-of-ownership (TCO) of the fleet relative to one-to-one replacement?
3. How do different charging setups (intershift charging and intrashift charging) and electrification objectives (cost minimization and electrification maximization) affect achievable electrification rates and fleet TCO?

This case study is based on real-world data from Germany's second largest retailer REWE's regional network in Northeastern Germany. The data provided covers over 38 000 shipments from February 2021 being delivered to over 500 stores served by two distribution centers, covering a roughly 300 km radius. Four generic vehicle types considered are heavy-duty trucks with gross vehicle weights of 18, 26, and 40 tonnes (all corresponding to Class 8 trucks) and include rigid solo trucks, tractor-trailer combinations, and rigid-trailer combinations which are all based on Link et al. [9]. We consider two different optimization objectives: electrification maximization and cost minimization. While both objectives aim to minimize total cost of ownership, the electrification maximization objective has the additional hard constraint that all shipments that are within range of an electric truck must be delivered by an electric truck. Additionally, two charging setups are considered: intershift charging with only 50 kW charging at the depot, which is available between shifts and overnight, and intrashift charging with additional 150 kW chargers placed at the loading bays which are available when loading. In answering these questions, we further investigate the underlying operational mechanisms; the changes in fleet scheduling and assignment patterns that drive the observed differences in electrification rates and costs.

Results

Re-optimized fleet planning increases electrification rate

The electrification rate is significantly higher when using re-optimization compared to one-to-one replacement. Re-optimization increases the share of payload that can be delivered by electric trucks, with increases between 32 and 49 percentage points depending on the scenario (see Table 1). The

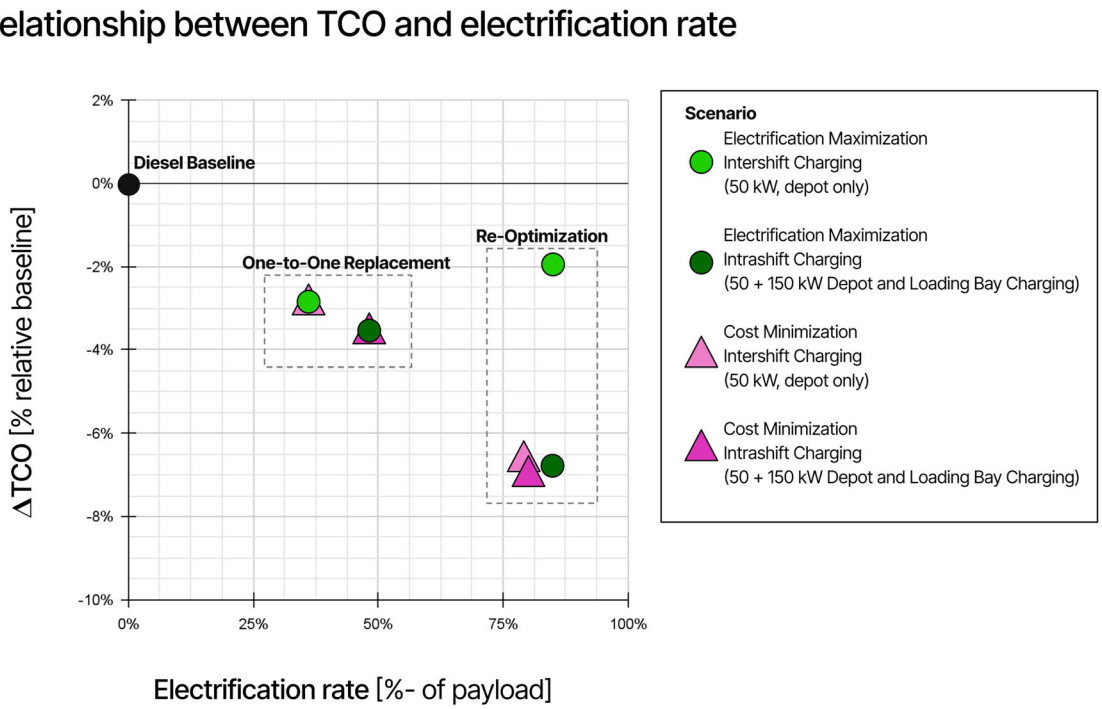


Fig. 1 | Relationship between change in fleet-level TCO and electrification. TCO is indexed relative to the diesel baseline and electrification rate is shown as share of payload operated by electric trucks, separated by charging scenario and optimization objective. Scenarios are coded as follows: black circle for the diesel baseline, green circles for electrification maximizing, pink triangles for cost-minimization.

higher electrification rate is consistent across all electrification metrics, charging setups, and optimization objectives (see Table 1). Overall, the re-optimization enables the electrification of 51–55% of tonne-kilometers, 49–55% of mileage, and even 79–85% of payload, depending on scenario and objective. These results compellingly indicate that mapping the operational patterns of diesel fleets to mixed electrified fleets with one-to-one replacement introduces significant sub-optimalities that inhibit the technical feasibility of electric trucks beyond their technical capabilities. In other words, the electrification rate is not constrained by, e.g. a lack of charging infrastructure or range, but by a lack of planning capabilities that take into consideration electric trucks' techno-economic characteristics. Thus, re-optimizing fleet operations is a key lever for achieving higher electrification rates.

Re-optimization reduces fleet TCO due to higher utilization and specialized operations

The greater energy efficiency of electric powertrains, relative to internal combustion of diesel, directly translates into energy cost savings[9–11], which is seen in both electrification approaches across all scenarios. However, potential cost reductions are contingent on whether or not the electric trucks achieve high enough utilization to amortize their higher fixed costs. The results show that the re-optimization approach, compared to one-to-one replacement, not only achieves substantially higher electrification rates, but also a significantly greater reduction in fleet TCO by reducing operational expenditures (see Supplementary Table 1 in the supplementary information). Comparing the best cost-minimizing scenario for each approach shows that re-optimization doubles the TCO reduction over the 8-year holding period, from a 3.5% to 7.0% (see Fig. 1). Similarly to electrification rates, mapping diesel fleet operations to mixed electrified fleets inhibits how well the electric trucks can be utilized, thus limiting their economic performance as well. The heterogeneity of operational patterns within the fleet further corroborates this, demonstrating that, in order to achieve high enough utilization, not only do electric trucks require distinctly different operational patterns than diesel trucks, but that the introduction of electric trucks also causes the operational planning of the diesel trucks in the fleet to change and adapt. This suggests that specialization in operations between powertrains is an emergent property of fleet electrification.

For one-to-one replacement the optimization objective, i.e. whether the replacement prioritizes electric trucks or only prioritizes cost, has no effect on the outcome. In other words, for one-to-one replacement, every truck that was technically feasible to electrify was also cost-effective to electrify, which would indicate that it is technical feasibility rather than economic feasibility that is the limiting factor when replacing one-to-one. Re-optimization, however, does exhibit a trade-off between minimizing cost and maximizing electrification rates when intrashift charging at the loading bays is not available. When considering the possibility to charge at the loading bays in addition to the depot however the electrification maximization objective and the cost-minimization objective perform similarly, with only a slight increase in cost associated with a ~ 5% increase in electrification rates.

Notably however, both objectives still lead to significant cost-reductions relative to the diesel baseline. The only scenario where re-optimization leads to a higher cost than one-to-one replacement is with the intershift charging setup with 50 kW between shifts and with electrification maximization as the objective, where this increase in cost is associated with the optimizer increasing fleet size to follow the electrification maximization constraint and reach comparable electrification metrics as the intrashift charging scenario (see Table 1). The benefit of having access to chargers at the loading bay is thus that each truck can reduce the amount of time spent charging by coordinating it with loading and therefore spend more time driving and delivering shipments. This translates to distinct improvements depending on the planning approach: for one-to-one replacement, it increases feasibility, significantly raising the electrification rate; for re-optimization, it improves utilization, allowing the same transport work to be covered by fewer vehicles, thereby driving down the total fleet cost.

For the one-to-one replacement approach, charging setup has a minor effect on cost, but the additional charging infrastructure at the loading bays is needed to meet the energy requirements of the diesel truck schedules and replace more of them. Re-optimization however is not reliant on this additional charging infrastructure as it is able to account for this by adapting

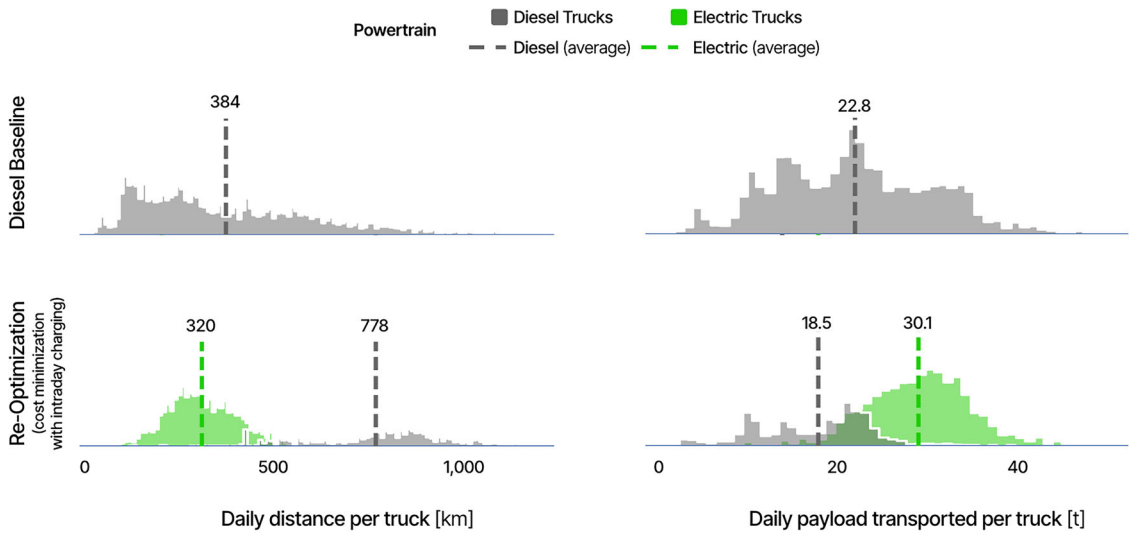


Fig. 2 | Distance driven and payload delivered distributions for electric and diesel trucks. Daily distance driven and daily payload transported for the diesel baseline and re-optimized cost minimization scenario with intrashift charging.

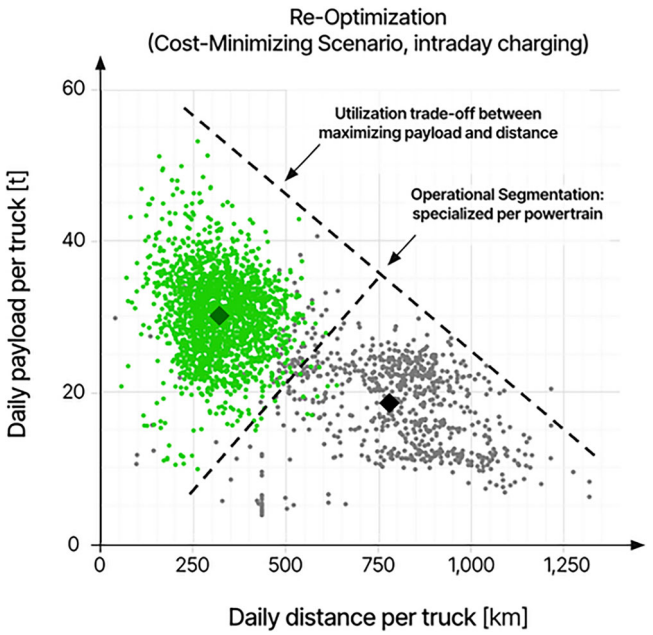


Fig. 3 | Scatterplot showing the utilization trade-off between daily payload delivered and daily distance driven. There is clear operational segmentation where electric trucks deliver higher payloads and drive lower total distances while diesel drives longer distances with lower payloads. Electric trucks marked in green, diesel trucks in gray, and averages for each powertrain marked.

the operational planning to accommodate longer charging times, particularly for the cost-minimizing scenario where the difference in fleet TCO and electrification rates are negligible. For the electrification maximization scenario without intrashift charging however, re-optimization required a substantially larger fleet to follow the constraint and ensure that as many shipments are delivered electrically as possible in the absence of chargers at the loading bays, thus sacrificing a significant amount of cost-reduction.

Operational heterogeneity as an emergent property of electrified fleets

Re-optimization leads to distinctly different operational patterns for both electric trucks and diesel trucks relative to the diesel baseline and one-to-one replacement scenarios. One-to-one replacement of trucks behaves as expected; routes that are short enough in terms of range and energy requirements that an electric truck can feasibly serve them yet also long enough that the lower energy costs can amortize the higher capital costs of electric trucks, are deemed electrifiable. Re-optimization however changes the characteristics of the operational plans for both powertrains. These changes in operational patterns are necessary in order to effectively utilize both the electric and diesel trucks[21], and there is a clear segmentation between 1) frequent deliveries, high volumes/payload, but low mileages for electric trucks and 2) fewer shipments delivered, lower volume/payload but higher mileages for diesel trucks (see Fig. 2). This segmented utilization indicates that the electric trucks specialize in delivering the bulk of the shipments within their operational range with frequent fully loaded trips, taking advantage of their superior energy efficiency to reduce operational costs. Diesel trucks on the other hand are dedicated to the more distant sites that generate more deadhead and empty miles, and thus instead are optimized for efficiently traversing the edges of the network between these farther-apart sites.

The operational heterogeneity can be seen as a consequence of two main constraining factors: time and energy. In order to minimize costs, the trucks ideally need to utilize their time on productive tasks such as loading shipments, driving, and delivering shipments. For both electric and diesel trucks, this provides some trade-off between delivering shipments that are farther away (more time spent driving that cannot be spent loading and unloading) or delivering a greater number of shipments. The former is limited by maximum driver duration per shift and day and, in the case of electric trucks, energy constraints. While the battery capacity limits how far the vehicle can drive in one tour, it also limits how much time can be spent on both driving (i.e. consuming energy) and loading/unloading shipments by increasing the time needed for charging. Even with sufficient range to reach a remote delivery, it might not be cost efficient when accounting for how much time needs to be spent charging before the next trip can be made. Thus, the lower energy requirements over the course of the shift when delivering a greater number of shipments becomes a more cost-efficient use of the electric trucks' operational time.

While this type of segmentation has been suggested in previous literature[20], it was with the consequence that the electric trucks have far lower utilization. However, this does not necessarily take into account the more nuanced view on truck utilization which, as shown in Fig. 3, can be viewed as a frontier between distance and payload. Even if a tour is within range of an electric truck, and sufficiently long to amortize the fixed cost, it might not be worth electrifying if it requires too much charging for the next delivery to be efficiently served within the shift. We show that re-

optimization of operational planning can solve this issue and achieve a high utilization of electric trucks, in particular when it comes to the amount of delivered shipments. Thus, while electric trucks may exhibit low mileage-based utilization and diesel trucks low payload-based utilization, this heterogeneity is required in order to obtain a system-level optimum for, and is an emergent property of, mixed fleets with high degrees of electrification.

Discussion

This study demonstrates how two distinct electrification approaches affect the technical and economic feasibility of heavy-duty electric trucks by comparing one-to-one replacement with re-optimization strategies. This comparison of methods applied to a large, regional grocery retail network in Northeastern Germany provides several significant findings: (1) Re-optimization enables substantially higher electrification rates than one-to-one replacement across all metrics. Maintaining the operational patterns and schedules of diesel trucks by replacing them one-to-one with electric trucks artificially inhibits their performance, both in terms of how much can be electrified and their cost performance. (2) Re-optimization of truck schedules achieves double the cost reductions relative to one-to-one replacement. This is achieved by taking into account the technical and economic characteristics of electric trucks and adapting the schedules and shipment allocation of both electric and diesel trucks to optimize utilization. (3) While one-to-one replacement is reliant on access to additional charging infrastructure to increase electrification rates and lower costs, re-optimization can compensate for charging infrastructure by adapting the truck schedules. Thus, the electrification approach, i.e. if re-optimization is used instead of one-to-one-replacement, is the most significant lever for electrifying heavy-duty freight. (4) Optimal utilization of electrified fleets containing both electric and diesel trucks exhibits operational heterogeneity, where electric and diesel trucks specialize in different and clearly segmented operational patterns. Notably, this indicates that large-scale electrification does not just require that electric trucks be operated differently than current diesel trucks, but that diesel trucks will also need to adapt their operations as fleets are electrified.

These novel findings indicate that previous studies and analyses on electrification based on historical diesel truck operations may in many cases underestimate both the technical feasibility and economic performance of electric trucks. The large discrepancy between optimal operational patterns for diesel fleets and mixed electrified fleets shows that extrapolating current diesel operations as indicative of electrified fleet operations introduces sub-optimalities into the schedules of the electric trucks, a finding corroborated by Zackrisson et al. [21]. Because previous studies have not considered the discrepancy between optimal diesel fleet operations and optimal mixed diesel-electric fleet operations, they instead inconclusively conclude that factors such as faster charging, longer range, or lower CAPEX are prerequisites for electrification[21]. Previous studies may therefore have overestimated the importance of improving range, battery costs, etc. by not differentiating between when these factors actually improve techno-economic feasibility and when they merely compensate for inefficient planning.

Furthermore, by not taking into account how diesel operations can be changed to accommodate electric operations, a key lever for increasing electrification rates and reducing costs is left out. By consolidating electrifiable shipments from multiple different diesel trucks, the schedules can be restructured such that fleet operations become more energy efficient, thus lowering the total costs. Creating schedules according to the transport demand itself, as this study did with the re-optimization approach, provides significant improvements in both cost and electrification rates that are not realizable with one-to-one replacement. This suggests that higher electrification rates can be achieved through better optimized planning rather than relying on the market to supply better and cheaper trucks and charging hardware.

For fleet expansion planners, the results indicate that the capability to optimize mixed fleet operations is a key enabler of accelerating the transition to electric vehicles in the heavy-duty sector. While experienced dispatchers can rely on intuition for managing homogenous diesel fleets due to their high operational flexibility, the introduction of electric trucks introduces interdependencies between range, payload, charging windows, and diesel trucks. The complexity of managing these constraints grows non-linearly with fleet size. In a network of this scale (~150 trucks and 38,000 shipments), relying solely on human dispatching or one-to-one replacement logic is unlikely to capture the efficiency gains of mixed fleets due to the computational intractability of manually balancing thousands of interdependent constraints. Consequently, successful large-scale electrification likely requires the adoption of algorithmic planning tools to support dispatchers in managing these new complexities.

While the study is based on real-world data and high-resolution simulated operations, it includes simplifications that may limit direct transferability. The data represents a specific month (February 2021), and the extrapolated fleet-level TCO assumes that the operational patterns remain representative over the holding period of eight years. Additionally, the optimization does not account for frame-route planning; pre-planned routes to simplify planning and efficiently serve consistent demand patterns, which, due to the relatively predictable and consistent demand patterns of grocery retail, are commonly used in their logistics planning. Furthermore, the optimization does not consider fluctuating or limited driver availability. Another aspect is the practical applicability of producing operational plans a priori. For the grocery retail case analyzed in this study, store replenishment orders are placed in advance making nightly pre-planning standard industry practice. However, in other logistics use cases with higher volatility in shipment demand or more frequent ad hoc pickup requests, pre-optimized plans may require adaptations. While our study dimensions the fleet based on known demand, real-world implementation would likely require operational buffers (e.g. spare vehicles or slack in schedules) to ensure robustness against spontaneous changes. Further investigations into robustness analyses and dynamic re-optimization to handle intraday disruptions are left for future work.

Furthermore, a broader spectrum of more modern or future vehicle configurations and battery capacities, potential store-based destination charging, or restrictions on additional grid connection at the depots that might limit the maximum charging power, are left unexplored. Particularly due to the study case setting being based on data from 2021, including the truck parameter specifications which have since then been improved, it is likely that the current rapid rate of advancements in battery technology leads to even further cost-savings and higher electrification rates. Recent meta-analysis indicates that heavy-duty battery system costs are projected to decline by 64% to 75% by 2050, driven by annual cost reductions of approximately 5–6.5% through 2030[22]. These rapid advancements suggest that battery costs could fall below €150 kWh^{-1} by 2035, significantly accelerating the economic viability of electric fleet adoption. However, these limitations are applied consistently across all scenarios and thus do not bias the comparison between the electrification strategies of one-to-one replacement and re-optimization. As such, the study's limitations may affect the scale but not the direction of the observed benefits of re-optimization. Additionally, the scope of the analysis could be extended to include the intelligent exploitation of flexibilities in grid capacities into the optimization model, such as the integration of PV energy generation, stationary battery storage, vehicle-to-grid applications, or dynamic grid pricing, which we leave for future research.

For one-to-one replacement, the most significant factor affecting the results between scenarios is the charging setup. Adding 150 kW charging during cargo loading improves both cost and electrification rate since it allows more tours, and thus also trucks, to operate electrically and increases the average utilization of electrifiable trucks (with battery capacities ranging from 200 to 450 kWh in this case setting). This highlights that evaluating technical and economic feasibility of electrification with one-to-one replacement may misrepresent which factors should be prioritized for electrification. With re-optimization however, the electrification rate is far less dependent on faster and more available charging (at the loading bays) due to being able to take into account the available charging infrastructure when

generating optimal fleet compositions and schedules. However, access to faster charging enables higher electric truck utilization and thus reduces the fleet size which reduces total fleet costs. Both scenarios do however align with previous results such as Speth & Plötz[23] which show that intershift charging at the depot alone is able to support high degrees of electrification without public chargers available. While this study did not consider public charging infrastructure for enroute charging, it is likely that the availability of such would positively affect the upper bound of what can be electrified within the network by providing additional range, however the economic effect may be more modest considering the higher costs of public charging relative to depot charging. Another form of charging infrastructure which could be explored in the case context of grocery retail is the installment of chargers at certain store locations, thus providing private enroute charging which can be combined with making deliveries.

The extent to which the results and findings are generalizable to other locations, industries, or networks depends on the characteristics of the transportation demand being fulfilled. The findings of this study are based on data from one of Germany's largest grocery retailers' regional network in Northeastern Germany, with over 38 000 shipments, over 1 million kilometers driven, more than 500 stores, and 2 distribution centers over the period of one month. The grocery-retail segment has characteristics that are rather favorable for electrification[24]; the transportation demand is quite stable and predictable, all the trucks return to their depot each night, and the volume and weight of the shipments rarely exceed the capacity of the electric trucks that are more limited due to heavy and bulky batteries. Furthermore, previous research has shown the size of the network to be correlated with electrification potential[21], and smaller networks might therefore have lower electrification rates than the case in this study.

The operations are also consistently less-than-truckload (LTL) which means that the solution space for how shipments are assigned to vehicles is large and provides ample room for optimization algorithms to identify efficient solutions. Consequently, the specific quantitative results are likely not directly generalizable to long-distance full-truckload (FTL) logistics. The qualitative findings regarding the trade-off between planning and hardware however require nuance when applied to FTL. In repetitive, dedicated line-haul FTL scenarios where each truck must travel from origin to destination, the operational flexibility is low. In such cases, the "re-optimization" potential is limited to solution design (e.g., battery sizing and charger placement) rather than daily routing. Here, the technical constraints of the hardware likely make hardware improvements more significant than algorithmic planning. However, for irregular FTL operations (e.g., carriers operating on load boards or spot markets), the complexity shifts from routing to shipment selection. While the route itself is fixed, the decision of which shipments to assign to an electric truck versus a diesel truck becomes a higher-dimensional optimization problem similar to the LTL case in this study. In this context, our finding that algorithmic planning significantly impacts economic feasibility likely holds true, as the "re-optimization" would focus on matching EV-compatible loads to the electric fleet to maximize utilization, rather than consolidating shipments into multi-stop tours. Thus, while the mechanism of optimization differs between LTL and varying FTL use cases, the necessity of adapting operational planning to the specific constraints of mixed fleets remains a universal requirement for successful electrification.

Thus, while the aforementioned characteristics of the case-study might affect the magnitude and scale of the results, it is highly likely that the comparative difference between the methods employed in this study, one-to-one replacement and re-optimization, will hold for other networks and industries as well with the exception of simpler FTL shuttles and line hauls. We can thus generalize the main findings that optimizing shipment demand according to the characteristics of mixed electrified fleets is necessary to fully realize the technical and economic potential of electric trucks and that divergent and segmented operational patterns are an emergent property of fleet electrification. For future research, other types of road freight can be considered, to validate the extent of which the observed effect of re-optimization can be generalized to other settings.

Methods

Research design

To compare the performance of one-to-one replacement and re-optimization, a baseline for optimized diesel-fleet operations is first computed using a vehicle routing problem (VRP) solver. This baseline scenario is used to benchmark the two electrification approaches and to serve as the basis for the one-to-one replacement using a greedy sequential assignment heuristic. The re-optimization approach is computed using a proprietary commercial electric vehicle routing problem (EVRP) solver. Furthermore, each of the two electrification approaches are evaluated for two charging-setups; with only low-powered intershift charging at 50 kW between driver shifts at the depot, and intrashift charging with additional higher-powered charging at 150 kW available at the loading bay while loading. Finally, two electrification objectives are considered: electrification maximization and cost minimization. The former has the hard constraint that electric trucks must be used when possible, even if that would incur higher costs, while the latter only considers cost. The performance metrics used to evaluate the scenarios are 1) the TCO of the entire fleet including the charging infrastructure based on an 8-year holding period and 2) electrification rates measured in fleet composition, payload, mileage, tonne-km, and volume. The data and methods used are further described in subsequent sections, with Fig. 4 depicting the overall research design.

Data

Several datasets are used for the study, see Table 2 for an overview. The first dataset, *raw shipment data*, includes data on all deliveries performed during February 2021 for a large grocery-retailer within a region corresponding to Northeastern Germany (see Fig. 5). This data is specified on a per-store basis with each row specifying the cargo delivered to a store on a given day, including assortment type, weight, volume, and origin-destination pairs. The distribution of the shipments' mass is given in Fig. 6. The *site data* contains locations for each of the stores and distribution centers as well as truck type accessibility i.e. the largest truck type which can physically access the site. To account for time window constraints, *delivery time windows data* was used describing the earliest and latest possible delivery time for each site. However, due to this dataset not being available for February 2021, a dataset with time windows for 2023 is used instead. Parameter values for cost models, energy models and associated truck-type specific parameters are adapted from Link et al.[9] which studied the same regional network. Finally, *path data* was computed for all origin-destination pairs using HERE maps[25] with any missing paths interpolated using a weighted haversine distance[26].

Total cost of ownership

The cost model and its parameters are adapted from Link et al.[9] for the EVRP solver according to Engholm et al. [27] and converted into a net present cost (NPC) model[28] that considers the time value of money by discounting the cashflows. The costs are given by Eqs. 1 through 9 where $CAPEX_v$ and $OPEX_v$ represent the capital and operational expenditures for vehicle v, and $TCO_{CS,v}$ denotes the allocated infrastructure cost. The term c_v^{acq} is the acquisition cost, $r_v^{residual}$ the residual value as a ratio of the acquisition cost, and i the interest rate. Operational terms include energy price c^{kWh}, maintenance $c_v^{maint.}$, and driver wages c^{wage}. For a complete definition of all variables and parameter values, see Supplementary Tables 3–6. The capital expenditures comprise acquisition costs and residual value (see Eq. 3). The scenarios in this study consider acquisition costs including the 'Climate-friendly commercial vehicles and infrastructure' (German: *Klimaschonende Nutzfahrzeuge und Infrastruktur*, KsNI) subsidy program and direct manufacturing costs for truck components. Residual values for each vehicle type and power train configuration are based on empirical data from the case-study network and lifespan projections. Operational expenditures comprise energy costs (Eq. 5) based on energy consumption (Eq. 6), driver costs (Eq. 7), maintenance costs, and toll-road costs (based on empirical data). Electric trucks are assumed to operate with reduced toll costs on certain roads. Until the end of 2025, electric trucks were fully exempted from the German LKW-Maut road tolls. At the time of writing this paper, details

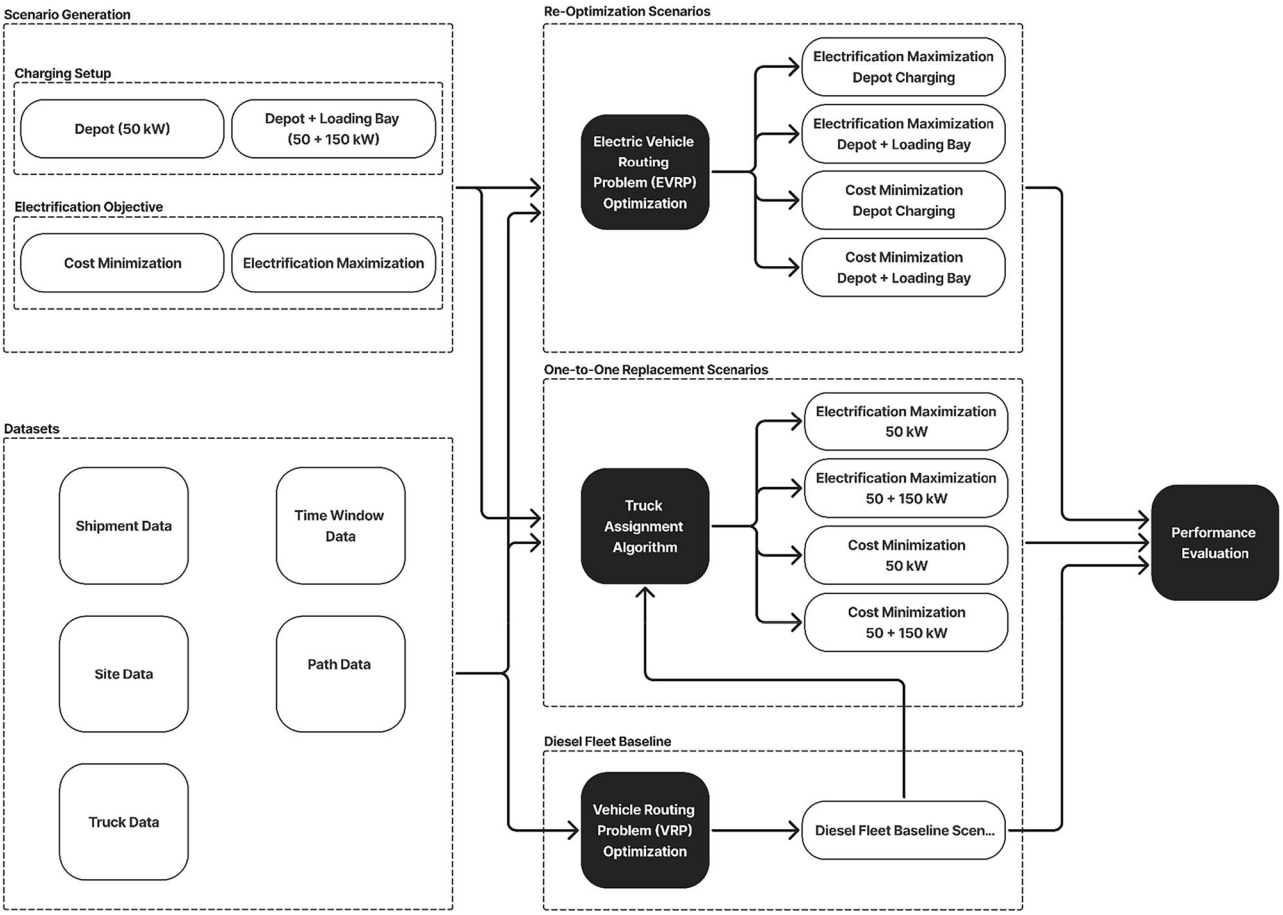


Fig. 4 | Overview of research design. Scenarios defined by 1) electrification approach, 2) optimization objective, and 3) charging setup.

Table 2 | Key datasets used in the study.

Dataset	Relevant data
Raw shipment data	HomeDC, siteID, date, tourID, volume, assortment type distribution and loading, unloading and setup at store time for all shipments
Site data	SiteID, location and truck type accessibility for all stores and distribution centers (DC).
Delivery time windows data	Delivery window for all assortment types per store and weekday
Refined shipment data	HomeDC, siteID, date, tourID, volume, assortment type distribution, loading and unloading time and payload and delivery window for all shipments
Path data	Origin, destination, distance, driving time, energy requirements

about electric trucks tolls from 2026 and onwards were uncertain. The TCO calculations in this study thus assume a full toll exemption for electric trucks during the first five years and then the same tolls as diesel trucks for the last three years of the assumed eight year holding period, as per Link et al. [9]. At the time of publishing, this exemption has been extended by the German government until the mid-2031.

Energy costs are based on each individual truck's total energy consumption. The cost of charging infrastructure is allocated according to the operational requirements of the fleet a posteriori for both one-to-one replacement and re-optimization. Additionally, vehicle payload capacity is calculated for each vehicle type according to their battery capacity and battery weight, while also including the increased allowance for zero-emission vehicles of an additional 2 tonnes of gross combination weight rating as per EU regulations. The input to the EVRP solver, which provides the optimal operational and strategic decisions of the LSP, is based on the total non-discounted cash outflows including annuity payments for a debt-financed fleet in order to accurately represent the trade-offs that the LSP make between fixed and variable costs. While the NPC values are lower than their undiscounted annuity-based counterpart, the relative ranking of the scenarios considered are unchanged (see Supplementary Table 2). Thus, the cost parameter values used for each daily instance of the EVRP solver has the capital cost divided into per-day values (Eqs. 11–12) with the assumption that the trucks have a mean utilization γ_t of 6 days a week, 50 weeks a year over their eight-year holding period.

$$TCO_v = CAPEX_v + OPEX_v + TCO_{CS,v}, v \in Fleet, CS \in DC \quad (1)$$

$$TCO_{CS,v} = \sum_{CS \in DC} \frac{CAPEX_{CS} + OPEX_{CS}}{N_{CS}} x_{CS,v}, v \in Fleet \quad (2)$$

$$CAPEX_v = c_v^{acq} - \frac{c_v^{acq} r_v^{residual}}{(1+I)^{HP}}, v \in Fleet \quad (3)$$

$$OPEX_v = \sum_{t \in HP} \frac{c_v^{energ.} + c^{driv.} + c_v^{ann.} + \sum_{(i,j) \in E'_v} (c_v^{maint.} + c_v^{toll}) d_{ij}}{(1+I)^t}, v \in Fleet, E'_v \subseteq E \quad (4)$$

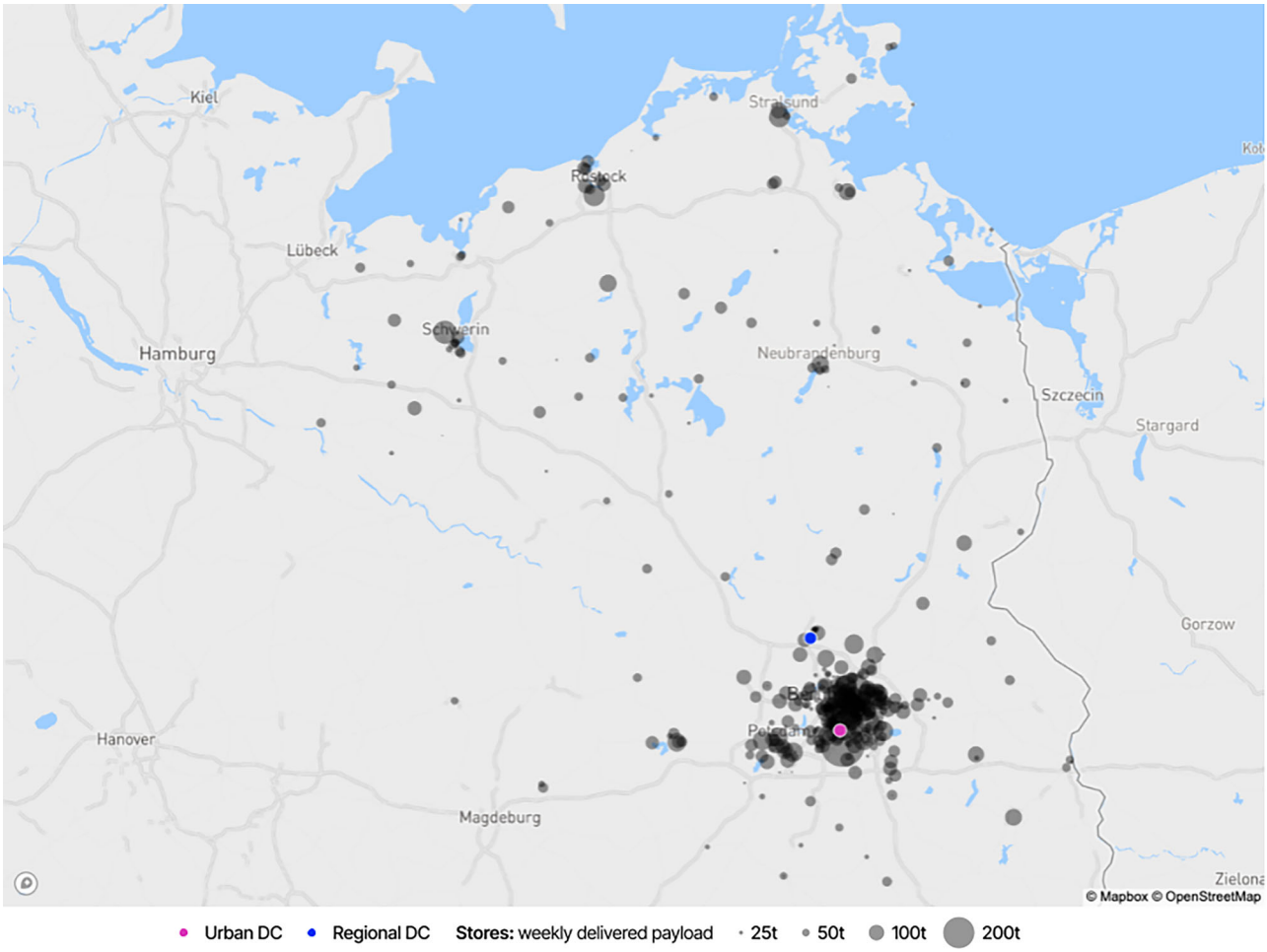
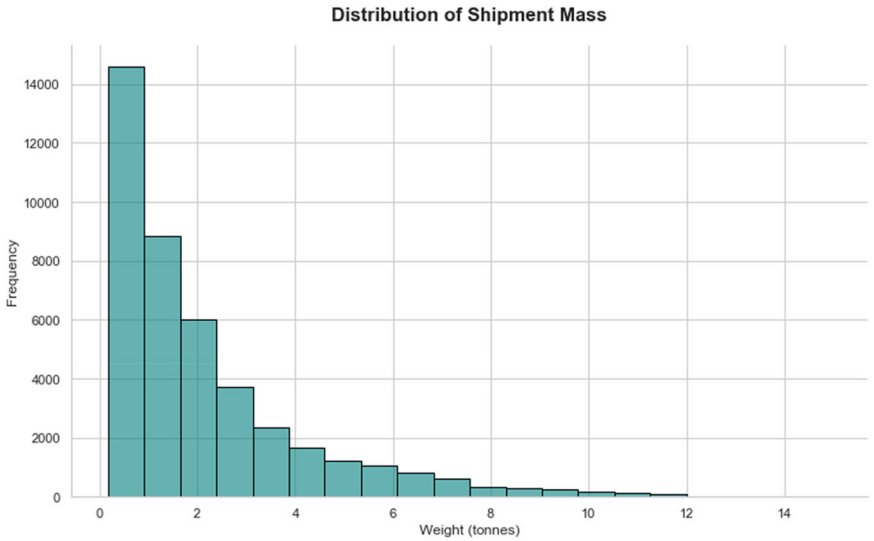


Fig. 5 | Map of Northeastern Germany showing the geographical distribution of shipment demand. Locations are sized according to the mean number of tonnes of goods delivered weekly. Map data courtesy of © Mapbox, © OpenStreetMap contributors.

Fig. 6 | Histogram of shipment mass in tonnes. Individual shipments in the dataset of 38,000 shipments range from 0.1 to 15 tonnes with a median of 1.1 tonnes.



$$c_v^{energy} = \sum_{(i,j)\in E\prime_v} c^{kWh} EC_\tau, v \in Fleet, E\prime_v \subseteq E \quad (5)$$

$$EC_\tau = \sum_{(i,j)\in E\prime_\tau} (e_v^{empty} d_{ij} + e_v^{aux} s_{ij} + e_v^{payload} p_{vij} d_{ij}), \tau \in T_v, v \in Fleet \quad (6)$$

$$c_v^{driver} = \sum_{(i,j)\in E'_v} c^{wage}(s_{ij} + s'_i + s'_j + s'_{ij}), v \in Fleet, E'_v \subseteq E \quad (7)$$

$$r_v^{residual} = \min\left(a_v e^{\left(b_v \sum_{(i,j)\in E'_v} d_{ij}\right)}, \frac{30}{100}\right), v \in Fleet, E'_v \subseteq E \quad (8)$$

$$CAPEX_{CS} = c_{CS}^{acq} - \frac{c_{CS}^{acq} r_{CS}^{residual}}{(1+I)^{HP}}, CS \in DC \quad (9)$$

$$OPEX_{CS} = \sum_{t\in HP} \frac{OPEX_{annual}}{(1+I)^t} \quad (10)$$

$$CAPEX_v^{daily} = \frac{CAPEX_v \frac{I(1+I)^{HP}}{(1+I)^{HP}-1}}{\gamma_t}, v \in Fleet \quad (11)$$

$$CAPEX_{CS}^{daily} = \frac{CAPEX_{CS} \frac{I(1+I)^{HP}}{(1+I)^{HP}-1}}{\gamma_t}, CS \in DC \quad (12)$$

EVRP for re-optimization and diesel baseline

To accurately model such a large-scale problem's constraints and solve it in a tractable manner while balancing realism and complexity, we use a proprietary commercial metaheuristic EVRP and VRP solver developed by Einride. The solver is developed and used for real-world industry applications to generate feasible, high-quality solutions for optimizing mixed fleet size and composition, shipment allocation, routing, and charging scheduling. It minimizes the defined cost objective while rigorously enforcing all operational constraints. The solver can be configured with two objective functions: either prioritizing the assignment of shipments that are within range of electric trucks available to them or pure cost minimization. While a global fleet size and composition optimized over the entire planning horizon is theoretically possible, it is computationally intractable due to the very large instances, the large number of vehicle types, varying interchangeability or complementarity between vehicle types, and the long planning horizon. Thus, to manage the computational load, the planning horizon is split into daily sub-problems that are solved independently. Since the optimal fleet composition varies between daily instances, we dimension the size and composition of the fleet for the full month heuristically according to the optimization objective. For electrification maximization, we identify the minimum fleet size and composition required to deliver all shipments for the five days with the highest shipment demand. The fixed cost of using the vehicles in this fleet is then set to zero (considering them already purchased) and then used as input for the optimization of the entire planning horizon. Should a shipment be unable to be delivered, the optimizer then has the option to add additional vehicles to the fleet at their original fixed cost. This is done to ensure that non-electrifiable shipments are not falsely flagged as such due to vehicle type requirements. For cost minimization, the fleet is dimensioned according to the mean number of each vehicle type required for the five days with the largest fleet size requirement. For both objectives, the final dimensioned fleet is run for the entire month to ensure that the fleet composition is indeed feasible for the given time period. By accounting for the peak demand and vehicle type constraints, this provides an effective approximation of a global optimum for the fleet composition while still remaining tractable. For each scenario, we obtain the daily optimized plans and fleet requirements. The average utilization per truck type is used as input together with the final fleet composition to evaluate performance.

One-to-one replacement

For the one-to-one replacement, a baseline diesel fleet plan is needed to serve as a basis for the replacement, and thus to ensure a fair comparison an optimized diesel baseline is derived with a VRP solver. The VRP solver provides optimized truck schedules for each day to meet that day's transportation demand given the provided fleet. This provides a highly detailed and optimized fleet schedule and allows for the fleet TCO and electrification rate to be accurately quantified. However, while the VRP solver is used to solve daily instances, each daily plan is allocated to a specific vehicle. As such, the schedules are interchangeable between trucks of the same vehicle type and home distribution center (DC). However, the assignment of daily schedules to each truck can impact the one-to-one replacement analysis and negatively affect the electrification rate, since assigning a single non-electrifiable daily schedule to a vehicle with otherwise only electrifiable schedules (in terms of range, payload constraints, and sufficient time for charging) would render it "non-electrifiable". Additionally, the assignment of schedules can affect the truck-level TCO performance of the individual vehicles if assigned in such a way that a vehicle has significantly lower utilization than the others. Such an imbalanced assignment can result in fewer vehicles being economically electrifiable.

To address this, we employ a greedy sequential assignment heuristic to assign the daily truck schedules while considering electrifiability and utilization. The algorithm takes the set of pre-computed daily tours for the entire planning horizon as input. It initializes the fleet of vehicles and iterates chronologically through each day, assigning each tour to the most suitable available vehicle based on a set of prioritization rules. The primary goal of the rules is to avoid assigning non-electrifiable tours to vehicles with electrifiable tours and vice versa assigning electrifiable tours to vehicles with non-electrifiable tours, thus maximizing the number of vehicles that are classified as fully electrifiable. The secondary goal is to balance vehicle utilization by prioritizing assignments to vehicles such that utilization is evenly distributed across the fleet. To evaluate the two different optimization objectives, the replacement algorithm can either include or exclude the economic feasibility condition that the electric truck must perform its assignments at a lower cost than an equivalent diesel truck. The pseudocode for the algorithm is given in Algorithm 1.

Data availability

The data that support the findings of this study are available from the corresponding author upon reasonable request, with the following restrictions: Shipment and Site Data: The raw shipment lists and site locations were provided by the retailer REWE under a Data Use Agreement and are not publicly available due to commercial confidentiality and privacy restrictions. Map and Path Data: The road network and travel time data were calculated using the HERE Maps API, which is a commercial third-party service. Restrictions apply to the availability of these data, which were used under license for the current study, and so are not publicly available.

Code availability

The code used for the EVRP solver is not available due to proprietary reasons. The code developed for this study to perform the analysis is not publicly available for legal reasons but can be made available from the corresponding author on reasonable request.

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Author contributions

Conceptualization: A.Z, A.E., and T.B.; Methodology: A.Z, A.E., and T.B.; Software: A.Z, A.E., T.B., and S.L.; Writing—original draft: A.Z, A.E., T.B., and P.P. Writing—review & editing: A.Z, A.E., T.B., S.L., and P.P. All authors have read and approved the final manuscript.

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Competing interests

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Additional information

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