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How optimization-driven planning enables large-scale electrification of heavy-duty freight

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Executive Summary

Previous studies using operational data for diesel trucks to assess electrification potential may underestimate by not accounting for scheduling and planning according to battery-electric trucks' characteristics. By instead using a novel demand-centric optimization-driven electrification planning approach tailored for electric truck fleets, the electrification potential may be increased; the question is to what extent. This study quantifies the benefits of using data-driven optimization tools for the design and planning of BET fleets by analyzing how optimization-driven fleet design, routing and charging planning can improve electrification potential in a large real-world distribution network compared to a 1-to-1 replacement approach. The results show that the optimization-driven approach increases electrification rates across all metrics while also lowering total cost of ownership.

Keywords: Heavy Duty Electric Vehicles & Buses, Intelligent Transportation Systems for EVs, Modeling and Simulation

1 Introduction

The transition to low-emission road freight is critical for achieving climate neutrality due to the significant amount of emissions caused by the transport sector [1]. Heavy-duty battery electric trucks (BETs) offer significant potential for reducing greenhouse gas emissions, and have been identified as a key pathway towards decarbonization [1, 2]. However, BETs face numerous barriers to widespread adoption 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 [2, 3, 4] which neccesitates dedicated charging infrastructure and scheduling, thus adding significant complexity to fleet management [5, 6, 7]. Supporting large-scale truck fleet electrification requires an understanding of how BETs can be efficiently integrated and operated at the fleet level, and how electrification affects overall fleet design and transport operations relative to conventional diesel-driven fleets.

However, an operational plan designed for ICETs is likely sub-optimal when introducing BETs due to their different constraints and cost structures. To account for this, the analysis must explicitly consider the techno-economic characteristics of BETs by using optimization techniques to redesign truck fleets and replan transport operations, an approach we denote as ”replanning”. This approach could potentially increase the achievable electrification rate by incorporating factors such as range constraints and charging scheduling directly into routing and fleet design. However, the extent to which such a replanning approach quantitatively outperforms directly substituting vehicles in a real-world setting has not been systematically quantified. Understanding the magnitude of these potential benefits is important for fleet owners weighing the complexities of transitioning toward optimized electric fleet operations.

This study investigates how a replanning approach incorporating fleet design, routing, charging scheduling, and shipment-to-truck allocation can enhance large-scale electrification, specifically within grocery retail distribution. This replanning approach aims to maximize the system's overall efficiency by explicitly modeling range limitations, charging requirements, and cost structures of both BETs and ICETs and using them as input to an electric vehicle routing problem (EVRP) optimization algorithm can provide detailed operational plans for a mixed fleet.

The aim is to compare the fleet-level electrification potential identified by 1:1 replacement and replanning. Thus, this study addresses the following research question: how does an optimization-driven replanning approach for heavy-duty fleet electrification compare with a 1:1 replacement approach in terms of (1) technical feasibility (measured in electrification rate) and (2) cost performance (measured in total cost-of-ownership (TCO)).

The comparison is made using a real-world case study of a large grocery distribution network in North-East Germany, which was previously analyzed in a 1:1 truck replacement study [8]. This study extends the 2021 study by analyzing the same transport network and demand, applying the same key assumptions for transport supply, costs, and parameter settings, and recreating the 1:1 analysis in addition to conducting a replanning analysis, thus allowing for a direct comparison between the two electrification approaches.

2 Background

Much of the early techno-economic analysis of BETs focused on vehicle-level Total Cost of Ownership (TCO) comparisons [9, 10, 11, 12, 13, 14]. While useful for establishing basic economic principles, such vehicle-level analysis may not sufficiently capture the complexities fleet owners face. It often overlooks fleet-level synergies, operational heterogeneity (e.g., wide variations in daily mileage across vehicles), and the system-wide impact of integrating vehicles with different operational needs like charging [6]. Later studies conducting fleet-level analyses often rely on simplified metrics, such as calculating costs per vehicle-kilometer or tonne-kilometer based on average utilization derived from existing ICET fleets [15, 16, 17, 18] which can obscure the impact of vehicle-specific utilization patterns, potentially misrepresenting both the challenges and opportunities of BET integration for individual fleet owners.

An alternative and more data-driven approach to these analyses is to assess technical and economic feasibility with a ”one-to-one” (1:1) replacement approach. This involves using historical operational data of ICET fleets to evaluate whether existing routes and schedules can be performed by an equivalent BET given range and charging constraints. One such study was conducted using high-resolution real-world data for a German grocery retail distribution network's ICET fleet [8, 19]. While this and other similar approaches [20] benefit from the analytical simplicity of analyzing each truck individually with minimal disruptions to fleet planning and operations, it does not consider the potential benefits of changing the operational planning itself. Thus, analyses using the 1:1 truck replacement approach are potentially significantly underestimating the technical and economic feasibility of electrification. Consequently, fleet owners using a 1:1 truck replacement approach to electrify their fleet might limit or delay electrification to perceiving the feasibility to be lower than it actually is.

To our knowledge, no study has yet directly compared the 1:1 approach with the optimization-driven replanning approach, and there is thus a need to quantify the potential benefits of such an approach. This study thus directly addresses this gap by comparing both approaches using identical network data, demand profiles, and technological assumptions.

3 Methodology

This study is based on a real-world case study of a grocery distribution network in north-eastern Germany, which was previously analyzed in a 1:1 truck replacement study by Link et al. (2021), from here on referred to as the 2021-study. To compare the replanning and 1:1 replacement approaches, both are applied to the analysis of the same real-world distribution network. Additionally, the original diesel fleet is also replanned with VRP for comparison. The results are then compared in terms of the achieved electrification rate and cost performance. This study analyzes the same transport network and demand while applying the same key assumptions for transport supply in terms of costs and performance characteristics for trucks and charging infrastructure. By applying both methods to the same problem setting, we are thus able to provide a direct and quantifiable comparison between these two electrification approaches.

3.1 Problem Setting

The problem setting of this case-study is the distribution logistics of a German grocery retailer in north-eastern Germany during February 2021. The transport network covers two distribution centers (DCs) serving more than 500 grocery stores with over 200 vehicles. One DC is located in Mariendorf (MAR) in south-eastern Berlin, and the other one in Oranienburg (ORB), roughly 30 km north of central Berlin. From Mariendorf, primarily stores in Berlin and its surroundings are provided with four different types of assortments: dry goods, fruit and vegetables, fresh goods, and fresh meat. Oranienburg serves the entire region and also delivers frozen goods in addition to the four aforementioned assortments.

3.2 Data

The case-study company provided data to the previous 2021 study, which this study also uses, in addition to further datasets to provide more detail. The data sets used are given in Table 1. The Tour data includes data of 8,281 tours performed during February 2021, aggregated shipment volume, shipment weight, and assortment type composition per tour, but not broken down for each delivery. This dataset also contains the data on time per tour split by driving time, loading time and a combined value for time for unloading and setup at stores. The Site data contains locations for each of the stores and DCs and truck type accessibility i.e. the largest truck type which can physically enter the site. Furthermore, the Truck-to-tour data mapping specifies the trucks that were operated to serve the tours in the Tour data and the specific Tour IDs that were operated by each truck. To enable the replanning approach, additional data was provided by the case study company. First, the raw shipment data which includes data on deliveries performed during the month of February 2021. This data is specified on a per-store basis with each row specifying the cargo delivered to a store during one day. The raw shipment data is complemented by a dataset with delivery time windows data. However, such data was not available for February 2021, thus, a dataset with time windows for 2023 is provided.

These datasets were processed and cleaned to provide a complete dataset, thus certain tours were filtered where shipment data was missing, resulting in a set of 8 235 tours (99.4% of the original dataset). Additionally, in cases of incomplete fields in the data, these were interpolated. These include assortment types included in certain shipments where these were missing, loading and unloading times of individual shipments where these were bundled into larger shipments, and time windows for stores where missing. Shipments of the same assortment type to the same store on the same day (i.e. with the same time windows) are bundled together for tractability, and values calibrated to ensure that no bias was introduced in any of the aforementioned interpolating steps. Finally, in order to accurately measure utilization, path data was obtained using HERE maps API [21].

Table 1: Datasets and their relevant data points used in this study.

Dataset	Datapoints Used	Timeperiod
Tour data	tourID, home DC, date, volume, payload, assortment type composition, total time and driving, loading and unloading and store setup time for all tours	February 2021
Truck-to-tour mapping data	truckID, truck type and tourIDs operated for all trucks in fleet	February 2021
Site data	siteID, location and truck type accessibility for all stores and DC	February 2021
Raw shipment data	homeDC, siteID, date, tourID, volume, assortment type distribution and loading, unloading and setup at store time for all shipments	February 2021
Delivery time windows data	Delivery window for all assortment types per store and weekday	January 2023
Refined shipment data	homeDC, siteID, date, tourID, volume, assortment type distribution, loading and unloading time and payload and delivery window for all shipments	February 2021
Path Matrix (HERE Maps API)	Routes between each site for each vehicle type, time and distance	2023

3.3 Vehicle Types

The vehicle types used in this study are adapted from the 2021 study, comprised of 4 vehicle classes, and updated with an enhanced energy consumption model. For BETs, different battery sizes were assigned depending on which DC they are based on, resulting in a total of eight different BET types. For the ICETs, the same specifications are used for both DCs, resulting in a total of 12 different vehicle types (see Table 2). The net battery capacity includes an anticipated 50 kWh degradation at end of life, a 92% of the gross capacity available for cycling, and a further reduction of 6% to take into account a battery capacity safety buffer representing a range of 20 km. All in all, this leads to a total net battery capacity of 86% of the gross capacity for new batteries, and 65-76% when including aging effects. The latter values are adopted as the available net battery capacity in the electrification analysis. For BETs, the max gross vehicle weight includes an additional two tonnes allowance for zero-emission trucks as approved by the European Commission to compensate for increased weight due to the batteries.

3.4 Model Formulation

The models for energy consumption and TCO are given in the following two sub-chapters with the model parameters given in Table 3.

3.4.1 Energy Consumption Model

The energy consumption model used in this study (see Equation 1) gives the energy consumption of a vehicle traversing a path τ with a payload p. This model utilizes three parameters: a baseline parameter for driving the vehicle empty, an incremental parameter for payload-induced consumption, and a parameter accounting for auxiliary system load (see Table 4). While applicable to both BETs and ICETs, the parameter values vary between vehicle types.

$$EC_\tau = \sum_{(i,j)\in E'_\tau} \left(e_v^{\text{empty}} d_{ij} + e_v^{\text{aux}} s_{ij} + e_v^{\text{payload}} p_{vij} d_{ij} \right), \text{ where } \tau \in T_v \text{ and } v \in \text{ Fleet} \tag{1}$$

3.4.2 TCO Model

The cost model, and its parameters, are adapted from the 2021-study such that they can be used as inputs to the EVRP mode as well as for the 1:1 replacement analysis. The TCO of each vehicle is given by Equations 2 through 8. The demand data is given for an entire month and the EVRP computes the optimal plan for a given day at a time, and we therefore use the associated fixed cost for a day's operation and month of operations according to Equations 9 and 10 respectively such that the EVRP optimization can include the fixed costs in addition to the variable cost of operations. For the 1:1 replacement analysis, the same cost parameters are used but computed using the planning described in the empirical tour data. The same equations used in the 2021-study are implemented to calculate the capital cost component of TCO which is then divided into per-day and per-month values with the assumption that the vehicles have a mean utilization of 6 days a week, 50 weeks a year over their 8 year holding period.

The cost of charging infrastructure is allocated according to the operational requirements of the vehicles. In both the 1:1 replacement analysis and the EVRP approaches, each BET is allocated the costs of one 50kW charger for overnight charging. In the 1:1 replacement analysis, those BETs that require a 150kW charger in order to be technically feasible to electrify are allocated the cost of one such charger accordingly. In the EVRP analysis, the number of 150kW chargers are chosen based on the maximum

Table 2: Vehicle type parameters used in this study, adapted from 2021 study.

Truck Type	Class	DC	Gross Battery Capacity (kWh)	Net Battery Capacity (kWh)	Maximum GVW (t)	Weight Capacity (t)	Volume Capacity (CTU)
BET-R18-MAR	Rigid	MAR	200	129	18	6.1	29
BET-R26-MAR	Rigid	MAR	350	258	26	12.5	36
BET-TT40-MAR	Tractor with trailer	MAR	400	301	40	23.5	55
BET-RT40-MAR	Rigid with trailer	MAR	350	258	40	20.0	60
BET-R18-ORB	Rigid	ORB	300	215	18	5.6	29
BET-R26-ORB	Rigid	ORB	350	258	26	12.5	36
BET-TT40-ORB	Tractor with trailer	ORB	450	344	40	23.2	55
BET-RT40-ORB	Rigid with trailer	ORB	350	258	40	20.0	60
ICE-R18	Rigid	MAR, ORB	n/a	n/a	18	6.3	29
ICE-R26	Rigid	MAR, ORB	n/a	n/a	26	13.3	36
ICE-RT40	Rigid with trailer	MAR, ORB	n/a	n/a	40	20.8	60
ICE-TT40	Tractor with trailer	MAR, ORB	n/a	n/a	40	24.4	55

Table 3: Model parameters used to calculate energy consumption and TCO.

Description	Dimension	Parameter
Vehicle (v_{Fleet})	-	v
Set of all purchased vehicles	-	Fleet
Set of paths in the network	-	E
Subset of paths in E that a vehicle v traverses	-	E'_v
Path from site i to site j ($(i, j) \in E'$)	-	(i,j)
Energy consumption for empty vehicle	kWh/km	e_v^{empty}
Energy consumption of auxiliary systems (e.g. cooling)	kW	e_v^{aux}
Additional energy consumption for payload	kWh/(km·t)	$e_v^{payload}$
Driving distance of path from site i to site j	km	d_{ij}
Time duration to traverse path from site i to site j	h	s_{ij}
Payload carried by vehicle v on path from site i to site j	t	p_{vij}
Total cost of ownership of vehicle v	€	TCO_v
Total cost of ownership of charging station CS allocated to vehicle v	€	$TCO_{CS,v}$
Number of vehicles utilizing charging station CS	-	N_{CS}
If vehicle v utilizes charging station CS ($x \in \{0, 1\}$)	-	$x_{CS,v}$
Charging station at DC ($CS \in DC$)	-	CS
Set of all DCs	-	DC
Acquisition cost of vehicle	€	c_v^{acq}
Annual insurance cost and registration tax	€	c_v^{annual}
Electricity wholesale price per kWh	€/kWh	c^{kWh}
Maintenance cost per kilometer for vehicle v	€/km	$c_v^{maintenance}$
Toll road cost per kilometer for vehicle v	€/km	c_v^{toll}
Driver wage	€/h	c^{wage}
Year in holding period	-	t
Holding period	-	HP
Interest rate	-	I
Driver break duration on path from site i to site j	h	s'_{ij}
Driver activity duration on site i (i.e. loading, unloading, and charging)	-	s'_i
CAPEX for charging station CS	€	$CAPEX_{CS}$
Annual OPEX for charging station CS	€	$OPEX_{CS}$
Fixed cost used for VRP input	€/day	$CAPEX_{vrp}$
Days per year that a vehicle is utilized (300 days per year)	day	γ_t

Table 4: Energy consumption parameters for each vehicle type.

Truck Type	Empty vehicle (kWh/km)	Payload-dependent (kWh/t·km)	Auxiliary Systems (kW)
BET-R18-MAR	0.512	0.0176	15.93
BET-R26-MAR	0.562	0.0176	18.70
BET-TT40-MAR	0.674	0.0176	19.64
BET-RT40-MAR	0.828	0.0176	22.86
BET-R18-ORB	0.660	0.0176	15.93
BET-R26-ORB	0.689	0.0176	18.7
BET-TT40-ORB	0.778	0.0176	19.64
BET-RT40-ORB	0.053	0.0176	22.86
ICE-R18	2.366	0.0853	4.42
ICE-R26	2.426	0.0853	5.20
ICE-TT40	2.372	0.0853	5.46
ICE-RT40	2.535	0.0853	6.35

number of 150kW chargers concurrently in use. The charging costs are therefore allocated a posteriori of the optimization in the EVRP analysis, and not dimensioned in the input.

$$TCO_v = CAPEX_v + OPEX_v + TCO_{CS,v}, \quad v \in \text{Fleet} \tag{2}$$

$$TCO_{CS,v} = \sum_{CS \in DC} \frac{CAPEX_{CS} + OPEX_{CS}}{N_{CS}} x_{CS,v}, \quad v \in \text{Fleet} \tag{3}$$

$$CAPEX_v = c_v^{acq} - \frac{r_v^{residual}}{(1+I)^t} + \frac{c_v^{acq} + r_v^{residual}}{2} I, \quad v \in \text{Fleet} \tag{4}$$

$$OPEX_v = \sum_{y \in HP} \frac{c_v^{energy} + c_v^{driver} + c_v^{annual} + \sum_{(i,j)\in E_v} (c_v^{maintenance} + c_v^{toll}) d_{ij}}{(1+I)^t} v \in \text{Fleet} \tag{5}$$

$$c_v^{energy} = \sum_{(i,j)\in E_v^*} c^{kWh} EC_{ij} v \in \text{Fleet} \tag{6}$$

$$c_v^{driver} = \sum_{(i,j)\in E_v^*} c^{wage} (s_{ij} + s_i' + s_j'' + s_{ij}''') v \in \text{Fleet} \tag{7}$$

$$CAPEX_{CS} = c_{CS}^{acq} - \frac{r_{CS}^{residual}}{(1+I)^t} + \frac{c_{CS}^{avg} + r_{CS}^{residual}}{2} I, \quad CS \in DC \tag{8}$$

$$CAPEX_v^{VRP} = \frac{CAPEX_v}{Y_t}, v \in \text{Fleet} \tag{9}$$

$$CAPEX_{CS}^{VRP} = \frac{CAPEX_{CS}}{Y_t}, CS \in DC \tag{10}$$

Total cost of ownership (TCO) for each vehicle is calculated according to Equation 2, covering all costs related to purchase, operation, and resale over the assets lifetime, including the vehicles and charging infrastructure over an 8 year holding period. The fleet-level TCO is calculated in Equation 11 as the sum of each vehicle's TCO, which includes the charging costs allocated to each vehicle. The same model is used to evaluate both the 1:1 replacement analysis and the EVRP optimization results based on the total fleet composition and utilization, thus obtaining the total system TCO for each approach and problem setting.

$$TCO_{Fleet} = \sum_{v \in Fleet} TCO_v \tag{11}$$

The capital and operational expenditures are synthesized into the following inputs to the EVRP model: fixed cost per day, energy cost per kWh energy consumed, and wage cost per hour of the drivers' shift (see Tables 5 and 6). The main scenarios in this study consider acquisition costs including the "Climate-friendly commercial vehicles and infrastructure" (KsNI) subsidy program as in the 2021-study. The acquisition costs used in the 2021 study are adjusted for both BETs and ICETs, with the acquisition costs covering certain components such as the transmission, inverter, fuel tank, and engine being based on the direct manufacturing costs instead of including risk premiums, sales overheads, etc., thus leading to a slightly lower acquisition cost for both BETs and ICETs.

The EVRP optimization is performed on one day at a time, and as such the input value for the fixed cost is adjusted to reflect the proportion of utilization represented. The input to the EVRP is therefore based on either a single day's worth of utilization, an entire month of 28 days, or without considering fixed costs depending on the fleet dimensioning step. Since each day might have a different optimal fleet size and composition, a fleet dimensioning algorithm is used to determine the fleet size required for the entire planning period based on the days with the highest required fleet sizes, thus ensuring a sufficient number of vehicles of each vehicles class are selected. The utilization of the vehicle over its entire lifetime is therefore estimated to be the holding period multiplied by the nominal utilization of days per year that the vehicle is active (50 weeks per year, 6 days per week). The fixed cost per day is therefore estimated to be the sum of the capital cost component of the TCO divided by the holding period and depreciation costs in addition to the yearly costs such as annual taxes for motor vehicles and insurance divided by the nominal utilization of 300 days per year.

Furthermore, while the 1:1 replacement analysis considers the cost of a charger to be included in the cost of a vehicle, the EVRP allows for chargers to be utilized more efficiently, and thus the charging infrastructure costs are not allocated to the fixed cost of adding a vehicle to the optimization, but instead added after the EVRP has provided the optimal schedules. This serves as the input to the EVRP model in order to get the optimized operational usage, but the final TCO calculations are performed the same way for the 1:1 replacement approach. The ICETs, while sharing the same characteristics for both DCs, have different nominal usage patterns affecting insurance and taxes, and therefore have different costs depending on which DC they originate from.

Table 5: Cost parameters for BETs as input for EVRP optimization

Vehicle Type	Acquisition cost without subsidy (€)	Acquisition cost with subsidy (€)	Fixed cost (€/day)	Energy cost (€/kWh)	Variable cost (€/km)	Wage cost (€/h)
BET-R18-MAR	169,400	132,720	69.5	0.18	0.06	20
BET-R26-MAR	220,990	153,878	78.1	0.18	0.06	20
BET-TT40-MAR	257,504	181,125	90.5	0.18	0.06	20
BET-RT40-MAR	265,990	199,518	98.1	0.18	0.06	20
BET-R18-ORB	195,500	137,940	76.5	0.18	0.06	20
BET-R26-ORB	220,990	153,878	78.3	0.18	0.06	20
BET-TT40-ORB	270,554	183,735	91.5	0.18	0.06	20
BET-RT40-ORB	265,990	199,518	98.4	0.18	0.06	20

Table 6: Cost parameters for ICETs as input for EVRP optimization.

Vehicle Type	Acquisition Cost (€)	Fixed Cost MAR (€/day)	Fixed Cost ORB (€/day)	Variable Cost MAR (€/km)	Variable Cost ORB (€/km)	Diesel Cost (€-cent/ Liter)	Diesel Cost (€-cent/ kWh)	Wage Cost (€/hr)
ICE-R18	123,550	68	71	0.16515	0.20840	125	11.84	20
ICE-R26	137,100	73	73	0.18220	0.22334	125	11.84	20
ICE-TT40	162,030	85	85	0.19903	0.23456	125	11.84	20
ICE-RT40	182,900	93	94	0.18407	0.24204	125	11.84	20

The TCO of the charging infrastructure is based on the number of charging points and their respective power output capacities (see Table 7). Similarly to the vehicles, the costs are discounted and distributed across the nominal utilization of the fleet and the lifetime of the charging infrastructure. For the 1:1 replacement analysis, the assumption is that each BET requires one 50kW charger each for overnight charging. Additionally, for the 50+150kW charging scenarios, those vehicles that require a 150kW charger to be technically feasible to electrify are allocated one 150kW charger each. For the replanning scenarios, the required number of charging outlets are determined a posteriori based on the maximum number of concurrent charging sessions as computed by the EVRP optimization instead of allocating on a per-truck basis. This also applies to the 150kW chargers at the loading bays, whose costs are shared by the entire fleet rather than allocated.

Table 7: Charging Infrastructure cost parameters from the 2021-study (without subsidies)

Power output capacity	CAPEX (€)	OPEX (€)	Holding Period (years)	TCO per charging point per day (€)
50 kW	41,900	1,257	12	11.76
150 kW	79,100	2,373	12	22.19

3.5 1:1 Replacement Approach

The 1:1 analysis follows the same methodology and uses the same data as the 2021 study, and is thus based on the historical tour data of diesel trucks and evaluates, for each of the 224 diesel trucks in the data-set, whether or not all of their tours could be performed by a battery-electric vehicle of the same type and weight class and whether or not it would obtain a lower TCO. The 1:1 truck replacement approach can thus consider either or both technical and techno-economic feasibility.

For a truck to be considered technically feasible to electrify, the battery-electric truck replacing it must be able to perform all of its tours with the same payload and distance given its battery capacity, energy consumption, and availability to charge at the DC during the time between each tour. The formulation is given in Equations 12 through 15. Furthermore, as in the 2021-study, two charging configurations are considered, with either only 50 kW chargers at the DC or with additional 150 kW chargers at the loading bays. Thus the technical feasibility 1:1 replacement analysis is done twice; with 50 kW charging between shifts and with 50 kW and/or 150 kW charging between shifts.

Vehicle v is technically feasible to electrify $\Leftrightarrow$ Constraints (12) and (13) are satisfied for vehicle v.

$$EC_\tau \leq BC_v, \quad \forall \tau \in T_v \tag{12}$$

$$SoC_\tau^{end} \geq SoC_v^{min}, \quad \forall \tau \in T_v \tag{13}$$

$$SoC_{\tau'}^{start} = \min(BC_v, SoC_\tau^{end} + ct_{\tau\tau'} \times P), \quad \forall \tau \in T_v \tag{14}$$

$$SoC_\tau^{end} = SoC_\tau^{start} - EC_\tau, \quad \forall \tau \in T_v \tag{15}$$

Table 8: 1:1 replacement analysis parameters

Description	Unit	Parameter
Vehicle ($v \in$ Fleet)	-	v
Set of all purchased vehicles	-	Fleet
Set of all tours performed by vehicle v	-	T_v
Tour ($\tau \in T_v$)	-	τ
Energy consumption for tour τ	kWh	EC_τ
Usable battery capacity of vehicle v	kWh	BC_v
State-of-Charge at the start of tour τ	kWh	SoC_τ^{start}
State-of-Charge at the end of tour τ	kWh	SoC_τ^{end}
Minimum allowed State-of-Charge for vehicle v	kWh	SoC_v^{min}
Charging time between tour τ and subsequent tour τ'	h	$ct_{\tau\tau'}$
Charging power	kW	P
Paths in the network	-	E
Subset of paths in E included in tour τ	-	E_τ^*

3.6 Replanning Approach with EVRP Optimization

To solve the routing and charging planning optimization problems, this study uses proprietary electric vehicle routing problem (EVRP) optimization software developed by Einride AB. The software uses a meta-heuristic approach to optimize the size and composition of a fleet of either or both BETs and ICETs, shipment allocation, routing, and charging scheduling seeking to deliver a set of shipments within a given transport network at minimal cost. The inputs to the optimizer consist of data on the sites, paths, shipments, vehicle types, vehicle set, and vehicle shifts which are used to formulate and solve the optimization problem. In order to study the benefit of EVRP for technical feasibility of electrification, the optimizer is set to prioritize using BETs given range constraints.

Vehicle operations and charging assumptions align with the 2021 study and German driver regulations. Operations are organized into predefined vehicle shifts (with start/end times and constraints like maximum driving/break times) which serve as inputs for an optimizer. The optimizer selects the necessary shifts and plans activities within them. Due to the problem's scale, standard 11-hour shifts (max 9h driving, 45min break after 4.5h driving or 6h work) starting at 00, 03, 11, and 13 are used, beginning and ending at the home DC. Partial shifts incur a full 8-hour cost. Driver scheduling and truck allocation are not modeled; driver availability for all shifts is assumed. A few long-distance shipments requiring extended driving times are handled separately using dedicated trucks with longer shifts (14h total, 10h driving) under regulatory exemptions.

4 Results

4.1 Electrification Rates and Operational Feasibility

The Replanning approach yielded significantly higher electrification rates than 1:1 replacement across all metrics (see Table 9). Furthermore, while 1:1 replacement is highly reliant on having faster chargers to increase electrification rate (from 57% to 85% tonnes), replanning is able to achieve just as high electrification rates even without the 150kW chargers, albeit at the cost of TCO (+4.7%) and fleet size (+23.3%). This is due to 1:1 schedules being highly constrained on charging times, while the more flexible replanning approach can adjust the schedules for slower charging without compromising electrification rates. For the 1:1 replacement scenario, 63% of stores are served by both BETs and ICETs while only 11% are served exclusively by BETs. In contrast, replanning allows for 84% of all stores to be exclusively served by BETs, thus giving a more accurate representation of BETs technical feasibility by not constraining scheduling to historical scheduling based on ICET operations.

4.2 Total Cost of Ownership and Cost Performance

Replanning, in addition to achieving higher electrification rates, also outperform the baseline diesel fleet and both 1:1 replacement scenarios in terms of cost performance (see Table 10 and Figure 1). While 1:1 replacement at best can reduce TCO by 2.7%, Replanning with 150kW charging can reduce TCO by 11.6% relative to the baseline diesel fleet, outperforming the 1:1 replacement case by over a factor of 4. Notably, the more limited 50kW charging scenario requires a larger fleet size (see Table 9), the larger CAPEX thereof only leading to a 7.2% reduction compared to the 50+150kW scenario.

Table 10: TCO values for each scenario.

Scenario	TCO (€)	TCO (delta %)
ICE Baseline	181,706,169	0%
1:1 Replacement 50k	179,245,480	-1.4%
1:1 Replacement 50+150kW	176,867,649	-2.7%
Replanning ICE	171,365,001	-5.7%
Replanning 50kW	168,627,462	-7.2%
Replanning 50+150kW	160,637,898	-11.6%

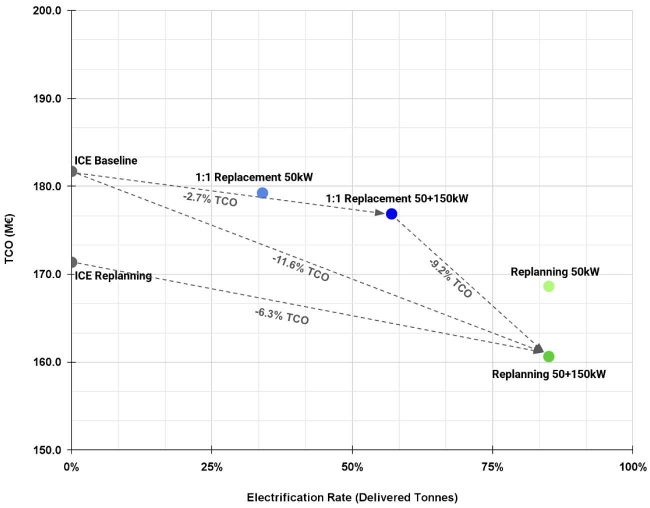

Figure 1: TCO and electrification rate for each scenario.

Table 9: Electrification rates for each scenario and charging setup.

Scenario	**1:1 Replacement**		**Replanning**	
Charging Setup	**50kW**	**50+150kW**	**50kW**	**50+150kW**
BETs in Fleet	81/224 (36%)	128/224 (57%)	150/185 (81%)	115/150 (77%)
Tonnes Delivered (BETs)	34%	57%	85%	85%
Tonne-Kilometers (BETs)	14%	26%	55%	55%
Kilometers Driven (BETs)	16%	32%	55%	54%

4.3 Fleet Size and Operational Patterns

Across all scenarios, the replanning approach achieved a higher share of Battery Electric Trucks (BETs) in the fleet compared to the 1:1 replacement approach (see Table 9). While the 1:1 scenarios have a fixed total fleet of 224 trucks based on the unique vehicle IDs in the tour data, the optimized replanning approach yielded varying total fleet sizes depending on the scenario, from 138 trucks up to 185 trucks.

Analysis of operating patterns for the ICET baseline and Replanning scenarios reveals distinct differences in operational patterns (see Table 11). The replanning approach achieves higher utilization rates on average across key metrics like distance driven, payload delivered and operational up-time. Faster 150kW charging generally increased the average daily distance and operational time for BETs in both approaches under the replanning scenarios.

Table 11: Mean Daily Utilization Metrics by Scenario

Scenario	Powertrain	Mean Distance (km)	Mean Payload (t)	Mean Operating Time (h)
1:1 ICET Baseline	ICET	245	15.1	10.3
1:1 50kW	BET	110	14.2	8.2
1:1 50kW	ICET	319	15.6	11.4
1:1 50+150kW	BET	137	14.8	8.9
1:1 50+150kW	ICET	392	15.5	12.1
Replanning ICET Baseline	ICET	384	22.8	16.5
Replanning 50kW	BET	215	18.7	12.4
Replanning 50kW	ICET	777	14.5	17.0
Replanning 50+150kW	BET	260	23.7	15.2
Replanning 50+150kW	ICET	777	14.5	17.0

5 Discussion

The results of this study highlight the significant impact of optimization-driven replanning on heavy-duty freight electrification. The replanning approach significantly outperforms 1:1 replacement strategies both in terms of technical feasibility and cost performance. This indicates that previous studies that have solely relied on historical ICET operational data might have substantially underestimated the scope and costs of electrification. The replanning method is able to identify and optimize for synergies and efficiencies that require different planning to realize. This demonstrates the necessity of employing advanced, data-driven planning tools when transitioning from fossil fuels to electric heavy-duty freight operations, particularly for large fleets where the potential emissions and cost savings are the greatest.

A key difference influencing results lies in how fleet composition is determined. The 1:1 replacement identifies electrifiable trucks in a fleet where each of the 224 individual trucks are considered individually, i.e. the fleet size is fixed. In contrast, the replanning approach optimizes the fleet size and composition required to meet the transport demand, assuming all trucks are dedicated to and utilized entirely within the network. This results in a significantly smaller and optimized fleet compared to the fixed 1:1 fleet. This is most clearly seen with the ICE Replanning fleet, with 138 instead of 224 vehicles. Therefore, while the direct comparison of absolute fleet sizes between the two approaches may be less informative, comparing the resulting share of BETs is still an accurate measure.

Notably, the Replanning 50kW scenario required the largest fleet size due to the lack of faster charging, thus requiring more vehicles to serve the demand. This is also shown by the utilization metrics, where adding faster charging improves the utilization of each vehicle and can thus reduce the fleet size. Another significant result that stands out is how BETs and ICETs have highly segmented utilization metrics, with BETs having higher payloads but lower mileage than ICETs, showing that optimizing for their respective characteristics leads to more specialized and segmented operational patterns within the fleet. This indicates that fleet-operators need to be cautious regarding the choice of metrics used to evaluate fleet and/or vehicle performance, as optimizing a truck for to e.g. cost-per-km or cost-per-tonne might lead to a less optimal system, thus further highlighting the importance of the system-wide fleet optimization approach used in this study.

The case-study, grocery retail distribution, represents about 25% of the annual transport performance in Germany and combines what this case-study and Link et al. [8] have shown to be favorable operational patterns and regulatory drivers, making it a high-potential candidate for short- and mid-term electrification. Specifically, routes and schedules are typically fixed and predictable with shorter distances compared to long-haul and centralized around distribution centers. Additionally, grocery retailers have been early adopters of BETs as part of a industry-wide trend of increasingly prioritizing sustainability to meet consumer expectations and corporate responsibility goals. The results of this study thus show how a significantly larger share of the network can be electrified with the same assets and hardware and without needing larger batteries or relying on public charging infrastructure, which can thus significantly accelerate the transition to battery-electric freight.

6 Conclusions

This study directly compared an optimization-driven replanning approach with a 1:1 replacement approach for electrifying a large-scale, real-world heavy-duty grocery distribution network. The results conclusively show that the replanning approach achieves significantly higher electrification rates, nearly doubling all metrics (fleet share, tonnes delivered, tonne-kilometers, and mileage), and yields substantially lower total cost of ownership (TCO) compared to both the 1:1 replacement scenarios and the original diesel fleet baseline, outperforming them by 9.2% and 11.6% respectively.

The results thus demonstrate that leveraging optimization for fleet design, routing, and charging scheduling to unlock operational synergies is crucial for maximizing the technical and economic benefits of electrification in heavy-duty freight. Relying on methods that do not fundamentally replan operations may underestimate and unnecessarily limit the identifiable electrification and cost savings potential. Therefore, optimization-driven planning represents a key enabler for accelerating the large-scale transition to sustainable freight logistics where such benefits are likely the most impactful.

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