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Can an Industry-Led infrastructure development strategy facilitate electric truck Adoption?

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ABSTRACT

Reverse logistics plays a critical role in sustainable development and circular economy by transforming waste into value. However, transporting large volumes of waste and recyclables generates significant carbon emissions. This paper explores an industry-led strategy for charging infrastructure development, which integrates the reverse logistics network designs with a network of charging stations to promote electric trucks (E-trucks) adoption and reduce carbon footprints in transportation. Our model optimizes operational costs while ensuring accessibility to charging infrastructure. A case study in Norway demonstrates that, despite higher operating costs due to additional charging stations, the adoption of E-trucks can decrease total reverse logistics costs by 0.18%—2.37% and cut carbon emissions by 16.3%—17.6%. These findings support the economic viability and environmental benefits of this strategy for advancing sustainable practices in transportation, and it further highlights the interdependencies between logistics network design and charging infrastructure planning.

1. Introduction

Today, the urgent need for sustainable practices across all economic sectors is underscored by the escalating concerns of resource depletion, climate change, global warming, as well as other environmental challenges. One of the most significant challenges faced by worldwide urban communities is the increase in waste generation. For instance, the generation of the waste of electrical and electronic equipment (WEEE) is expected to increase by 3–5% per year (Shittu et al., 2021). Besides, with the booming of the e-commerce industry, the associated annual generations of plastic waste and paper waste have reached 1.8 million tons and 9 million tons, respectively (Lin et al., 2023a). To tackle this challenge, the adoption of reverse logistics not only addresses the immediate concerns of waste accumulation but also promotes a systemic shift towards more sustainable consumption and production patterns. Due to its fundamental role in transforming waste into value, reverse logistics has increasingly garnered global attention (Khan et al., 2023). To extract the remaining value of end-of-life (EOL) products, reverse logistics refers to the process of moving goods from their typical final destination back through the supply chain toward various value recovery activities, e.g., recycling, refurbishment, remanufacturing, and even energy recovery, with the goal of extending the product lifecycle and reducing waste (Rogers and Tibben-Lembke, 1999). Reverse logistics not only mitigates environmental impact but also contributes to economic sustainability by creating new business opportunities for cost reduction and revenue generation from recovered products and materials (Ni et al., 2023). The proper design of a reverse logistics system is of crucial importance in facilitating these processes, as it involves both strategical design of facility locations

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and operational planning of the effective transportation and capacity utilization to support the collection, processing, and redistribution of EOL products for value recovery (Yu and Solvang, 2016).

Despite its crucial role in promoting sustainability and circular economy, inadequate reverse logistics practices can lead to adverse environmental consequences (De Oliveira et al., 2021). For instance, inefficient recycling processes may result in the release of hazardous substances and pose significant risks to the workers and nearby residents (Ahirwar and Tripathi, 2021), while the transportation of goods for reverse logistics purposes can contribute to increased carbon emissions if not well managed in effective and eco-friendly ways. Thus, the benefits of reverse logistics are highly contingent upon the logistics network structure, technologies, planning, operations, and management. In this regard, a large number of researchers have recently focused on green and sustainable reverse logistics practices to balance the interplay between economic, environmental, and social sustainability (Safdar et al., 2020). Besides, the incorporation of cutting-edge technologies in Industry 4.0 to improve the sustainability of reverse logistics has also been extensively studied (Sun et al., 2022, Govindan and Gholizadeh, 2021).

One of the most promising solutions to reducing the carbon footprint and greening transportation in reverse logistics is the adoption of electric trucks (E-trucks). Despite the transport sector plays an essential role in the global economy, it yields almost one-quarter of the total carbon emissions (Ahmed et al., 2020). Thus, in recent years, electric vehicles (EVs) have been widely adopted, especially in Norway and the EU, due to their lower carbon footprint and environmental impact. Furthermore, the wide adoption of EVs can also contribute to reducing the high reliance on fossil fuels, enhancing energy efficiency, and lowering noise pollution in transportation systems (Asamer et al., 2016). In Norway, the market share of EVs in the total passage vehicle sales has increased to 88 % in 2022 (Figenbaum et al., 2020). Furthermore, the targets for large zero-emission trucks and coaches are also set to 50 % and 75 % by 2030 (Figenbaum et al., 2020). For the effective deployment of E-trucks, several technological and infrastructural factors need to be considered, e.g., the driving range of E-trucks (He et al., 2018), purchase and maintenance costs (Cheng and Lin, 2024), technology maturity and safety issues (Gnanavendan et al., 2024), and accessibility to charging infrastructure (Alp et al., 2022). A recent survey by Konstantinou and Gkritza (2023) illustrates that the primary influencing factors for companies to integrate E-trucks into their transportation fleets include the availability of E-trucks, recharging time, business models, and partner networks, while consumer expectations, the resilience of grid and other infrastructure, along with the technology maturity and reliability of E-trucks remain the major hindrances.

The appropriate selection of the number and locations of charging stations plays a crucial role in E-truck adoption (He et al., 2018, Shoman et al., 2023). However, establishing an effective and efficient charging infrastructure network is a complex decision-making problem. Cheng and Lin (2024) show that even though E-trucks can help reduce 43 % of energy consumption in long-haul transportation compared to their diesel counterparts, 31.7–41.7 % non-revenue time and 16–35 % prolonged total journey time are incurred due to the recharging. In this regard, an inadequately designed charging infrastructure network with limited accessibility can substantially diminish the incentive for companies to adopt E-trucks, while, on the other hand, an excessively expansive charging infrastructure network could result in substantial setup and maintenance costs. Moreover, the establishment of a charging infrastructure network will largely impact the operations of existing distribution and logistics networks (Ahmad et al., 2022), and research has revealed that local industrial clusters have shown great interest and need for the charging infrastructure development (Yu et al., 2023). Thus, to facilitate the adoption of E-trucks in green reverse logistics and the transport sector, we investigate an industry-led infrastructure development strategy for the joint network design. For instance, within the domains of reverse logistics and waste management, Build-Operate-Transfer (BOT) and Build-Own-Operate-Transfer (BOOT) agreements are frequently employed (Levy, 1996) to support infrastructure development. The charging stations established under these public–private partnership models are envisioned to serve not only the entities within the reverse logistics network but also external freight transport companies, on a fee-based usage model.

In this paper, through modeling efforts and numerical analysis, we aim to answer the following two research questions:

- *RQ1*: How can a joint reverse logistics and charging infrastructure network be designed for E-truck adoption?
- *RQ2*: What are the economic viability and environmental benefits of E-truck adoption through an industry-led infrastructure development strategy?

The rest of the paper is organized as follows. The review of related scientific works is first given in Section 2. Section 3 describes a generalized joint reverse logistics and charging infrastructure network design problem, based on which a new mathematical model is formulated in Section 4. Section 5 gives numerical experiments for model validation and result analyses. Section 6 provides the conclusion of the research with future research suggestions.

2. Literature review

In order to model and evaluate an industry-led infrastructure development strategy in green reverse logistics, we reviewed the relevant literature related to reverse logistics network design, charging infrastructure network design, and charging network design for E-trucks, based on which the literature gaps and our contributions are discussed.

2.1. Reverse logistics network design

Given the complexity of managing strategic and tactical decisions across multiple material flows, reverse logistics network design has attracted extensive research efforts since the late 1990s (Fleischmann et al., 1997). Govindan et al. (2015) and Islam and Huda

(2018) provided comprehensive reviews on recent developments in modeling, algorithm design, and practical applications, while Van Engeland et al. (2020) focused on network optimization models for waste reverse logistics management. Early modeling efforts primarily emphasized the economic viability, efficiency, and benefits from the value recovery of EOL products (Srivastava, 2008). For instance, Pishvaee et al. (2010) proposed a mixed-integer program aimed at minimizing the total setup and operating costs of a generalized three-echelon reverse logistics network, where a simulated annealing method was used to solve the optimization problem. Mutha and Pokharel (2009) modeled a cost-efficient remanufacturing reverse logistics network design problem. Taking into account the dynamicity, Min and Ko (2008) and Alumur et al. (2012) investigated multiple-period mixed-integer models to minimize the total logistics costs over several consecutive periods. On the other hand, Soleimani and Govindan (2014) addressed the economic benefits of recovering value from EOL products by formulating a multi-product two-stage reverse logistics network design problem to maximize the total profits generated under stochastic demand.

In the last decade, sustainability and uncertainty have emerged as two major challenges driving comprehensive model development in reverse logistics network design. Multi-objective models have been developed to minimize carbon footprints in reverse logistics flows (Yu and Solvang, 2016). Different carbon policies, i.e., carbon tax (Reddy et al., 2020, Kannan et al., 2023) and carbon cap-and-trade (Kushwaha et al., 2020), have been integrated into decision-making for sustainable reverse logistics network design. Apart from environmental considerations, various studies have addressed the triple bottom line of sustainable development (Safdar et al., 2020). For example, Govindan et al. (2016) investigated a multi-objective reverse logistics network design model to balance cost, environmental impact, job creation, and days lost due to workplace injuries. Given the unpredictable and unstable nature of EOL product flows, dealing with uncertainty in reverse logistics network design is crucial. In this context, stochastic optimization models have been developed to address situations where historical data is available to inform decision-making. For instance, Azizi et al. (2020) and Trochu et al. (2020) investigated two-stage stochastic programs for sustainable reverse logistics network design, where first-stage variables determine strategic facility locations and second-stage flow decisions are flexible and can be dynamically adjusted to optimize the system performance. However, in scenarios where historical data is not readily available, uncertainty in reverse logistics network design has been addressed through robust optimization (Govindan and Gholizadeh, 2021, Ghahremani Nahr et al., 2020) and fuzzy methods (Govindan et al., 2016, Hashemi, 2021). Moreover, the impact of hybrid uncertainties has also been modeled and analyzed by integrating various methods (Yu and Solvang, 2020, Farrokh et al., 2018).

Recently, several new challenges have been addressed in the optimization models of reverse logistics network design. Considering the need for facility reconstruction and updates for hybrid processing, Gao and Cao (2020) formulated a scenario-based multi-objective model for sustainable reverse logistics network redesign. To address the sustainable management challenges posed by the sharply increasing returns of EOL batteries from EVs, Tadaros et al. (2022) and Lin et al. (2023b) optimized the lithium-ion battery recycling reverse logistics network in Sweden and China, respectively. To effectively deal with the rapid medical waste generation in the early stages of the COVID-19 pandemic, Zhao et al. (2021) investigated temporary reverse logistics network design problems in Wuhan, China. Govindan and Gholizadeh (2021) modeled a robust and resilient reverse logistics network design problem considering the utilization and impact of big data. Wang et al. (2023a) developed and evaluated various mode selection and cooperation strategies within a reverse logistics network, taking into account the effects of smart recycling technologies. Hu et al. (2024) combined a disassembly line balancing problem into a multi-product multi-objective uncertain reverse supply logistics network design problem. Battaïa et al. (2023) incorporated Gini-index-based measurement to enhance environmental performance and promote social equality across various regions in an integrated forward/reverse logistics network design model. Considering smart pricing and collaborative resource sharing in a reverse logistics network, Wang et al. (2024) proposed a multi-deport vehicle routing problem, which was solved by a combined clustering and enhanced heuristic method. In addition, Pitakaso et al. (2024) and Sun et al. (2024) explored the influence of artificial intelligence (AI), digitalization, and Industry 4.0 on the planning of reverse logistics networks.

2.2. Charging infrastructure network design

Due to the extensive EV adoption across many countries, significant research efforts have been dedicated to the design and optimization of charging infrastructure networks. Comprehensive literature reviews have addressed this topic from various perspectives, including infrastructure development (Chen et al., 2020), impacts on grid networks and the utility sector (Shariff et al., 2022), optimization models and methods (Kchaou-Boujelben, 2021), effects on distribution and logistics networks (Ahmad et al., 2022), and influences from charging behaviors (Patil et al., 2023). The modeling of the charging infrastructure network problem began in the early 2010 s (Frade et al., 2011). Liu et al. (2012) developed an optimization model for the site selection of charging stations to minimize the overall setup, operating, and maintenance costs, and an enhanced primal–dual interior point algorithm was proposed to solve the problem. Sadeghi-Barzani et al. (2014) modeled a mixed-integer nonlinear program for a discrete location and sizing problem of fast charging stations, and a genetic algorithm was employed to solve the optimization problem. Based on 11 evaluation criteria selected for performance measurements on the triple-bottom-line of sustainable development, Guo and Zhao (2015) employed a fuzzy TOPSIS approach for charging infrastructure network design.

To model the charging infrastructure network design problem, several variants of classic covering location problems have been investigated (Kchaou-Boujelben, 2021). Based on the maximal covering location problem (MCLP), Frade et al. (2011) optimized the charging infrastructure network in Avenidas Novas, Portugal, with the maximum number of charging stations installed. Wang et al. (2013) expanded the MCLP to a flow-based covering location problem that maximizes the on-route traffic flows served by the charging infrastructure network with a limited number of charging stations. Huang et al. (2016) proposed a novel flow-based MCLP model aimed at minimizing the total cost of establishing an EV charging network while, simultaneously, ensuring sufficient infrastructural coverage for the busiest roads. Kınay et al. (2021) developed a mixed-integer program to minimize the total charging and infrastructure operating costs, ensuring full coverage of the charging demand on routes. Inspired by the set covering location problem (SCLP), (Yu et al., 2023) modeled a network-based covering model to minimize either the total costs or the total number of charging stations, while providing full coverage to the charging demands generated in both the nodes and the arcs of the network.

Recently, more practical operational situations and constraints have been considered in the charging infrastructure network design. For example, Çapar et al. (2023) proposed a new model for designing charging service networks, which aims to simultaneously maximize demand coverage and minimize waiting times. Mubarak et al. (2021) investigated a cost-effective wireless charging network design problem in urban environments. Yazdekhasti et al. (2021) modeled a mixed integer program to optimize the charging station location and capacity by taking into account the driver's risk preferences. Ngo et al. (2020) investigated the optimal charging infrastructure network design for dynamic wireless charging for EVs. Considering charging station sharing and time windows, Wang et al. (2023b) developed a bi-objective nonlinear program to optimize the routing of EVs within a multi-depot collaborative urban logistics network. To tackle this computationally intensive optimization challenge, a clustering-based pre-solving algorithm was developed, and an improved multi-objective genetic algorithm incorporating tabu search was also proposed.

Taking into account the EV's driving range, He et al. (2018) proposed a two-level approach to optimize the locations of the charging stations. The upper stage maximizes the user's flows covered by the charging infrastructure network, while the lower stage considers the user equilibrium in route selection within the driving range. Considering the impact of congestion pricing on drivers' travel choices, to effectively manage the uncertainty of charging demand, Faridimehr et al. (2018) and Fazeli et al. (2020) formulated two-stage stochastic optimization models, while Li et al. (2022) investigated a robust charging infrastructure network design problem with renewable energy sources. Wu et al. (2024) proposed a two-stage method to tackle uncertainty, where a robust optimization was used for locating and sizing the EV's charging network and a discrete-event simulation was then used to comprehensively evaluate the network performance using real-time traffic data. Huang and Kockelman (2020) maximized the profits of charging infrastructure network design with stochastic demands, congestions for charging stations, and network equilibrium. Kavianipour et al. (2021) investigated a two-stage method for urban EV charging network design considering user behavior. A mesoscopic simulation first was used to estimate the trips and charging behavior, whose results were then used as the input of the optimization model for EV charging network design.

2.3. Charging infrastructure network design for electric truck adoption

Compared to the extensive research on charging network design for small passenger EVs, the development of charging infrastructure for large vehicles remains underexplored, with primary attention focused on electric buses in urban areas (e.g., He et al. (2023) and Ji et al. (2023)). The development of the charging infrastructure network for electric truck adoption has only been investigated in recent years. For example, Hurtado-Beltran et al. (2021) modeled and determined a nationwide public charging network for short-haul truck electrification in the US. Speth et al. (2022) designed a public charging network for electric truck adoption in Europe, whose results revealed that 1468 and 660 charging stations would be needed with respect to 50 km and 100 km coverage distances. Whitehead et al. (2022) and Qian et al. (2024) investigated data-driven optimization methods for public charging infrastructure network design for E-truck adoption.

These studies have primarily concentrated on designing a nationwide charging infrastructure network to facilitate the adoption of E-trucks. However, unlike the widespread usage of small passenger EVs, the initial adoption of electric trucks may be constrained by several factors, e.g., limited product availability and high purchasing costs. Furthermore, the electrification of long-haul transportation is expected to be a gradual transition. Consequently, a nationwide approach to infrastructure development may not be economically efficient. Therefore, there is a need to explore a multi-period infrastructure development model that accommodates initial adopters and anticipates future expansion.

2.4. Literature gaps and contributions of our research

The literature review indicates that the design of reverse logistics networks and charging infrastructure networks has traditionally been approached as separate problems, with no research efforts yet directed toward modeling and joint decision-making in an integrated network design problem. However, given that the initial demand for charging infrastructure of E-trucks is often driven by a cluster of industrial companies and stakeholders aiming to minimize transportation-related carbon footprints, these two aspects of network design may be highly interrelated; treating them separately could lead to sub-optimal solutions that do not effectively utilize available resources. The interplay between these two network design decisions also needs to be better analyzed. Furthermore, the economic viability and environmental gains of E-truck deployment through an industry-led infrastructure development strategy remain largely unexplored. Therefore, to fill the identified literature gaps, our research aims at making the following contributions:

- From the ***methodological development*** perspective, a new mathematical optimization model is developed for decision-support of joint reverse logistics and charging infrastructure network design. This model initially addresses the infrastructure needs for enabling en-route charging within the reverse logistics system, with provisions for subsequent expansion to meet the growing demand from additional users.
- From the ***practical implication*** perspective, we evaluate the interplay between the two network design decisions and the economic viability and environmental benefits of E-truck adoption through an Industry-led charging infrastructure development strategy in the context of green reverse logistics management.

3. Problem description

The use of E-trucks in reverse logistics and waste management has become an increasingly popular topic (Erdinç et al., 2019, Baral et al., 2021). In this paper, we consider an industry-led infrastructure development strategy through a green reverse logistics network design problem, where charging stations need to be installed in, at least, a part of the network for the adoption of E-trucks to reduce the carbon footprints and environmental impacts in transportation. Fig. 1 illustrates the joint reverse logistics and charging infrastructure network design problem. In the reverse logistics system, the operation commences with the local collection of EOL products, which is typically performed by municipal waste management entities. These EOL items are then conveyed to larger collection hubs, which consolidate the material flows from multiple local origination points. Preliminary inspections, disassembly, and categorization are also done at these collection centers, and the sorted components and materials embark on divergent paths to one of three facilities, namely, remanufacturing plants, recycling plants, or disposal sites. Components that retain substantial value and meet quality criteria, e.g., compressors, are dispatched to remanufacturing plants, where they undergo processes designed to restore their functionality to a standard commensurate with new products. Conversely, other parts and materials that are not suitable for remanufacturing can be directed to recycling plants, and this stream typically constitutes the majority of materials processed at the collection centers. Lastly, residuals that are non-repurposable are sent to disposal sites, where they may be utilized for energy recovery or relegated to landfills.

To minimize the carbon emissions associated with industry-related transportation activities, companies and stakeholders within the reverse logistics system are among the initial adopters of E-trucks. Consequently, it is essential to first establish a charging infrastructure network that meets the needs of these initial users. This network should provide comprehensive coverage and accessibility to facilitate en-route charging among various facilities and users within, at least, a part of the reverse logistics network. Fig. 1 gives an example where the routes connecting several selected generation points of EOL products to the designated collection centers are covered by the charging infrastructure network. Depending on the specific operational demands, this charging infrastructure network's reach can also be expanded to include additional nodes within the reverse logistics system, e.g., remanufacturing plants, recycling centers, disposal sites, and other generation points of EOL products and collection centers.

The construction of such a charging infrastructure network necessitates thorough consideration of the charging demands at each selected node as well as along the transportation arcs. Consequently, the development of the whole system is a complex decision-making process, which involves not only the strategic facility placement and allocation of flows within the reverse logistics network but also the simultaneous determination of charging station locations to ensure infrastructural readiness for E-truck deployment. Moreover, the decisions regarding the reverse logistics network configuration significantly influence the location decisions for charging stations, and this interdependence underscores the complexity of the problem. Therefore, our research introduces a new mathematical model to address the joint design of reverse logistics and charging infrastructure networks. This model aims to optimize location-allocation strategies for the reverse logistics system while simultaneously ensuring the charging infrastructure coverage for E-truck adoption, say, a charging station is accessible with a predefined distance no matter where the trip starts in the network.

4. Mathematical model

In this section, the notations are first given, and the mathematical model for the joint reverse logistics and charging infrastructure

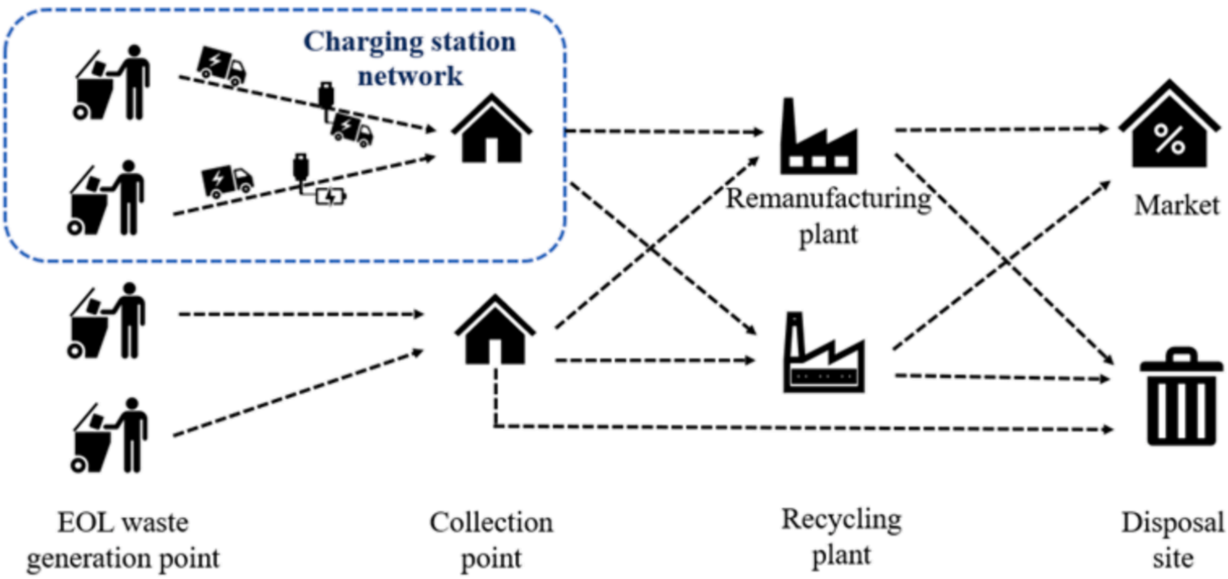


Fig. 1. Reverse logistics network design with partial coverage of first-stage transportation by the charging infrastructure network.

network design problem is then formulated.

4.1. Notations

Notations	
Sets	
G	Set of generation points of EOL products, indexed by g
C	Set of potential locations for collection points, indexed by c
P	Set of potential locations for remanufacturing plants, indexed by p
R	Set of potential locations for recycling plants, indexed by r
D	Set of potential locations for disposal sites, indexed by d
M	Set of markets, indexed by m
G *	Set of generation points covered by the charging network $G^* \subseteq G$, indexed by g *
C *	Set of potential collection points covered by the charging network $C^* \subseteq C$, indexed by c *
P *	Set of potential remanufacturing plants covered by the charging network $P^* \subseteq P$, indexed by p *
R *	Set of potential recycling plants covered by the charging network $R^* \subseteq R$, indexed by r *
D *	Set of potential disposal sites covered by the charging network $D^* \subseteq D$, indexed by d *
M *	Set of markets covered by the charging network $M^* \subseteq M$, indexed by m *
I	Set of potential locations for charging stations, indexed by i
Parameters	
fc_c	Fixed cost for operating collection point c
fp_p	Fixed cost for operating remanufacturing plant p
fr_r	Fixed cost for operating recycling plant r
fd_d	Fixed cost for operating disposal site d
vc_c	Variable handling cost at collection point c
vp_p	Variable handling cost at remanufacturing plant p
vr_r	Variable handling cost at recycling plant r
vd_d	Variable handling cost at disposal site d
ta_{gc}	Unit transportation cost between g and c
tb_{cp}	Unit transportation cost between c and p
tc_{cr}	Unit transportation cost between c and r
td_{cd}	Unit transportation cost between c and d
te_{pd}	Unit transportation cost between p and d
tf_{rd}	Unit transportation cost between r and d
tg_{pm}	Unit transportation cost between p and m
th_{rm}	Unit transportation cost between r and m
u_i	Fixed cost for opening and operating charging station i
E_g	Amount of EOL products at generation point g
ϑ_p	Fraction of remanufacturable components
ϑ_r	Fraction of recyclable components
ϑ_d	Fraction of non-recoverable waste generated at collection point
τ_d	Fraction of remanufactured product
τ_m	Fraction of waste generated in the remanufacturing process
ρ_d	Fraction of recycling products and materials
ρ_m	Fraction of waste generated in the recycling process
Cc_c	Capacity of collection point c
Cp_p	Capacity of remanufacturing plant p
Cr_r	Capacity of recycling plant r
Cd_d	Capacity of disposal site d
O_{ig^*}	Coverage matrix for the generation points served by the charging network
S_{im^*}	Coverage matrix for the markets served by the charging network
T_{ic^*}	Coverage matrix for the collection points served by the charging network
U_{ip^*}	Coverage matrix for the remanufacturing plants served by the charging network
V_{ir^*}	Coverage matrix for the recycling plants served by the charging network
Z_{id^*}	Coverage matrix for the disposal sites served by the charging network
$N_{ij}\{j \in I \backslash j \neq i\}$	Coverage matrix between charging stations
Decision Variables	
yc_c	Binary variable determining if a collection point is open at c
yp_p	Binary variable determining if a remanufacturing plant is open at p
yr_r	Binary variable determining if a recycling plant is open at r
yd_d	Binary variable determining if a disposal site is open at d
x_i	Binary variable determining if a charging is open at i
wc_c	Amount of EOL products handled at collection point c
wp_p	Amount of components remanufactured at plant p
wr_r	Amount of components recycled at plant r
wd_d	Amount of waste processed at disposal site d
qa_{gc}	Amount of EOL products transported between g and c
qb_{cp}	Amount of components transported between c and p
qc_{cr}	Amount of components transported between c and r
qd_{cd}	Amount of waste transported between c and d

(continued on next page)

(*continued*)

Notations	
qe_{pd}	Amount of waste transported between p and d
qf_{rd}	Amount of waste transported between r and d
qg_{pm}	Amount of remanufactured products transported between p and m
qh_{rm}	Amount of recycled products transported between r and m

4.1.1. Mathematical model

Research on modeling reverse logistics network design problems has been extensive since the early 2000s (Fleischmann et al., 2000). Typically, these models aim to either maximize profit through value recovery or minimize operating costs while adhering to constraints related to logistics flow and capacity constraints (Govindan et al., 2015). Based on the network structure given in Fig. 1, we formulated a cost-minimization problem in this paper. Equation (1) is the objective function designed to minimize the total operating cost of the reverse logistics system with associated charging infrastructures. Specifically, the total operating cost consists of fixed facility cost for reverse logistics operations, variable processing cost, transportation cost, and the fixed cost for the installation and maintenance of charging stations, respectively:

$$\text{Minimize } Totalcost = Fixed\_cost + Varible\_cost + Transportation\_cost + Charging\_infrastructure\_cost, \tag{1}$$

Equations (2) and (3) are formulated to compute the fixed and variable processing costs at various nodes in the system including collection centers, remanufacturing plants, recycling plants, and disposal sites. Equation (4) enumerates the transportation costs of EOL products, components, materials, and wastes across different locations, while Equation (5) accounts for the expenses associated with the charging network. Notably, these cost items are considered recurring costs and are assessed per period, such as annually. In this model, the non-recurring investment is annualized throughout the life cycle, i.e., capital expense recovery, and is thus considered as a part of fixed operating costs, which can be estimated with discounted cash flow (DCF) analysis:

$$Fixed\_cost = \sum_{c\in C} fc_c yc_c + \sum_{p\in P} fp_p yp_p + \sum_{r\in R} fr_r yr_r + \sum_{d\in D} fd_d yd_d, \tag{2}$$

$$Variable\_cost = \sum_{c\in C} vc_c wc_c + \sum_{p\in P} vp_p wp_p + \sum_{r\in R} vr_r wr_r + \sum_{d\in D} vd_d wd_d, \tag{3}$$

$$\begin{aligned} Transportation\_cost = {} & \sum_{g\in G}\sum_{c\in C} ta_{gc} qa_{gc} + \sum_{c\in C}\sum_{p\in P} tb_{cp} qb_{cp} + \sum_{c\in C}\sum_{r\in R} tc_{cr} qc_{cr} + \sum_{c\in C}\sum_{d\in D} td_{cd} qd_{cd} + \sum_{p\in P}\sum_{d\in D} te_{pd} qe_{pd} + \sum_{r\in R}\sum_{d\in D} tf_{rd} qf_{rd} \\ & + \sum_{p\in P}\sum_{m\in M} tg_{pm} qg_{pm} + \sum_{p\in P}\sum_{m\in M} th_{rm} qh_{rm}, \end{aligned} \tag{4}$$

$$Charging\_infrastructure\_cost = \sum_{i\in I} u_i x_i, \tag{5}$$

The model is subject to constraints (6)–(33). Constraints (6)–(21) are for reverse logistics network design, while the others are related to locating charging stations and the requirements on decision variables. Constraint (6) ensures the effective collection and handling of EOL products from every generation point, which establishes a foundational requirement for the network's operation:

$$\sum_{c\in C} qa_{gc} \geq E_g, \forall g \in G, \tag{6}$$

Equations (7)–(10) impose flow balance constraints at the collection center, which specify the relationship between the incoming flows of EOL products and the outgoing flows of components, materials, and wastes:

$$\sum_{g\in G} qa_{gc} = wc_c, \forall c \in C, \tag{7}$$

$$wc_c \vartheta_p = \sum_{p\in P} qb_{cp}, \forall c \in C, \tag{8}$$

$$wc_c \vartheta_r = \sum_{r\in R} qc_{cr}, \forall c \in C, \tag{9}$$

$$wc_c \vartheta_d = \sum_{d\in D} qd_{cd}, \forall c \in C, \tag{10}$$

Equations (11)–(16) extend these flow balance constraints to remanufacturing plants and recycling plants, respectively:

$$\sum_{c\in C} qb_{cp} = wp_p, \forall p \in P, \tag{11}$$

$$wp_p\tau_d = \sum_{d\in D} qe_{pd}, \forall p \in P, \tag{12}$$

$$wp_p\tau_m = \sum_{m\in M} qg_{pm}, \forall p \in P, \tag{13}$$

$$\sum_{c\in C} qc_{cr} = wr_r, \forall r \in R, \tag{14}$$

$$wr_r\rho_d = \sum_{d\in D} qf_{rd}, \forall r \in R, \tag{15}$$

$$wr_r\rho_m = \sum_{m\in M} qh_{rm}, \forall r \in R, \tag{16}$$

Equation (17) calculates the total amount of waste directed to and disposed of at each site:

$$\sum_{c\in C} qd_{cd} + \sum_{p\in P} qe_{pd} + \sum_{r\in R} qf_{rd} = wd_d, \forall d \in D, \tag{17}$$

Constraints (18)–(21) enforce facility capacity limitations at respective locations, which prevent the violation of resource availability:

$$wc_c \leq Cc_c yc_c, \forall c \in C, \tag{18}$$

$$wp_p \leq Cp_p yp_p, \forall p \in P, \tag{19}$$

$$wr_r \leq Cr_r yr_r, \forall r \in R, \tag{20}$$

$$wd_d \leq Cd_d yd_d, \forall d \in D, \tag{21}$$

Constraints (22)–(28) are dedicated to ensuring adequate accessibility to the charging infrastructure. As previously discussed, the design of charging infrastructure networks exemplifies a classic service facility location problem, which requires a balance between cost-effectiveness and service accessibility (Wang et al., 2013, Çapar et al., 2023). To support the integration of E-trucks in reverse logistics operations and their adoption in the corresponding regions, we employed an improved SCLP. The covering location problem was first proposed by Hakimi (1965) and later formulated by Toregas et al. (1971). The SCLP is a classic facility location problem that ensures the full coverage of the node-based demands with minimal cost or the number of facilities installed. However, the classic SCLP neglects the demand from the arc. Thus, an improved network-based SCLP formulated by Yu et al. (2023) is used to ensure full infrastructure coverage across both selected nodes and arcs. Specifically, constraints (22) and (23) guarantee that all the generation points of EOL products in G^* and all the markets in M^* are covered by the charging network. Herein, G^* and M^* are subsets of G and M, and these subsets represent nodes that require E-truck coverage and are crucial for the deployment of the charging infrastructure network. With a given level of accessibility, the coverage matrices O_{ig^*} and S_{im^*} can be generated based on the distance matrices between respective nodes:

$$\sum_{i\in I} x_i O_{ig^*} \geq 1, \forall g^* \in G^*, \tag{22}$$

$$\sum_{i\in I} x_i S_{im^*} \geq 1, \forall m^* \in M^*, \tag{23}$$

Constraints (24)–(27) ensure the demand for other facilities can be met by the charging infrastructure network with the given accessibility level. For instance, constraint (24) stipulates that a candidate location, identified within the subset C^*, once selected for establishing a collection center, at least one charging station within the predetermined coverage distance must be open in order to ensure adequate infrastructure support for E-truck adoption:

$$\sum_{i\in I} x_i T_{ic^*} \geq yc_{c^*}, \forall c^* \in C^*, \tag{24}$$

$$\sum_{i\in I} x_i U_{ip^*} \geq yp_{p^*}, \forall p^* \in P^*, \tag{25}$$

$$\sum_{i\in I} x_i V_{ir^*} \geq yr_{r^*}, \forall r^* \in R^*, \tag{26}$$

$$\sum_{i\in I} x_i Z_{id^*} \geq yd_{d^*}, \forall d^* \in D^*, \tag{27}$$

Constraint (28) is the accessibility requirement throughout the charging infrastructure network across both nodes and arcs. Based on Yu et al. (2024), this constraint ensures that, upon selection of a candidate location for a charging station, another candidate location within the predetermined coverage distance must also be chosen. This constraint guarantees that charging stations are spaced such that, irrespective of the starting point of a journey within the network, a charging station is always accessible within the set coverage distance:

$$x_i \leq \sum_{j \in I \setminus i \neq j} N_{ij} x_j, \forall i \in I, \tag{28}$$

Finally, equations (29)–(33) delineate the domains of binary variables, while the other continuous variables maintain non-negative values:

$$x_i, x_j \in \{0, 1\}, \forall i, j \in I, \tag{29}$$

$$yc_c \in \{0, 1\}, \forall c \in C, \tag{30}$$

$$yp_p \in \{0, 1\}, \forall p \in P, \tag{31}$$

$$yr_r \in \{0, 1\}, \forall r \in R, \tag{32}$$

$$yd_d \in \{0, 1\}, \forall d \in D. \tag{33}$$

5. Experiments and analyses

In this section, the case description and the setup of experimental data are first given, and then the numerical results are analyzed and the implications are discussed.

5.1. Case description and experimental data

In this paper, under an industry-led strategy, we considered a joint reverse logistics and charging infrastructure network design problem for the recycling of waste electrical and electronic equipment (WEEE) in Southern Norway. With approximately 26 kg/person/year in 2019, Norway has the highest amount of WEEE generation per capita in Europe (Statista, 2023). Based on Statistics Norway 2022, the total amount of WEEE has reached 139,000 metric tons, among which 78 % were recycled and the others were sent for energy recovery and proper disposal through incineration and landfill (Ssb, 2024b). In addition, Norway has set an ambitious goal

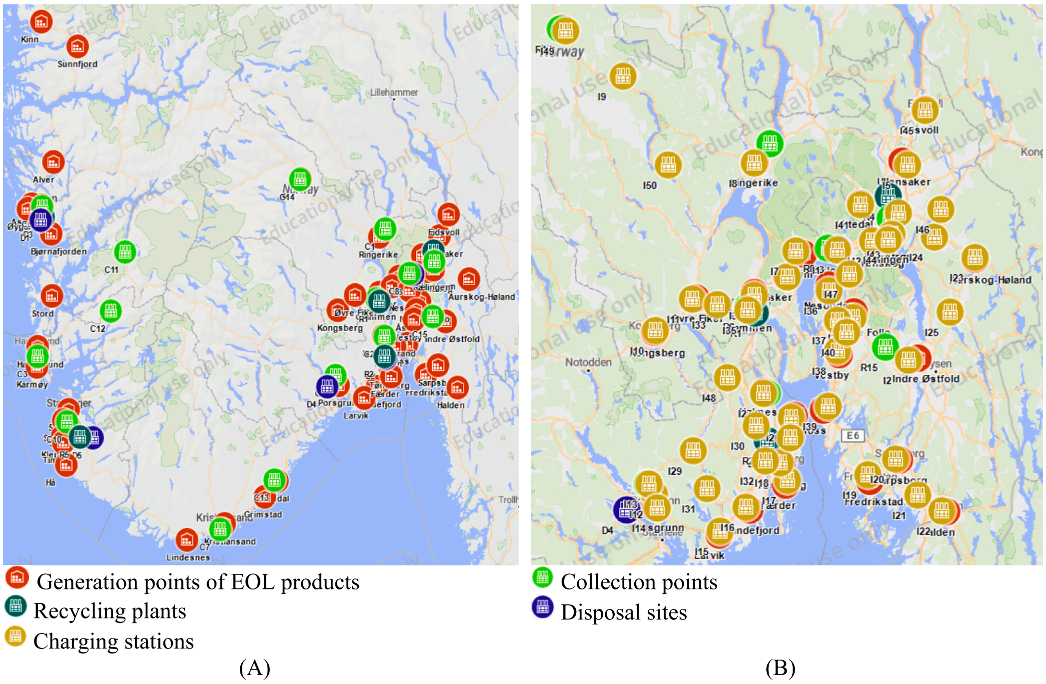


Fig. 2. Joint reverse logistics and infrastructure network design problem: (A) Generation points of WEEE and candidate locations for collection centers, recycling plants, and disposal sites; (B) Candidate locations for charging stations in the selected region.

for greening and decarbonizing the transport sector through the adoption of EVs. The share of EVs has reached nearly 65 % in 2021, and all newly sold lightweight vehicles in the market should be green with zero emissions by 2025 (Yang et al., 2023). Furthermore, the target for decarbonizing the freight transportation and logistics sectors by adopting large zero-emission trucks is set to 75 % by 2030 (Figenbaum et al., 2020). Currently, this initiative is led by several industry clusters, e.g., the postal service and aquaculture industry (Yu et al., 2023), through investigating the technological solutions for E-trucks and infrastructure network planning.

Inspired by the industrial need for decarbonization of their logistics activities, we considered a reverse logistics design problem with partial adoption of E-trucks in transportation. The studied area includes 9 counties in the southern part of Norway including Oslo, Akershus, Østfold, Vestfold, Buskerud, Agder, Telemark, and Rogaland. At the initial stage, a charging infrastructure network needs to be established to support the transportation in the reverse logistics system in Oslo, Akershus, Østfold, Vestfold, and several large municipalities in Telemark and Buskerud. With a threshold of 15,000 residents, we selected the 53 largest municipalities in the study area for the generation points of WEEE. In our experiment, taking into account fair geographical accessibility, we selected 15 candidate locations for collection centers, 5 candidate locations for recycling plants, and 5 candidate locations for disposal sites. The generation of WEEE was assumed to be proportional to the population of respective municipalities, obtained from Statistics Norway (Ssb, 2024a), and the annual average generation per capita was set to 26 kg/year (Statista, 2023). In addition, to set up the charging infrastructure network in the selected region, we chose 50 candidate locations for charging stations. Due to the fact that charging an E-truck may take up to 2 h with fast charging, most of the selected candidates are with existing service facilities like café or shops, which can help improve drivers' experiences and likelihood to charge (Hoen et al., 2023). Fig. 2 illustrates the generation points of WEEE and the candidate locations for collection centers, recycling plants, disposal sites, and charging stations. Table 1 presents the parameter generation intervals for the fixed and variable facility-related costs. For the fixed cost of opening and operating a charging station at candidate location i, we considered the annualized installation investment cost and maintenance cost (Nelder and Rogers, 2019). The initial capacities for collection centers, recycling plants, and disposal sites were set to 15,000,000 kg/year, 30,000,000 kg/year, and 12,500,000 kg/year, respectively. Then, we recalculated the capacity of each candidate location considering their fixed costs by $Cap_x = Cap_{x-inital}\left(1+\frac{(f_x - f_{min})}{f_{min}}\right)$, where x belongs to C, R and D, and f_x and f_{min} are the fixed cost generated and the lower bound of the generation interval at respective candidate locations.

For the transportation of WEEE, the Volvo FL diesel and electric trucks with a loading capacity of up to 16 tons (Wietschel, 2020) were selected. The unit transportation cost and unit carbon emissions were calculated based on the distance matrix generated from the Bing Maps API. Besides, the loading rate of the vehicles also impacts the unit transportation cost and the unit carbon emissions. In this experiment, the average loading rates for both types of trucks were set to 0.85. We first calculated the unit transportation cost for diesel trucks using $\frac{Fuel\_Consumption\_per(L/km) \times Fuel\_cost(NOK/L)}{Loading\_rate}$, where fuel consumption of 0.3 L/km (Suthar, 2024, Volvo, 2022, Mårtensson, 2018) and the diesel cost of 25 NOK/L were used. Besides, the CO_2 emissions were estimated based on (Mårtensson, 2018, Comparethemarket, 2023, Nowtricity, 2024), where 0.0014557 kg/km/kg and 0.0000208 kg/km/kg were calculated for diesel trucks and E-trucks, respectively. In Norway, the cost of fast charging significantly surpasses that of normal charging, with prices of approximately 8.4 NOK/kWh for fast charging compared to 1.6 NOK/kWh for normal charging at company premises (Comparethemarket, 2023, Suthar, 2024). Therefore, in our experiment, we utilized expected values derived from scenarios where the distribution between fast charging and normal charging was 20 % and 80 %, respectively. This allocation reflects that a substantial portion of E-truck charging can be effectively managed through depot-based slow charging (Speth and Plötz, 2024).

Taking into account fleet composition and accessibility of the charging network, we compared five scenarios. The first scenario (S1) only employs diesel trucks in the reverse logistics network, while the other four scenarios use both diesel and E-trucks. As discussed by Speth et al. (2022), the average distance between two charging stations should be around 100–150 km in order to provide an effective charging service. Thus, we tested four different coverage distances including 150 km, 100 km, 75 km, and 50 km in scenarios S2, S3, S4, and S5. Coverage matrixes were subsequently derived from the corresponding distance matrixes for each specified coverage distance. In addition, Cheng and Lin (2024) revealed that while E-trucks offer energy savings, their use could extend journey times by as much as 36 % due to charging-related delays (non-revenue time). Furthermore, in areas with sparse charging infrastructure, increased travel distances and detours for charging are often necessary (Yu et al., 2023). Both factors may significantly affect the transportation costs and carbon emissions in the reverse logistics system. Given the inverse relationship between these factors and the pre-defined coverage distance, we adjusted the unit transportation cost across scenarios S2, S3, S4, and S5 with compensation multipliers of 1.25, 1.2, 1.15, and 1.1. Similarly, for carbon emissions in these scenarios, the compensation multipliers were set to 1.15, 1.1, 1.05, and 1, respectively. All the data used in the experiment is given in Appendix A.

Table 1
Parameter generation interval for reverse logistics and charging facilities.

Facility	Parameter generation interval	
	Fixed cost (NOK/year)	Variable cost (NOK/kg)
Collection center	[8000000, 9000000]	[0.06, 0.07]
Recycling plant	[15000000, 16000000]	[0.04, 0.05]
Disposal site	[9000000, 10000000]	[0.04, 0.05]
Charging station	[335000, 400000]	N/A

5.2. Numerical results

The optimization problem was solved on a PC with Intel(R) Core(TM) i5-6400 T CPU @ 2.20 GHz 2.21 GHz and 8 GB RAM under the Windows 10 operating system. The fleet composition, required coverage distance, total costs, facility costs, carbon emissions, and carbon emissions are given in Table 2. Fig. 3 presents the optimal networks for scenarios utilizing solely diesel trucks (S1) and those incorporating mixed fleets of diesel and E-trucks (S2—S5). In S1, the optimal reverse logistics network includes collection centers C2, C3, C6, C8, and C10, along with recycling plants R1 and R5, and disposal sites D3 and D5. On the other hand, the optimal reverse logistics network in other scenarios consists of collection centers C3, C6, C8, C10, and C15, recycling plants R4 and R5, and disposal sites D3 and D5. The results revealed that the reverse logistics network structure could be affected when jointly designing the charging infrastructure network for E-truck adoption.

As shown in Table 2, the integration of E-truck results in an escalation in facility operational costs, particularly associated with maintaining the charging infrastructure network. Conversely, transportation costs experience a substantial reduction. This decrease in transportation expenses contributes to a lower total operational cost, which enhances the economic efficiency of the reverse logistics system. Specifically, Fig. 4 compares the change in the charging infrastructure costs and transportation costs with respect to the total costs across the five scenarios. Furthermore, the carbon emissions are significantly reduced when using E-trucks for transportation. For example, in scenario S2, utilizing a hybrid fleet with a coverage distance of 150 km results in a 0.34 % increase in facility operating costs compared to scenario S1, which employs exclusively diesel trucks. However, this adjustment yields a significant 26.7 % decrease in transportation costs. Consequently, these changes led to an overall reduction of 2.37 % in total costs and a 16.3 % decrease in carbon emissions associated with transportation.

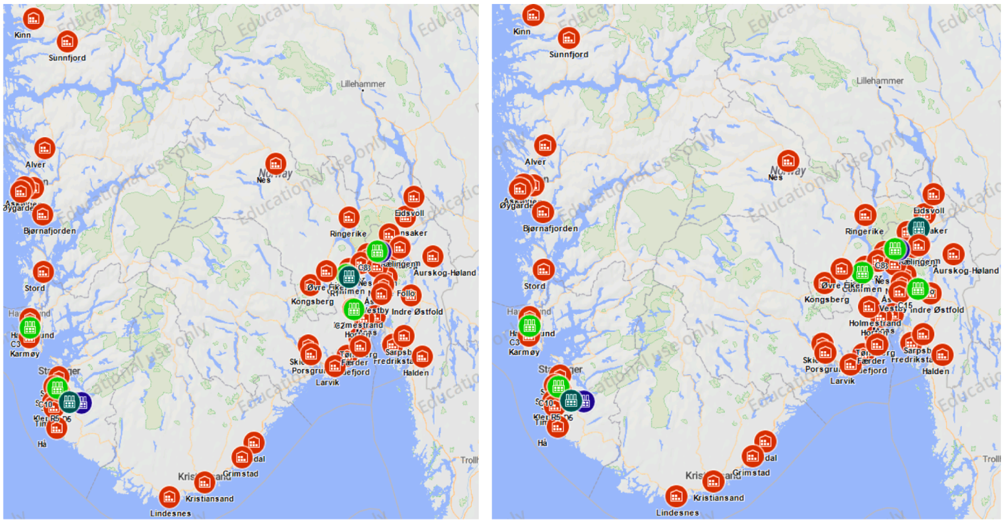
When the required coverage distance reduces from 150 km to 50 km, the number of charging stations increases from 2 to 9, leading to different charging infrastructure network structures, as shown in Table 3 and Fig. 5. Besides, Table 3 also illustrates accessibility measured by the average minimum distance from demand points to charging stations and the average minimum distance between two charging stations in scenarios S2—S5. First, we analyzed the change in different cost components and carbon emissions. When a shorter coverage distance is required, there is an increase in the facility costs due to the operation of additional charging stations in the system, but the transportation costs decrease consistently. However, the total costs demonstrate a tradeoff between facility operating costs and transportation costs. In these experiments, the minimum total costs are achieved in scenario S2, where two charging stations are selected at I33 and I44. When the required coverage distance decreases in scenarios S3—S5, the operating costs of the charging infrastructure network consecutively increase by 54 %, 105.2 %, and 51.6 %, and the total costs of the reverse logistics system consecutively increase by 0.29 %, 0.97 %, and 0.96 %. In addition, with the decrease in the required coverage distance, carbon emissions of the reverse logistics system can be reduced consistently, as shown in Fig. 6. In comparison to scenario S2, 4.7 %, 10 %, and 14.7 % reductions of carbon emissions in transportation can be achieved in scenarios S3—S5.

Next, we compared the accessibility of the charging infrastructure network across scenarios S2—S5. Two performance indicators are taken into account. First is the mean value of the minimum distance from all demand points to the charging stations (charge-to-demand distance), and the other is the mean value of the minimum distance from one charging station to another in the charging network (charge-to-charge distance). As demonstrated in Table 3 and Fig. 6, there is a general decrease in both performance indicators across scenarios S2 to S5, which suggests that higher accessibility of the charging infrastructure network can be achieved through a reduction in coverage distance coupled with the addition of more charging stations. The only exception is observed in S2, where the minimum charge-to-charge distance is lower than that in S3. This anomaly can be attributed to the fact that only two charging stations are selected in S2. Consequently, the charge-to-charge distance in this scenario is significantly influenced by their relative locations, provided that all demand points are adequately covered at minimum costs. Therefore, this indicator becomes meaningful only when more than three charging stations are operational, forming a connected network that minimizes the impact of such spatial randomness.

Table 4 compares the computational performance of six different optimization solvers. In scenario S1 with only diesel trucks, all solvers can obtain the optimal results within 10 s. Xpress and Highs are the fastest commercial and open-source solvers, respectively. As the computational complexity escalates in scenarios S2—S5, most solvers exhibit increased solver times. In particular, the average solver time of Xpress and Scip increased by 704 % and 445.6 % even though they show high levels of performance consistency. On the other hand, the average solver time of Cplex and Copt was reduced by 19.2 % and 4.6 %, respectively. However, the CV and SD of Cplex, Copt, and Gurobi are relatively high. For example, the solver times for Cplex are less than 2 s for scenarios S2—S4, while it becomes nearly 12 s to solve S5, which leads to a high level of variation. Taking into account the overall performance, Highs shows a high and consistent performance across scenarios for solving the given problem. It is noteworthy that the current experiments are performed based on a specific problem structure under small-scale instances, so the choice between different solvers needs to consider

Table 2
Optimal objective value and performance indicators for the five scenarios.

Scenario	Fleet	Coverage distance (km)	Cost (NOK)			Carbon emissions (kg)
			Facility	Transportation	Total	
S1	Diesel trucks	N/A	99,455,729	11,068,437	110,524,166	972,249
S2	Diesel and E-trucks	150	99,794,300	8,113,530	107,907,830	813,379
S3	Diesel and E-trucks	100	100,158,765	8,066,487	108,225,252	809,523
S4	Diesel and E-trucks	75	101,251,092	8,019,444	109,270,536	805,281
S5	Diesel and E-trucks	50	102,350,760	7,972,401	110,323,161	801,425



(A) (B)

Fig. 3. Optimal reverse logistics network in (A) S1 with only diesel trucks; (B) S2—S5 with both diesel and E-trucks.

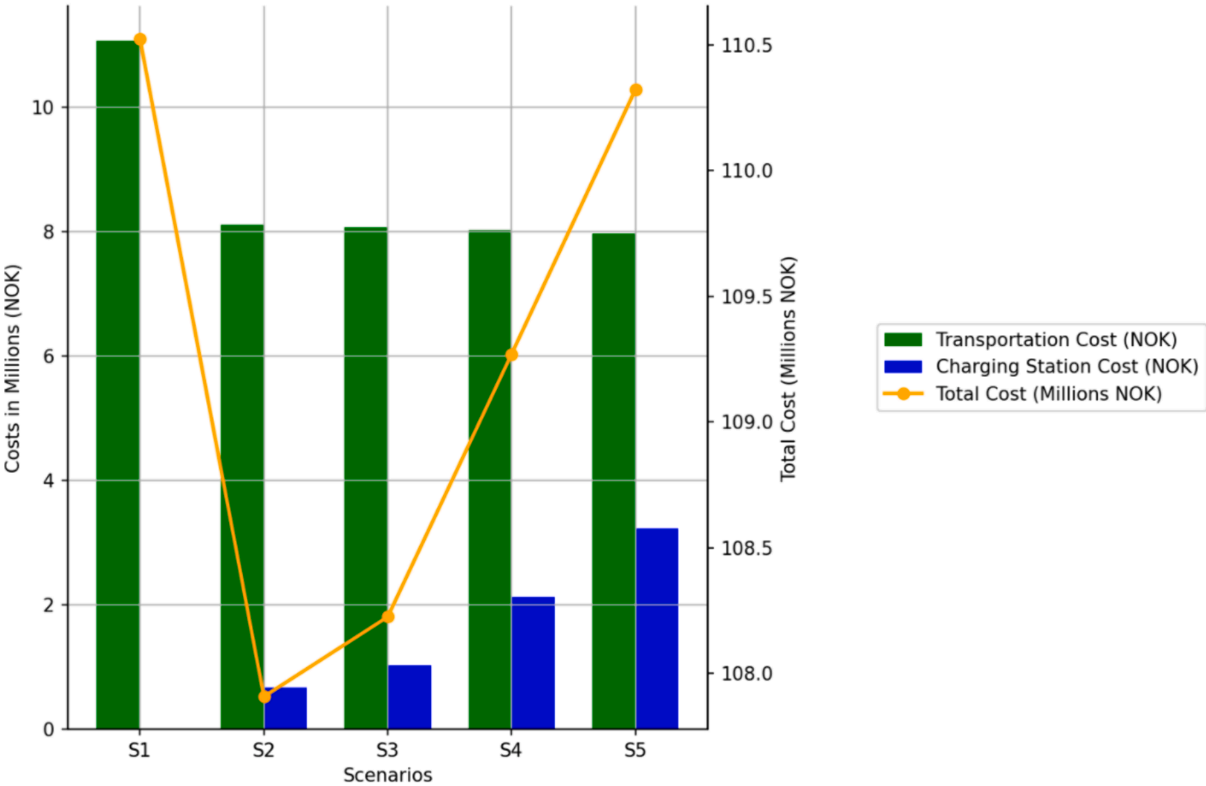


Fig. 4. Comparison of charging infrastructure costs and transportation costs with respect to the total costs.

several factors under a specific application scenario, e.g., problem structure, budget constraints, computational requirements, etc.

5.3. Analyses, Discussions, and implications

In this section, we analyze the results and discuss the similarities and differences between our findings and existing literature. Finally, we summarize the managerial and research implications.

Table 3
Charging infrastructure network and accessibility.

Scenarios	Number of charging stations	Locations of charging stations	Accessibility/distance (km)	
			Charge-to-demand	Charge-to-charge
S2	2	I33, I44	58.5	75.0
S3	3	I1, I26, I50	41.7	92.3
S4	6	I9, I10, I29, I39, I44, I50	32.3	59.3
S5	9	I1, I4, I8, I9, I19, I20, I29, I48, I50	30.7	35.5

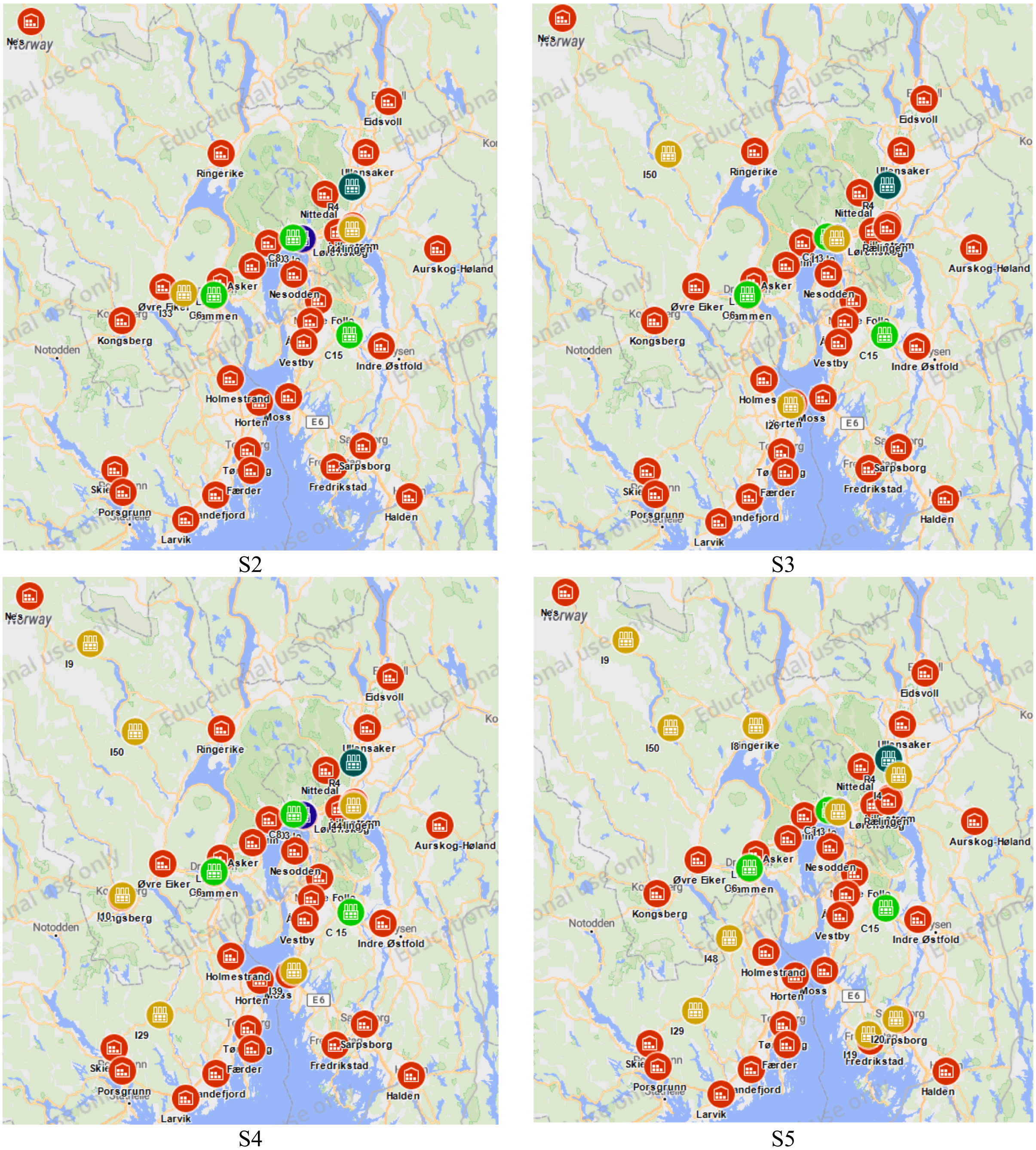


Fig. 5. Charging infrastructure network in S2—S5.

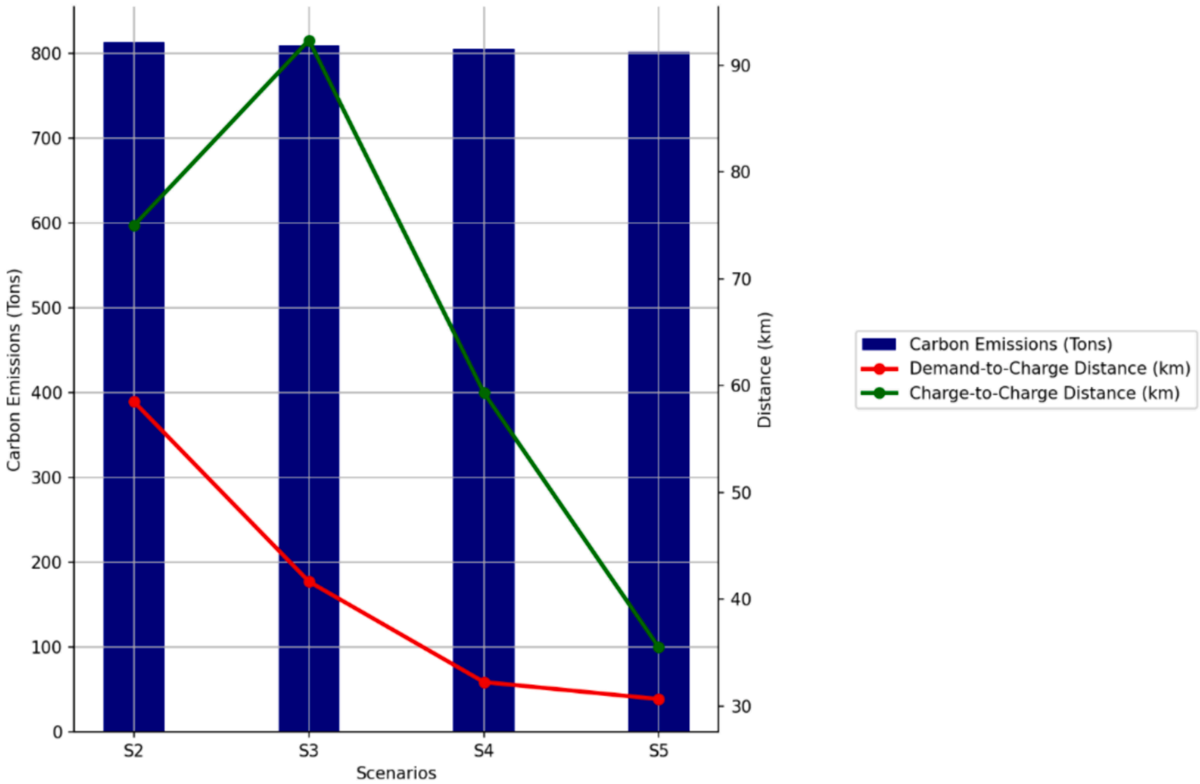


Fig. 6. Comparison of carbon emissions and the accessibility of charging infrastructure network across scenarios S2—S5.

Table 4
Computational performance of different optimization solvers.

Scenarios/Evaluation	Solver time (s)					
	Gurobi	Cplex	Copt	Xpress	Highs	Scip
S1	3.625	5.078	8.234	2.578	1.891	6.547
S2	6.016	1.516	5.938	20.234	3.578	24.703
S3	8.719	1.859	5.344	20.625	3.406	36.859
S4	1.609	1.297	5.719	21.422	2.391	38.250
S5	5.609	11.750	14.422	20.641	2.750	43.063
Mean (S2—S5)	5.488	4.105	7.855	20.730	3.031	35.719
SD (S2—S5)	2.538	4.418	3.797	0.431	0.482	6.764
CV (S2—S5)	46.25 %	107.62 %	48.34 %	2.08 %	15.90 %	18.94 %

5.3.1. Result Analysis: Similarities with existing literature

In recent years, the adoption of E-trucks in greening and decarbonizing transportation activities has increasingly become a global focus (Wu et al., 2023), especially in reverse logistics (Erdinç et al., 2019). Among others, the requirement of a highly accessible charging infrastructure network is one of the most significant challenges for the adoption of E-trucks (Deng et al., 2023). In this regard, Menter et al. (2023) and Hurtado-Beltran et al. (2021) investigated national-wide E-truck charging infrastructure network planning in Germany and the United States. Furthermore, considering the coverage distances of 100 km and 50 km, Speth et al. (2022) designed a charging infrastructure network across Europe with 660 and 1468 charging stations for these two scenarios. Our research confirmed the findings from these previous studies that coverage distance plays an important role in determining the configuration, structure, and accessibility of the charging infrastructure network. As shown in our experiment, while the required coverage distance is reduced from 150 km to 50 km, the number and locations of the charging stations change dramatically, and both demand-to-charge and charge-to-charge distances are reduced gradually, indicating an increase in the accessibility of the charging infrastructure network. For instance, when the coverage distance decreases from 100 km to 75 km, the demand-to-charge distance and the charge-to-charge distance can be reduced by 22.6 % and 35.7 %, respectively. When the coverage distance decreases to 50 km, these two indicators can be further reduced by 4.9 % and 40.2 %. Consequently, higher accessibility and density of charging stations may help promote the adoption of E-trucks in the transport sector.

5.3.2. Result Analysis: Unique findings from the research

However, the development of a charging infrastructure network and the adoption of E-trucks typically represent a gradual and costly multi-year process. Consequently, implementing such a charging infrastructure network on a national scale may not be feasible in a short period. Distinct from prior research, our study is motivated by the specific needs of an industrial cluster in Norway aimed at decarbonizing its transport activities (Yu et al., 2023) and thus provides new findings and implications. We investigate and model an industry-led charging infrastructure network development strategy by a cluster of users in a reverse logistics system. Our experiments show that, by the adoption of E-trucks, even though the facility operating costs may increase due to the operations and maintenance of additional charging stations, the total reverse logistics costs can be reduced by 0.18 %—2.37 %, and the carbon emission in transportation can be reduced by 16.3 %—17.6 %. The results illustrate both the economic viability and environmental benefits of industry-led development of charging infrastructure networks through, for example, a public–private partnership or a private-private partnership. Furthermore, as the accessibility of the charging infrastructure network increases, both transportation costs and carbon emissions are reduced. However, the total costs may be increased due to the infrastructure costs incurred from additional charging stations. For example, when increasing the number of charging stations from 3 (S3) to 6 (S4), the transportation costs and carbon emissions are reduced by 0.58 % and 0.52 %, but the total costs increase by nearly 1 %.

Our results suggest that even though adopting E-trucks through an industry-led strategy has shown both economic viability and environmental benefits in reverse logistics management, establishing a charging infrastructure network should be a multi-stage process with potential expansion to accommodate increased charging demands. For instance, our experiments demonstrate that replacing diesel trucks with E-trucks and installing three charging stations within the region can reduce total costs and carbon emissions by 2.1 % and 16.7 %, respectively. We observed average distances of 41.7 km from demand points to charging stations and 92.3 km between charging stations. Although expanding the charging infrastructure network to six charging stations markedly improves accessibility, the additional reductions in transportation costs and carbon emissions are marginal. Moreover, this expansion would increase the annual operating costs of the reverse logistics system by 1,045,284 NOK. Furthermore, in scenario S5 where nine charging stations are proposed, three of them are installed along the way to Nes. This configuration, driven by coverage requirements for remote areas, may lead to potential resource redundancy given the minimal demands from these locations, particularly in the initial stage.

Thus, under this industry-led strategy for charging infrastructure network development, establishing two to three charging stations initially is deemed appropriate to meet the primary demands of users in the reverse logistics system. As the adoption of E-trucks expands across other companies and users, the existing charging infrastructure can become profitable for service providers and may be further expanded in response to increasing demand. This proactive approach not only facilitates the early-stage integration of sustainable transport solutions in a specific industrial cluster but also sets a precedent for scaling the charging infrastructure network in response to evolving market dynamics. Furthermore, the initial economic viability and environmental gains from limited deployments could serve as a compelling business case, which encourages further investments from both the public and private sectors.

5.3.3. Managerial implications

Our research provides managers in logistics sectors and industrial clusters with a quantitative methodology to design a joint network and to evaluate the economic viability and environmental benefits of E-truck adoption through an industry-led strategy for charging infrastructure network development. Our findings suggest that starting with a few charging stations in the initial stage can optimally support the existing demand under accessibility requirements and set a foundation for scalable infrastructure in response to future needs. The economic analysis highlights that while expanding the charging network offers marginal additional benefits in cost and emission reductions in the initial E-truck adoption stage, the potentially significant increase in total system costs needs to be thoroughly evaluated.

5.3.4. Research implications

Rather than adopting a nationwide approach to the planning of charging infrastructure networks, it is imperative for researchers to focus on the specific needs of industrial clusters and develop tailored decision-support models for the joint design of logistics and charging infrastructure networks. Furthermore, from an optimization perspective, the comparative analysis of six solvers highlights the critical importance of context-dependent solver selection, which emphasizes the need for a targeted approach in solver selection based on specific problem structures and datasets. In our experiment, although Highs, as an open-source solution, provides a robust example of both performance and consistency, commercial solvers such as Gurobi and Cplex may still be favored in scenarios demanding specific solver features or where budget is less of a constraint.

6. Conclusions

To promote the widespread adoption of E-trucks for the purpose of greening and decarbonizing the transport sector, the development of a highly accessible charging infrastructure network is of critical importance. Unlike infrastructure designed for small EVs used by the general public, the initial demand for a charging infrastructure network for E-trucks typically originates from an industrial cluster. This distinction necessitates a tailored approach to infrastructure development that focuses on the specific requirements and operational dynamics of commercial and industrial transportation systems. In this paper, through modeling a joint network design problem, we evaluate the economic viability and environmental benefits of integrating E-trucks in green reverse logistics management of WEEE in the southern part of Norway. The experiments demonstrate that the design and configuration of the reverse logistics network are significantly influenced by the integration of charging infrastructure network design, which highlights the interdependence of infrastructure planning and logistics network efficiency in the context of E-truck adoption. Furthermore, our findings indicate that the adoption of E-trucks could potentially reduce total reverse logistics costs by 0.18 %—2.37 %. Simultaneously, carbon emissions from transportation could be diminished by 16.3 %—17.6 %. The results affirm the economic viability of the proposed strategy and highlight its potential environmental benefits, paving the way for broader adoption across the transport sector.

The main contributions of the paper are summarized as follows:

- A joint reverse logistics and charging infrastructure network design problem is modeled to assess the viability of an industry-led infrastructure development model for E-truck adoption.
- The viability of E-truck adoption in green reverse logistics in Norway is evaluated, and strategies and implications for industry-led charging infrastructure development are discussed.

The current research is subject to four primary limitations that open avenues for future improvements. First, the generalizability of the findings may be constrained by the specific geographic, regulatory, and industrial contexts of the study. Second, the evaluation primarily considers the reduction of tailpipe emissions and operational costs, which overlooks other critical factors, e.g., the environmental impact of battery production and disposal, cost addition in purchasing E-trucks, etc. Zheng and Peng (2021) reveal that the life-cycle carbon emissions of EVs, which include production, operation, and recycling, vary significantly with a country's power generation mix. In Norway, where power is predominantly sourced from clean and renewable energy, widespread EV adoption could have beneficial environmental impacts. Conversely, countries reliant on thermal power generation might see greater environmental costs from EV adoption, so future research should incorporate country-specific characteristics in the analysis. Third, the current research does not adequately address the uncertainties inherent in the optimization model, such as variability in charging demand and fluctuations in energy prices, which can drastically influence the outcomes. Future studies are thus needed to better capture and evaluate the impacts of these uncertainties. Last but not least, the current research overlooks certain critical practical considerations, e.g., driving and charging behavior (Qian et al., 2024), truck routing, collaborative resource sharing (Wang et al., 2020, Wang et al., 2023b), and changes on the driving range due to advancements in battery technology (He et al., 2022), all of which could significantly affect the overall performance of the reverse logistics system with charging stations. Moreover, incorporating uncertainties and these practical elements would greatly increase the model's computational complexity. Therefore, future research should focus on modeling these practical scenarios and developing effective solution methods, e.g., enhanced heuristics/metaheuristics, clustering algorithms, etc.

Declaration of generative AI and AI-assisted technologies in the writing process

During the preparation of the manuscript, the authors used ChatUiT (a tailored version of ChatGPT) to polish the scientific writing. After using this tool, the authors reviewed and edited the content as needed and take full responsibility for the content of the paper.

CRediT authorship contribution statement

Hao Yu: Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Resources, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization. **Xu Sun:** Writing – review & editing, Writing – original draft, Visualization, Investigation, Data curation, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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Appendix A. Supplementary material

Supplementary data to this article can be found online at https://doi.org/10.1016/j.trd.2024.104356.

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