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Scaling up dynamic charging infrastructure: Significant battery cost savings

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ABSTRACT

Large-scale electrification of heavy-duty road freight faces challenges including scarcity of charging infrastructure and high battery costs. Dynamic charging could help overcome these challenges by enabling trucks to charge while driving. Important additional benefits for carriers related to lower required sizes and longer lifetimes of batteries could justify the required investments. The study investigates the optimal configuration of network sections to be electrified so that the balance between costs and benefits turns out positive. A case study for a highway network spanning 4 countries in Europe suggests that dynamic charging can lead to a significant reduction in overall transport system costs, up to very large network sizes. The study supports the decision-making of policymakers and road authorities by providing new insights into the costs and benefits of dynamic charging networks, and simultaneously considering the perspectives of investors and users.

1. Introduction

Heavy-duty road freight transport is responsible for 5.6% of Europe's Greenhouse gas emissions (ACEA, 2020). Electrification of heavy-duty trucks is an important solution for decarbonization. However, installing charging stations poses several challenges, such as the need for large batteries for long haul movements, the net payload loss of vehicles and the very high power levels needed (Transport&Environment, 2021). In addition to these practical complexities, another challenge is the potential shortage of batteries once new European measures and regulations to decarbonize road transport take effect (ACEA, 2023).

A recent alternative for charging electric vehicles is dynamic charging, also known as Electric Road System (ERS) (Gustavsson et al., 2019), and it provides continuous power supply during driving through wireless/inductive charging, catenary and rail-based infrastructure. The introduction of ERS can impact transport costs in several ways. A recent research conducted by Shoman et al. (2022) in Sweden about passenger vehicles found that ERS combined with home-based charging would reduce the required battery range by 62%–71%, as batteries would mainly be needed to allow movements away from the main charging lines. Importantly, the savings in battery costs would be sufficient to cover the investment costs in ERS. As an additional benefit, fewer discharging and charging cycles would be needed with ERS, which improves battery lifespan. Moreover, directly tapping electricity from catenary lines leads to higher energy efficiency than charging stations and battery-swapping stations (Speth and Funke, 2021). In short, ERS appears to be a promising alternative for charging electric vehicles. In this paper, we focus on the application of ERS for heavy-duty freight transport. As with stationary charging, the introduction of ERS requires a major investment in the construction and maintenance of the system. In light of this, one question becomes paramount: how do investment and transport cost savings

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determine the economically feasible network size and its configuration? Information about the impact of ERS on net system costs, and on the resulting advisable network length is an important input for authorities to initiate investments in dynamic charging. Only a few studies have delved into this issue, and research has been limited to examining the impacts of ERS through fixed network scenarios, where it was unclear whether the designs evaluated were the best ones possible, given the underlying cost structures. For instance, in de Saxe et al. (2022), possible reductions in battery size were explored with three specific scenarios related to the UK freight road network. While the results were positive for ERS, it is unclear whether different networks would have produced significantly different results. We argue that to provide an assessment of the full potential of ERS, it is crucial to consider the best possible networks for different magnitudes of investment. This requires a form of network optimization, beyond pragmatic or scenario-wise network designs.

To address this void in the literature, our contributions are the following. Firstly, we propose an approach to identify the optimal ERS network for a given investment budget, minimizing infrastructure costs and operational costs. We develop a model for optimal dynamic charging infrastructure network design, where the objective functions consider the relevant cost trade-offs. Secondly, we present the outcomes of a case study conducted on a European freight network. The results reveal significant net societal benefit of investments in ERS, mainly due to reduction in battery sizes. Dynamic charging not only alleviates the challenge of deploying stationary charging infrastructure but also achieves this at lower costs to society. Our findings suggest that large-scale ERS investments could play a key role in expediting the electrification of road freight transport. This insight holds relevance for various stakeholders, particularly policymakers and the logistics industry.

The paper is structured as follows: Section 2 provides an overview of the existing literature on the charging infrastructure planning approach and identifies research gaps. Section 3 introduces the main research question and presents the methodology. The case study and its key results are presented and discussed in Section 4 while the main assumptions and their potential impacts are discussed in Section 5. Finally, Section 6 summarizes the contributions and recommendations. Details about the model and the solution approach are included in the Appendix.

2. Literature review

Studies addressing charging-infrastructure planning focus majorly on fixed charging infrastructure and only some studies address dynamic charging capable of providing electric power to the moving vehicles, hence enabling vehicles to charge while driving. Dynamic charging has been studied mostly in the context of wireless dynamic charging (WDC) since 2013 (He et al., 2013) and the impact on battery capacity has been considered as an element in most of them (Riemann et al., 2015; Jang et al., 2015, 2016; Liu and Song, 2017; He et al., 2020). Additionally, Chen et al. (2020) considers battery life cycles in a multi-route network. DWC offers flexibility in terms of vehicle movement, making it better suited for passenger transport at the cost of some lost efficiency. These studies are predominantly evaluated in theoretical or small-scale scenarios, nevertheless, they provide valuable insights and methodologies for optimizing other categories of dynamic charging infrastructures. Alwesabi et al. (2020) develop an optimization model minimizing total cost based on a trade-off between battery size and wireless dynamic charging allocation, including a method for battery size reduction for E-buses. The model is applied to a small bus network at Binghamton University. Mubarak et al. (2021) design a model from the perspective of decision-makers to optimally place wireless dynamic charging tracks in the urban networks, meeting all EVs' energy demands at minimum cost, considering traffic congestion where several lanes are available for EVs to choose from. Moreover, Chen et al. (2017) and Hassane et al. (2022) both create an optimization model considering dynamic and static charging facilities placement for EVs and explore their potential competition.

Electric road systems (ERS), especially those offering continuous charging like overhead catenary lines, employ physical conductive elements to directly and constantly provide power to vehicles. This enhances efficiency but limits flexibility in vehicle positioning. Nevertheless, these systems are well-suited for electrifying road freight due to the additional efficiency they provide as trucks spend most of their working time on highways and normally move along a certain lane. There is a significant research gap in the extensive planning of dynamic charging infrastructure (ERS) for Heavy-Duty Trucks (HDTs). Most literature on freight focuses on stationary charging facilities, and detailed studies considering aspects such as battery downsizing and the associated cost savings resulting from reduced battery requirements are lacking.

Few research works study ERS implementation using optimization models; Colovic et al. (2022) present a multi-objective network design model for determining optimal electrified roads using ERS-Overhead Catenary technology with the objective of maximizing truck flows served by ERS, minimizing diesel-caused environmental cost and ERS investment without battery cost considerations. This model is applied in a simple highway structure and targets hybrid trucks specifically. Schwerdfeger et al. (2022) provides an optimization approach for modeling optimal electrified highways to guarantee an ample energy supply for trucks on a German highway. This model is applicable to a single highway consisting of some small road segments. Their study targets hybrid trucks and the aim is to minimize ERS investment costs with various battery charge levels as input(parameters) of the model. As continuous decision variables are considered, the small segments on the highway may only partially be electrified thereby constraining the model's applicability to less extensive cases due to the substantial computational load. The study does not consider battery costs and discounting the ERS investment over its lifespan. Recently, de Saxe et al. (2022) investigate the potential battery size reductions under 3 discrete scenarios for the UK road network. As the scenarios were exogenously defined, however, the aspect of network optimality has not been addressed. To address these gaps in the literature, our study considers the large-scale implementation of dynamic charging, considering both government and carriers' perspectives, accounting for the complexity of freight trip chains. Additionally, in an attempt to address an overlooked impact, a battery lifespan estimation model is integrated that sketches a positive correlation between battery lifespan and electrification rate.

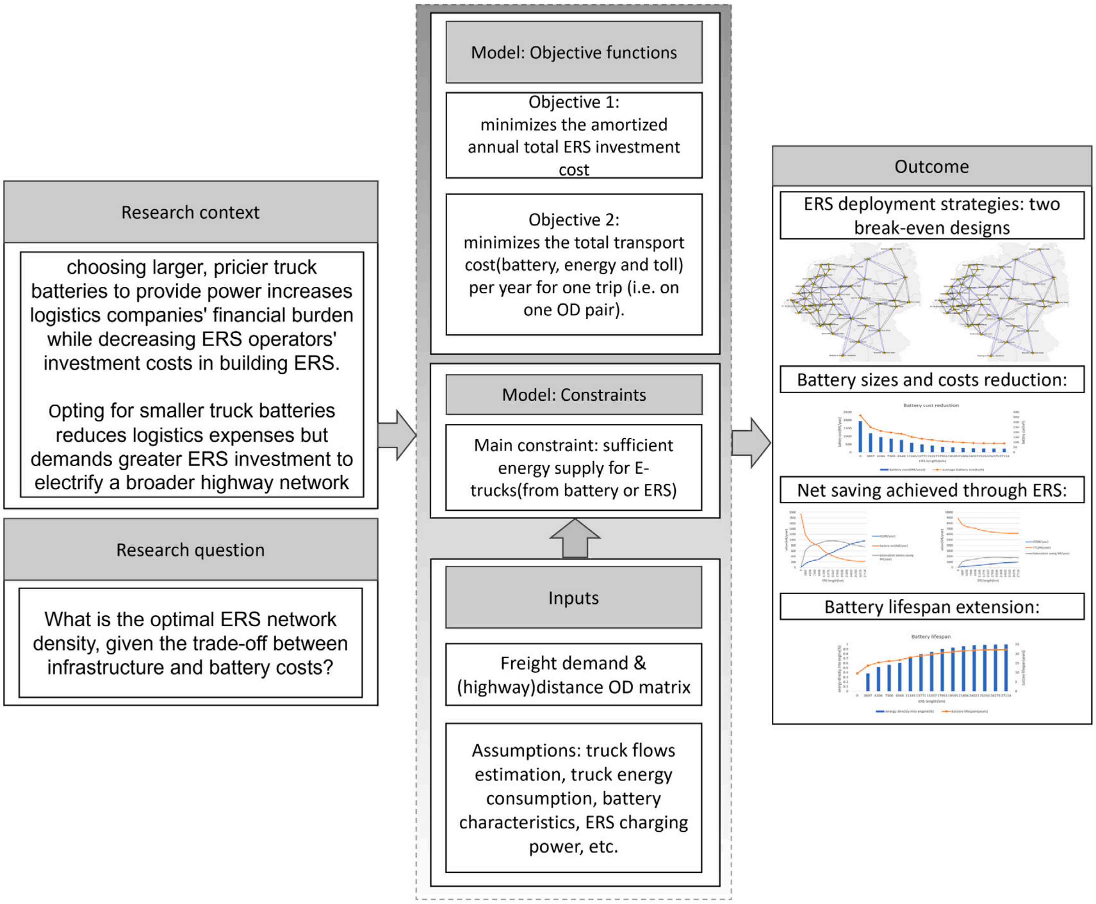

Fig. 1. Research framework.

3. Problem description and methodology

The question of the trade-off between network investments and transport costs needs to be studied in the context of the question of optimality: what are the investments that minimize costs on both fronts? Out of the many options available, we aim to rule out those investments that are unfavorable in both aspects and focus solely on the specific set that cannot be improved upon, known as the Pareto set. Within this set, network and battery costs are interconnected, meaning that an increase in one will immediately result in reductions in the other. Fig. 1 shows the main questions investigated by this paper and a brief presentation of the methodology and the outcome of the analysis.

The primary goal is to identify the optimal highway segments for electrification and determine the appropriate battery pack capacity. Optimal segments are those that can minimize infrastructure investment (i.e., construction and operation) and transport operation costs (i.e., battery usage, energy consumption, and toll expenses). The model accounts for the complexity of freight transport trip chains, considering urban center origins, sequential paths, and destination cities. The bi-objective function concerns two key goals: minimizing network investment costs as well as the operational costs. The model output is the optimal level of electrification of the network and the required size of batteries. Trucks should have sufficient energy to fulfill their order at all times and logistics companies are obliged to pay a toll which is different for electrified and non-electrified links. Since batteries and infrastructures are high-value assets and are operated for many years, discounting these costs over their lifespan is considered by applying the equivalent annual cost concept.

An important consideration is the extended battery life, which is an additional hidden benefit of large-scale implementations of dynamic charging. Since the energy provided by ERS can be directly bypassed to the engine, it is not necessary to always use energy from the battery. As a result, the total equivalent cycles of the battery for each trip and the subsequent battery degradation can be significantly reduced. Here a lifespan estimation model is used that assumes a positive linear correlation between lifespan and electrification rate. Details of the model and its solution approach can be found in the Appendix. It should be noted that the purpose of the model presented here is to obtain a Pareto front to support policy decisions. In cases that entail the requirement to arrive at accurate design recommendations, further work may include deploying other search methods or using additional computational time and resources.

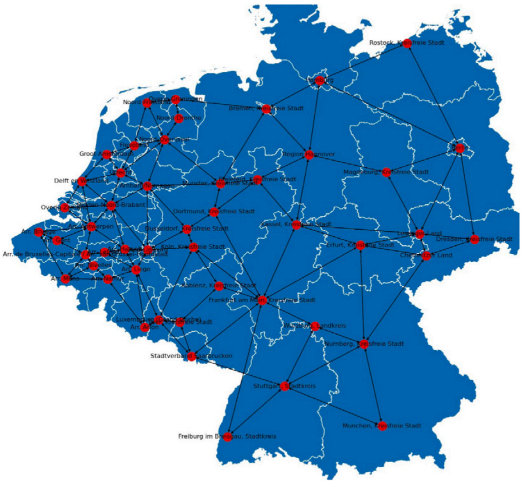

Fig. 2. Highway network depicted by directed links and nodes.

The next section includes the presentation of the results of the case study, along with a discussion about the main limitations, and policy implications.

4. Insights from the case study

4.1. Case description and data

The case study concerns the highway network spanning the Netherlands, Germany, Luxembourg, and Belgium (depicted in Fig. 2). The network is represented by a set of directed highway links connecting a set of nodes. The demand nodes refer to the cities where freight demand (in vehicles, m_t) is picked up/delivered. This requires the movement of E-trucks along the links in the network connecting the demand nodes.

The freight demand data is extracted from ETIplus dataset (Speth et al., 2022; Szimba et al., 2013) which includes freight demand flows between European Union member states. To make this data more manageable, data clustering is adopted to aggregate the demand from smaller regions (NUTS-3 level) into larger ones (NUTS-2 level) where NUTS are administrative divisions in Europe. Then, the distance matrix was obtained using Networkx and Openstreet map packages. An average payload factor of 14 tons was assumed (Mercedes Benz HDTs' information from Leonard et al. (2022)) to calculate the number of trucks required for transporting the freight demand. This calculation aligns with a freight trip estimation model (Tavasszy and De Jong, 2013), as shown in the equation below:

$$m_t = \frac{U_t \cdot BET_{share}}{payload} \tag{1}$$

where m_t represents the converted freight demand in vehicles for trip t, connecting demand points, as explained in the Appendix; U_t denotes the freight demand in tons for trip t before conversion; BET_{share} is the market share of Battery-Electric Trucks (BETs), which is set at 50%; and $payload$ denotes the payload factor. Additionally, we need to estimate the number of E-trucks that will utilize the ERS. The assumption is that a truck will operate 250 times per year, $q = 250$, based on research (Shoman et al., 2023). Therefore, the number of trucks operating per OD trip is calculated by dividing its truck flows, m_t, by the average trips per truck per year, q, as formulated in the objective function. The values of other parameters used in this case are reported in detail in Tables 5 and 6 in the Appendix.

4.2. General observations

The combination of optimal solutions for both objectives, the infrastructure and total transport costs is presented in a Pareto front, as shown in Fig. 3. There is a clear trade-off between the yearly total transport cost and the ERS infrastructure investment across the Netherlands, Germany, Luxembourg, and Belgium. By increasing investments in ERS construction, the overall transport cost, which includes battery, energy, and toll costs, significantly decreases. This trade-off gives policymakers insight into how ERS implementation can impact total transport costs given different budget scenarios.

Importantly, as can be seen by the scaling of the two axes of the figure, this cost reduction greatly surpasses the ERS investment cost, signaling a strong economic viability of the system.

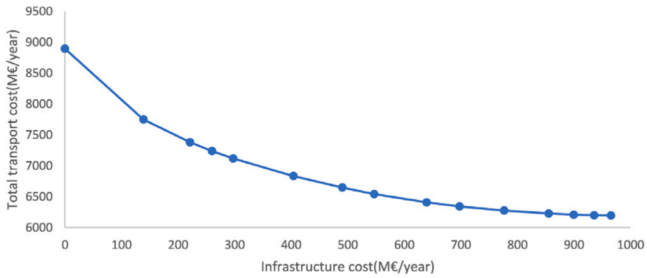

Fig. 3. Pareto front associated with the two optimization objectives.

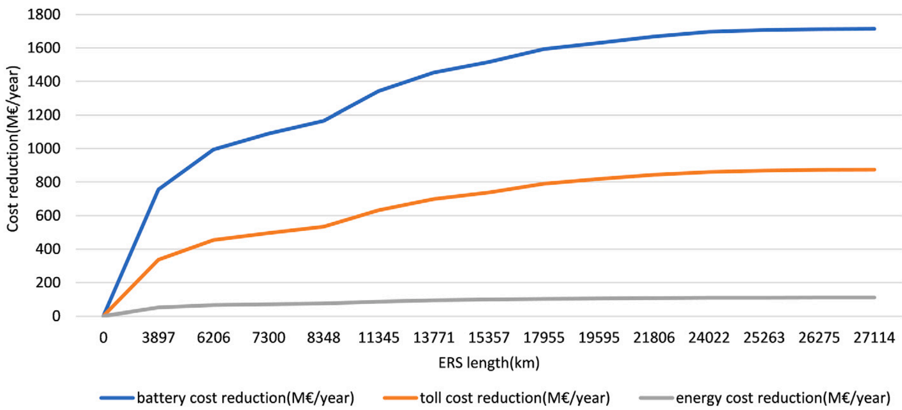

Fig. 4. Transport costs reduction per year under different ERS deployment sizes.

4.3. Trade-off between infrastructure and transport costs

For a comprehensive insight, each optimal solution within the Pareto set has been individually extracted. Sorted for increasing ERS network size, the set is shown in Fig. 4. This illustration depicts the alterations in individual cost components of the total transport cost per year. The overarching trend indicates a consistent reduction in the total transport cost as the ERS length increases. The most significant impact is observed in the reduction of battery costs, while the influence on energy costs and toll costs is relatively minor. This remains valid despite reductions in onboard battery weight and the application of lower toll rates for using electrified highways, as the battery weight accounts for a very small part of a vehicle's gross weight. The maximum energy cost reduction observed through modeling is relatively modest, amounting to 2.5%—from 4.3 billion to 4.2 billion Euros annually. This marginal reduction stems from the fact that battery weight, albeit reduced, constitutes only a fraction of the vehicle's gross weight, exerting limited influence on total energy consumption. This observation is reaffirmed by Fig. 5, which shows a less distinct trade-off between the total transport cost, TTC, and infrastructure cost, IC. The considerable portion of energy and toll costs within total transport cost prevents the total transport cost from being substantially impacted by ERS implementation.

In cases of limited budget, smart choices are crucial to maximize benefits for both the transportation system and stakeholders, especially logistics companies. This is ensured at the break-even point, denoted by the red point in Fig. 5, representing the optimal balance between cost savings in total transport expenses for logistics companies and the incurred ERS construction costs. In this context, the break-even point (IC+TTC) is 7.04 billion Euros per year, achieved by electrifying 19,595 kilometers of highway with an average battery size of 105 kWh. Beyond this point, the total system cost (infrastructure and total transport cost) increases, despite continuous reductions in total transport costs. This indicates that although total transport cost continues to decrease, it no longer fully compensates for the cost of ERS construction beyond 19,595 kilometers. Consequently, the economic justification for further ERS expansion diminishes.

This observation was also reflected in the net TTC saving annually represented by a gray line in Fig. 6, which is obtained by deducting ERS investment from TTC saving (Table 1), i.e. electrifying 19,595 kilometers of highway leads to the highest net total TTC saving of 1855 million euros per year. The two competing costs (TTC and IC) balance out at 19,595 km of ERS length (see Fig. 6). Finally, the break-even ERS network design with 19,595 kilometers of electrified highway considering TTC is shown in Fig. 7 where links marked in red indicate the electrified links (see Fig. 10).

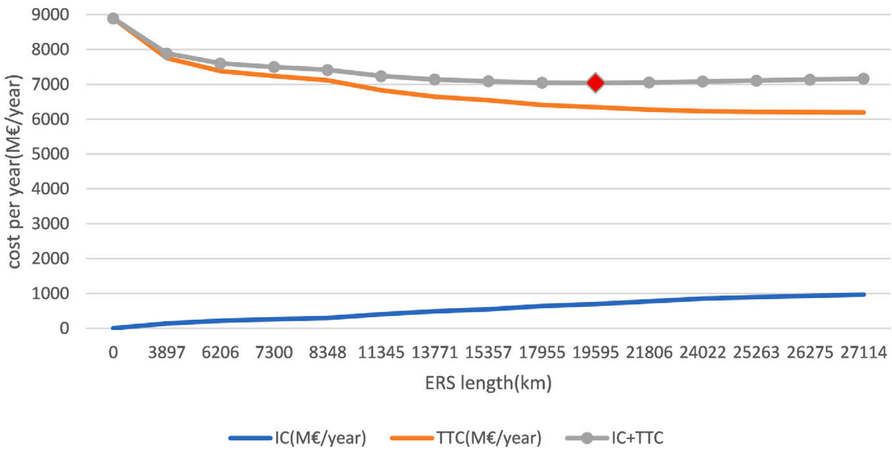

Fig. 5. Trade-off between infrastructure cost (IC) and total transport cost (TTC) per year.

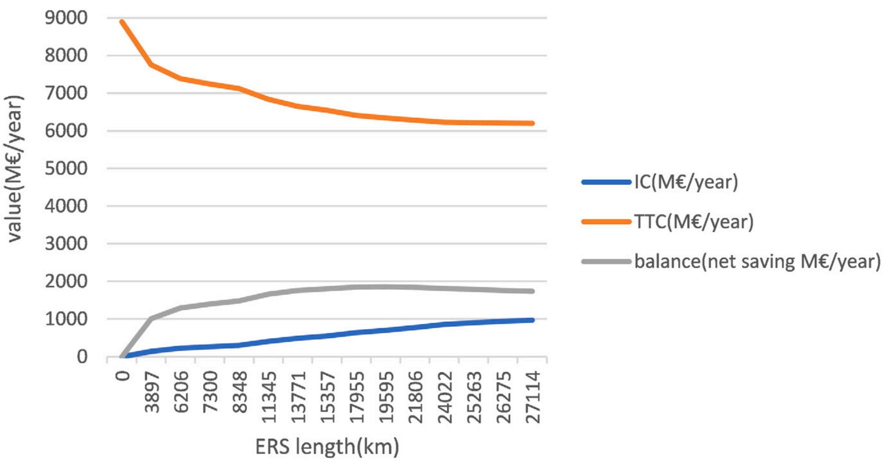

Fig. 6. Net total savings in total transport cost (TTC) achieved through ERS per year after deducting the infrastructure cost (IC).

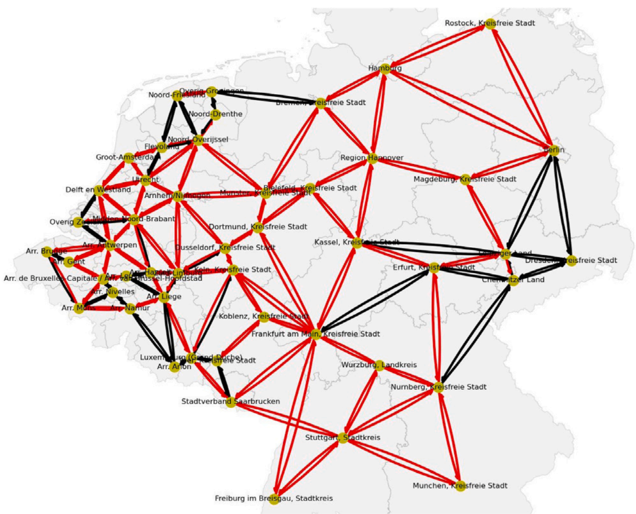

Fig. 7. Break-even network design considering total travel cost (TTC). Electrified links are marked in red. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

Table 1
Net total transport cost savings per year.

ERS length (km)	Toll (M€/year)	IC (M€/year)	Total TTC saving (M€/year)	Net total TTC saving (M€/year)
0	262	0	0	0
3897	229	139	1145	1006
6206	217	221	1514	1293
7300	213	260	1656	1396
8348	209	297	1775	1478
11 345	199	404	2061	1657
13 771	193	490	2246	1756
15 357	189	547	2353	1806
17 955	183	639	2487	1848
19 595	181	698	2553	1855
21 806	178	777	2619	1842
24 022	176	855	2666	1811
25 263	175	900	2686	1787
26 275	175	936	2695	1759
27 114	174	966	2700	1734

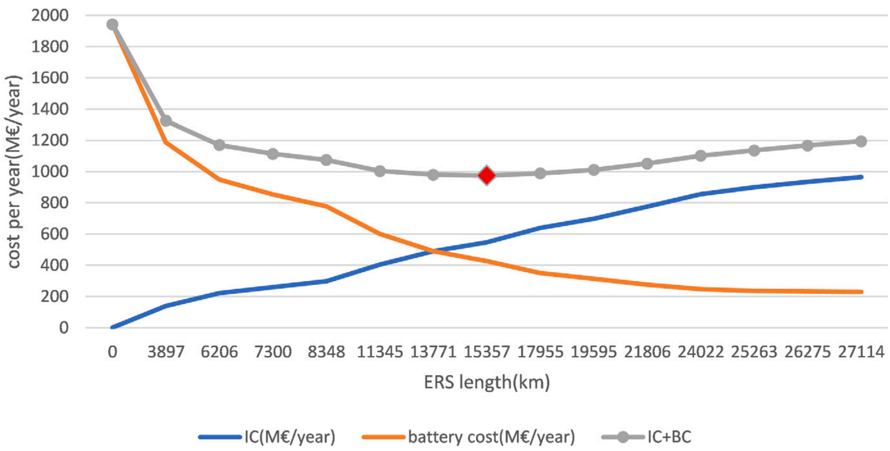

Fig. 8. Trade-off between battery cost (BC) and infrastructure cost (IC) per year.

4.4. Trade-off between battery cost and infrastructure cost

The previous section discusses the impact of ERS implementation on total transport cost reduction. This section carries out an analysis of battery savings by focusing on showcasing the major trade-off between battery cost and infrastructure cost, as depicted in Fig. 8.

Similarly as in the above, but now more clearly visible, different levels of investment in ERS construction yield substantial reductions in annual battery costs. If the investment budget for ERS is unrestricted, the total annual battery cost reduces from 1.94 billion Euros without ERS, to 0.23 billion Euros with a fully electrified highway network. The average onboard battery size reduces with the expansion of the ERS network. The initial maximum average onboard battery size of 370 kWh when no ERS is implemented, lowers to 90 kWh when the highway is entirely electrified (see Fig. 10). This reduction in average onboard battery size is indicative of a battery weight reduction and subsequently lowers energy consumption for E-trucks.

The break-even point focusing solely on battery cost is represented by the red point in Fig. 8. The horizontal axis represents the solutions obtained from model, i.e. the total length of electrified highway links of one solution. In this figure, the break-even point signifies the lowest total system cost, that is, infrastructure and battery costs, showing where battery savings from users optimally offset the expenses of constructing ERS. Beyond this point, further ERS expansion triggers a situation where the reduction in battery costs achieved through ERS adoption no longer adequately offsets the incurred costs of ERS construction. Thus, without any toll reductions, the most beneficial strategy involves electrifying 15,375 kilometers of highway with an infrastructure investment of 0.55 billion Euros per year and an average onboard battery capacity of 124 kWh (as shown in Fig. 10). Here, battery costs decrease by 78%, from 1.9 billion Euros to 0.43 billion Euros annually, leading to an annual battery cost saving of 1.6 billion Euros.

The total battery cost saving is summarized in Table 2 and Fig. 9. The two costs, IC and BC, balance out at 15,375 km of ERS length (see Fig. 9). The results also highlight an interesting finding; it is evident that there is an immediate cost reduction from the start of ERS operation until around 5000 kilometers. This implies that already a first ERS network implementation on a relatively small scale can be efficient.

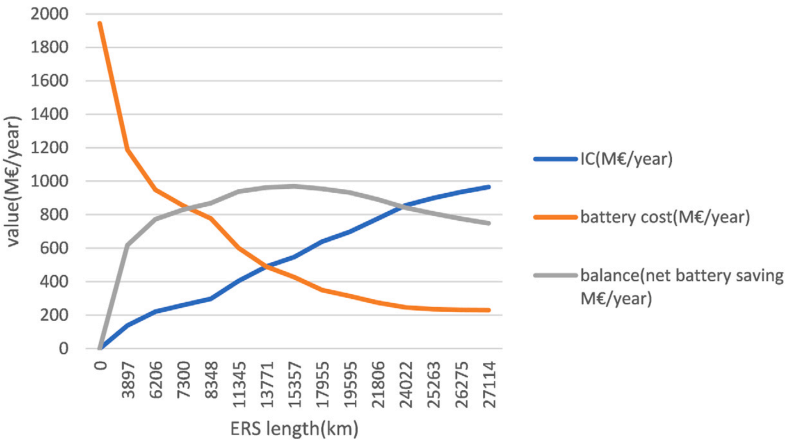

Fig. 9. Net total battery savings achieved through ERS per year.

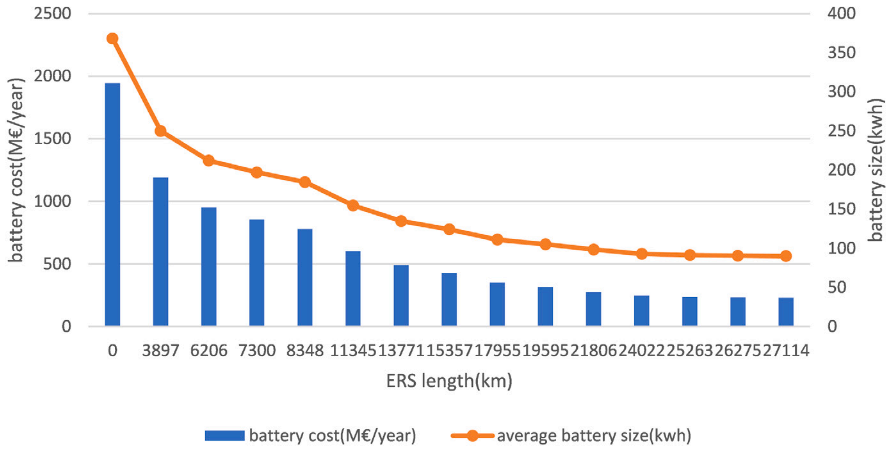

Fig. 10. Battery cost and size reduction.

Table 2
Net total battery cost savings per year.

ERS length (km)	Total battery saving per year (M€/year)	Infrastructure cost (M€/year)	Net battery cost saving (M€/year)
0	0	0	0
3897	756	139	617
6206	995	221	774
7300	1089	260	829
8348	1166	297	869
11 345	1343	404	939
13 771	1453	490	963
15 357	1517	547	970
17 955	1594	639	954
19 595	1630	698	932
21 806	1668	777	892
24 022	1697	855	841
25 263	1707	900	808
26 275	1712	936	776
27 114	1714	966	749

4.5. Impacts on battery lifespan

ERS potentially improves battery lifespan, due to the fact that when Heavy-Duty Battery Electric Trucks (HDBETs) operate on electrified highways equipped with ERS, they can bypass the battery and draw power directly from the overhead contact line for

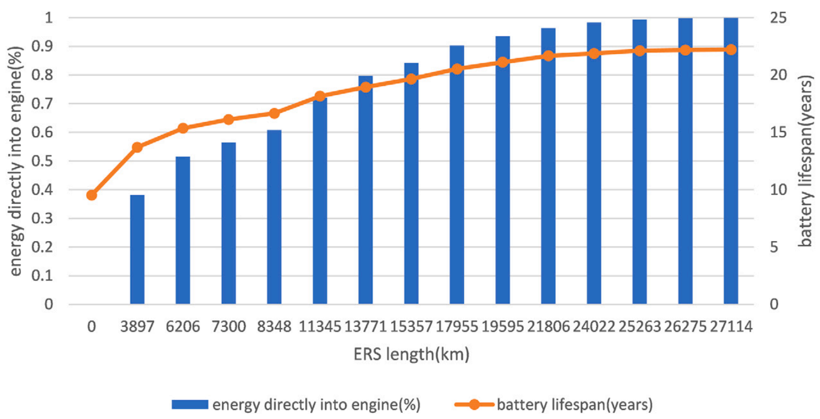

Fig. 11. Battery lifespan and energy transmission.

propulsion. Consequently, the charging and discharging cycles experienced by the battery are reduced, contributing to an extended battery lifespan. Additionally, in scenarios where enough length of the chosen route is fully equipped with ERS infrastructure, BETs may not need to use the onboard battery, as they can rely exclusively on grid power until reaching their destination.

This phenomenon is depicted in Fig. 11, showcasing how, as the ERS network expands, a growing proportion of energy consumption by HDBETs is met by ERS rather than the battery. This energy directly bypasses the battery and powers the engine during intercity transport on electrified highways. Consequently, the battery utilization rate decreases, leading to an increase in battery lifespan. For instance, considering the break-even point design with 15,357 kilometers of electrified highway, approximately 84.3% of HDBETs' energy consumption per year is supplied directly by ERS, resulting in a substantial increase in battery lifespan. This effect is significant, as it extends the average lifespan under normal driving conditions from around 10 years (without any ERS) to 19 years.

This improved battery lifespan is advantageous for both logistics companies and truck manufacturers (Original Equipment Manufacturers, or OEMs). For logistics companies, there are two primary benefits. Firstly, a lower battery utilization rate correlates with fewer quality-related battery problems. Secondly, due to the extended battery lifespan, companies incur lower battery replacement costs each year. From the perspective of OEMs, a prolonged battery lifespan is favorable, especially since they typically provide battery warranties for a set number of years when selling the trucks. Consequently, the possibility of decoupling the value of the battery from that of the trucks arises.

Finally, the break-even network design considering BC only with 15,357 kilometers of electrified highway is shown in Fig. 12, where links marked in red indicate the electrified links:

4.6. Impacts on energy demand

The implementation of ERS will undoubtedly impact the energy market and the vehicle charging industry. Fig. 13 illustrates the annual energy demand from ERS based on varying lengths of the ERS network.

As the ERS network expands and more Heavy-Duty Battery Electric Trucks (HDBETs) adopt this technology, the energy demand from ERS will naturally increase. For instance, in the case of the break-even design that considers battery cost only (Fig. 12) with 15,357 kilometers of electrified highway, ERS will deliver around 168 billion kWh of electricity to E-trucks annually. This equates to a daily energy demand of approximately 4.6 million kWh by the year 2030, assuming that only BETs use this technology along the highway.

Considering the potential profit of selling electricity via ERS to E-trucks, which is estimated at 0.14€/kWh (Aronietis and Vanelslander, 2021) (compared to the base price of electricity at 0.08€/kWh from the electricity company), a substantial business opportunity arises in operating ERS infrastructure in these four countries. The potential profits from operating the ERS infrastructure, given the break-even design, could amount to as much as 2.3 billion Euros per year.

Moreover, it is worth noting that three busy highway links with the highest energy demand in the break-even design have been identified. These links include the highway from Frankfurt to Freiburg, as well as both directions of the highway between Freiburg and Stuttgart. These highways exhibit high energy demand due to their lengthy stretches and heavy truck traffic flow.

4.7. Sensitivity analysis

The results depend on the initial selection of some key parameters (i.e., battery price, market share and ERS cost per km). Thus, this section analyses the sensitivity of the results to the assumed values. We specifically consider the break-even designs, where the two conflicting objective functions—battery cost and ERS investment cost are given equal importance. In Table 3, the variation of parameters in the format of $(min; max; \mathbf{interval})$ in the analysis was presented.

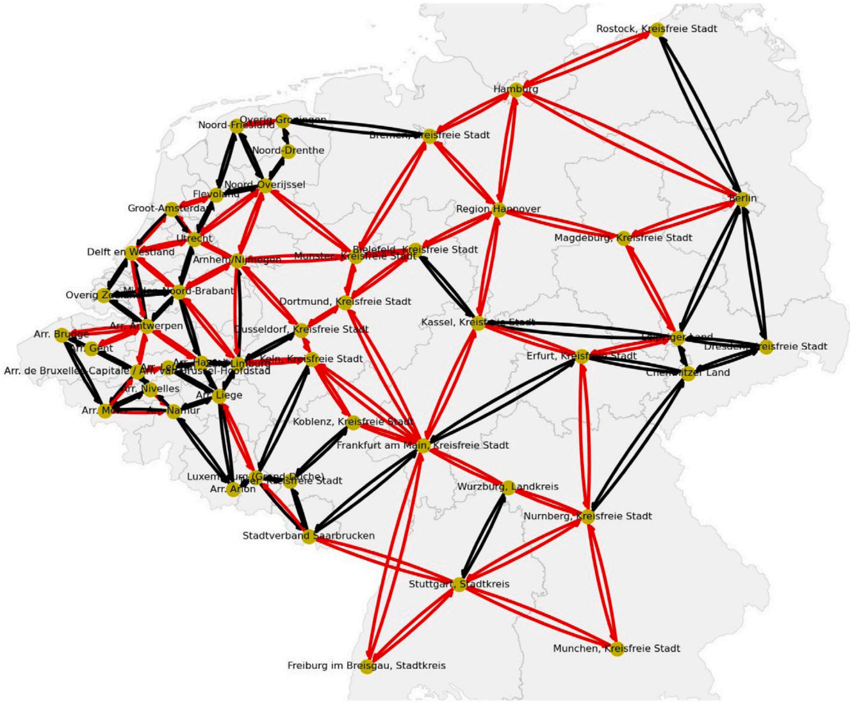

Fig. 12. Break-even network design considering trade-off between BC and IC, electrified links marked in red. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

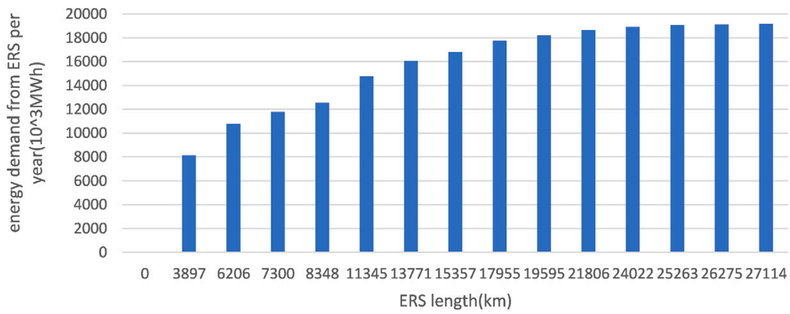

Fig. 13. Annual energy demand associated with different ERS deployment levels.

Table 3
Summary of the sensitivity tests.

Sensitivity test	Battery price (€/kWh)	BET market share	ERS cost (M€/km)
Test on battery price	(100; 200; **25**)	0.5	0.5
Test on BET market share	150	(0.3; 0.5; **0.05**)	0.5
Test on ERS cost	150	0.5	(0.5; 2.0; **0.5**)

Initially, the primary focus was directed towards the dynamic fluctuations in battery pricing within the market. With reference to Figs. 14 and 15, as battery prices vary between the range of 100 to 200 €/kWh, a corresponding extension of approximately 7000 kilometers and 30% reduction of onboard battery size in the break-even design were observed. Concurrently, the net total battery savings show a tripling effect, elevating from 500 million to 1500 million euros. Consequently, it is evident that as battery prices increase, the output of the optimization model shows an increase in the electrification of additional highway segments, subsequently mitigating the reliance on batteries within the system, which can serve as a countermeasure to the escalating battery costs. In essence, the prevailing high battery prices in the market encourage ERS implementation across these four countries as a more economically viable solution.

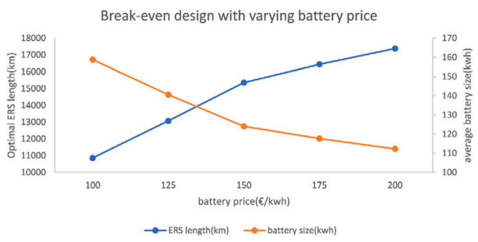

Fig. 14. Varying battery price.

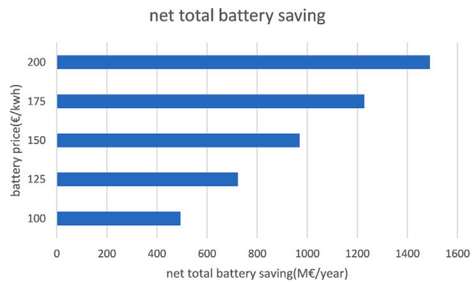

Fig. 15. Cost–benefit analysis.

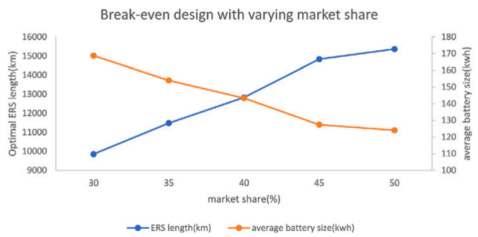

Fig. 16. Varying market share.

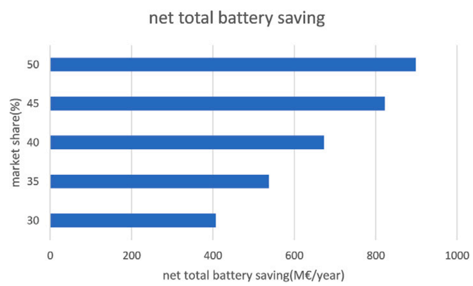

Fig. 17. Cost–benefit analysis.

A similar trend is observed as a result of the sensitivity analysis of the BETs market share, as depicted in Figs. 16 and 17. It is evident that a higher market share yields greater advantages in the context of constructing an extensive ERS network. The net total battery saving doubles (from 400 million to 900 million euros) when the market share of BETs varies from 0.3 to 0.5.

Lastly, a sensitivity analysis is carried out regarding the ERS construction costs per km, illustrated in Figs. 18 and 19. With an increase in ERS expenses per kilometer, the model tends to curtail the total length of electrified highway infrastructure within the system. The impact of variations in ERS construction cost per km on the optimal ERS length and net total battery savings are therefore substantial. A threefold increase in ERS cost per kilometer would result in a staggering 83% reduction in the optimal ERS length and a decline of 76% in net total battery savings. This highlights that higher ERS costs per km render the implementation of ERS in this region less feasible, making the acquisition of larger batteries a more economic consideration.

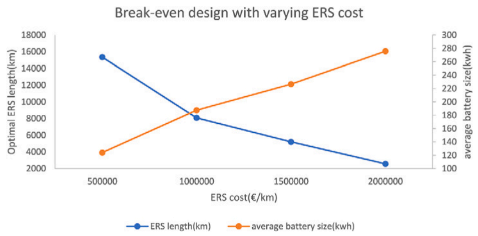

Fig. 18. Varying ERS cost per km.

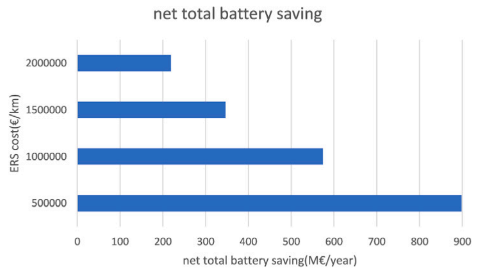

Fig. 19. Cost–benefit analysis.

5. Discussion

We present a multi-objective optimization model for identifying the optimal network for Electric Road Systems (ERS) catering to Heavy-Duty Battery Electric Trucks (HDBETs). The application presents new insights about the potential impact of ERS implementation on cost savings in terms of total transport expenses, with a particular focus on reduction of battery-related costs. The analysis substantiates the economic viability of ERS deployment for HDBETs . In our case, the ERS investment costs can be balanced with cost reduction, up to a network length of around 20,000 km.

Overall, results confirm earlier findings (de Saxe et al., 2022) that significant savings in battery size are possible: 20,000 km of ERS will help save around 2/3 onboard battery size on average. In addition, our study addresses the design question that has not been answered so far: how do these savings determine the economically feasible network size? We find that a large expansion of the ERS network is possible, with net positive economic effects.

Below we reiterate the main assumptions and simplifications that were made to allow the large-scale application of the model and discuss their possible impacts on the results. Where relevant, these present future lines of research building upon the results of this study.

- The above problem explanations only consider the battery-electric trucks with pantograph. Induction and rail-based charging systems may yield different results.
- In this stylized case all the highway network links were allowed to be electrified regardless of any prohibited sections, such as tunnels or bridges. The unavailability of certain links in the network may negatively impact the results.
- We have not studied possible savings in high-power stationary charging stations if ERS becomes widely adopted. From this perspective, our results underestimate the net societal benefits. Ideally, the implementation of stationary, both public and private connections, and dynamic charging facilities would be coordinated and optimized together. Clear assumptions about the nature of coordination would be needed in such studies. This is a subject for future research.
- We assume a predefined constant charging rate for ERS per unit of time. In reality, the energy consumption will be influenced by many factors such as battery size, speed and weather as well as technological advancements. Conservative assumptions have been made here and more detailed models will probably show longer charging times. Their effect could be investigated further.
- The number of vehicles needed for each trip was estimated based on the freight demand of each OD trip and average truck operation times per year. The assumption that all BETs are operating with maximum cargo loads inevitably leads to an underestimation of the number of trucks in service. Results for the future will also depend on changes in trip patterns and vehicle utilization, which we have ignored. Furthermore, the analysis focused exclusively on direct point-to-point transportation, neglecting scenarios where a single trip involves multiple stops or when trucks are operating empty, which could impact the cost savings. The net effect of these simplifications is hard to predict and would require additional research.
- The effect of underlying mechanisms of pricing and technology adoption has not yet been studied. Here, a constant electricity cost per unit of kWh has been assumed. Variations during the day could affect the results. Also, the fleet of trucks using ERS has been assumed fixed in this study, while this could also depend on the availability of infrastructure.

- It was assumed that all infrastructure will be available in the year 2030 and the initial investments spread out over its lifespan, discounted over this lifespan with a fixed discount rate. In reality, infrastructure will be built out gradually and benefits will materialize more slowly.
- Battery sizes were considered to be the same for all trips on one OD pair, assuming that the OD pair is the relation that determines the battery dimension. More intricate trip and tour structures will undoubtedly exist. These would require detailed trip data for the entire population of trucks in the area, however, which are not available for networks of this size.
- A critical assumption is related to our prediction of the battery price by 2030. This projection might be conservative, considering ongoing advancements in battery technology and the anticipated scale of mass in battery production in the future. Consequently, the cost reduction potential in battery expenses could be lower than anticipated.
- Battery lifespan is described by a simple model while in reality, degradation is influenced by a multitude of factors, including depth of discharge, environmental conditions, and current levels. This introduces additional uncertainty in the lifespan estimations.
- We have not addressed effects on battery disposal and recycling resulting from the reduction in battery size and extended replacement cycles. These would be additional benefits that can be added in a life cycle analysis framework.
- Lastly, constraints related to network capacity or grid power are not incorporated in our model. The interactions between power grid capacity and highway capacity are intricate and challenging to estimate accurately based on current conditions.

On balance, although further refinement can still be done based on assumptions that will bias the results up- or downward, the main implication remains that battery cost savings are to be taken into account when deciding about investments, as the savings are of the same order of magnitude as the costs. While the single optimal network length as found here is quite sensitive to several external factors, two robust findings are that (1) a break-even situation can be reached already with a relatively modest network length, which will be cost-neutral in the worst case and very profitable in the best and (2) the objective function being quite flat, the societal net benefit is insensitive to network length and can be obtained with many different near-optimal network designs.

One should note that, although catenary dynamic charging systems have a high TRL level and have seen several public trials (PIARC, 2023), there is less experience with rail-based conductive and induction-based systems. Which specific solution will prevail is not a subject of our study. The expectation of important savings on the part of the users, however, is an important result that could motivate the creation of extensive trials for the relatively new technologies.

The study shows that there are net societal benefits of the introduction of an ERS network mainly due to the battery size reduction effect. These net benefits result from aggregating effects across all public and private actors. In practice, each of these actors will have its own accounting of the new system. The initiation of investments will require a set of consistent and valid business models for each actor. Issues to consider here include (1) the mission of governments to invest in collective infrastructure without direct return, based on benefit to the commons; (2) the need of government to replace the loss of fuel-based taxes due to electrification; (3) the approach towards building of ERS, with or without a commercial concessioning business model; (4) the new role of the electricity providers, possibly as part of consortia operating transport infrastructures; (5) transfers between actors in the form of taxes and subsidies to compensate for losses.

6. Conclusion

The ERS network design model presented in this paper offers crucial insights into the sizing and location of the network. It balances the trade-offs between transport costs and infrastructure investments and produces optimal network designs, for all cases where the relative importance of these costs may differ. In the case when these are equal, the societal optimum where the two objective functions can be added to reflect a societal optimum, the optimal network size is nearly 20,000 km of ERS lines, almost the entire network considered. The benefits of reduced battery size appear to be dominant in the savings booked with ERS, and of such magnitude that they more than balance out the investment needs for ERS, up to this optimal network size. Societal savings will still exist for even larger network sizes, albeit at lower levels than the required investments.

The main policy implication is that it appears to be worthwhile to consider large-scale public investment in dynamic charging systems, to help accelerate the energy transition in transport. The study provides evidence on three points to support this position. Firstly, dynamic charging creates significant new benefits that stationary charging cannot offer. Secondly, these new benefits in themselves outweigh the costs, up to investments in very large network sizes. Thirdly, the availability of dynamic charging considerably reduces the investment need for the transport sector, which may help accelerate fleet renewal.

The research underscores the importance of quantitative, model-based analysis, in the pursuit of a sustainable and efficient transportation system. Future work could extend the model to include various vehicle types that can leverage ERS technology, as well as other ERS technologies, like induction. In addition, network designs could include the use of stationary chargers to complement dynamic charging and the resulting possible savings in high-power stationary charging. Although recent simulations suggest that stationary charging could have a role when considering the total system costs, network optimization would be needed to (1) understand whether these solutions are Pareto optimal, guaranteeing the best network for combined public and private expenditures, and (2) determine quickly which network designs can be traded off under different relative importance of public and private expenditures. Various assumptions related to energy consumption rate as influenced by factors such as battery size, speed and weather as well as technological advancements, additional benefits resulting from battery disposal and recycling, would further enrich the model and its outcome.

CRediT authorship contribution statement

Ximeng Liao: Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Methodology, Investigation, Formal analysis, Conceptualization. **Mahnam Saeednia:** Writing – review & editing, Supervision, Methodology, Conceptualization. **Maria Nogal:** Writing – review & editing, Supervision, Methodology, Conceptualization. **Lori Tavasszy:** Writing – review & editing, Supervision, Resources, Project administration, Methodology, Conceptualization.

Data availability

Data will be made available on request.

Appendix

Model formulation

This section includes the details of the bi-objective optimization model. The solution of the model will identify links in a network to be equipped with ERS as well as the battery levels for all individual OD relations, that are needed to complete trips successfully. Below, we introduce the optimization model, the underlying cost functions and further assumptions in detail.

Sets

The highway network is considered as a directed graph *G=(I, L)* where:
$I = \{1, \dots, i, \dots, n\}$: set of network nodes, which can be the origin and destination points of demand;
$T = \{1, \dots, t, \dots, t_u\}$: set of trips connecting demand OD pair $i, j \in I$ in the network;
O: origin nodes matrix, and element O_t represents the origin node of trip $t \in T$;
$L = \{l_{i,j}\}, i \in I, j \in I | i \neq j$: set of highway links;
D: distance matrix with elements $d_{l_{i,j}}$ representing the distance (km) of directed highway link $l_{i,j} \in L$;
M: freight demand matrix with elements m_t representing the truck flows (in vehicles) of trip $t \in T$;
A_t: ordered set of consecutive highway links $l_{i,j}$ on route of trip $t \in T$.

Parameters:

a: weight of truck+trailer+payload excluding battery weight (kg)
a_f: frontal area of E-truck (m^2)
c_a: aerodynamic drag coefficient
c_f: calendar fade rate per year
c_b: battery price (€ $/kWh$)
c_d: cost of building ERS (Catenary) (€ $/km$)
c_e: electricity price (€ $/kWh$)
c_{rr}: rolling resistance coefficient
d_{max}: maximum battery degradation rate per year
e_f: ERS energy transfer efficiency (%)
end: battery replacing threshold (%)
g: gravity
h_1 and h_2: toll costs for HGVs when using battery-only (non-electrified highway) and electrified highway (€ $/km$)
p_{ERS}: ERS charging power (kW)
q: operation trips per truck per year
r: discount rate per year. Given that the assets (infrastructure and battery) will be owned and operated for several years, discounting the cost is essential for economic comparison
SOC_{max} and SOC_{min}: maximum and minimum allowed state of charge of battery
v: E-truck speed (km/h)
y_{min} and y_{max}: minimum and maximum cycle fade rate per year
z: battery energy density (wh/kg)
μ: operation and maintenance cost rate per year
ρ: air density (kg/m^3)
τ: operational life of infrastructure (years)

Decision variables:

b_t: integer decision variable; the battery size selected for trip $t \in T$ (kWh).
$x_{l_{i,j}}$={0,1}: binary decision variable; If directed highway link $l_{i,j} \in L$ is electrified, $x_{l_{i,j}} = 1$, otherwise 0.

Other variables:

a^I: annuity factor of infrastructure investment
a_t^b: annuity factor of battery cost of trip $t \in T$

$e_{l_{i,j}t}$: energy consumption when E-truck of trip $t \in T$ running on link $l_{i,j} \in A_t$ (kWh)
$e^{ERS}_{l_{i,j}t}$: energy supply from ERS when E-truck of the trip (OD pair) $t \in T$ running on electrified link $l_{i,j} \in L$ (kWh)
e_t: total energy consumption of trip $t \in T$ (kWh)
f_t: battery lifespan of E-truck of trip $t \in T$
n_t: non-electrification rate of route of trip $t \in T$
p^{truck}_t: energy consumption rate of E-truck of trip $t \in T$ (W)
$SOC_{l_{i,j}t}$: state of charge of E-truck on link $l_{i,j}$ of route of trip $t \in T$ at node j, $l_{i,j} \in A_t$ (%)
θ^{ERS}_t and θ^{BAT}_t: total toll cost when E-truck of (OD pair) trip $t \in T$ running on electrified and non-electrified links (€)
w_t: battery weight of E-trucks of trip $t \in T$ (kg)
y_t: cycle fade rate per year of E-truck battery of trip $t \in T$

The E-trucks are assumed to depart with the maximum allowable State of Charge (SOC_{max}) and an assigned battery pack, b_t, which serves as one of the decision variables. A constant energy consumption rate p^{truck}_t associated with the battery weight, w_t, is applied to the travel on link $l_{i,j}$ of trip t, resulting in the corresponding energy consumption, denoted as $e_{l_{i,j}t}$. If $x_{l_{i,j}}$ equals 1, the E-truck can constantly receive energy from ERS when running on the link $l_{i,j}$ with the fixed charging rate of p_{ERS}.

This enables calculation of both energy supply from ERS and consumption, i.e. $e^{ERS}_{l_{i,j}}$ and $e_{l_{i,j}}$, on each link $l_{i,j} \in L$ and the charging state $SOC_{l_{i,j}t}$ of E-trucks of (OD pair) trip $t \in T$ at node j after passing through link $l_{i,j}$. In addition, as the SOC of the E-truck battery cannot fall below SOC_{min}, which is the minimum allowable state of charge of the battery, either the selected route of trip t must be equipped with adequate length of electrified links or E-trucks need to be assigned a bigger battery to ensure a sufficient energy supply. Consequently, various combinations of electrified links, $x_{l_{i,j}}$, within the network and the battery pack assigned to each trip t lead to distinct combinations of cost related to investment, operation, and battery cost.

Multi-objective model:

Firstly, two objective functions representing the interests of investors and operators are introduced.

$$\min_{\mathbf{x}} IC = \min_{\mathbf{x}} \sum_{l_{i,j} \in L} x_{l_{i,j}} \cdot d_{l_{i,j}} \cdot c_d \cdot \left(\frac{1}{a^I} + \mu \right) \tag{2}$$

$$\min_{\mathbf{x},\mathbf{b}} BC + TC = \min_{\mathbf{x},\mathbf{b}} \sum_{t \in T} \frac{m_t}{q} \cdot \frac{b_t \cdot c_b}{a^b_t} + m_t \cdot \left(e_t \cdot c_e + \theta^{ERS}_t + \theta^{BAT}_t \right) \tag{3}$$

Eq. (2) minimizes the total amortized infrastructure investment cost, IC, for constructing ERS along the highway, while Eq. (3) minimizes the total transport cost, TTC per year for each trip (OD pair) t, which consists of total battery costs, BC, and transport costs, TC. These two objectives present a clear interplay, i.e., the total transport cost of companies is influenced by the ERS availability and network. The amortized BC per year pertains to the cumulative purchase expenditure incurred for all batteries essential to sustain the freight transport system throughout its operational life span. This incorporates the comprehensive battery procurement costs, given our specific scenario where maintenance expenses are encompassed within the battery price. We assume that batteries retain no residual value upon the culmination of their operational life. BC is calculated as the summation of the anticipated battery count for each distinct trip. This count is subsequently multiplied by the unit battery cost, c_b, and the chosen battery pack, b_t. This product is then divided by the corresponding discounted battery annuity, a^b_t, to ascertain the amortized total battery cost per year. The generalized TC consists of toll and energy costs that the logistics companies have to pay on the highway.

Constraints:

1. Annuity factor of infrastructure, a^I, and battery of each trip t $\in T$, a^b_t. The EAC (equivalent annual cost) is applied to reflect the annual cost for owning, operating, and maintaining an asset over its entire lifespan. This enables the comparison of the amortized annual cost of infrastructure and battery costs that have unequal lifespans (Kenton, 2023).

$$a^I = \frac{(1 - (1 + r)^{-\tau})}{r} \tag{4}$$

$$a^b_t = \frac{(1 - (1 + r)^{-f_t})}{r}, \quad t \in T \tag{5}$$

2. Energy supply from ERS, $e^{ERS}_{l_{i,j}}$, on link $l_{i,j} \in L$ if $l_{i,j}$ is electrified:

$$e^{ERS}_{l_{i,j}} = p_{ERS} \cdot e_f \cdot d_{l_{i,j}} \cdot \frac{x_{l_{i,j}}}{v}, \quad \forall l_{i,j} \in L \tag{6}$$

3. The battery weight specific to a given trip denoted as w_t signifies a crucial variable. The optimization model, in its pursuit of optimal outcomes, systematically designates an appropriate battery pack for each individual trip. Importantly, the battery weight allocated to the E-truck associated with trip t is intrinsically tied to the battery's physical dimensions—expressed as its size, b_t, a factor that is normalized by the battery's energy density, symbolized as z:

$$w_t = \frac{b_t}{z}, \quad \forall t \in T \tag{7}$$

4. The energy consumption rate of an E-truck on a specific trip is denoted as p_t^{Etruck} (in watts). A larger battery leads to a higher E-truck total weight and, consequently, more energy required. The adopted energy demand model is based on research (Gao et al., 2017) and industry insights, factoring in acceleration, inertia, aerodynamic drag, rolling resistance, and road gradient. However, for this study, E-trucks are assumed to operate at a constant speed v without considering road gradient:

$$p_t^{Etruck} = \frac{\rho \cdot c_a \cdot a_f \cdot v^3}{2 \cdot 3.6^3} + (a + w_t) \cdot g \cdot c_{rr} \cdot \frac{v}{3.6}, \quad \forall t \in T \tag{8}$$

5. Energy consumption, $e_{l_{i,j}t}$, on each link $l_{i,j} \in A_t$ of route of trip $t \in T$, which is calculated as

$$e_{l_{i,j}t} = \frac{d_{l_{i,j}}}{v} \cdot \frac{p_t^{Etruck}}{1000}, \quad \forall l_{i,j} \in A_t, t \in T \tag{9}$$

6. The lifespan of an E-truck battery for a given trip t represents the duration that the battery can endure under average driving conditions. This lifespan estimation encompasses two primary facets: cycle aging and calendar aging, driven by the interaction between charging/discharging cycles and time. Under average driving conditions, a maximum allowable degradation rate per year, d_{max}, for EV batteries, as established in prior research, is considered. The battery is deemed ripe for replacement when its capacity dips below a predefined threshold, denoting the maximum permissible degradation rate. Accordingly, the proposed model assumes that the battery's capacity fades until reaching the threshold triggering its replacement.

Furthermore, the battery degradation process entails two primary drivers: cycle age, linked to charging/discharging cycles, and calendar age, linked to time. A parameter c_f accounts for the average calendar aging ratio per year. Given these assumptions, the maximum cycle aging rate per year (y_{max}) is derived through the equation:

$$y_{max} = d_{max} - c_f \tag{10}$$

This model correlates the battery's cycle aging rate per year, y_t, with the non-electrification rate of the chosen truck route, n_t. We incorporate a fixed minimum cycle aging rate, y_{min}, for fully electrified routes (n_t=0%) to account for battery degradation stemming from E-trucks using battery power to access highways from logistics hubs and potential charging actions at these hubs. When no electrification exists (n_t=100%), the annual cycle aging rate is maximum, y_{max}.

Accordingly, y_t is calculated as follows:

$$y_t = (y_{max} - y_{min}) \cdot n_t + y_{min}, \quad \forall t \in T \tag{11}$$

The variable n_t denotes the non-electrification rate of the route of trip t. The electrification rate is calculated as the ratio of the total electrified distance of the selected route of trip t and its total route distance. Thus, the non-electrification rate of the route is calculated by 1 subtracting the electrification rate of the selected route:

$$n_t = 1 - \frac{\sum_{l_{i,j} \in A_t} x_{l_{i,j}} \cdot d_{l_{i,j}}}{\sum_{l_{i,j} \in A_t} d_{l_{i,j}}}, \quad \forall t \in T \tag{12}$$

In this way, the estimated lifespan of the battery of trip t can be obtained as follows:

$$f_t = \frac{end}{y_t + c_f}, \quad \forall t \in T \tag{13}$$

where end refers to the battery's capacity threshold triggering its replacement.

7. The energy conservation equation tracks the state of charge, $SOC_{l_{i,j}t}$, at node j after passing through link $l_{i,j} \in A_t$ of the route of trip t, and it cannot exceed its maximum SOC. This is expressed as follows:

$$SOC_{l_{i,j}t} = \begin{cases} min\left(SOC_{max}, SOC_{l_{s,i}t} + \frac{e_{l_{i,j}}^{ERS} - e_{l_{i,j}t}}{b_t} \right), & \forall l_{i,j}, l_{s,i} \in A_t, t \in T, i \neq O_t \\ min\left(SOC_{max}, SOC_{max} + \frac{e_{l_{i,j}}^{ERS} - e_{l_{i,j}t}}{b_t} \right), & \forall l_{i,j} \in A_t, t \in T, i = O_t \end{cases} \tag{14}$$

where the first row is used when node i is not the origin node of trip t, while the second row is used in case node i is the origin node.

8. The total energy consumption of trip t, e_t is related to the energy consumption, $e_{l_{i,j}t}$, on each link of its selected route as follows:

$$e_t = \sum_{l_{i,j} \in A_t} e_{l_{i,j}t}, \quad \forall t \in T \tag{15}$$

9. The total toll cost, θ_t^{ERS}, for using the electrified infrastructure during trip $t \in T$. The logistics companies must pay for the usage of the highway depending on the distance traveled by the E-truck. This is calculated as

$$\theta_t^{ERS} = \sum_{l_{i,j} \in A_t} h_2 \cdot x_{l_{i,j}} \cdot d_{l_{i,j}}, \quad \forall t \in T \tag{16}$$

Table 4
GA parameters.

Parameters	Values
Generations	2000
Population size	100
Crossover probability	0.9
Mutation probability	0.6
Number of mutation locations	30

Table 5
Assumed cost-related parameter values.

Cost-related parameters	
ERS Investment cost, c_d (Sven Kühnel, 2018; Taljegard et al., 2020)	€500,000/km
ERS O&M cost rate per year, μ (Taljegard et al., 2020)	2%
Discount rate, r (van Infrastructuur en Waterstaat, 2022)	2%
Operational life, τ (Taljegard et al., 2020; Peter and Lelieveld, 2022)	25 years
Battery price, c_b	€150/kWh
Electricity price, c_e (Aronietis and Vanelslander, 2021; Eurostat, 2022)	€0.22/kWh
Toll (ERS), h_2 (Ministerie van Algemene Zaken, 2020; Peter and Lelieveld, 2022)	€0.1/km
Toll (highway), h_1 (Ministerie van Algemene Zaken, 2020; Peter and Lelieveld, 2022)	€0.15/km

10. On the other hand, the total toll cost when using only the battery, θ_t^{BAT}, which occurs when traveling through non-electrified roads of trip $t \in T$, is calculated as

$$\theta_t^{BAT} = \sum_{l_{i,j} \in A_t} h_1 \cdot (1 - x_{l_{i,j}}) \cdot d_{l_{i,j}}, \quad \forall t \in T \tag{17}$$

11. The upper and lower bounds of the SOC of the battery to account for the highest and lowest allowable charging states, which are fixed for a specific battery type. The SOC of the E-truck on each link of each trip when transversing a series of links to reach its destination should always be within this range:

$$SOC_{min} \le SOC_{l_{i,j}t} \le SOC_{max}, \quad \forall l_{i,j} \in A_t, t \in T \tag{18}$$

Search method

Given that the problem defined above is essentially a network design problem, there is a need for a search method able to deal with the computational complexity of this class of problems (Menendez et al., 2015). While (mix-integer) linear problems are often solved through exact methods in an efficient manner, large instances of non-linear optimization problems cannot be solved with exact methods. In these cases, heuristic-based solving methods are the most efficient search methods. The meta-heuristic Genetic Algorithm has proven helpful in tackling this type of problem (Marler and Arora, 2010) and has been selected as the preferred search method where Elitism operators are introduced to improve the algorithm's performance in finding the global optimal solution (Ahn and Ramakrishna, 2003). Parameters of the GA are summarized in Table 4. Given that the problem involves 208 directed links within the network and 20 battery sizes, the probabilities of crossover and mutation are set at sufficiently high levels to enhance the exploration of a broader range of solutions, mitigating the risk of premature convergence to local optima during computation.

Detailed model parameters

See Tables 5 and 6.

Table 6
Assumed vehicle-related parameter values.

Vehicle-related parameters	
Maximum total degradation rate per year, d_{max} (Geotab, 2020)	4.20%
Fixed average calendar aging rate per year, c_f (Ali et al., 2023)	0.80%
Fixed cycle aging rate per year, y_{min}	1%
Battery replacing threshold, end (Gorzelany, 2023)	40%
Truck speed, v	80 km/h
Aerodynamic drag coefficient, c_a (Leonard et al., 2022)	0.6
Rolling resistance coefficient, c_{rr} (Leonard et al., 2022)	0.005
Frontal area of E-truck, a_f (Leonard et al., 2022)	10.2 m^2
Air density, ρ (Leonard et al., 2022)	1.3 kg/m^3
Gravity, g	9.8 m/s^2
Weight of truck+trailer+ full payload excluding battery, a (Leonard et al., 2022)	40,000 kg
Battery pack option, b_t (VolvoTrucks, 2022; Leonard et al., 2022)	90–1800 kWh(90 kwh each)
Energy density, z (Leonard et al., 2022)	232 Wh/kg
Maximum SOC, SOC_{max}	0.9
Minimum SOC, SOC_{min}	0.1
ERS charging power, p_{ERS} (Rogstadius, 2022; Gustavsson et al., 2019)	150 kW
Energy transfer efficiency, e_f (Rogstadius, 2022; Gustavsson et al., 2019)	0.9

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