Final Report

Charged with Knowledge: Insights from a Live Pilot Freight Charging Hub

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VTI unpublished report

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Summary

The transition to battery electric heavy-duty trucks (BETs) presents significant challenges due to increasing demand for sustainable transport driven by customer expectations and regulatory pressures. A primary hurdle of such transition is the insufficient public charging infrastructure along key transport corridors, limiting operational flexibility. Additionally, the high upfront costs of BETs and depot charging facilities pose financial constraints, slowing large-scale adoption. Operational challenges further complicate the transition as the limited range of BETs and longer charging times require significant adjustments to delivery schedules and route planning, impacting efficiency and ultimately economic viability. Despite these obstacles, leading companies are proactively investing in solutions. The project partner has established its first charging hub with 15 charging points at a home depot and deployed 10 BETs, marking an important step toward electrification (https://trans.info/charging-station-sweden-301562).

This primary goal of this project thus is: 1) to understand how existing charging hub and BETs are utilized in everyday logistic operations using evidence and insights drawn from real-world operational data; 2) provide data-driven decision support for future charging infrastructure investments. To achieve this, the research group has established a comprehensive database consisting of approximately 2.5 million files that collectively store around 60 million precision events of vehicle movements and 3 million vehicle start/stop events from 60 vehicles owned by 2 logistic companies. By analysing the data, vehicle movement patterns of both Internal Combustion Engine Vehicles (ICEVs) and BETs that are currently in operation are revealed. Results show that significant differences in ICEV and BET usages are observed where both a low utilization of BETs and a low utilization of charging hub are observed.

Further, the project formulates an optimization problem to incrementally maximize the utilization of available charging infrastructure while integrating existing charging stations into each expansion phase. This approach serves two key purposes. First, it quantifies the theoretical maximum of vehicle driving distances that can be electrified with the current charging hub, revealing the optimal utilization of existing charging infrastructure. Second, it provides logistics companies with data-driven insights for strategic infrastructure investments by identifying optimal charging station placements. Furthermore, the optimization model is extended into a multi-company co-optimization framework, enabling the potential sharing of charging locations. The optimization framework has been applied to two logistic companies with distinct characteristics in their service transport network.

Results indicate that with the existing charging hub at company A, 2.3% of the driving distance can be electrified, while for company B, which currently lacks a charging hub, the electrification rate remains 0% with a single hub. Expanding to three charging hubs significantly increases the theoretically electrified driving distance share to 15.9% for company A and 2.9% for company B. This disparity highlights the impact of network structure— company A's concentrated transport network benefits more from strategically placed charging stations, whereas company B's dispersed network sees a more limited effect. These findings contribute to the advancement of sustainable freight transport by providing a scalable, data-driven approach to charging infrastructure planning.

1. Introduction

1.1. Introduction and background

The freight transport industry operates in a highly competitive market with narrow profit margins, making financial sustainability a constant challenge. Compounding this pressure is the growing demand for environmentally friendly transport solutions, driven by customer expectations and regulatory requirements. As a result, the transition to Battery Electric Trucks (BETs) is no longer just an option for freight carriers - it is becoming a necessity to maintain competitiveness and long-term viability.

However, integrating BETs into freight transport presents several significant challenges. One of the primary obstacles is the lack of sufficient charging infrastructure, particularly along major transportation routes. The limited availability of public charging stations makes route planning more complex and less flexible. Additionally, the substantial upfront costs associated with purchasing EVs and installing depot-based charging infrastructure create financial barriers for many companies.

Beyond infrastructure and cost challenges, freight carriers must also adjust operational strategies to accommodate the unique characteristics of BETs, such as their shorter driving range and longer charging times compared to conventional diesel trucks. These adjustments may require changes in delivery scheduling, fleet management, and overall logistics planning.

In Sweden, the electrification of freight transport is still in its early stages. The industry currently lacks the necessary expertise and a well-structured deployment strategy to support large-scale adoption. Meeting future demands—shaped by EU regulations and national transport policies—will require coordinated efforts from industry stakeholders, policymakers, and technology providers to develop a sustainable and efficient electrification roadmap.

1.2. Purpose and goal

This research initiative, led by the Swedish Road and Transport Research Institute (Statens Väg- och Transportforskningsinstitut, VTI), financed by Vinnova FFI accelerate program, aims to generate data-driven insights that will accelerate the electrification of the freight transport sector. The study specifically examines the requirements for charging infrastructure, focusing on the strategic placement of charging stations and the optimization of fleet configurations based on the operational standards.

This primary goal of this project thus is:

1. to understand how existing charging hub and BETs are utilized in everyday logistic operations using evidence and insights drawn from real-world operational data.
2. to provide data-driven decision support for future charging infrastructure investments.

The project thus will equip freight carriers with innovative, scalable strategies for integrating BETs into their operations. By emphasizing infrastructure planning and deployment, this research seeks to identify effective ramp-up approaches that ensure both a smooth initial transition and long-term expansion. The findings will serve as a foundation for logistics carriers to develop sustainable and cost-effective electrification models, ultimately supporting a more efficient and environmentally friendly transport system.

1.3. Knowledge collection

Existing research highlights a widespread underutilization of BETs and charging infrastructure among logistics companies, posing a significant challenge to fleet electrification efficiency. Several key factors contribute to this issue, including range anxiety (Witt, 2023), lack of confidence about BET performance (Gonçalves et al., 2022), and suboptimal placement of charging stations (Li et al., 2024). Many logistics firms have installed charging infrastructure in locations that do not align with actual vehicle movement patterns, prompting drivers to favor more accessible or faster public charging stations (Yong et al., 2023). Additionally, the lack of smart EV routing tools (Teoh et al., 2018) and prolonged charging times compared to conventional refueling further deter operators from relying on internal charging networks (Huang et al., 2018).

Economic and operational constraints further contribute to this problem. The high upfront and maintenance costs of private charging stations discourage companies from actively promoting their usage (Azarova et al., 2020). Moreover, inadequate driver training in EV operations fosters behavioral reluctance to adopt charging strategies optimized for efficiency and cost-effectiveness (Li et al., 2024). Addressing these challenges requires a combination of strategic charging station placement, advanced route optimization tools, targeted driver education, and robust business models to ensure efficient utilization of charging infrastructure in logistics operations.

Despite the growing body of research in this area, much of the existing literature relies on simulated or synthetic datasets rather than real-world empirical observations. Many optimization models and policy recommendations are based on hypothetical routing scenarios or assumptions about driver behavior, which may not accurately reflect the operational realities faced by logistics companies (Huang & Ma, 2024; Li et al., 2024). Studies indicate that actual EV charging behaviors often diverge from simulation-based predictions, particularly in fleet operations where factors such as station congestion, vehicle load, and seasonal energy fluctuations influence decision-making (Maurya et al., 2024). This gap in real-world validation has been recognized in infrastructure planning research, emphasizing the need for empirical studies to refine theoretical models (Jain et al., 2024; Jurdak et al., 2024). Consequently, there is an urgent need for studies that examine how targeted interventions—such as optimized charging station placement, improved route planning, and operational process adjustments—can enhance the practical utilization of charging infrastructure and BETs.

1.4. Research approach

The primary motivation for this project stems from a recent collaboration with two freight transport companies, which have provided an extensive database of registered traffic records spanning several years. The goal is to develop a data process pipeline that enables the transformation of raw data entry into suitable data format that enables the analysis of vehicle movements at individual vehicle level. Thus, descriptive statistics of vehicle distance travelled as well as durations at charging hub can be derived and descriptive statistics can be performed to reveal key insights of existing utilization rate of ICETs, BETs and the charging hub. The process data further serves as input for the optimization model for modelling future electrification scenarios, operating under the key assumption that driving patterns remain consistent with historical traffic records.

A central challenge of this study is determining the optimal placement of a limited number of charging stations while also identifying which trucks to electrify in order to maximize charging station utilization for each company. To address this, the research adopts a mathematical optimization approach, formulating the problem into a computational model that enables efficient and data-driven decision-making. This framework allows for solving the problem to optimality, ensuring an effective and scalable electrification strategy.

Furthermore, it is important to highlight that the data-driven optimization methodology developed in this study is not limited to the specific case of the two collaborating freight companies but is designed to be broadly applicable across the industry. By leveraging real-world traffic data and mathematical modelling, the proposed framework can be adapted to different transport networks, fleet compositions, and operational constraints. This generalizability makes it a valuable tool for other freight carriers, policymakers, and infrastructure planners seeking to develop cost-effective and strategically viable electrification strategies.

Additionally, the study's approach enables scalability, meaning that as new data becomes available or operational conditions evolve, the model can be updated and refined to reflect changing requirements, which is achieved within the design of data process pipeline. This adaptability ensures that the framework remains relevant in guiding long-term electrification efforts, even as technology advances and regulatory landscapes shift. Ultimately, the insights gained from this research contribute to a more systematic and data-driven transition to electric freight transport, supporting industry-wide sustainability goals while maintaining operational efficiency.

The report is thus structure as follows. Section 2 describes the methodology of processing raw data and pipelining the data process stream for descriptive analysis and inputs to the optimization model. Section 3 describes the formulation of the optimization model for optimal allocation of charging hubs. Section 4 presents the application of the methodology to the two case studies, COMPANY A and Company B transport networks. Section 5 concludes.

1.5. Declaration

The findings and the method developed in this project are intended for submission to the IEEE Intelligent Transportation Systems Conference 2025 (IEEE ITSC 2025). To maintain the originality of the submission and adhere to conference guidelines, the detailed methodology and comprehensive results of this study are not fully disclosed in this document. However, we acknowledge the interest of readers who may wish to gain a deeper understanding of the research. Those seeking additional information about the project are encouraged to reach out to the project leader for further discussions and insights.

2. Data process pipeline

2.1. The raw data

The raw data for this project contains fleet data from two logistics companies. Data collection has been ongoing from November 2021 to March 2024 without major interruptions. As a result, the dataset is substantial, consisting of approximately 2.5 million files that collectively store around 60 million precision events and 3 million start/stop events. Each data entry includes the vehicle's geographic location, a timestamp, and a unique vehicle ID for identification. Together, these datasets provide detailed movement patterns of individual vehicles over time.

The dataset is categorized into two main types:

1. **Start and Stop Events** – These are recorded when the vehicle controller detects an ignition startup or shutdown.
2. **Precision Events –** Logged continuously at intervals of approximately 10–30 seconds while the engine is running.

Company A, based in Gothenburg, operates primarily in western Sweden, with its transport network shown in Figure 1, extending south toward Skåne and east toward Stockholm. Figure 1, left, shows the precision data and Figure 1, right, shows the stop locations of all vehicles. Company B, headquartered in Växjö, manages an extensive transport network (depicted in Figure 2) covering southern Sweden. In the similar fashion as Figure 1, Figure 2, left, shows the precision data and right shows the stop locations of the transport network of company B.

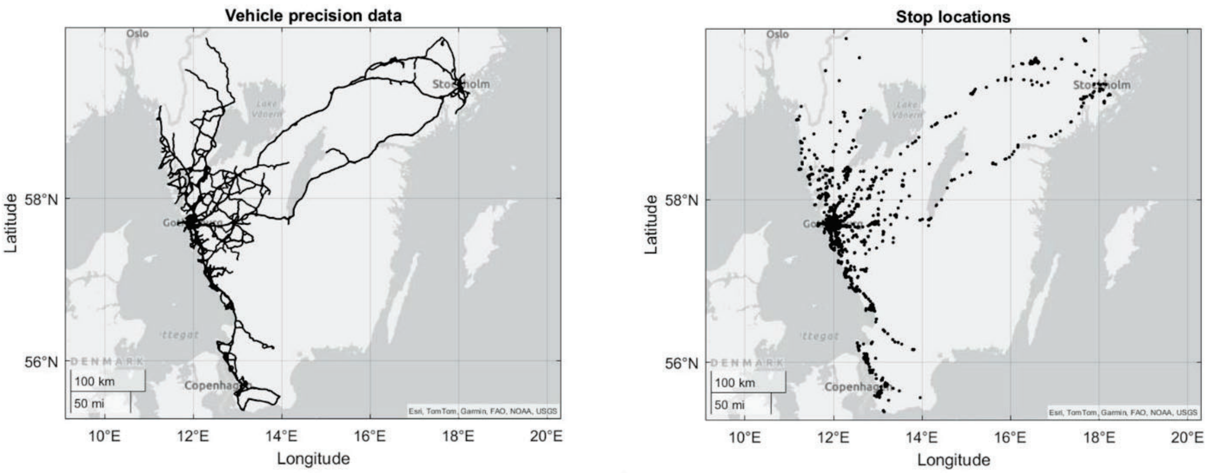

Figure 1. Data from Company A. Left: vehicle precision data. Right: stop locations of the vehicles.

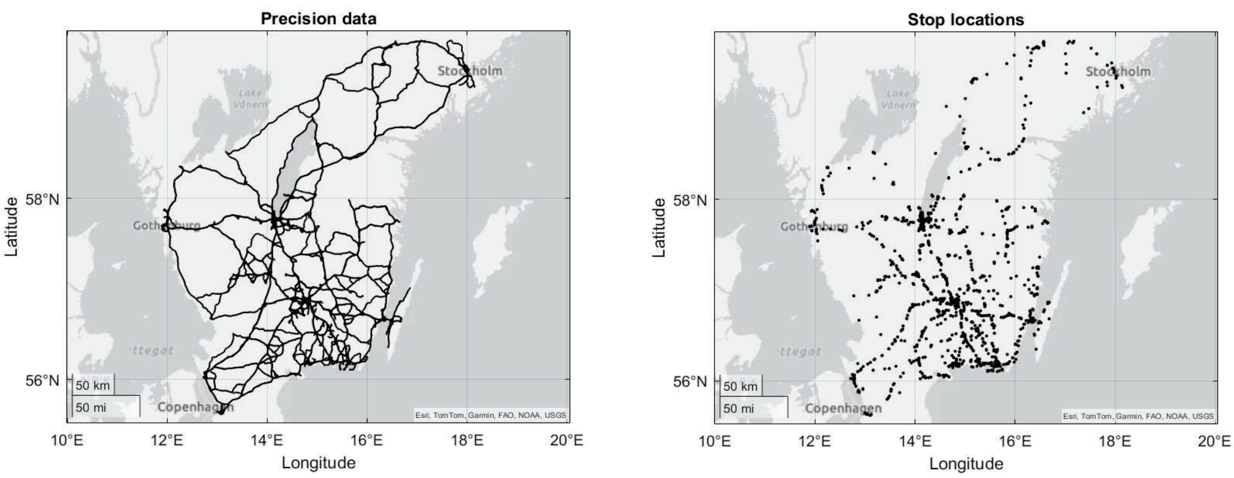

Figure 2. Data from Company B. Left: vehicle precision data. Right: stop locations of the vehicles.

2.2. Data processing

Raw data from the provided database must be pre-processed into a usable format and should enable the scalability for future integration of data from other companies if available. This involves cleaning, storing, organizing, and aggregating data to eliminate inconsistencies. An overview of this process is shown in Figure 3.

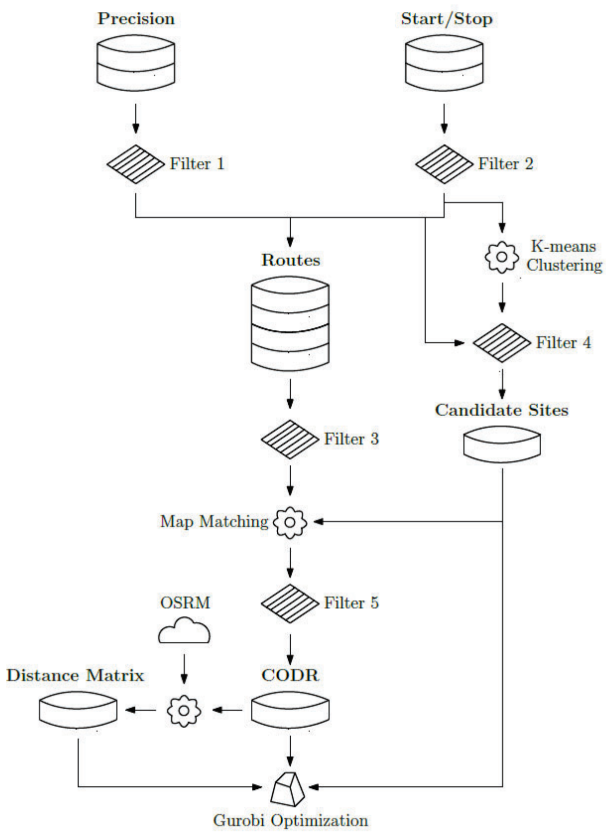

Figure 3. Data processing procedure.

The process begins by filtering out events with missing or inconsistent data (Filters 1 and 2) and reconstructing vehicle routes, defined as chronological sequences of stops and precision events. Some GPS data may be missing due to errors in the transmission process, causing apparent teleportation between distant locations. To address this, Filter 3 segments routes where data discontinuities occur, ensuring consistency in event sequences.

Next, a route-based logistic network is generated. Key freight activity locations, such as depots and customer facilities, serve as network nodes, connected by edges representing adjacent locations. Since explicit origin-destination (OD) data is unavailable, a K-means clustering method is applied to identify high-intensity stop locations, which also serve as potential charging sites. To ensure feasibility, Filter 4 relocates these candidate sites to the nearest registered stop in the dataset.

Then a Map-Matching technique is developed in the study to refine vehicle routes. Vehicles may pass candidate charging sites without stopping, so network nodes are analyzed against precision events on each route segment. If a candidate site falls within a defined distance threshold, it is considered a passed site. This method does not alter actual routes but identifies adjacent charging stations as viable options. The resulting sequence of passed sites forms Chained Origin Destination Routes (CODRs), representing continuous travel segments.

Over longer time periods, a truck's operations may include multiple CODRs. Filters further refine the dataset by removing implausible CODRs—such as those with excessive OD distances or too few OD elements—and excluding vehicles with excessive discrepancies (Filter 5). The final traffic network is constructed from all CODRs, where edges between nodes exist only if at least one vehicle has travelled the corresponding OD pair. The shortest physical distances between nodes are obtained using the Open Source Routing Machine (OSRM).

A visualization of this data processing procedure applied to the dataset presented in Figure 1 is shown in Figure 4.

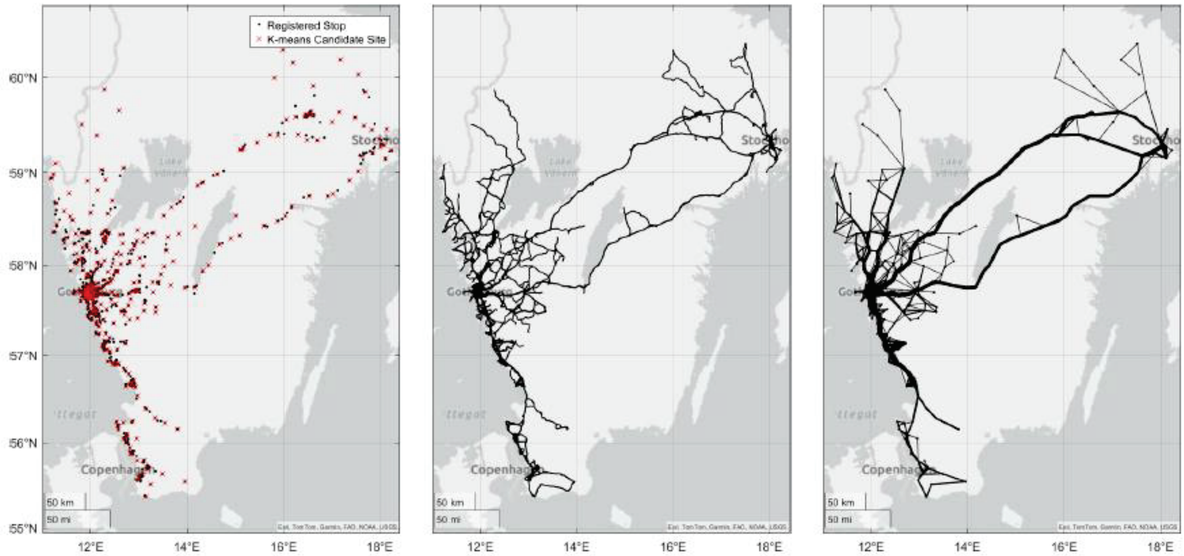

Figure 4. Transformation of model input data from Company A. (top row). The left figure displays stop locations alongside 300 candidate sites identified through K-means clustering. The middle one illustrates precision points, while the right figure presents the traffic graph network, constructed by map-matching precision coordinates to network nodes.

3. Formulation of the optimization problem

3.1. Model structure

The problem is formulated as a Mixed-Integer Linear Program (MILP) to model the relationship between real-world logistics and a mathematical optimization framework.

1. **Indexation**: Defines truck locations within a network based on discrete time steps, focusing on event order rather than exact timestamps.
2. **Decision Variables**:
   - $\boldsymbol{y_i}$: Binary variable indicating whether a charging station is placed at a node.
   - $\boldsymbol{z_{h,l}}$: Binary variable indicating if a truck is electric.
   - $\boldsymbol{d_j}$: Continuous variable representing the remaining driving distance before recharging is needed.
3. **Parameters**:
   - **Distance matrix $\boldsymbol{D_{p,q}}$**: Stores distances between adjacent nodes.
   - **Vehicle categories $\boldsymbol{c_k}$**: Classifies trucks based on daily driving distance.
4. **Constraints**:
   - Remaining driving distance is bounded by battery capacity.
   - Distance depletion is modelled as trucks move between nodes.
   - Charging is only possible at nodes with stations.
   - Vehicles recharging must reset their range without exceeding battery limits.
   - Pre-existing charging stations and electric trucks are predefined.
5. **Objective**: Maximize the total electric distance driven while ensuring an optimal placement of charging stations, constrained by a maximum number of charging stations .

This MILP integrates all constraints to determine optimal station locations and maximize electric truck usage within the network. The detailed optimization problem formulation is omitted in this report.

3.2. Assumption in the optimization problem formulation

The models defined in this study operate within an ordered discrete-time framework, where temporal events such as charging are treated as instantaneous. In reality, charging heavy-duty electric vehicles can take several hours. However, this simplification assumes that charging at candidate sites with a charging station does not introduce any delays. As a result, there is no incentive to limit or optimize charging behaviour, since vehicles can fully recharge without penalties. This effectively removes any variability in charging levels, as the charged amount is always assumed to be the maximum battery capacity, aligning with the constraints defined above.

Additionally, charging stations are modelled with unlimited service capacity, meaning that constraints related to queuing or wait times are not considered. Incorporating such factors would require explicit time-dependent modelling, significantly increasing computational complexity and making the problem infeasible to solve within reasonable time limits.

Despite these simplifications, they are not expected to impact the primary objective of the study—identifying optimal locations for charging stations. Since the focus remains on placement decisions based on vehicle routing and driving patterns, rather than detailed charging dynamics, the core findings of the model remain valid.

4. Results

4.1. Utilization analysis of existing BETs and charging station

A deeper analysis of the processed dataset (result of the data process pipeline) for the BETs in Company A’s fleet reveals significant underutilization in freight operations. Figure 5 illustrates this discrepancy, showing that BETs are active for only a limited time of the day. In the given example, the BET operates primarily in the morning, remaining idle for the rest of the day.

On average, BETs cover just 100 km per day where the maximum driving range of market available BETs are 300 km. The driving distance of ICETs in the fleet is on average 219 km daily. This limited range of operation for BETs suggests inefficiencies in BET utilization, possibly due to operational constraints, route planning challenges, or concerns over charging infrastructure reliability.

Furthermore, Figure 6 highlights the low utilization rates of the existing charging station. Despite having 15 available charging points, only 4 to 5 BETs are observed charging at different times throughout the day. This suggests that either the existing infrastructure exceeds current demand, or operational strategies do not fully leverage the available charging capacity. These findings emphasize the need for better integration of BETs into freight logistics, optimizing both vehicle deployment and charging station usage to maximize efficiency and return on investment.

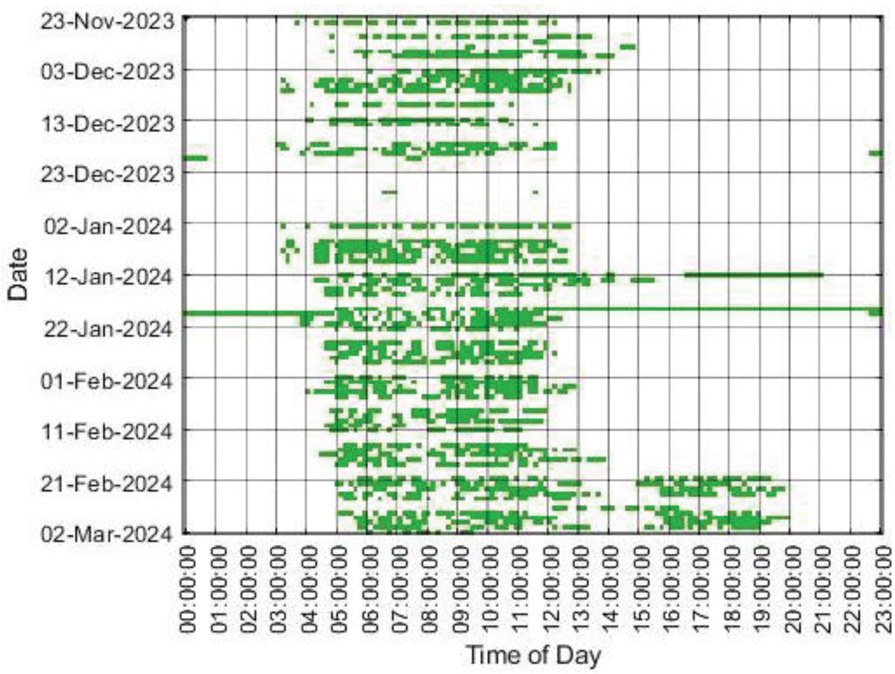

Figure 5. The usage pattern of an example BET over different time-of-day (green shows the vehicle is in driving mode)

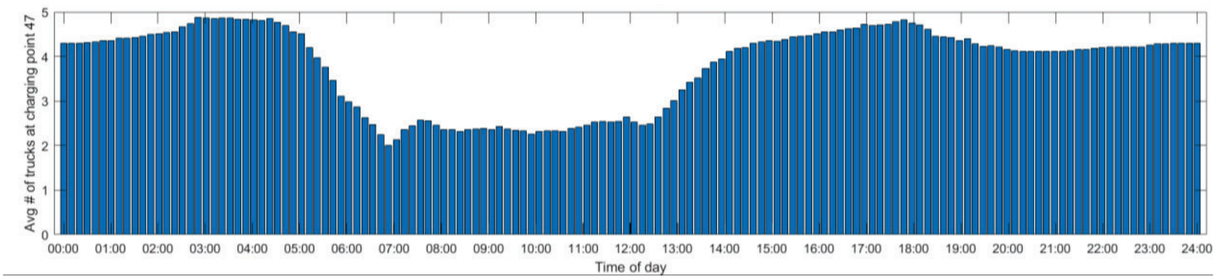

Figure 6. Average number of charging points used by BETs over different time-of-day.

4.2. Results of the optimal charging station allocation problem

The optimization problem outlined in the previous section is solved using the Gurobi optimization software. Figure 7 illustrates the optimal placement of charging stations for Company A during the initial phase of electrification in in four sequential steps with 1, 3, 6 and 10 charging station.

In the very initial step with just one charging station (Figure 7, top left), Company A can theoretically electrify 3 out of 58 trucks, covering 2.3% of the total transport distance. As shown in the top left diagram of Figure 7, the optimal location for the first charging station is the company's main home depot in Gothenburg (marked by a green dot). This selection is ideal, as a significant number of vehicles are stationed at this depot, making it a strategic and practical choice for initial electrification efforts.

In the second phase, company A's optimal strategy focuses on electrifying the west coast corridor of Sweden by installing two additional charging hubs along the corridor shown in Figure 7, top right. This approach proves highly effective, increasing the electrified driving distance to 15.9%. The success of this strategy is largely attributed to the concentrated transport network and high traffic density in the west coast region, as shown in Figure 4.

In the third phase, expanding the charging network with three additional stations further strengthens the west coast corridor (Figure 7, bottom left), raising the electrified driving distance share to 35.2%.

In the fourth phase, the network extends toward Stockholm (Figure 7, bottom right) with four more charging stations, three of which are strategically placed along key corridors near the city. This expansion significantly boosts the electrified driving distance share to 48.1%, demonstrating the impact of a stepwise, strategic infrastructure rollout.

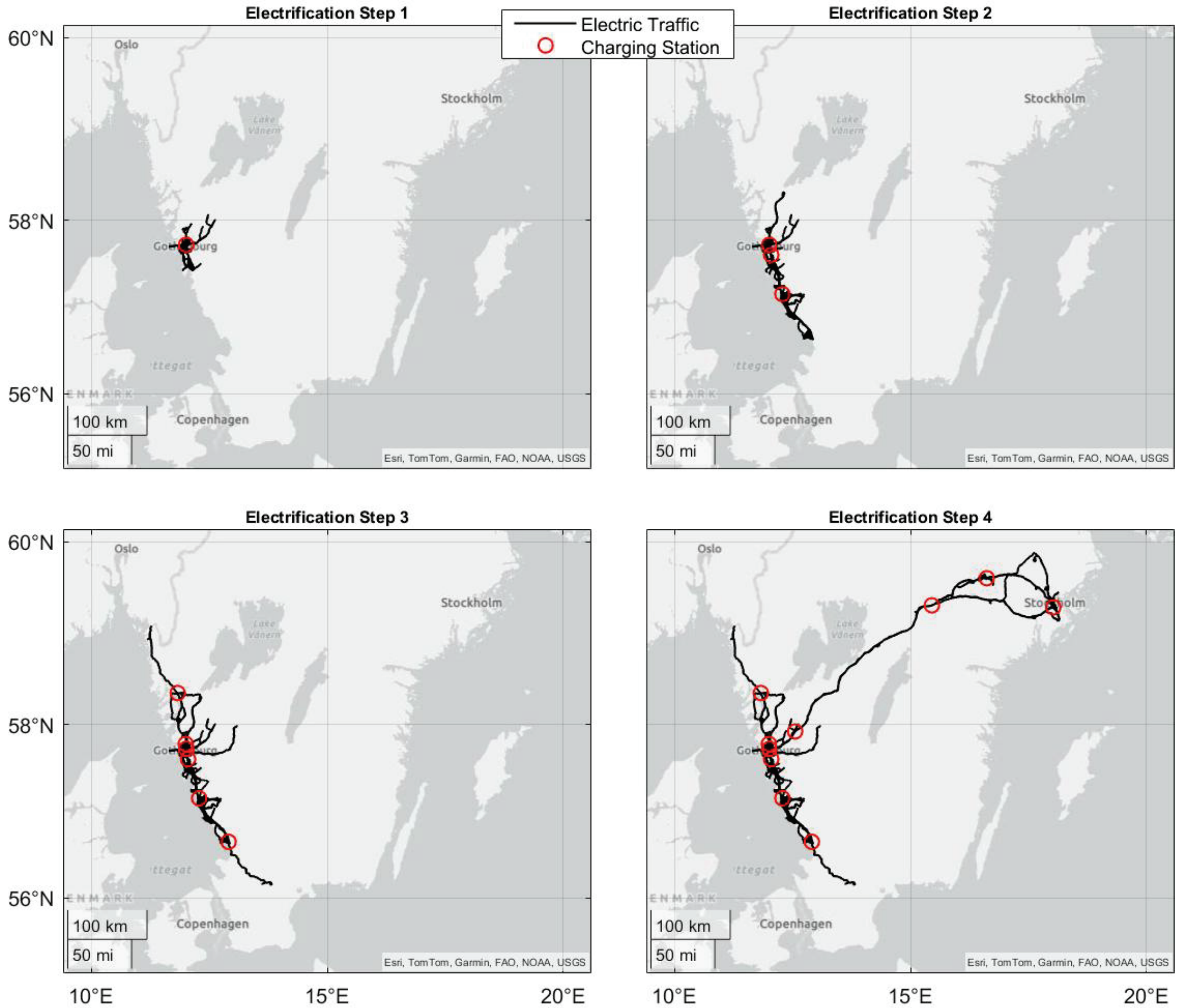

Figure 7.Visualization of the optimal solutions for Company A's dataset. In this example, the maximum number of charging stations is set to 1, 3, 6 and 10 in four sequential steps. The optimal charging station locations are indicated by green dots.

In the similar fashion as Figure 7, Figure 8 shows the optimal locations of charging stations for Company B in the ramping-up phase in the four same sequential steps. In contrast, Company B struggles to make progress with just a single charging station shown in Figure 8, top left diagram. This challenge can be traced back to the distribution of trucks relative to available locations. As depicted in Figure 4, Company B's more dispersed transport network and longer delivery route requires additional infrastructure in the ramping-up phase.

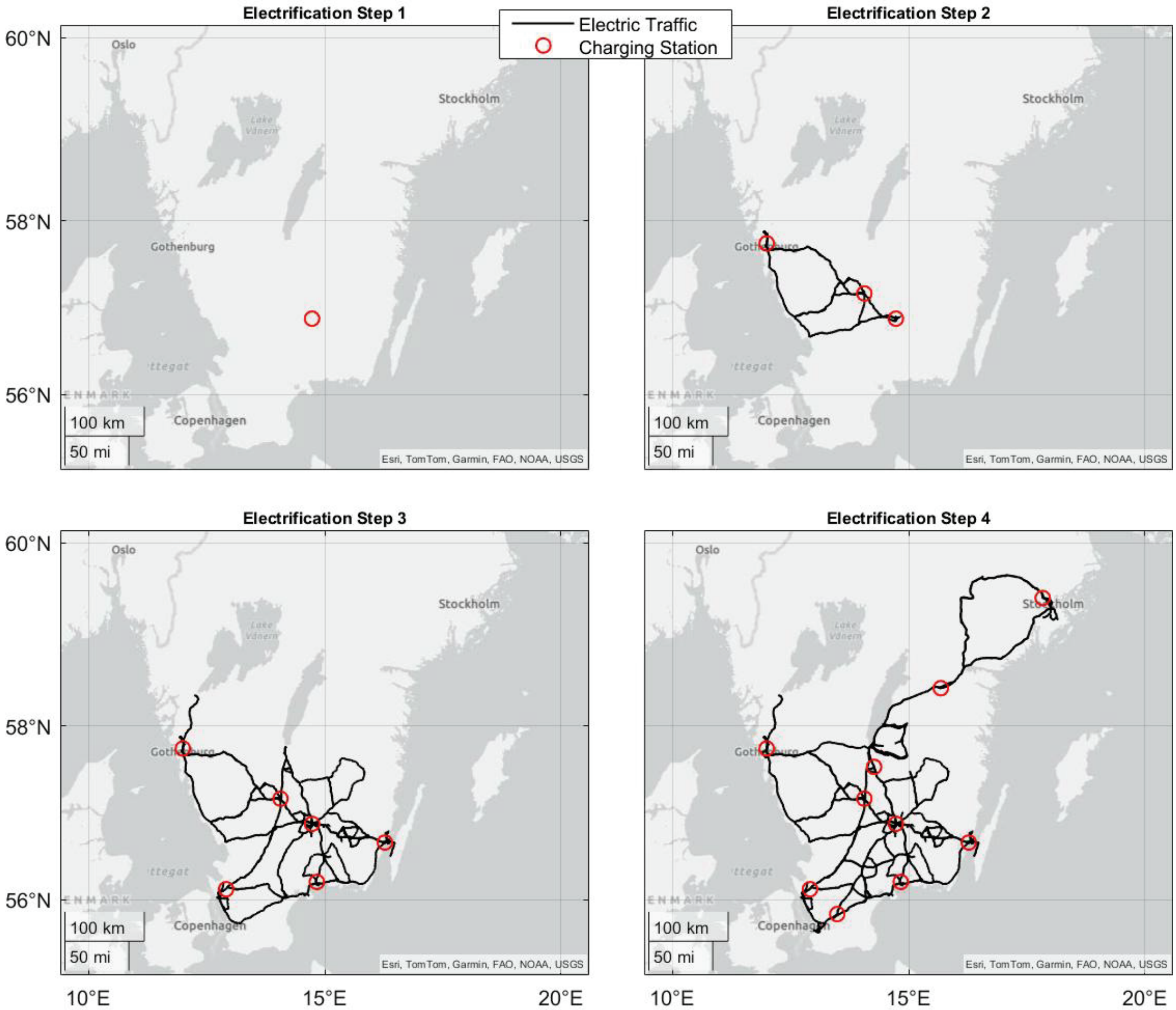

Figure 8. Visualization of the optimal solutions for Company B's dataset. In this example, the maximum number of charging stations is set to 1, 3, 6 and 10 in four sequential steps. The optimal charging station locations are indicated by green dots.

In the second step, Company B's optimal strategy focuses on electrifying a single high-utilization truck. This is likely because the largest sub-network supported by three charging stations (Figure 8, top right) is still too small to accommodate multiple trucks or because this particular truck alone contributes more to the total driven distance than several others combined. This finding suggests that, in the early stages of electrification, prioritizing charging infrastructure along high-utilization routes may be more effective than attempting to expand overall network coverage with a dispersed transport network.

By the third step, the addition of three more charging stations increases the flexibility of the electric sub-network, bringing the total number of stations to six (Figure 8, bottom left). Company B makes substantial progress by extending charging infrastructure further south. Despite Company B's network now covering a larger geographical area than Company A's, only four of its trucks can be sustained within the available charging infrastructure. This highlights the challenge of electrifying highly dispersed transport network, where individual trucks operate across multiple locations over large geographical area, making comprehensive coverage more complex and resource intensive.

In the fourth step with 10 charging stations, both Company A and Company B extend their networks toward Stockholm. Although this segment experiences relatively high traffic volume, electrification only becomes viable after previous network expansions. Longer routes require multiple charging stations for full coverage, which increases costs but also maximizes the total electrified distance, making it a strategic yet resource-intensive investment.

Tabel 1 summarizes the proportion of electrified traffic and number of electric trucks required in the 4 sequential steps in the ramping-up phase for both Company A and B.

Tabel 1. Numerical values of the solution of optimization problem.

	Step	Fraction of electric traffic (%)	Number of electric trucks
Company A	1	2.3	3/58
	3	15.9	8/58
	6	35.2	14/58
	10	48.1	18/58
Company B	1	0.0	0/66
	3	2.9	1/66
	6	8.3	4/66
	10	20.0	11/66

5. Conclusion

In this project, a data process pipeline has been established and applied to data from two logistic companies. The data consist of approximately 2.5 million files that collectively store around 60 million precision events of vehicle movements and 3 million vehicle start/stop events from 60 vehicles owned by 2 logistic companies. By analysing the data, vehicle movement patterns of both ICEVs and BETs that are currently in operation are revealed. Further, the project formulates an optimization problem to incrementally maximize the utilization of available charging infrastructure while integrating existing charging stations into each expansion phase. Furthermore, the optimization model is extended into a multi-company co-optimization framework, enabling the potential sharing of charging locations.

The analysis of current BET and charging infrastructure usage reveals low utilization rates at the existing charging station. Despite having 15 charging points, only 4 to 5 BETs are observed charging at different times throughout the day. This discrepancy suggests either an oversupply of charging capacity relative to current demand or inefficiencies in operational planning that fail to maximize infrastructure usage. These findings underscore the need for improved integration of BETs into freight logistics, ensuring optimal vehicle deployment and more effective use of charging stations to enhance efficiency and return on investment.

The results from optimization presented above demonstrate how network structure and operational patterns influence the effectiveness of charging infrastructure deployment. Company A, benefits from its operating characteristic with its centralized traffic around a smaller geographical area, allowing for higher electrification rates with fewer stations. In contrast, Company B faces greater challenges due to its dispersed transport network over a larger geographical area, requiring more extensive infrastructure to achieve similar results.

Further, the results indicate that early-stage electrification proves to be more effective when prioritizing high-utilization routes rather than attempting widespread coverage. As more charging stations are introduced, flexibility increases, enabling longer routes and greater electrified distances. However, fully integrating electric trucks into large-scale freight operations remains resource-intensive, requiring strategic placement of infrastructure to balance cost and efficiency. These findings obtained in this study highlight the importance of tailoring electrification approaches based on transport network characteristics to maximize impact and sustainability.

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