38th International Electric Vehicle Symposium and Exhibition (EVS38)
Göteborg, Sweden, June 15-18, 2025

Decision support for optimized utilization of electric trucks in a mixed fleet

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Executive Summary

In this paper, we present a study on a multilevel optimization of freight shipments from the perspectives of both shippers and transporters. On the higher level, a method with a cold-starting recommender algorithm for choosing the most suitable transporter is applied. Then, the operation of a mixed truck fleet for a transport company is optimized to maximize the advantages of having battery electric trucks as a part of the fleet. The results show that the chosen strategies for operation have a significant impact on the costs in terms of fuel use, emissions, and time use.

Keywords: Heavy Duty Electric Vehicles and Buses, Intelligent Transportation System for EVs, Modelling & Simulation, Energy Management, Environmental impact.

1 Introduction

Electrification of the transport sector is considered a crucial step in addressing climate goals. The increased focus on battery electric vehicles (BEVs) and the subsequent expansion of BEV car models have led to high global sales. In Norway, 9 out of 10 new cars in 2024 were BEVs [1]. Other types of road vehicles are expected to follow. Vans and small trucks are already available, and battery electric buses are being sold in significant numbers [1]. Although BEVs have a considerably higher tank-to-wheel efficiency than internal combustion engine vehicles (ICEVs), their limitations in range and high refueling times are notable drawbacks. However, for short-distance, fixed-route operations, these limitations are less concerning, as evidenced by the high number of BEV city buses leading the heavy-duty vehicle segment.

Another important aspect is that carriers, freight forwarders, and traffic managers—those responsible for the purchase and sale of transport—still operate in a very manual and inefficient manner, relying mostly on email and telephone. This approach is both expensive and unsustainable. Our study aims to develop services that simplify transportation brokerage processes and facilitate the green shift within the industry by increasing the utilization of residual capacity. The purpose of the research is to find solutions that reduce the number of empty vehicles, illegal cabotage, and the associated environmental impact both globally and domestically. This involves developing solutions to automate or simplify several manual operations associated with transport brokerage while also enabling a sustainability focus, thus achieving increased efficiency, information flow, and profits.

The electric vehicle routing problem (EVRP) has been extensively studied in recent years due to the growing adoption of electric vehicles (EVs) and the need for efficient routing solutions. Various studies have explored different aspects of EVRP, such as the electric vehicle routing problem with time windows, multiple recharging options, and capacitated stations. For instance, a comprehensive review categorizes EVRP into nine classes, including the electric traveling salesman problem, green VRP, and electric pickup and delivery problem [2]. Another study introduces an EVRP model with synchronized mobile partial recharging and a non-strict waiting strategy, addressing the challenges of short EV range and limited recharging infrastructure [3]. These studies highlight the complexity and diversity of EVRP, emphasizing the need for innovative solutions to optimize routing and recharging strategies.

Despite the progress made in EVRP research, several gaps remain unaddressed. Our study aims to fill these gaps by focusing on the integration of digital freight brokerage systems with EV routing optimization. While previous research has primarily concentrated on routing algorithms and recharging strategies, there is limited work on how digital platforms can enhance the efficiency of EV routing and freight brokerage. By developing a recommender system that leverages historical job data and real-time information, our study seeks to improve the allocation of transport resources, reduce empty runs, and minimize environmental impact.

Digital freight brokerage, where freight shippers and trucks are connected, is an emergent trend in digital logistics. Such digital brokerage systems can potentially be used to support planning for efficient allocation of transport resources (vehicles or trucks) to transport applications, thereby allowing single vehicles to serve multiple customer orders through approaches such as agents and constraint logic programming [4] or using approaches such as Markov Decision Process (MDP) for more dynamic cases [5].

The application of AI in recommender systems for freight transport has shown significant potential in enhancing efficiency and reducing operational costs. Studies have demonstrated that AI-driven recommendation systems can analyze vast amounts of data to provide personalized and accurate recommendations for freight brokerage. For instance, a deep learning-based freight recommendation system developed by Kim et al. utilizes techniques such as Autoencoder, Word2Vec, and Graph Neural Networks (GNN) to classify freight categories and suggest suitable freight matches for vehicle owners [6]. This system aims to reduce failed contracts and improve market efficiency by learning complex patterns from users' past behaviors and preferences. Another study highlights the use of AI in supply chain recommendation systems to optimize logistics strategies, such as recommending the most efficient routes and best carriers, thereby reducing transportation costs and improving delivery times [7].

Despite these advancements, there are still gaps in the integration of AI recommender systems with real-time data and dynamic decision-making processes in freight transport. Most existing systems focus on static data and predefined rules, which may not fully capture the complexities of real-world logistics operations. Our study addresses these gaps by developing a recommender system that leverages historical job data to optimize the allocation of transport resources. Merging the electric vehicle routing problem (EVRP) with recommender systems can provide a highly efficient and sustainable service for stakeholders in the logistics and transportation sectors. By integrating EVRP solutions with AI-driven recommender systems, companies can optimize route planning and vehicle utilization based on real-time data and historical job patterns. This integration allows for dynamic adjustments to routes, considering factors such as traffic conditions, energy consumption, and charging station availability. For instance, a recommender system can suggest optimal routes that minimize energy use and emissions while ensuring timely deliveries. Additionally, it can recommend suitable transport operators who are already in the vicinity of new job requests, facilitating freight pooling and reducing empty runs. This approach not only enhances operational efficiency and reduces costs but also supports environmental sustainability by promoting the use of electric vehicles and reducing the carbon footprint of transportation activities [8, 3].

In this study, we have designed and prototyped a recommender system to help freight brokers match new transport operators to transport jobs. Potential transport operators should preferably already be operating in the area of the new job to enable the possibility of freight pooling. The input to the recommender system includes, at a minimum, the origin and destination of the job request as GPS coordinates (though vehicle definitions are supported for better estimations of required energy use). The top N jobs with the lowest distances are then recommended, and further sorted and filtered based on expected energy use, expected emissions, and/or expected time requirements for the job.

2 Methodology

Recommender systems are algorithms designed to suggest relevant items to users based on their preferences and behaviors. They are widely used in streaming services, e-commerce platforms, and social media applications. One popular type of recommendation algorithm is collaborative filtering, which suggests items to users by analyzing the behaviors and preferences of other users. In our case, the users are requesting transport jobs, and the algorithm recommends potential transport companies capable of executing these jobs. The collaborative filtering-inspired approach used here recommends companies that have successfully completed similar jobs in the past. By "similar," we refer to attributes such as origin, destination, and other job-specific characteristics available in the dataset.

Advanced recommender algorithms often employ deep learning methods, including transformers, neural networks, and graph neural networks, to capture complex user-user and user-item relationships. These methods typically require large, comprehensive datasets. A significant challenge for many recommender systems is overcoming the "cold start" problem—when data is sparse, underrepresented, or heavily skewed, it is difficult to generate reliable recommendations. However, in our context, the user-item relationships are relatively straightforward and can be effectively handled without relying on complex learning-based methods.

In particular, users are unlikely to engage with transport companies that lack a proven history of handling jobs involving the specific origin and destination of the requested job. This allows us to filter out irrelevant transporters based on their historical job data. This approach assumes access to a comprehensive dataset of past jobs, accurately representing each transporter's available routes and services.

The assignment of vehicles represents a Vehicle Routing Problem (VRP) which, over the years, has been the subject of extensive research [9, 10]. The VRP formulation involves several key components. Each vehilce must visit a set of stops, which include pick-up and delivery points. The sequence of these visits must be optimized to minimize total travel costs, e.g., distance or time. Each vehicle has a maximum load capacity that cannot be exceeded, including both weight and volume constraints, ensuring that the vehicle can carry the assigned shipments without overloading. Certain shipments may require specific vehicle capabilities, such as refrigeration or crane equipment, and these constraints ensure that only compatible vehicles are assigned to these shipments.

Time constraints are also critical, as each shipment may have time windows associated with the time for pick-up or delivery, and the routing plan must ensure that all shipments are picked up and delivered within their respective time windows. For battery electric vehicles, the range constraint is crucial. The routing plan must ensure that the vehicle can complete its route within its battery capacity, including considerations for recharging if necessary. The Origin-Destination (OD) matrix provides the travel times, distances, energy consumption and emission values between all pairs of stops, which is essential for calculating the total travel distance or time for each route and for each type of vehicle. The primary objective is to minimize the total cost, which can include travel distance, travel time, energy consumption, emission or a cost based on a weighted sum of these components. Secondary objectives may include balancing the load among vehicles and minimizing the number of vehicles used.

The next step in the methodology is to find an optimal assignment and use of vehicles on a specific set of stops. This involves an estimation of which vehicles to serve which routes, as well as how to order the sequence of stops on a specific route. The required information for each vehicle is load capacities, specific vehicle capabilities, start location and stop location. For each shipment, the required information is the pick-up point, delivery point, time window for pick-up and delivery, physical dimensions, and specific vehicle capabilities. This is supplied in the synthetic data set, and a specific subset was chosen for the optimization study of a mixed fleet. The mixed fleet consisted of two battery electric trucks and two diesel trucks. The specifications of the trucks are shown in Table 1.

Table 1: Vehicle definitions

Vehicle type	Fuel type	Vehicle weight (kg)	Payload weight capacity (kg)	Accelerating power (kW)	Battery capacity (kWh)
6x2	Battery	11 000	15 000	490	540
6x2	Diesel	8 000	18 000	490	-
6x2 with crane	Battery	13 000	13 000	490	540
6x2 with crane	Diesel	10 000	16 000	490	-

As a solution, we designed a pipeline where we generate synthetic data based on a combination of existing data, O-D matrices based on travel surveys, and extracts from various historical data and registered market actors. This feeds into a data-synthesizer, generating enough data to bootstrap a recommender (as a hybrid between random recommendations when there is no data, and trying for a probable recommendation relying on statistics for missing values). Over time, the system should blend synthetic data with real data in the platform as the amount of matched jobs in the system increases.

Generating synthetic trips and empty return-trips based on the proximity between demand and existing market actors (i.e., interpolating how statistical market demand is solved) is not only an effective way to address the cold-start problem for a recommendation engine, but it also helps counteract popularity bias. This bias tends to reinforce existing actors, making it difficult for new or niche actors to be discovered. Therefore, the relevance of such a data synthesizer extends beyond the initial phase and remains significant in the long term.

3 Analysis

For this study, we utilized historical job data provided by a freight broker company. This dataset includes information on transporters that have previously handled similar jobs, though it is naturally limited to the geographical scope and transporters represented in the system. Such limitations may lead to an overemphasis on established relationships, a known drawback in recommender systems that rely solely on historical data.

To address this, we introduced a synthetic dataset generator to supplement the historical data. This dual-data approach balances reliability with exploration, ensuring the recommender system considers both well-established transporters and potential new candidates. This strategy mitigates the cold start problem and avoids reinforcing existing biases within the dataset. The core of this idea was to blend between synthetically augmented data and pure historical transactions as the amount of historical data grows. The model generates two types of recommendations. The first is derived from historical data, prioritizing transporters with a proven track record for handling similar jobs and have the possibility to take into account parameters such as energy use, cost, historic geographic locations for jobs and how fully loaded the vehicles usually are (i.e. potential for available space for a shipment job in future transports). While this ensures reliability, it may limit opportunities for exploring alternative options. The second recommendation leverages the synthetic dataset, suggesting transporters that may not appear in the historical records but are potentially well-suited for the job. This complementary approach allows the recommender system to provide balanced suggestions that incorporate both reliability and innovation.

To solve the VRP, we use a local search algorithm, which is a type of metaheuristic. Local search algorithms iteratively explore the solution space by making small changes to the current solution and evaluating the resulting solutions. The process continues until no further improvements can be found. Local search algorithms are particularly effective for VRP due to their ability to handle complex constraints and large solution spaces. They can be combined with other metaheuristics, such as tabu search or simulated annealing, to enhance their performance [9].

In our study, the local search algorithm starts with an initial feasible solution, which is generated based on the given constraints and objectives. The algorithm then iteratively improves this solution by exploring neighboring solutions. For each iteration, the algorithm evaluates the cost of the new solution and accepts it if it improves the overall objective. Our algorithm also applies a ruin-and-recreate principle to escape from local optima. The process continues until a stopping criterion, such as a maximum number of iterations or a time limit, is reached. The effectiveness of local search algorithms in solving VRP has been well-documented in the literature. The study by Hoff et al. provides a comprehensive survey of fleet composition and routing problems, highlighting the industrial applications and the effectiveness of various metaheuristics, including local search [10].

Several studies have contributed to the understanding of energy consumption in electric vehicles. Miri et al.

emphasized the importance of accurately modeling drag and rolling resistance to predict energy consumption under various driving conditions [11]. Their work highlights the need for detailed vehicle dynamics modeling to simulate real-world scenarios and provide reliable energy demand estimates. Liu et al. explored the impact of accessory loads, such as air conditioning and heating, on energy consumption. They found that accessory loads can significantly affect total energy use, especially in extreme weather conditions, and should be accurately estimated for realistic predictions [12].

Furthermore, the cost optimization aspect of the model is designed to balance the trade-offs between time, distance, and energy consumption. By assigning specific costs to each parameter, the model can identify the most cost-effective routes and operational strategies. This approach not only helps in reducing operational costs but also supports sustainable transportation practices by minimizing energy use and emissions. Sun discussed the integration of cost factors into energy consumption models, providing a comprehensive tool for transport planners and operators [13]. Additionally, Mediouni et al. proposed a hybrid approach that combines physical and data-driven models to enhance the accuracy of energy consumption predictions [14]. This method takes into account driving behavior, road conditions, and environmental factors, providing a robust framework for energy consumption estimation.

The energy consumption model developed by Hjelkrem et al. is utilized in this study [15]. This model, which has been validated with data from bus fleets in China and Norway, provides accurate estimations of energy consumption for battery electric buses. It incorporates factors such as vehicle dynamics, auxiliary systems, and real-world driving conditions, making it a reliable tool for strategic planning in electric vehicle operations.

To estimate the energy demand from the vehicles in this study, a set of general parameters for the drag and rolling resistance was specified as shown in Table 2. The model also considers the impact of accessory loads, such as air conditioning and heating, which can significantly affect energy consumption. The cost optimization aspect of the model is designed to balance the trade-offs between time, distance, and energy consumption. By assigning specific costs to each parameter, the model can identify the most cost-effective routes and operational strategies.

Table 2: General parameter definitions

Front area (m^2)	Drag coefficient	Rolling resistance coefficient	Accessory load (kW)	Cost per hour (NOK)	Cost per km (NOK)	Cost per kWh Electricity (NOK)	Cost per kWh Diesel (NOK)
8	0.45	0.015	2	500	1	1.5	2.0

4 Results and discussions

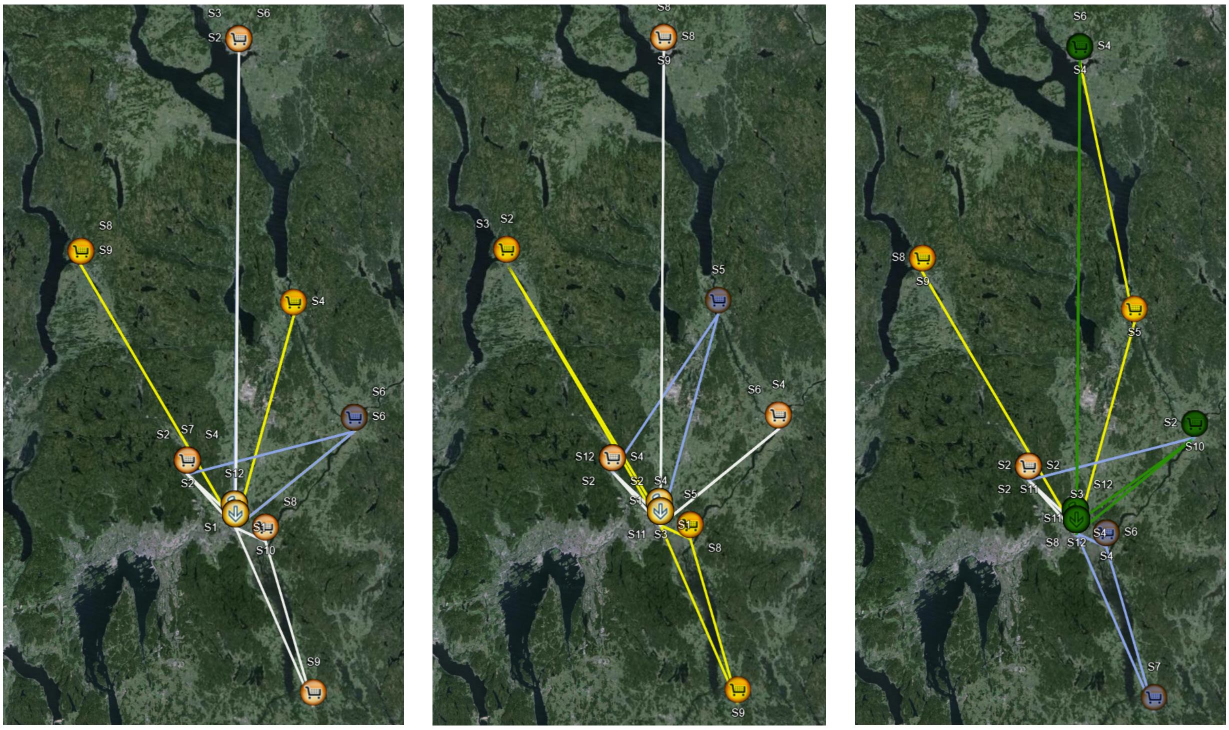
For the case study, 9 shipments with pick-up points and delivery points in the greater Oslo area were selected. The 9 shipments were further split into 15, as the size of 6 of the shipments exceeded the maximum capacity of all trucks in the fleet. Then, three different optimizations were carried out based on the following criteria:

- Time: Minimization of time use (hours)
- Emissions: Minimization of greenhouse gases (kg CO_2)
- Cost: Minimization of total transport costs (CostPerHour * time + CostPerKm * distance + CostPerKWH * kWh)

The results are presented in Table 3 and Figure 1. It is apparent that the solutions are affected by the chosen optimization criteria. It is especially interesting to notice that an optimization based on time yields significantly higher emission and total cost than the two other criteria. We find the reason for this difference in emission by looking into the details of each vehicle within each solution. The solution optimized for time uses the diesel trucks for 70% of the work, while the other two solutions use the diesel trucks only for 30 % of the work. As diesel trucks are the source of most of the CO_2 emissions, we lower the total emissions the more we are able to allocate work to the battery electric trucks. Only when the optimization criterion captures this difference between the trucks are we truly able to minimize the total emission.

Table 3: Optimization results

Minimization criteria	Time (h)	Distance (km)	Emissions (kg CO_2)	Cost (NOK)
Time	17:40:05 (BEST)	1 074.629 (BEST)	1 178.5 (+93%)	18 068.50 (+19%)
Emissions	19:28:56 (+10%)	1 203.525 (+12%)	611.8 (BEST)	16 222.34 (+7%)
Cost	17:45:29 (+1%)	1 081.220 (+1%)	648.4 (+6%)	15 189.21 (BEST)



(a) (b) (c)

Figure 1: Optimization results in terms of chosen sequences for Time (a), Emissions (b) and Cost (c)

Digital freight brokerage where freight shippers and trucks are connected, is an emergent trend in digital logistics. Such digital brokerage systems can potentially be used to support planning for efficient allocation of transport resources (vehicles or trucks) to the transport applications, thereby allowing single vehicles to serve multiple customer orders through approaches such as agents and constraint logic programming [4], or through the use of approaches such as Markov Decision Process (MDP) for more dynamic cases [5]. However, in Norway brokerage is performed mostly manually, supported by tools. This is partially due to the small market, limited transport jobs required by providers and geographic limitations on available transport resources. In discussions with a targeted group of freight shippers and transport providers in Norway, it was found that they did not wish for actual automatic digital freight brokerage but were open to more tools that could help simplify the brokerage process.

The integration of digital freight brokerage systems represents a significant advancement in the logistics industry. By connecting freight shippers and transport providers through digital platforms, these systems can streamline the allocation of transport resources, enhancing efficiency and reducing operational costs. In Norway, the manual nature of brokerage processes presents a unique challenge, but the introduction of digital tools can simplify these operations. The intended use of the recommender system is twofold: first, to recommend new and potential transport providers to freight shippers for specific new jobs, and second, to enable the freight shippers to more easily find and include new or unknown transport providers into their set of preferred providers. As such this approach to usage of a recommender system helps to support the manual brokerage process instead of trying to completely remove the manual tasks and decisions, and as such maintaining the companies need for discission control.

As the application of recommender systems in transport brokerage also offers a promising solution to optimize resource utilization (the potential for available space in future transport can be taken into account for recommended transport providers). This approach addresses the cold start problem and avoids reinforcing existing biases within the dataset. The ability to recommend transport companies suitable for transport jobs based on past performance and potential suitability for new jobs enhances the operational efficiency of freight brokers, promoting higher utilization of electric vehicles and reducing carbon emissions.

Increasing the utilization of electric vehicles in a mixed fleet is crucial for achieving sustainable transportation goals. By integrating recommender systems with VRP optimization, companies can dynamically adjust routes to minimize energy use and emissions, supporting the broader goal of environmental sustainability. The integration of AI-driven recommender systems with real-time data and dynamic decision-making processes can further improve the allocation of transport resources. Exploring additional cost factors, such as potential CO_2 taxes, can provide a more comprehensive understanding of the economic implications of sustainable transport practices.

5 Concluding remarks

The electrification of the transport sector is an important step towards achieving climate goals and promoting sustainable transport. Our study has demonstrated some of the potential of integrating digital freight brokerage systems with advanced recommender algorithms to optimize the allocation of transport resources. By leveraging historical data and synthetic datasets, we have provided recommendations that enhance operational efficiency and reduce environmental impact. The findings underscore the importance of adopting innovative solutions to overcome the limitations of manual processes and support the green shift within the industry.

The optimization of transport routes based on time, emissions, and cost has revealed significant insights into the trade-offs involvde in routing decisions. Prioritizing emissions reduction by increasing the utilization of battery electric trucks can substantially lower CO_2 output, highlighting the need for environmentally conscious routing strategies. The introduction of digital tools and AI-driven recommender systems offers a promising avenue for improving the efficiency of transport operations, ensuring timely deliveries, and minimizing energy consumption and emissions.

Our study also emphasizes the importance of considering future economic implications, such as potential CO_2 taxes, in transport planning. By integrating cost factors into energy consumption models, transport planners and operators can make informed decisions that balance economic and environmental objectives. The development of robust frameworks for energy consumption estimation, incorporating real-world driving conditions and accessory loads, provides a reliable basis for strategic planning in electric vehicle operations.

In conclusion, the integration of digital freight brokerage systems with recommender algorithms and VRP optimization represents a significant advancement in the logistics industry. By continuing to refine these digital tools and exploring additional cost factors, the industry can move towards a more efficient, cost-effective, and environmentally friendly future.

Acknowledgments

The authors would like to thank the Research Council of Norway and industry partners for the support in writing this scientific paper under project 331981 Swipload Next.

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Presenter Biography

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