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of electric commercial vehicles in
retail logistics**

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G-2017-47

June 2017

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La publication de ces rapports de recherche est rendue possible grâce au soutien de HEC Montréal, Polytechnique Montréal, Université McGill, Université du Québec à Montréal, ainsi que du Fonds de recherche du Québec – Nature et technologies.

Dépôt légal – Bibliothèque et Archives nationales du Québec, 2017
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The publication of these research reports is made possible thanks to the support of HEC Montréal, Polytechnique Montréal, McGill University, Université du Québec à Montréal, as well as the Fonds de recherche du Québec – Nature et technologies.

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Are ECVs breaking even? Competitiveness of electric commercial vehicles in retail logistics

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June 2017

Les Cahiers du GERAD

G-2017-47

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Abstract: In this paper, we evaluate the competitiveness of electric commercial vehicles in medium-duty mid-haul logistics for a specific case study. This is done combining an aggregated total cost of ownership analysis with an integrated location-routing model with simultaneous locating of charging stations at stores and multi-shift, multi-period pickup and delivery routing of vehicles within the logistics network. This allows for a fair comparison of electric commercial vehicles and internal combustion engine vehicles. Results show that nearly no operational limitations arise by electrifying the mid-haul logistics fleet for this specific case. Moreover, electric commercial vehicles show clear advantages in this case with regard to total costs and emission savings. Based on these positive results, managerial insights are derived for logistics fleet operators.

Keywords: Electric commercial vehicles, medium-duty logistics, real-world case study, sustainable logistics

1 Introduction

Transportation contributes significantly to climate change at global level as well as to noxious air emissions, particulate matter, and noise emissions at local level. Therefore, a change towards environmentally friendly freight distribution is necessary. This can be achieved by implementing sustainable means of transportation. Within this context, electric commercial vehicles (ECVs) can significantly contribute to greener road transportation as they are considered to be one of the cleanest means of transportation for small and medium-duty transports: At local level (*tank-to-wheel*), ECVs produce neither greenhouse gases, nor noxious emissions, nor particulate matter. If all energy used for charging ECVs is produced from renewable sources, this zero-emission balance holds even for the so called *well-to-wheel* perspective. Furthermore, noise emissions can significantly be reduced by using ECVs instead of internal combustion engine vehicles (ICEVs). Despite these advantages, the overall market penetration and the share of ECVs in logistics fleets is still negligibly low. This is mainly due to major disadvantages of electric vehicles: limited driving range, long charging times and missing charging infrastructure. Also, the offer of small and medium-duty ECVs with sufficient load capacity is still sparse.

However, pilot projects on implementing ECVs in logistics fleets have been launched several years ago, and first electric logistics fleets have already been installed. For instance, the Deutsche Post DHL group (DPDHL) tested a first electric fleet of 12 Renault Kangoo ZE for postal services in German cities as early as 2011 (DPDHL, 2011). A larger pilot project was launched in 2013 aiming at zero-emission deliveries for a city region with 310,000 inhabitants. Within this project, custom-build ECVs were used (Pieringer, 2013; DPDHL, 2013, 2014b), and DPDHL eventually bought the company that manufactured the ECVs as reaction to the project's success (DPDHL, 2014a). However, these and other projects (e.g., UPS, 2013) focus on short-haul applications. In short-haul applications, range limitations and charging en route play only a minor role, since average trip distances remain below 80km and recharging of vehicles once a day (e.g., over night at the depot) is sufficient. For mid-haul applications (e.g., arising in retail logistics networks), limited driving ranges, long charging times and missing infrastructure still hold as disadvantages for ECVs. As a consequence, mid-haul logistics fleet operators still perceive ECVs as less efficient with regard to time and costs, and thus as less competitive as ICEVs. As a result, even pilot projects on medium-duty ECVs are still sparse.

In order to push the usage of ECVs in mid-haul logistics, the German government initiated (and partly funded) the pilot project ELMO 'Elektromobile urbane Wirtschaftsverkehre' ('electrified commercial transport in urban areas'). In this project, an extensive field test was conducted with different stakeholders, managed by Fraunhofer IML. The objective was to evaluate the competitiveness of ECVs compared to ICEVs, and to assess how ECVs can be integrated in existing mid-haul logistics fleets. Herein, several logistics fleet operators (for instance the retail company TEDi that constitutes our case study) used ECVs for their delivery processes. During the project period from 2011 to 2015, energy consumption and charging behavior of twelve mid-range ECVs were tracked. The field test yielded over 3,000 records of transportation round trips, covered a total mileage of 158,209 kilometers and a total amount of 108,543 kWh of consumed energy. Besides these data, vast experience was gained on every-day operation as well as on potentials and limitations of the utilization of mid-haul ECVs. One of the key results of this project was that medium-sized ECVs are on the verge of breaking even in (urban) mid-haul distribution. However, several topics remained open in the ELMO project with respect to service areas, network operations and total costs:

Service areas: In ELMO, ECVs were only used within a limited vicinity, and vehicles were charged at the depot. As a result, limitations in range and infrastructure were vastly neglected. However, specific accessibility and network operations depending on range, consumption rate and infrastructure development have to be evaluated in order to account for real-world service areas with larger vicinities and mid-haul distances. The question has to be answered if and under which circumstances it is possible and worthwhile to cover the complete service area of mid-haul logistics fleets by ECVs.

Network operations: In ELMO, the assessment was limited to a small number of vehicles that were operated on single route patterns. The same route patterns as for ICEVs were chosen, but vehicles were only

operated within a small vicinity in order to account for limited ranges. Route planning for ECVs was done relying on expert experiences. Interdependencies with other vehicles that were operated within the network were vastly neglected. However, simultaneous routing of all vehicles of the fleet is necessary in order to account for coordination between vehicles. Herein, specific network structures, customer patterns, working shifts, service times and delivery frequencies have to be regarded. Especially, the pickup and delivery characteristics of retail logistics networks have to be considered. Only if these aspects are accounted for, the complex planning tasks of real-world applications can be answered. As result, the question if and how ECVs can be operated on tailored routes regarding location of charging stations, recharging times and driving ranges remains and must be answered using advanced quantitative planning algorithms.

Total costs: In the ELMO project, costs were derived for single vehicles. However, this does not allow to evaluate the impact of an electrification of complete logistics fleets. Thus, a total cost analysis of the implementation of ECVs within mid-haul logistics fleets is required, based on detailed results for infrastructure (charging stations) development and vehicle routing. Integrating the results regarding coverage of (parts of) the service area and of the routing of the vehicles within the network, the question can be answered if and under which circumstances a (complete or partial) transformation of a conventional logistics fleet towards ECVs is worthwhile.

The target of our analysis is to overcome the limitations of the pilot project ELMO and to explore the potential for the complete electrification of mid-haul logistics fleets. To do so, it is necessary to compare routes and driving patterns of ICEVs and ECVs in order to assess the impact of the electrification of a logistics fleet. Herein, specific characteristics of the vehicles (e.g., driving range, energy consumption, recharging time) have to be regarded as these provide the main challenges compared to ICEVs. Also, the locating of charging stations has to be taken into account, since recharging en route is essential if the complete service area is to be operated by ECVs. Additionally, specific characteristics of the service area (e.g., spatial demand patterns, time windows) as well as requirements of retail logistics (delivery frequency, pickup processes, driver shifts) have to be accounted for, since these determine the future routes of the ECVs.

In order to answer the derived questions, we first analyze related literature on cost assessment and location of charging stations as well as routing of ECVs (Section 1.1), before detailing the scope and organization of our study (Section 1.2) in order to set it apart from recent research.

1.1 Related literature

Recent research on ECVs can be divided in two streams focusing on *i*) aggregated cost analysis (i.e., total cost of ownership (TCO) calculations) to investigate the competitiveness of ECVs and *ii*) operational decision support on routing and charging, especially vehicle routing problems (VRPs) with additional ECV specific constraints. In the following, we review both streams concisely.

Most approaches that evaluate the competitiveness of ECVs use aggregated TCO calculations in order to compare the life cycle costs of ECVs and ICEVs. Usually, these analyses are based on very general suppositions and assumptions for operational parameters (e.g., average total distances instead of specific routes), which are often discussed using a sensitivity analysis. Lee et al. (2013) provided a TCO calculation for medium-duty ECVs, taking realistic energy consumption and realistic driving cycles within a range between 48km and 96km into consideration. Feng and Figliozzi (2013) compared the TCO of ECVs and ICEVs analyzing different fleet and battery replacement scenarios. Davis and Figliozzi (2013) provided a TCO analysis taking fuel consumption, approximated routing constraints, battery replacement and real-world speed profiles into consideration. Taefi et al. (2016) provided a TCO analysis of ECVs focusing on the cost-optimal balance between a high vehicle utilization and the resulting increase in required battery replacement due to battery degradation. All of these analyses find that ECVs become the more competitive, the higher the overall traveled mileage is (e.g., a daily mileage threshold of 129km is stated in Feng and Figliozzi (2013)). Furthermore, specific driving pattern characteristics like frequent stops, congested streets, idling motors, and low speed increase the competitiveness of ECVs compared to ICEVs.

Although these analyses are based on reasonable assumptions, they are not sufficient to alleviate the skepticism of practitioners, since operational limitations and case specific restrictions are not taken into account. For example, within the use case of the DPDHL for postal services, ECVs became competitive for significantly less daily mileages than expected by general TCO assessments. Thus, doubts on results of aggregated TCO assessments, i.e. over- or underestimations of costs, seem to be justified.

Within the transportation sector, operations research tools are commonly used to make daily planning tasks more efficient and profitable. In this context, various kinds of VRPs have been proposed to address the operational planning of pickup and/or delivery networks for conventional logistics fleets. These models have recently been extended addressing additional constraints for logistics fleets with ECVs, i.e., recharging operations and limited driving ranges.

Conrad and Figliozzi (2011) presented the recharging VRP (RVRP), considering battery capacity limitations of ECVs and charging opportunities at customer vertices. Erdoğan and Miller-Hooks (2012) introduced the first model that considers additional vertices allowing for charging activities for any kind of alternative fuel vehicle (AFV). Schneider et al. (2014) developed the electric VRP (EVRP) with time windows (EVRP-TW), the first model that explicitly focuses on ECVs. Later publications then extended the basic EVRP-TW considering heterogeneous fleets (Goeke and Schneider, 2015; Hiermann et al., 2016), partial recharging (Felipe et al., 2014; Keskin and Çatay, 2016; Desaulniers et al., 2016; Montoya et al., 2017), charging stations with different charging rates and costs (Felipe et al., 2014; Montoya et al., 2017), and hours of service regulations (Schiffer et al., 2017a). First exact solution methods were presented by Desaulniers et al. (2016); Hiermann et al. (2016); Roberti and Wen (2016). In addition, first publications that consider charging station location and vehicle routing decisions simultaneously were published as variants of the location routing problem (LRP) with intra-route facilities (LRPIFs) (Yang and Sun, 2015; Schiffer and Walther, 2017b,c,a; Schiffer et al., 2017b). VRP models that account for specific characteristics of retail logistics, like driver shifts, delivery over several time periods (e.g., working days of one week) as well as combined pickup and delivery processes, were considered for ICEVs. In this context, approaches for ECVs as well as LRPIF approaches are still missing. For an extensive overview of research on electric vehicles, we refer to Pelletier et al. (2016) for goods distribution, and to Pelletier et al. (2017) for battery behavior.

Most of the presented papers are based on artificial instances and focus on a pure methodological contribution by extending the problem class or presenting a solution method. A competitiveness analysis that is based on these models is so far missing. Also, none of the papers discussed above analyzes a real-world case study for ECVs with all requirements.

Concluding, neither aggregated TCO analyses nor mathematical models for the planning of electric logistics fleets are so far able to carry out a fair comparison between ECVs and ICEVs, and as a result to derive information on feasibility and profitability of the electrification of logistics fleets in mid-haul logistics. Especially, retail logistics requirements like accounting for pickup and delivery, multiple shifts and a multi-period planning horizon have not been addressed, neither by existing EVRP nor by respective LRPIF approaches.

1.2 Aims and scope

Against this background, the aim of this paper is to derive the first feasibility study for the usage of ECVs in mid-haul retail logistics. Based on this study, we provide the first analysis on the competitiveness of ECVs, which is neither limited to aggregated cost analysis nor to operational planning tasks, nor to artificial instances.

In order to address these aims, it is no longer sufficient to calculate costs on an aggregated level based on a number of assumptions or on data from tracking single vehicles. Instead, it has to be analyzed if and how medium-duty ECVs can be integrated into logistics networks, while fulfilling all real-world requirements on demand, deliveries and pickups. Herein, the challenge is to minimize operational disadvantages of ECVs with regard to range limitations and charging times (Stütz et al., 2016). This is only possible if optimal routing decisions are taken, considering the specific characteristics of ECVs and accounting for all requirements of the real-world case. Additionally, a cost efficient charging infrastructure must be installed to keep vehicles

operational, as ECVs are integrated in a network for the first time. Because these decisions are interdependent (since routing decisions depend on charging station locations, and the locating of charging stations depends on underlying route patterns, cf. Schiffer and Walther, 2017b), integrated routing and network design aspects have to be regarded.

Aiming at a solution approach that covers all requirements stated above, the contribution of this paper is severalfold: First, we develop a new integrated approach for the assessment of the competitiveness of ECVs. Herein, we combine a comprehensive TCO analysis with a detailed model on network design and operations in order to optimize the integration of ECVs in retail logistics fleets. This approach allows for a profound and as accurate as possible competitiveness analysis of ECVs in retail logistics networks.

Second, we develop a mixed integer program (MIP) that is new in that it is the first model which is able to account for real-world characteristics of retail fleets, like multiple shifts, delivery frequencies over several periods, and combined pickup and delivery services. In addition, we present a competitive algorithmic framework to solve large-sized instances.

Third, we analyze a real-world case with empirical data, assessing the competitiveness of ECVs against ICEVs for the distribution network of a large retail company in Germany. We discuss results with respect to the overall costs for ECV as well as ICEV fleets in order to assess the competitiveness of medium-duty ECVs within mid-haul retail transportation. Furthermore, we investigate the emission savings to quantify the ecological benefit of an electric logistics fleet. We show the applicability of the model for real-world cases, and ascertain the reliability and relevance of the derived managerial insights for practitioners.

Fourth, besides specific recommendations for the case study, we derive deeper managerial insights into the current potential of ECVs in logistics fleets as well as more general recommendations for practitioners, municipalities and researchers.

The remainder of this paper is structured as follows: First, we introduce our case study in Section 2. Then, we derive a mixed integer program formulation for our integrated planning approach in Section 3. Section 4 contains our experimental design and detailed information on the used data. In Section 5, we present results on the competitiveness of ECVs compared to ICEVs from an economic as well as an ecological perspective. Based on these results, we discuss managerial insights in Section 6. Section 7 concludes this paper with its main findings and an outlook on future research.

2 Case study

As mentioned above, the operation of ECVs in mid-haul logistics fleets is case specific, i.e., depending on characteristics of the logistics network and the service area. Therefore, we analyze the competitiveness of ECVs for one specific use case, i.e. we cooperated with the German retail company 'TEDi' as one of the companies that participated in the research project ELMO. TEDi (as well as other retail logistics companies) is highly interested in using ECVs for distribution, since stores are often located in inner city districts and thus companies are confronted with noise and emission restrictions and potential (future) bans of ICEVs.

TEDi operates about 1,400 stores all over Europe, selling a broad range of non-food articles (TEDi, 2016). In our studies, we focus on a representative distribution area of the overall network. This area (cf. Figure 1) is located within Northrhine Westfalia, a federal state of Germany. As can be seen in Figure 1, 302 stores are supplied from a central warehouse of about 42,000 square meters, which is located in Dortmund. The stores are located within a vicinity of 190 kilometers around the central warehouse. This network is representative for other retail logistics networks with respect to the spatial distribution and the number of customers. Therefore, we analyze a representative case to evaluate the operation and competitiveness of ECVs in retail logistics. The company's logistics are carried out by the 'TEDi Logistik GmbH & Co. KG' (from here on referred to as 'TEDi Logistik'), which is a direct subsidiary of TEDi. TEDi Logistik's main purpose is to supply TEDi's stores with new goods, coming on pallets or roller containers from the central warehouse, and to collect empty pallets and roller containers from each store in order to haul them back to the central warehouse.

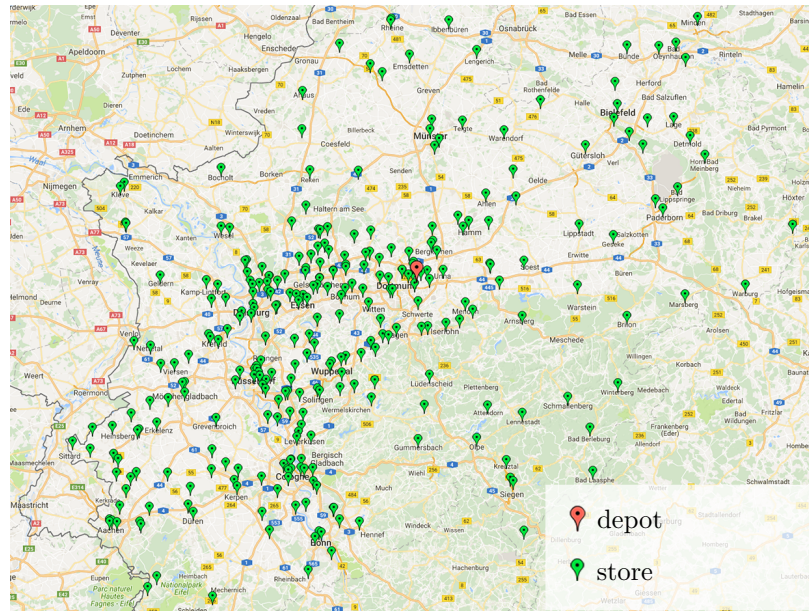


Figure 1: Logistics network structure of TEDi.

Starting from the central warehouse, TEDi Logistik is operating a fleet of medium-duty 12-tonne trucks that can carry 18 pallets with a payload of about five tonnes. On average (median), each store receives six pallets per delivery stop (standard deviation=2.06, min=4, max=12). Each truck is driven during two shifts per day, i.e., early morning and afternoon shift. Thus, the trucks perform two delivery tours per day, since they drive back to the central warehouse between the first and the second shift in order to allow for a change of drivers and for reloading of freight. Stores are served once a week within given time windows.

The average weekly demand of each store is taken from 2015 data. In contrast to package or general cargo companies, the network and demand structure of TEDi does not allow for an assignment of vehicles to fixed service areas. Instead, specific routing decisions must be taken in order to calculate optimal delivery plans that allow for a high utilization of vehicles. This holds even more for ECVs, since an integration of ECVs in the logistics network of TEDi requires optimal routing decisions considering range limitations and charging times. Additionally, charging en route (i.e., at TEDi stores), and thus the installation of charging stations within the network has to be considered to enable the ECVs to travel larger distances. Thus, the competitiveness of ECVs in mid-haul transportation can only be determined if vehicle routing and charging station location decisions are taken simultaneously.

Within the ELMO project, two 12-tonne medium-duty electric trucks were tested by TEDi within a catchment area of 70 km around the central warehouse to replenish selected TEDi stores. The vehicles (model CM1216) were developed by the company EMOSS and introduced in May 2014 (EMOSS, 2016). Data covering a total mileage of 33,000 km was gathered during the field test in the ELMO project. As the field test was carried out in Northrhine Westfalia, real-world data is available for the operations of the ECVs with respect to travel times, energy consumption and recharging rates (cf. Section 4). This data basis provides a unique opportunity to assess the applicability and competitiveness of ECVs in mid-haul retail logistics.

Using the information on network structure, customer and delivery patterns as well as characteristics of ECVs, a detailed TCO analysis is carried out in the following in order to determine the feasibility and the profitability of electrifying the current ICEV fleet of TEDi Logistik. Herein, exogeneous data is needed in order to determine cost rates (investment per vehicle, maintenance per km), but endogeneous data on cost drivers (e.g, the number of vehicles and charging stations, travelled distances) has also to be derived.

3 Methodological background

In this section, we explain our integrated planning approach in order to provide a comprehensive basis that backs the evaluation of our case study. First, Section 3.1 gives a short introduction into TCO calculations that are used to assess the total costs for the logistics operator. Second, a MIP is presented that accounts for the strategic and operational planning tasks that have to be solved to gather the essential data on endogenous cost drivers for network design and operation. The derived approach is the first that overcomes limitations of aggregated cost analysis as detailed case specific routing results are used. Also, limitations of operational planning on artificial instances are overcome as all real-world requirements are considered by a multi-shift, multi-period pickup and delivery model.

3.1 Total cost of ownership calculation

In order to assess the costs for the described retail logistics case appropriately, a TCO calculation is carried out. In general, total discounted costs of ownership are calculated as follows:

$$TCO = Inv + Fix + Oper = \sum_{t=0}^T \frac{Inv_t}{(1+r)^t} + \sum_{t=0}^T \frac{Fix_t}{(1+r)^t} + \sum_{t=1}^T \frac{Oper_t}{(1+r)^t}. \quad (1)$$

While Inv_t represents one-time strategic investments taken in period t (e.g., investments in vehicles and in charging stations), Fix_t denotes periodical (annual) fixed costs (e.g., circulation tax, annual maintenance of vehicles and charging stations), and $Oper_t$ denotes distance dependent costs (e.g., energy costs, distance dependent maintenance). The discount rate $(1+r)^{-t}$ is defined by the discount factor r .

Detailing the three cost components for our application case, the following dependencies result:

- Inv_t represent the investment for vehicles and charging stations. The required cost rates are the purchase price per vehicle ($\bar{c}^{inv,v}$) and the installation cost per charging station ($\bar{c}^{inv,s}$). Cost rates are multiplied with the respective cost drivers, i.e., the total number of vehicles (for ICEV operations), respectively the number of vehicles and charging stations (for ECV operations) utilized within the logistics network. These cost drivers depend on strategic network decisions.
- Fix_t covers annual costs for taxes and maintenance. Again, cost rates result for annual taxes and maintenance per vehicle ($\bar{c}^{fix,v}$) and per charging station ($\bar{c}^{fix,s}$), and are multiplied with the total number of used vehicles and the total number of charging stations respectively.
- $Oper_t$ represents the operational costs that result from the overall driven distance within the logistics network and the necessary driver shifts. Thus, we consider a distance dependent cost rate ($\bar{c}^{oper,di}$) as well as a driver wage cost rate ($\bar{c}^{oper,dr}$). Again, these cost rates are multiplied with the total driven distance or respectively the number of necessary shifts to calculate $Oper_t$. Thus, the route schedules that are used to operate the network have to be determined.

The calculation of these three cost components requires information on specific cost rates as well as on cost drivers for network design and operation. Information on cost rates can usually be derived from external sources (e.g., data on vehicle prices derived from manufacturers of ECVs and ICEVs, data on distance-related consumption rates derived from tracking of vehicles within the ELMO project). However, data on cost drivers can only be gathered after endogenous decisions have been taken on network design and routing of vehicles for the specific use case (e.g., the total number of vehicles needed to fulfill network demand, the total driven distance resulting from routing decisions).

As can be seen, the outcome of the TCO analysis is highly sensitive to these cost drivers as endogenous parameters depending on *i*) the fleet size (i.e., the number of vehicles), *ii*) the network infrastructure (i.e., the number of charging stations), and *iii*) the total driven distance (i.e., derived from the route schedules used in a weekly turn). Over- or underestimating these endogenous parameters leads to large deviations of calculated minimum costs and real costs. These deviations may lead to wrong results when comparing different scenarios (e.g., utilization of ECVs and ICEVs). Therefore, we develop a MIP to determine optimal

endogenous parameters in Section 3.2. This allows to derive cost drivers for the TCO analysis based on optimal design and operation of the logistics network.

3.2 Mixed integer program

In general, planning models in which decisions on network infrastructure as well as on vehicle routes are taken simultaneously belong to the class of LRPIFs (cf. Schiffer and Walther, 2017a). Herein, our problem has to be developed for the case at hand, since real-world constraints have to be considered that are not standard in LRPIFs. Summarizing from Section 2, we aim at determining the cost-optimal number of vehicles as well as the corresponding routes and the location and number of charging stations to deliver goods and collect pallets in a retail distribution network under the following constraints:

- A homogeneous vehicle fleet is used with each vehicle starting at and returning to the same central warehouse.
- Each store in the given network has to be visited once in a week of five working days in order to supply new goods that are transported on pallets.
- Besides supplying goods, empty pallets are collected at each visited store and hauled back to the central warehouse.
- Each store can only be supplied in a given time window which might vary for each day of the week.
- A vehicle is used for two consecutive shifts. A break at the central warehouse between both shifts allows to change the driver, un- and reload freight, and recharge the ECVs' batteries.

To consider these constraints, a new LRPIF variant that covers real-world constraints of retail logistics is required. Thus, we develop the first LRPIF that accounts for pickup and delivery, multiple driver shifts, and multiple planning periods in the following. Furthermore, we are the first to show how such a modeling approach can be combined with a profound TCO objective function to allow for comprehensive competitiveness assessments.

In the following, we present a MIP that defines the planning task which arises out of our application case. We focus on this planning task for ECVs first. Second, we explain how this MIP can be easily simplified to assess ICEV operations. The corresponding MIP is defined on a directed and complete Graph $G = (\mathcal{V}_{0,n+1}, \mathcal{A})$ with a set of vertices $\mathcal{V}_{0,n+1}$ and a set of arcs \mathcal{A} using the following notation as summarized in Table 1: Vertices are assigned to different subsets of $\mathcal{V}_{0,n+1}$. If a vertex κ is representing a customer, $\kappa \in \mathcal{C}$ holds. \mathcal{F} defines a set of additional potential charging station vertices. To allow for multiple visits to charging stations, a set of dummy vertices \mathcal{D} is used and divided into subsets \mathcal{D}_κ , each containing dummy vertices for each real vertex κ . Indices 0 and $n+1$ represent the start and end-vertex of the central warehouse. Thus, sets indexed by 0, by $n+1$, or by $0, n+1$ include the respective vertices. To provide a concise model formulation, we define a cut set $\delta(\mathcal{B})$ of any arbitrary subset \mathcal{B} of $\mathcal{V}_{0,n+1}$ as $\delta(\mathcal{B}) = \{(i, j) \in \mathcal{A} : i \in \mathcal{B}, j \notin \mathcal{B}\}$ as the set of all arcs with both endpoints in \mathcal{B} . Analogously, $\delta^+(\mathcal{B}) = \{(i, j) \in \mathcal{A} : i \in \mathcal{B}, j \notin \mathcal{B}\}$ defines all outgoing arcs of \mathcal{B} and $\delta^-(\mathcal{B}) = \{(i, j) \in \mathcal{A} : i \notin \mathcal{B}, j \in \mathcal{B}\}$ defines all ingoing arcs of \mathcal{B} respectively. In the following, we also use these definitions for singleton sets $\mathcal{B} = \{i\}$. To account for multiple shifts and multiple periods, we define the set \mathcal{S} that contains all shifts and the set \mathcal{P} that contains all periods. Instead of using two additional indices for shifts and periods, we derive a concise model formulation with only one additional index. Doing so, we use only an additional shift index s and account for periods within the shift set, such that $\mathcal{P} \subset \mathcal{S}$. Further, we define a cutset $\gamma(i)$ that returns the consecutive shift of i . Thus, periods and shifts can each be identified, although only one index is used. Note that this technique works independent of the number of consecutive shifts. In the following, all shift dependent variables and parameters are indexed with s without further explanation.

Each store $i \in \mathcal{C}$ has a time window that defines the earliest (e_i^s) and latest (l_i^s) time at which service is allowed to start. At any store i , unloading goods and picking up pallets takes s_i time units, while τ_i^s denotes the arrival time at any vertex i . If an arc (i, j) is traversed, t_{ij} denotes the required time units and d_{ij} denotes the distance of the respective arc. In order to consider freight constraints, f_i^s depicts the amount of freight

Table 1: Decision variables and parameter definitions.

Sets	
0	depot vertex departure
$n + 1$	depot vertex arrival
\mathcal{C}	set of customer vertices
\mathcal{F}	set of potential recharging vertices
\mathcal{D}_κ	set of dummy vertices for vertex $\kappa \in \{\mathcal{C} \cup \mathcal{F}\}$
\mathcal{D}	set of all dummy vertices ($\bigcup_{\kappa \in \{\mathcal{C} \cup \mathcal{F}\}} \mathcal{D}_\kappa$)
\mathcal{V}	set of all vertices without depot vertices ($\mathcal{C} \cup \mathcal{F} \cup \mathcal{D}$)
\mathcal{P}	set of periods
\mathcal{S}	set of shifts
Decision variables	
x_{ij}^s	binary: arc (i, j) is traveled
y_i	binary: recharging station is sited at vertex i
τ_i^s	arrival time at vertex i
w_i	amount of energy charged at vertex i
q_i^s	battery load at vertex i
f_i^s	delivery freight load at vertex i
u_i^s	picked up freight load at vertex i
z	total number of vehicles
Parameters	
e_i^s	earliest start time of service allowed at vertex i
l_i^s	latest start time of service allowed at vertex i
s_i	service time at vertex i
p_i	freight demand at vertex i
v_i	pick up demand at vertex i
t_{ij}	driving time from vertex i to vertex j
d_{ij}	distance along arc (i, j)
h_{ij}	energy consumption on arc (i, j)
r	recharging rate
Q	battery capacity
F	freight capacity

that is to be supplied at vertex i , while u_i^s denotes the amount of collected pallets at vertex i . Each store i has a demand p_i for the delivery of goods and a demand v_i for the pickup of pallets. Each vehicle's freight capacity is limited to F . To model constraints on energy consumption, q_i^s denotes a vehicle's state of charge at vertex i , while w_i states the amount of energy recharged at vertex i , if a charging station is installed at this vertex. The recharging time results out of w_i multiplied by a recharging rate r . Note that w_i is not shift dependent, since single assignment holds for each vertex. The energy consumption along an arc (i, j) is given by h_{ij} and each vehicle has an overall battery capacity of Q . To trace the routing decision, binary x_{ij}^s states whether arc (i, j) is traversed or not and z denotes the overall number of vehicles. Binary y_i determines if a charging station is located at vertex i . With this notation, a multi-shift, multi-period pickup and delivery MIP can be derived with a case specific TCO objective function (cf. Section 3.1).

We first derive this MIP for ECV operations, which is the more demanding case. Afterwards, we show how this model can easily be reduced to a model that accounts for ICEV operations. Before detailing the constraints of our problem, we show how the different cost terms from the TCO calculation in Section 3.1 can be linked to discounted cost rates and the decision variables of our MIP. Because this link between the TCO calculation and the MIP objective is not intuitive, we discuss it in Appendix A.

Total investment costs are based on discounted cost factors for vehicle investments $\bar{c}^{\text{inv},v}$ and charging stations $\bar{c}^{\text{inv},s}$ and depend on the number of vehicles z and the number of charging stations $\sum y_i$.

$$Inv = \sum_{t=0}^T \frac{Inv_t}{(1+r)^t} = \bar{c}^{\text{inv},v} z + \bar{c}^{\text{inv},s} \sum_{i \in \mathcal{C} \cup \mathcal{F}} y_i \quad (2)$$

Annual fixed costs result analogously considering discounted cost terms for annual fixed vehicle costs $\bar{c}^{\text{fix},v}$ and annual fixed charging station costs $\bar{c}^{\text{fix},s}$.

$$Fix = \sum_{t=0}^T \frac{Fix_t}{(1+r)^t} = \bar{c}^{\text{fix},v} z + \bar{c}^{\text{fix},s} \sum_{i \in \mathcal{C} \cup \mathcal{F}} y_i \quad (3)$$

Operational costs $Oper_t$ comprise discounted cost terms related to distance-related costs $\bar{c}^{\text{oper},di}$ multiplied with the driven distance, and related to driver wages $\bar{c}_t^{\text{oper},dr}$ multiplied with the number of trips that are taken (4).

$$Oper = \sum_{t=0}^T \frac{Oper_t}{(1+r)^t} = \bar{c}^{\text{oper},di} \sum_{(i,j) \in \delta(\mathcal{V}_{0,n+1}), s \in \mathcal{S}} d_{ij} x_{ij}^s + \bar{c}^{\text{oper},dr} \sum_{(i,j) \in \delta^+(0), s \in \mathcal{S}} x_{ij}^s \quad (4)$$

With these definitions ((2)–(4)) and the TCO equation (1) from Section 3.1, our MIP results as follows: The objective minimizes TCO considering investment costs for vehicles and charging stations, annual fixed costs as well as operational costs for driving (5). Within our cost analysis, we assume that decisions on investments for network design, i.e. decisions on the number of vehicles and charging stations, are taken at the beginning of the planning horizon. Salvage values are taken into account at the end of the planning horizon and annual fixed costs are only considered for vehicles (cf. Appendix A). Decisions on network operation, i.e. decisions on the number of driver shifts and driven distances, consider a weekly schedule, but hold for the complete planning horizon. Thus, the objective of the MIP is calculated for the complete planning horizon (i.e. multiplying cost drivers with discounted 5-year cost factors).

Constraints (6) and (7) account for the maximum number of vehicles over all periods and shifts. Note that for more than two consecutive shifts constraints (7) must be defined recursively. Constraints (8) enforce any customer to be visited exactly once and single assignment is relaxed in (9) for non-customer vertices. To create connected tours, (10) obtains flow conservation for any vehicle. Freight constraints for pickup and delivery services are given by (11)–(13). Constraints (11) obtain the delivery freight balance, while constraints (12) contain the pickup freight balance. Constraints (13) secure that the maximum vehicle freight load is not exceeded at any vertex. With these constraints, Miller-Tucker-Zemlin subtour elimination is used to avoid circles in tours. Constraints (14)–(16) obtain time window feasibility. While constraints (14) determine the arrival time at vertex j after departing from a customer vertex i taking service and driving time into consideration, constraints (15) integrate charging times. Constraints (16) force arrival times to match the time windows. Constraints related to the energy consumption are added by (17)–(20). Constraints (17) and (18) model energy consumption along arcs. Note that charging processes are only considered in (18), because vehicles are assumed to start with a full battery at the depot. Constraints (19) and (20) limit the vehicle's state of charge (SOC) to the battery capacity and constraints (21)–(23) integrate charging station location decisions. While (21) only allow for charging at vertex i if a charging station is located, (22) prevent a charging station to be located at a vertex at which charging is not necessary. Since we use dummy vertices to allow for multiple visits to charging stations, location decisions have to be mirrored between real and dummy vertices by (23). The definition range of binary and integer variables is given in (24).

minimize

$$TCO^{\text{ECV}} = (\bar{c}^{\text{inv},v} + \bar{c}^{\text{fix},v}) z + \bar{c}^{\text{inv},s} \sum_{i \in \mathcal{C} \cup \mathcal{F}} y_i + \bar{c}^{\text{oper},dr} \sum_{(i,j) \in \delta^+(0), s \in \mathcal{S}} x_{ij}^s + \bar{c}^{\text{oper},di} \sum_{(i,j) \in \delta(\mathcal{V}_{0,n+1}), s \in \mathcal{S}} d_{ij} x_{ij}^s \quad (5)$$

subject to

$$z \geq \sum_{j \in \mathcal{V}_{n+1}} x_{0j}^s \quad s \in \mathcal{P} \quad (6)$$

$$z \geq \sum_{j \in \mathcal{V}_{n+1}} x_{0j}^s \quad s \in \gamma(\mathcal{P}) \quad (7)$$

$$\sum_{(i,j) \in \delta^+(i), s \in \mathcal{S}} x_{ij}^s = 1 \quad i \in \mathcal{C} \quad (8)$$

$$\sum_{(i,j) \in \delta^+(i)} x_{ij}^s \leq 1 \quad i \in \{\mathcal{V} \setminus \mathcal{C}\}, s \in \mathcal{S} \quad (9)$$

$$\sum_{(j,i) \in \delta^-(i)} x_{ji}^s - \sum_{(i,j) \in \delta^+(i)} x_{ij}^s = 0 \quad i \in \mathcal{V}, s \in \mathcal{S} \quad (10)$$

$$0 \leq f_j^s \leq f_i^s - p_i x_{ij}^s + F(1 - x_{ij}^s) \quad (i, j) \in \delta(\mathcal{V}_{0,n+1}), s \in \mathcal{S} \quad (11)$$

$$0 \leq u_j^s \leq u_i^s + v_i x_{ij}^s + F(1 - x_{ij}^s) \quad (i, j) \in \delta(\mathcal{V}_{0,n+1}), s \in \mathcal{S} \quad (12)$$

$$0 \leq f_i^s + u_i^s \leq F \quad i \in \mathcal{V}_{0,n+1}, s \in \mathcal{S} \quad (13)$$

$$\tau_j^s \geq \tau_i^s + (t_{ij} + s_i) x_{ij}^s - l_0^s (1 - x_{ij}^s) \quad (i, j) \in \delta^+(\mathcal{C}_0), s \in \mathcal{S} \quad (14)$$

$$\tau_j^s \geq \tau_i^s + t_{ij} x_{ij}^s + r w_i - (l_0^s + rQ)(1 - x_{ij}^s) \quad (i, j) \in \delta^+(\mathcal{V}), s \in \mathcal{S} \quad (15)$$

$$e_i^s \leq \tau_i^s \leq l_i^s \quad i \in \mathcal{V}_{0,n+1}, s \in \mathcal{S} \quad (16)$$

$$q_j^s \leq q_0^s - h_{ij} x_{ij}^s + Q(1 - x_{ij}^s) \quad (i, j) \in \delta^+(0), s \in \mathcal{S} \quad (17)$$

$$0 \leq q_j^s \leq q_i^s + w_i - h_{ij} x_{ij}^s + Q(1 - x_{ij}^s) \quad (i, j) \in \delta(\mathcal{V}_{n+1}), s \in \mathcal{S} \quad (18)$$

$$0 \leq q_0^s \leq Q \quad s \in \mathcal{S} \quad (19)$$

$$0 \leq q_i^s + w_i \leq Q \quad i \in \mathcal{V}, s \in \mathcal{S} \quad (20)$$

$$w_i \leq Q y_i \quad i \in \mathcal{V} \quad (21)$$

$$y_i \leq w_i \quad i \in \mathcal{D} \quad (22)$$

$$y_i \geq y_j \quad i \in \{\mathcal{V} \setminus \mathcal{D}\}, j \in \mathcal{D}_i \quad (23)$$

$$x_{ij}^s \in \{0; 1\} \quad (i, j) \in \delta(\mathcal{V}_{0,n+1}) \quad y_i \in \{0; 1\} \quad i \in \mathcal{V} \quad z \in \mathbb{N} \quad (24)$$

The proposed MIP can also be used to estimate the TCO for an ICEV fleet. In this case, there is no need to account for charging stations and range limitations due to battery capacity and energy consumption. Thus, we use objective (25) instead of objective (5) to assess an ICEV fleet. Furthermore, we neglect constraints (15) and (17)–(24) in this case.

$$\text{minimize} \quad TCO^{\text{ICEV}} = (\bar{c}^{\text{inv},v} + \bar{c}^{\text{fix},v})z + \bar{c}^{\text{oper},\text{dr}} \sum_{(i,j) \in \delta^+(0), s \in \mathcal{S}} x_{ij}^s + \bar{c}^{\text{oper},\text{di}} \sum_{(i,j) \in \delta(\mathcal{V}_{0,n+1}), s \in \mathcal{S}} d_{ij} x_{ij}^s \quad (25)$$

The presented multi-shift, multi-period pickup and delivery problem belongs to the class of LRPIFs, which are NP hard. Thus, results for large-sized instances cannot be derived with a commercial solver. Therefore, efficient solution methods are required to be able to solve real-world problems. Herein, we present an adaptive large neighborhood search (ALNS) metaheuristic that is enhanced by dynamic programming techniques. This approach has to be enhanced in order to account for multiple shifts and combined pickup and delivery of the specific logistics network. Using the resulting approach, large instances of this kind of problem can be solved for the first time. To keep this paper concise, we detail this algorithm in Appendix B and focus on the application case instead in the following.

4 Design of experiments

In the following, we provide detailed information on the cost data and technical vehicle data used in our experiments in Section 4.1. In Section 4.2, we describe our experimental design to evaluate the competitiveness of medium-duty ECVs in the mid-haul retail transportation network of TEDi.

4.1 Cost terms and technical data

Real-world data is used for all calculations. Consumption profiles of vehicles are taken from the extensive field test conducted in ELMO. Driving times are derived from measured speed patterns, i.e., case specific

real-world driving times and driving speed are determined based on road types and traffic. In addition, information on the real-world energy consumption of the vehicles is used.

Within the TCO analysis, we derive data for a MAN TGL 12.250 as 12-tonne ICEV, and for the EMOSS CM1216 as 12-tonne ECV. The purchase price of the MAN TGL is taken from Taefi et al. (2016), while the purchase price of the EMOSS CM1216 is derived from personal communication with the EMOSS sales support. For both vehicles, the price is considered without value added taxes. We consider annual vehicle taxes for the MAN TGL derived from information of the federal ministry of finance, but neglect annual taxes for the EMOSS CM1216, as ECVs are waived from annual taxes within the European Union for at least five years (IEA, 2016). Information on the fuel consumption of the MAN TGL 12.250 is taken from Taefi et al. (2016), while battery capacity and energy consumption for the EMOSS CM1216 are derived from the ELMO field test.

Table 2 shows all vehicle specific parameters. We consider an average driver wage as stated in Statistisches Bundesamt (2017) plus an additional employer contribution of 20%. Average prices for diesel are derived for 2015 from the Eurostat database and the EU's weekly oil bulletin. Electricity prices are determined as company tariff for a consumption between 2,000 and 20,000 MWh per year. Prices for charging stations are actual prices that were paid within the ELMO project for the installation of charging stations. Herein, it must be noted that prices for the installation of charging stations at TEDi stores are rather low compared to other ECV applications, since sockets can be directly installed in the walls next to the loading ramps of the TEDi stores and strong current is already available at the stores in the TEDi case.

The planning horizon is scheduled to 5 years, considering a discount rate of 5% (cf. Taefi et al., 2016). Since we account for a limited planning horizon and assume steady weekly network operations during the whole planning horizon, we assume that investment decisions have to be taken at the beginning of the planning horizon, i.e., $Inv_t \leq 0$, $t > 0$ holds, since we consider salvage values for the vehicles at the end of the planning horizon.

To calculate the respective emissions, we use carbon dioxide equivalent conversion factors from Edwards et al. (2014).

Table 2: Cost data and technical data used within the TCO calculation.

	MAN TGL			EMOSS CM1216		
Purchase price	75,000	€	Taefi et al. (2016)	160,000	€	EMOSS
Yearly taxes	534	€/a	FMoF (2016)	0	€/a	IEA (2016)
Driver wage	29,000	€/a	Statistisches Bundesamt (2017)	29,000	€/a	Statistisches Bundesamt (2017)
Battery capacity	-	-	-	160	kWh	ELMO
Consumption	0.19	l/km	Taefi et al. (2016)	0.73	kWh/km	ELMO
Energy price	1.18	€/l	European Union (2016c)	0.07	€/kWh	European Union (2016a)
Charging station	-	-	-	4500	€	ELMO
CO ₂ equivalent	2624.89	gCO _{2,eq} /kWh	Edwards et al. (2014)	507.97	gCO _{2,eq} /kWh	Edwards et al. (2014)

The table shows all necessary cost terms and parameters used within the TCO calculations.

4.2 Experimental design

To evaluate the competitiveness of ECVs against ICEVs, we conduct an integrated TCO based on a network design and operational analysis as described in Section 3 for both vehicle types. As depicted in Section 3, the planning tasks to estimate the overall costs vary with respect to the considered vehicle type. For both fleets, the number of vehicles and the overall driven distance have to be calculated. Additionally, the number of charging stations has to be determined for the ECV fleet. Thus, we calculate the overall costs according to the MIP objective function given in Section 3 for ECVs and ICEVs.

In the following, we present the experimental design describing how different levels of electrification are modeled within our competitiveness analysis.

In the field test, ECVs have only been used and proven to be operational within a vicinity of 70 km around the central warehouse. However, the aim is to determine if and to what extent an electrification of the mid-haul logistics fleet of TEDi is feasible and worthwhile. Therefore, we analyze increasing levels of electrification of the fleet. Herein, we assume that stores within a certain vicinity around the central warehouse are operated by ECVs. Using a step-width of 10km, we thus derive 12 scenarios, considering stores of catchment areas between a radius of 80km and 190km around the central warehouse. The resulting instances contain between 144 and 302 stores (cf. Table 3). For each scenario, we calculate the TCO for the exclusive operation by ICEVs and by ECVs in order to assess competitiveness of these two vehicle types. For larger catchment areas, recharging en route has to be enabled by installing charging stations. Based on statements from TEDi, we assume that charging stations can be located at stores and that service times can be used for charging.

Additionally, we perform a sensitivity analysis in order to analyze the impact of central cost terms on the overall TCO results. First, we assume that investments for charging stations are higher than in the TEDi case. As already mentioned, installation of charging stations at TEDi stores is rather inexpensive as strong current is already available and sockets can be installed besides the loading ramps. However, the installation of charging stations may be much more expensive, e.g., if strong current wires have to be installed or if inductive charging is aimed at. Thus, we additionally analyze the impact of an investment of 30,000€ instead of the 4,500€ that were required within the TEDi case. Second, discounts of 10% and 20% on the current ECVs price for the EMOSS CM1216 are regarded as vehicle prices might drop in the future, e.g., with decreasing battery prices.

Since the overall political target is to reduce local and global emissions within the transportation sector, there is increasing pressure on logistics fleet operators to implement emission reduction measures. As stated in Section 1, utilizing ECVs for mid-haul delivery might be an option to reduce the ecological impact of the transportation sector. Therefore, we determine the ecological performance as overall (i.e., well-to-wheel) CO₂ emissions that can be reduced by using ECVs. Thus, we calculate energy respective fuel consumption and finally emissions based on the calculated overall traveled distance. As a result, we are able to quantify the ecological impact of using ECVs instead of ICEVs. Note, that we do not minimize emissions. We could also substitute the objective of the ECVs respectively the ICEVs optimization model, thus minimizing total emissions instead of total costs. However, our focus is on an economic analysis, and thus we only calculate emissions subsequently.

Table 3: Number of customers per instance.

Scenario	I	II	III	IV	V	VI	VII	VIII	IX	X	XI	XII
cat. area [km]	80	90	100	110	120	130	140	150	160	170	180	190
no. stores	144	171	190	211	236	252	267	278	283	295	301	302

The table shows the radius of the catchment area around the central warehouse (cat. area) and the corresponding number of considered stores (no. stores) for each scenario.

5 Computational results

Results were calculated assuming that a homogenous ICEV respectively ECV fleet covers each of the 12 scenarios given in Table 3. In the following, we present these results with a focus on *i*) the network structure and operation (Section 5.1), *ii*) the resulting TCO and the respective cost structure (Section 5.2), and *iii*) the emission savings that can be achieved by using ECVs (Section 5.3). In the following, we limit the illustration of results to figures and include detailed tables in Appendix C.

5.1 Network structure and operation

Figure 2 illustrates results for the operation of the network for each of the 12 scenarios. For each scenario (i.e., the coverage radius), it shows the number of served stores (n^{store}) and the number of charging stations (n^{stat}) needed for operating the network with ECVs. In addition, it details the weekly distance driven ($D^{\text{ICEV}}, D^{\text{ECV}}$), the weekly number of driver shifts ($n^{\text{driver,ICEV}}, n^{\text{driver,ECV}}$), the average distance driven per tour ($\bar{D}^{\text{ICEV}}, \bar{D}^{\text{ECV}}$), and the total number of vehicles ($n^{\text{ICEV}}, n^{\text{ECV}}$) needed for operating the network. While continuous lines represent the results for the ICEV fleet, the dashed lines represent the results for the ECV fleet.

As can be seen, all depicted quantities increase monotonously with an increasing coverage radius around the central warehouse from scenario I to XII for ICEVs as well as ECVs. The total distance driven increases proportionally to the number of stores, while the average distance driven per tour, the weekly number of driver shifts, and the total number of trucks needed for operating the network each increase with a lower gradient. While no charging stations are necessary to operate the ECVs up to a vicinity of 100km, the number of installed stations increases monotonously between a vicinity of 100km and 180km and remains equal for a vicinity of 180km and 190km.

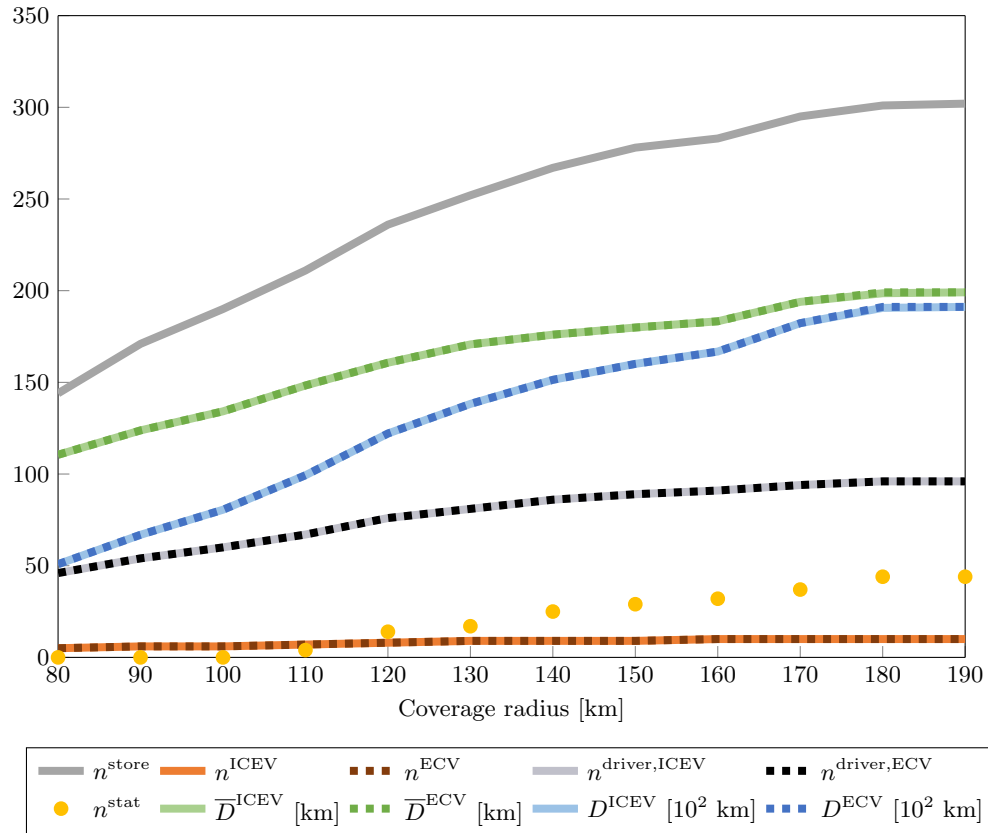


Figure 2: Results for the network operation structure for ICEVs and ECVs with respect to the coverage radius.

Comparing the operation of ICEVs and ECVs, Figure 2 shows that results for the ICEV fleet and results for the ECV fleet nearly match with respect to the number of vehicles and the number of driver shifts. The weekly and average driven distances match for all but the 180km scenario in which the distances are slightly lower for ICEV. Thus, nearly no operational disadvantages arise from using ECV within the TEDi network, despite of range limitations.

Note that the monotonously increasing results and the matching of the ECV and the ICEV curves also indicate that the metaheuristic presented in Appendix B yields very robust and stable results.

5.2 TCO and cost structure

In the following, we detail results with respect to the TCO of ICEVs and ECVs and the resulting cost structure.

Figure 3 shows an in-depth analysis of the overall costs, their single components and the respective cost savings for the coverage of different vicinities around the central warehouse using ICEVs and ECVs. As can be seen, vehicle costs Inv^v are significantly higher for ECVs than for ICEVs although the number of used vehicles is equal. Furthermore, additional costs Inv^s arise for the installation of charging stations for networks with ECVs for vicinities larger than 100km. Annual costs for vehicle taxes Fix^v arise for ICEVs only (cf. Section 4.1), but are negligibly low. Operational driver costs $Oper^{driver}$ are equal for ICEVs and ECVs, since the number of driver shifts needed to operate the network is equal. The main advantage of ECVs lies in operational distance dependent costs $Oper^{dist}$, which are significantly lower for ECVs than for ICEVs. In the TEDi case, these savings in operational costs more than compensate for the higher investment costs of ECVs. This results in cost savings ΔTCO of ECVs compared to ICEVs of 2.43%–4.86% (shown by the dashed orange line that is corresponding to the left hand side axis in Figure 3). While these savings increase up to a vicinity of 110km, they remain nearly constant for larger vicinities. This shows, that for larger vicinities, additional charging station costs compensate additional savings in operational driving costs that result out of higher total traveled distances.

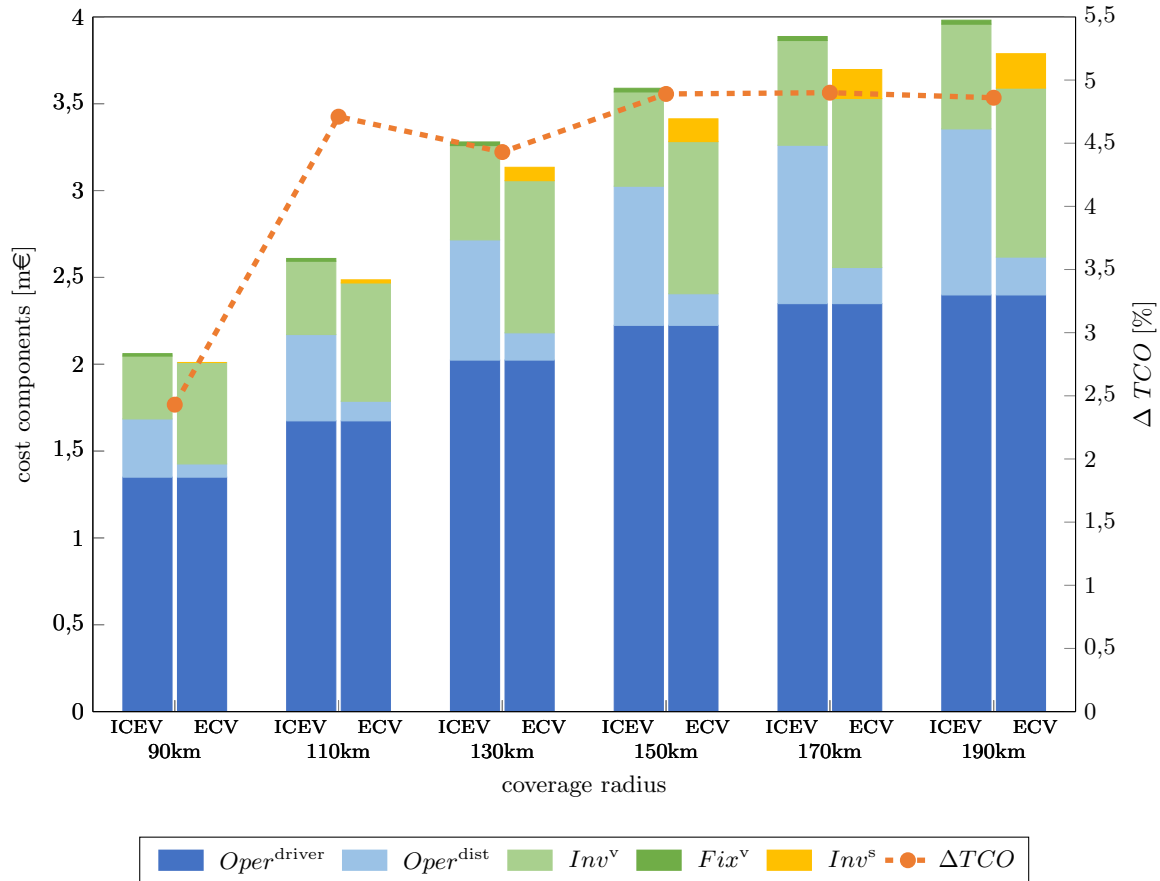


Figure 3: Overall costs for ICEVs and ECVs with respect to the coverage radius.

Additionally, we perform a sensitivity analysis regarding installation costs of charging stations and purchase prices of ECVs. For charging stations, we assume (much) higher installation costs of 30.000€ (instead of 4500€) as costs that would apply if not only the socket but also the high voltage infrastructure and the

station chassis would have to be installed. For ECVs, we consider a reduction of purchase prices of 10% and 20% in order to account for potential future price reductions e.g., due to decreasing battery prices or scale effects. With this sensitivity analyses, we generalize results for retail logistics networks which are less specific than our investigated case.

Figure 4 shows the TCO for the different coverage radii of the 12 scenarios for ICEVs (TCO^{ICEV}) and for ECVs with 100, 90 and 80% of the current vehicles' purchase prices, each for the TEDi case with low investment costs for charging stations ($TCO^{ECV100l}$, TCO^{ECV90l} , TCO^{ECV80l}) but also for cases with high investment costs for charging stations ($TCO^{ECV100h}$, TCO^{ECV90h} , TCO^{ECV80h}). As can be seen, in the TEDi case (i.e., with low investment costs for charging stations), total costs are lower for ECVs than for ICEVs for all scenarios. Cost savings of 1.33%-4.90% result regarding the current purchase price of ECVs. Thus, cost savings of up to 193,000€ can be realized within the planning period of 5 years if the logistics network of TEDi is operated by ECVs instead of ICEVs. Cost savings increase even up to 9.75%, if purchase prices of ECVs decrease to 80%.

However, this advantage of ECVs disappears, if high investments into charging infrastructure are needed, e.g., if the installation of high voltage wires at the TEDi stores would be necessary. For this case, the TCO of ECVs are up to 23.32% higher than the TCO of ICEVs (cf. Table 8). Cost savings only remain for vicinities of less than 110km for which (nearly) no charging stations are necessary. In this case, decreased vehicle costs are not sufficient to compensate higher charging station costs.

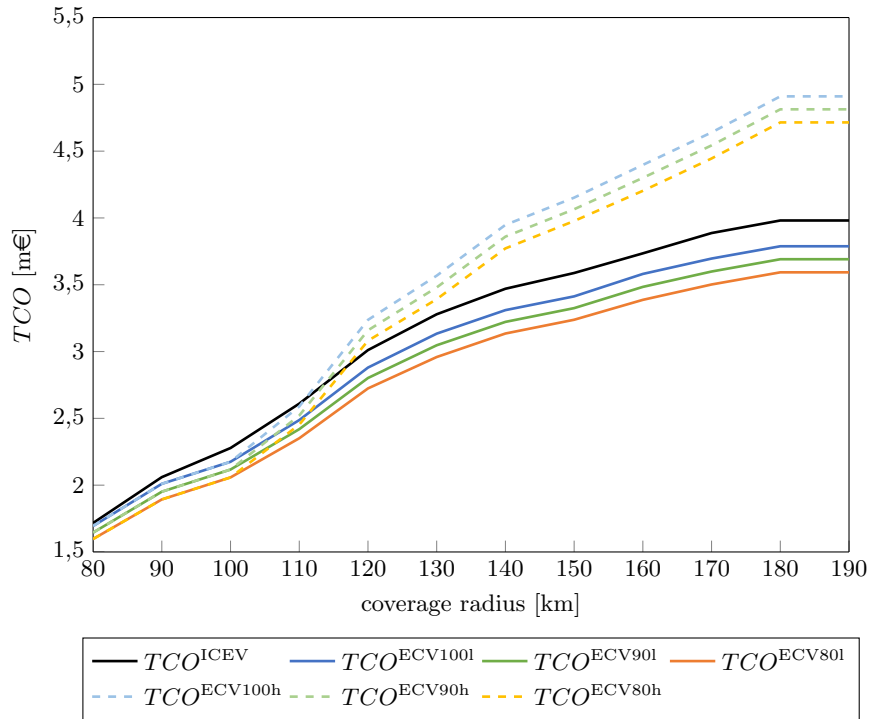


Figure 4: Overall costs for ICEVs and ECVs with respect to the coverage radius.

Concluding, cost savings can be realized by the electrification of the logistics fleet in the TEDi case. Herein, cost savings of ECVs compared to ICEVs increase with increasing vicinity around the central warehouse. However, this advantage of ECVs disappears if investment costs for charging stations are higher than in the TEDi case.

5.3 Emissions

Figure 5 illustrates results on total CO₂ emissions for a fleet of ICEVs (E^{ICEV}) as well as of ECVs (E^{ECV}) for all scenarios. In addition, it presents emission savings (ΔE) due to the usage of ECVs. As can be seen, ECVs emit around 25% less CO₂ emissions than ICEVs within a well-to-wheel system boundary (i.e., regarding all emissions from the well to the combustion respective to the electricity generation and transmission) for all scenarios. As the total distance driven by ECVs and ICEVs is (nearly) identical (cf. Figure 2), the CO₂-saving is mainly due to a higher efficiency of ECVs and lower CO₂ emission factors for electricity compared to Diesel.

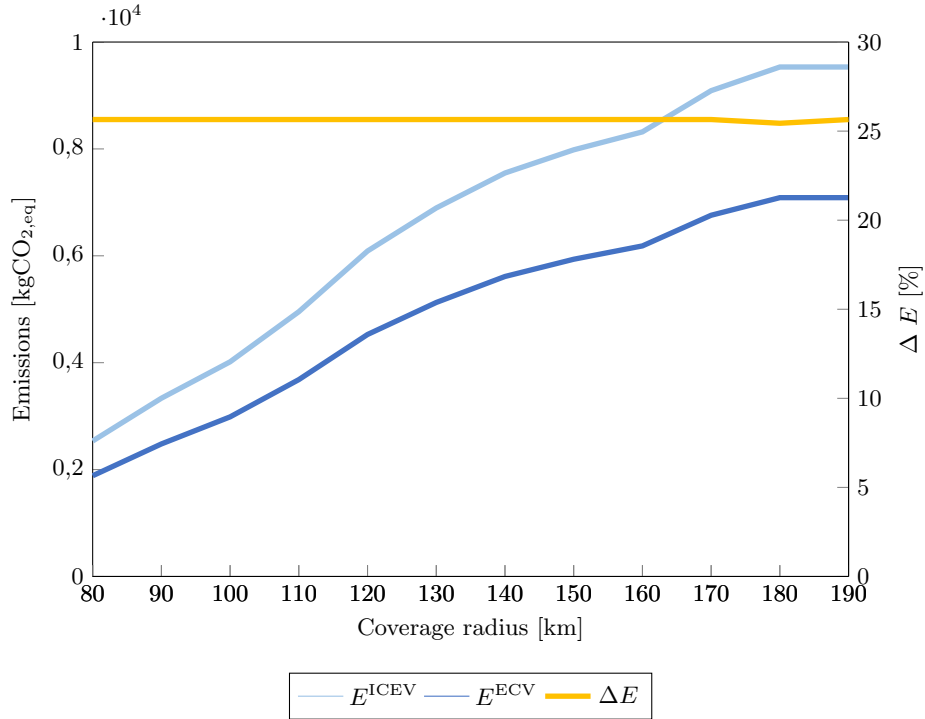


Figure 5: Emissions and emission savings with respect to the coverage radius.

6 Managerial insights

Analyzing the results from Sections 5.1–5.3, insights can be drawn for logistics fleet and network operators. First, we discuss managerial insights for the TEDi case with respect to specific network characteristics and resulting advantages and disadvantages in Section 6.1. Second, we alleviate these findings to derive general managerial insights for future design and operation of mid-haul ECV logistics networks in Section 6.2.

6.1 Case specific insights

In the TEDi case, specific characteristics with regard to service area, network structure and costs determine the benefit of ECVs.

Service areas: Regarding the vicinity around the central warehouse, our analyses show that a complete coverage of the service area by ECVs is possible and worthwhile in the TEDi case. One main factor that contributes to this result are the limited distances of optimized routes. Often, distances of less than 200km with three to four customer stops have to be covered per route and vehicles go back to the depot at least once a day (cf. Network operations). Thus, the actual range of the specific mid-haul

ECV EMOSS CM1216 of 200km is higher than the average length of many routes. Therefore, only few charging stations have to be installed and few recharging processes have to be integrated in the network operation. Thus, the coverage of the complete service area is possible with limited strategic and operative expenditures.

Network operations: In the TEDi case, vehicles go back to the warehouse between shifts for reloading freight and for changing drivers. Additionally, vehicles regularly return to the depot in order to pick up palletized goods, often after only a few service stops. Thus, vehicles can be fully charged at the depot at least once a day. Even if vehicles are charged at the TEDi stores, service times can be used for recharging. As a consequence, operational disadvantages of ECVs due to range limitations and charging demand are low for this specific application case. This is also backed by the fact that the number of vehicles and the average distances of routes do not differ between ICEVs and ECVs. Thus, ECVs are competitive to ICEVs with regard to network operation for this specific case.

TCO: In the TEDi case, extra costs for ECVs, e.g., higher purchase costs for vehicles and installation costs for charging stations, are at least compensated by lower operational distance based costs. Thus, it is worthwhile to invest in an electrification of the retail logistics fleet in the TEDi case. However, this is mainly due to two reasons. First, investment costs for charging stations are low as only sockets have to be installed at the ramps of the TEDi stores and heavy current infrastructure is already available. Thus, costs for installation of charging stations are much lower than in other ECV applications. As we show in our sensitivity analysis, cost advantages of ECVs disappear if investment costs for charging stations are higher than in the TEDi case. Second, the number of needed vehicles and weekly driver shifts is equal for ICEVs and ECVs. Thus, increases in vehicle costs are only due to the price difference between the vehicle types. In the TEDi case, these can be compensated by lower operational costs. If more vehicles would be needed, this might not be the case.

As can be seen, ECVs are advantageous in the TEDi case, and the benefit of an electrified mid-haul logistics fleet can be constituted to specific network characteristics. Our industry partner had not expected the results for ECVs to be this positive. Although first positive evaluations were available from the ELMO project, these results were not sufficient to convince the company that the electrification of the mid-haul logistics fleet would be feasible and worthwhile without further analysis. This shows the importance of detailed analysis in the course of the electrification of mid-haul logistics fleets.

6.2 Generalized managerial insights

Alleviating the results from Section 5 and the findings from Section 6.1, the following key findings can be drawn for mid-haul ECV networks in general.

A detailed network analysis at an operational level is necessary to estimate the competitiveness of ECVs appropriately: Route patterns as well as considered cost structures and charging options might vary significantly with respect to the analyzed network. Thus, an aggregated cost analysis is not sufficient to assess the competitiveness of ECVs. Instead, a detailed analysis is necessary to assess each application case individually. Herein, operational routing decisions as well as strategic network design aspects must be taken into account. This shows the necessity for an integrated model for network design and operation using VRP and LRP components. This approach avoids over- or underestimation of ECVs in logistics networks by an individual case-specific assessment of the competitiveness of ECVs compared to ICEVs. This might on the one hand help to identify other logistics networks that could be operated by ECVs, but on the other hand also prevent fleet operators from overrating ECVs. In practice, fleet operators often decide based on one monetary key performance indicator (cf. Section 5.2). Thus, the proposed solution approach adds a significant benefit to provide decision support for practitioners.

Operational planning components affect strategic network structure decisions: Especially if intermediate stops are necessary, the integrated models that are presented in this paper show results on a beneficial network structure (i.e., the number of vehicles and charging stations needed to operate the network) and the resulting network operation (i.e., the total distance driven and routes chosen to fulfill the demand at all stores). Thus,

network operators might profit from more efficient network structure design and operation, especially within large and complex networks where manual routing and strategic design is no longer possible.

For certain mid-haul application cases, ECVs are already on the verge of breaking even: In the TEDi case, results revealed that ECVs had nearly no operational disadvantages compared to ICEVs. Thus, the utilization of ECVs within mid-haul logistics networks might be worthwhile, even under contemporary cost and technical conditions. As the example of the TEDi case shows, specific network characteristics might work in favor for the competitiveness of ECVs. Thus, analysing logistics networks with similar characteristics might reveal comparable results. However, results might change if essential parameters or conditions change, e.g., if high investments for charging stations are required.

Additional (ecological) advantages can be realized: The utilization of ECVs contributes to a reduction of CO₂ emissions as well as of local hazardous emissions (NO_x, particulate matter) and noise. This can especially be important in the future as increasing pressure is put on the logistics sector to decrease emissions. The relevance might even increase if advanced legal measures, like access restrictions for ICEVs, are enforced. Such restrictions are already established in 500 European cities. Over 200 of them are based on vehicle emissions (cf. European Union, 2016b). Therefore, logistics companies are increasingly aiming at low and zero-emission strategies in retail logistics networks.

7 Conclusion and outlook

Within this paper, we evaluate the competitiveness of ECVs in medium-duty retail logistics for a specific case study of a large retail company delivering non-food goods from a central depot to 302 stores in Northrhine-Westfalia, a federal state of Germany. A TCO analysis combined with a new LRPIF variant that considers pickup and delivery, multiple periods, and multiple driver shifts provides the methodological basis for our studies. Doing so, we consider case specific logistics requirements, the limited driving range, and the need for charging ECVs en route in mid-haul logistics. Thus, a fair assessment of advantages and disadvantages of an electrification of the logistics fleet is possible. In addition, a parallelized hybrid of ALNS and dynamic programming is developed to solve large-sized instances.

The results show that for the analyzed application case, the electrification of the retail logistics network is worthwhile regarding economic, but also ecological objectives. For the investigated application case, nearly no operational limitations result when using ECVs instead of ICEVs. The number of vehicles needed to operate the network, the total distance driven and the average tour duration are nearly identical to ICEVs. This holds even for a complete electrification of the logistics fleet delivering goods and collecting pallets within a vicinity of up to 190 km around the central depot. The reason for this positive assessment of ECVs is to be seen in several network characteristics that work in favor of ECVs, e.g., the return of the vehicles to the depot at least once a day as well as the limited vicinity of stores around the depot. Although positive results of the utilization of single vehicles within a limited vicinity of the network was known to the network operator, the benefit of the complete electrification of the mid-haul fleet was not expected. Thus, integrated planning approaches that consider operational as well as network design aspects were necessary in order to show these advantages. However, results show that with changing conditions, e.g., higher investment costs for charging stations, ECVs are no longer competitive.

Even if this case study shows that ECVs are already economically advantageous for the considered application case, open research questions remain within this context: First, despite the positive evaluation for this case study, advantages and disadvantages of an electrification of mid-haul fleets should be analyzed for logistics networks with other characteristics, since solutions for the network design as well as routing decisions are sensitive to network characteristics. Such an analysis for a large set of different network structures would allow to derive general factors of success for the utilization of ECVs in mid-haul logistics.

Second, even for companies that focus mainly on economic objectives, emission savings might be a very important asset for electrification of logistics fleets in the future. There are political targets aiming at saving

more than 40% of total CO₂ emissions in the transportation sector until 2020 (cf. European Commission, 2014). Hence, many (larger) logistics companies already aim at significant short and long-term emission reductions (cf. Green Freight Europe, 2014). Within this context, low-emission zones, which are already realized in several cities resulting in high penalty costs or even a ban of ICEVs in certain areas, can be considered. It has to be analyzed how these developments might increase the benefit of using ECVs instead of ICEVs even further.

Third, the future development of technological parameters (e.g., battery capacity, charging times) should be focused on, too.

Appendices

A Cost function

In the following, we detail the link between the TCO cost components and the MIP objective for investment costs Inv , annually fixed costs Fix , and operational costs $Oper$, for a planning period T .

Investment costs

In general, the total investment costs for a planning period with $t = 0, \dots, T$ time steps result from considering the investment costs Inv_t over the planning horizon (26). Recall from Section 3.1 that investments arise for vehicles (Inv_t^v) as well as for charging stations (Inv_t^s), so that in general $Inv_t = Inv_t^v + Inv_t^s$ holds. Investment costs can be calculated multiplying the investment costs per vehicle ($c_t^{\text{inv},v}$) with the number of vehicles (z) and the investment costs per charging station ($c_t^{\text{inv},s}$) with the number of charging stations (y). Since we assume continuous operation of the network (i.e. repetition of the optimized delivery processes of one week over the whole planning horizon), the decision on the number of vehicles and the number of charging stations is taken in $t = 0$. Thus, investment costs may arise only in $t = 0$ ($c_0^{\text{inv},v} \geq 0, c_0^{\text{inv},s} \geq 0$). Salvage values are taken into account at the end of the planning horizon T ($c_T^{\text{inv},v} \leq 0, c_T^{\text{inv},s} \leq 0$). Thus, (27) results due to distributive law. To keep the notation concise, we use $\bar{c}^{\text{inv},v}$ and $\bar{c}^{\text{inv},s}$ as discounted cost factors, and thus the overall investment costs can be written as in (28), calculating the number of stations by $y = \sum y_i$.

$$Inv = \sum_{t=0}^T \frac{Inv_t}{(1+r)^t} = \sum_{t=0}^T \frac{Inv_t^v}{(1+r)^t} + \frac{Inv_t^s}{(1+r)^t} \quad (26)$$

$$= \sum_{t=0}^T \frac{c_t^{\text{inv},v} z}{(1+r)^t} + \frac{c_t^{\text{inv},s} y}{(1+r)^t} = z \sum_{t=0}^T \frac{c_t^{\text{inv},v}}{(1+r)^t} + y \sum_{t=0}^T \frac{c_t^{\text{inv},s}}{(1+r)^t} \quad (27)$$

$$= \bar{c}^{\text{inv},v} z + \bar{c}^{\text{inv},s} \sum_{i \in \mathcal{C} \cup \mathcal{F}} y_i \quad (28)$$

Annual fixed costs

In analogy to investment costs, total annual fixed costs Fix can be derived, summing up annual costs for vehicles (Fix_t^v) and charging stations (Fix_t^s) as $Fix_t = Fix_t^v + Fix_t^s$. Again, we consider cost factors $c^{\text{fix},v}$ and $c^{\text{fix},s}$ and derive an aggregated representation with discounted cost factors $\bar{c}^{\text{fix},v}$ and $\bar{c}^{\text{fix},s}$. Note that annual fixed costs for charging stations are assumed to be zero in our case study.

$$Fix = \sum_{t=0}^T \frac{Fix_t}{(1+r)^t} = \sum_{t=0}^T \frac{Fix_t^v}{(1+r)^t} + \frac{Fix_t^s}{(1+r)^t} \quad (29)$$

$$= \sum_{t=0}^T \frac{c_t^{\text{fix},v} z}{(1+r)^t} + \frac{c_t^{\text{fix},s} y}{(1+r)^t} = z \sum_{t=0}^T \frac{c_t^{\text{fix},v}}{(1+r)^t} + y \sum_{t=0}^T \frac{c_t^{\text{fix},s}}{(1+r)^t} \quad (30)$$

$$= \bar{c}^{\text{fix},v} z + \bar{c}^{\text{fix},s} \sum_{i \in \mathcal{C} \cup \mathcal{F}} y_i \quad (31)$$

Operational costs

Operational costs $Oper$ result out of the daily operation of the fleet. Thus, for each time step t , operational costs result from the sum of distance-related costs ($Oper_t^{\text{dist}}$) and driver costs ($Oper_t^{\text{driver}}$) as $Oper_t = Oper_t^{\text{dist}} + Oper_t^{\text{driver}}$ (32). $Oper_t^{\text{dist}}$ are calculated multiplying a distance-related cost factor $c_t^{\text{oper,di}}$ that reflects the price per driven kilometer with the total distance resulting from the vehicles' route plans ($\sum d_{ij}x_{ij}^s$), and $Oper_t^{\text{driver}}$ are calculated multiplying the cost of a working shift ($c_t^{\text{oper,dr}}$) with the total number of shifts for operating the vehicles ($\sum x_{0j}^s$) (33). Because the operation of the retail network is planned with milk runs (i.e. the optimized delivery processes of one week are repeated over the whole planning horizon), cost terms can be separated from the decision variables due to distributive law (34). Again, discounted cost rates $\bar{c}^{\text{oper,di}}$ and $\bar{c}^{\text{oper,dr}}$ are derived (35).

$$Oper = \sum_{t=0}^T \frac{Oper_t}{(1+r)^t} = \sum_{t=0}^T \frac{Oper_t^{\text{dist}}}{(1+r)^t} + \frac{Oper_t^{\text{driver}}}{(1+r)^t} \quad (32)$$

$$= \sum_{t=0}^T \frac{c_t^{\text{oper,di}} \sum d_{ij}x_{ij}^s}{(1+r)^t} + \frac{c_t^{\text{oper,dr}} \sum x_{0j}^s}{(1+r)^t} \quad (33)$$

$$= \sum_{(i,j) \in \delta(\mathcal{V}_{0,n+1}), s \in \mathcal{S}} d_{ij}x_{ij}^s \sum_{t=0}^T \frac{c_t^{\text{oper,di}}}{(1+r)^t} + \sum_{(i,j) \in \delta^+(0), s \in \mathcal{S}} x_{ij}^s \sum_{t=0}^T \frac{c_t^{\text{oper,dr}}}{(1+r)^t} \quad (34)$$

$$= \bar{c}^{\text{oper,dr}} \sum_{(i,j) \in \delta(\mathcal{V}_{0,n+1}), s \in \mathcal{S}} d_{ij}x_{ij}^s + \bar{c}^{\text{oper,di}} \sum_{(i,j) \in \delta^+(0), s \in \mathcal{S}} x_{ij}^s \quad (35)$$

B Solution method

The basic LRPIF is a NP-hard and even simplified variants can only be solved up to 15 customers with commercial software (cf. Schiffer and Walther, 2017b). Thus, we developed an efficient metaheuristic to solve the large-sized instances of this case study. In the following, we briefly describe this algorithm.

Figure 6 shows a pseudocode of our algorithm, which is a hybrid of ALNS and dynamic programming (DP). We use a generalized cost function (cf. Section B.1) to handle infeasible solutions during the search phase. The core of the algorithm is an ALNS, which has been introduced by Ropke and Pisinger (2006), extending a large neighborhood search (LNS) (cf. Shaw, 1998) by an adaptive learning mechanism for the

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1: while ( $\iota < \eta^{\text{max}}$ ) and ( $\iota - \iota_{\text{imp}} < \eta_{\text{noi}}^{\text{max}}$ ) do
2:   if (modulo ( $\iota, \eta^{\text{lrg}}$ ) = 0) then
3:      $\sigma' \leftarrow \text{destroyAndRepair}(\mathcal{D}_l, \mathcal{R}, \pi, \sigma)$ 
4:   else
5:      $\sigma' \leftarrow \text{destroyAndRepair}(\mathcal{D}_s, \mathcal{R}, \pi, \sigma)$ 
6:   if ( $\lambda(\sigma') < \lambda(\sigma^*) (1 + \delta^l)$ ) then
7:      $\sigma' \leftarrow \text{localSearch}(\sigma')$ 
8:     if ( $\lambda(\sigma') < \lambda(\sigma^*) (1 + \delta^d)$ ) then
9:        $\sigma' \leftarrow \text{dynamicProgramming}(\sigma')$ 
10:  if ( $\lambda(\sigma') < \lambda(\sigma)$ ) then
11:     $\sigma \leftarrow \sigma'$ 
12:    if ( $\lambda(\sigma') < \lambda(\sigma^*)$ ) then
13:       $\sigma^* \leftarrow \sigma'$ 
14:       $\sigma'_f \leftarrow \text{generateFeasibleSolution}(\sigma')$ 
15:      if feasible ( $\sigma'_f$ ) and ( $\lambda(\sigma'_f) < \lambda(\sigma_f^*)$ ) then
16:         $\sigma_f^* \leftarrow \sigma'_f$ 
17:         $\iota_{\text{imp}} \leftarrow \iota$ 
18:  if (modulo ( $\iota, \eta^{\text{res}}$ ) = 0) then
19:     $\sigma \leftarrow \sigma_f^*$ 
20:   $\iota \leftarrow \iota + 1$ 

```

Figure 6: Pseudocode overview of the metaheuristic.

operator choice in each search step. Before starting the search, we remove infeasible arcs (cf. Section B.2)

and create an initial solution (cf. Section B.3). Then, we conduct a destroy and repair step (cf. Section B.4). If the objective value of the resulting temporary solution ($\lambda(\sigma')$) is not higher than $(1 + \delta^l) \lambda(\sigma^*)$, we use a local search (cf. Section B.5) to further improve the solution. Afterwards, we use a dynamic programming procedure (cf. Schiffer and Walther, 2017a) to optimally place recharging visits on routes if $\lambda(\sigma')$ is not higher than $(1 + \delta^d) \lambda(\sigma^*)$. During the search phase, we store feasible and infeasible solutions separately (cf. Cordeau et al., 2001). Doing so, the temporary solution σ' is forwarded to the current solution σ and the so far best found solution σ^* after each search step, if it leads to improvements. Then, a temporary feasible solution σ'_f is obtained out of σ' using the method described in Vidal et al. (2014). Again, σ'_f is forwarded to the so far best feasible solution σ_f^* , if it leads to an improvement. After η^{res} iterations, the current solution is set back to the so far best feasible solution σ_f^* to intensify the search. The search stops after η^{max} overall iterations or if no improvement has been found within the last $\eta_{\text{noi}}^{\text{max}}$ iterations. Section B.6 gives an overview of the used algorithmic parameters.

B.1 Generalized cost function

Instead of accepting only feasible solutions during the search, we allow the acceptance of infeasible solutions to overcome local optima. Thus, we use a generalized cost function as proposed in Schiffer and Walther (2017a) to evaluate infeasible solutions. This function considers the costs $\lambda'(\sigma)$ of the current solution σ , but also prices constraint violations by adding penalty terms for freight violations ($FR(\sigma)$), time window violations ($TW(\sigma)$) and battery capacity violations ($FL(\sigma)$). These penalty terms are each multiplied with an adaptive weighting factor (α, β, γ) . The weighting factors may vary between $(\alpha_{\min}, \beta_{\min}, \gamma_{\min})$ and $(\alpha_{\max}, \beta_{\max}, \gamma_{\max})$. After initializing $(\alpha = \alpha_0, \beta = \beta_0, \gamma = \gamma_0)$, we divide each penalty factor by ω if no respective penalty occurs in the last η^P iterations of the search. Analogously, if a penalty occurs in the last η^P iterations of the search, we multiply the respective penalty weight by ω . Doing so, our algorithm is more likely to accept an infeasible solution if the solution remained feasible over a large number of iterations and less likely to accept it if penalties remain. Thus, the adaptive mechanism guarantees both, feasible solutions and avoiding local optima.

$$\lambda(\sigma) = \lambda'(\sigma) + \alpha FR(\sigma) + \beta TW(\sigma) + \gamma FL(\sigma) \quad (36)$$

Common bookkeeping of freight on routes is sufficient to calculate freight penalties. However, for time window and battery capacity violations, calculating penalty terms is rather complex because a trade of between time window feasibility and recharging arises. In this course, a corridor-based evaluation approach is necessary to calculate penalty terms in a time-efficient manner. To keep this paper concise, we refer to Schiffer and Walther (2017a) for the explanation of this evaluation approach. The equations presented there can be used for this application case without any changes.

B.2 Preprocessing

To reduce the neighborhood size, we remove infeasible arcs from G before starting the search. Infeasible arcs for freight violations are identified by (37) and (38). Equations (39)–(40) identify arcs that are infeasible due to time window restrictions (cf. Savelsbergh, 1985). Infeasible arcs due to battery capacity restrictions are identified by (41).

$$(i, j) \in \delta(\mathcal{C}) \quad \wedge \quad p_i + p_j > F \quad (37)$$

$$(i, j) \in \delta(\mathcal{C}) \quad \wedge \quad v_i + v_j > F \quad (38)$$

$$(i, j) \in \delta(\mathcal{V}_{0,n+1}) \quad \wedge \quad e_i^s + s_i + t_{ij} > l_j^s \quad (39)$$

$$(i, j) \in \delta(\mathcal{V}_0) \quad \wedge \quad e_i^s + s_i + t_{ij} + s_j + t_{jn+1} > l_{n+1} \quad (40)$$

$$(i, j) \in \delta(\mathcal{V}_{0,n+1}) \quad \wedge \quad h_{ij} > Q \quad (41)$$

B.3 Construction algorithm

We use a modified savings algorithm (cf. Clarke and Wright, 1964) to construct an initial solution. This algorithm works as follows:

- First, we construct back-and-forth tours for all customers.
- Then, potential merge moves are sorted in decreasing order due to their respective cost-savings.
- The merge move with the highest savings is conducted. This step is repeated until no positive cost savings remain. In the merge moves, violations of the vehicle's freight capacity, time windows, and the vehicle's battery capacity are allowed. However, infeasible arcs are already considered at this step, such that merge moves that use infeasible arcs are prohibited.
- Finally, we use the local search procedure (cf. Section B.5) to improve the initial solution once.

B.4 Destroy and repair phase

In each iteration of the ALNS the current solution σ is destroyed using a destroy operator, before a repair operator is used to create a new solution. Contrary to common destroy and repair phases, we handle changes in the facility configuration (in this case charging stations) besides removing and inserting customers. To do so, we use different types of destroy operators: a small destroy operator from set \mathcal{D}_s only removes customers, while a large destroy operator from set \mathcal{D}_l changes the facility configuration before removing customers. After both types of destroy operators, a repair operator from set \mathcal{R} reinserts the removed customers to create a new temporal solution σ' . A large destroy operator is used every η^{lg} iterations so that the new facility configuration can be evaluated with the search steps in between.

We choose the destroy and the repair operator in each search step based on an operator specific probability that reflects the operator's success in improving the objective in former search steps. Herein, the probability for each operator ψ_j out of n operators results based on a roulette wheel distribution due to the weight π_j of each operator.

$$P(\psi_j) = \frac{\pi_j}{\sum_{i=1}^n \pi_i} \quad (42)$$

We use exponential smoothing to calculate these weights. Every $\eta^{\text{al},l}/\eta^{\text{al},s}$ iterations the weights are updated for large respectively small operators, considering a smoothing factor $\phi \in [0,1]$, the number of times an operator j was chosen in the last learning period χ_j and the cumulated score the respective operator yielded in the last learning period $\bar{\pi}_j$.

$$\pi_j = \phi \frac{\bar{\pi}_j}{\chi_j} + (1 - \phi) \pi_j \quad (43)$$

During a learning period, we add ε^f to $\bar{\pi}_j$ if the operator yields a new best feasible solution, ε^b if it yields a new best solution, and ε^i if it improves the current solution.

As large destroy operators of set \mathcal{D}_l , we use an **add** and a **drop** operator (Hemmelmayr et al., 2012), as well as a **swap perfect** and a **swap perfect out** operator (Schiffer and Walther, 2017a). The set of small destroy operators \mathcal{D}_s contains a **worst remove** (Ropke and Pisinger, 2006), a **related remove** (Pisinger and Ropke, 2007), a **route remove** (Hemmelmayr et al., 2012), and a **modified Shaw remove** as well as a **station vicinity remove** (Goeke and Schneider, 2015) operator. The set of repair operators \mathcal{R} contains a **sequential insertion** (Hiermann et al., 2016) and a **sequential perturbed insertion** (Schiffer and Walther, 2017a) operator.

B.5 Local search

We use a composite neighborhood with a best out of 100 improvement criterion and consider the following operators: We use a **2-opt*** (Potvin and Rousseau, 1995) and an **Or-opt** (Or, 1976) operator. In addition, an **exchange** and a **relocate** operator (Savelsbergh, 1992) are used in inter and intra-route fashion. To yield feasible solutions with respect to the vehicle's battery capacity, we use an additional **stationInsertion** operator that inserts recharging stops into routes if necessary.

B.6 Algorithmic setup

We ran all numerical experiments on a desktop computer with an Intel Core i7 3.60 GHz and 16 GB RAM running Ubuntu 16.04 LTS. Our ALNS is implemented in C++ as a single thread code.

To identify a suitable parameter setting, we used the method of Ropke and Pisinger (2006). Table 4 shows the final parameter setting for the number of maximum total iterations η^{\max} , the maximum number of iterations without improvement η_{noi}^{\max} , the number of iterations after which a large destroy step is conducted η^{lrg} , the number of iterations after which the current solution is set back to the so far best feasible solution η^{res} , the number of iterations after which operator weights are updated for large $\eta^{\text{al},\text{l}}$ and small $\eta^{\text{al},\text{s}}$ operators, the number of iterations after which the penalty weights are updated η^{p} , the ranges for the local search δ^{l} and the dynamic programming δ^{d} corridor, the smoothing factor ϕ , the penalty correction factor ω , the minimum $(\alpha_{\min}, \beta_{\min}, \gamma_{\min})$ and maximum $(\alpha_{\max}, \beta_{\max}, \gamma_{\max})$ as well as initial $(\alpha_0, \beta_0, \gamma_0)$ penalty weights, and the scoring parameters $(\varepsilon^{\text{f}}, \varepsilon^{\text{b}}, \varepsilon^{\text{i}})$. Operator specific parameters are used as stated in the respective references.

Table 4: Algorithmic parameters.

η^{\max}	η_{noi}^{\max}	η^{lrg}	η^{res}	$\eta^{\text{al},\text{l}}$	$\eta^{\text{al},\text{s}}$	η^{p}	δ^{l}	δ^{d}	ϕ	ω
20000	5000	150	10000	1500	50	50	0.3	0.02	0.8	1.15
$(\alpha_{\min}, \beta_{\min}, \gamma_{\min})$			$(\alpha_{\max}, \beta_{\max}, \gamma_{\max})$			$(\alpha_0, \beta_0, \gamma_0)$			$(\varepsilon^{\text{f}}, \varepsilon^{\text{b}}, \varepsilon^{\text{i}})$	
100			10000			100			(9,4,1)	

The table shows the parameters used in our algorithm.

C Computational results

Tables 5–8 show the detailed results for our discussion in Section 5.

Table 5: Results for all investigated scenarios for the ICEV vehicle fleet.

Scenario	I	II	III	IV	V	VI	VII	VIII	IX	X	XI	XII
Cat. area	80	90	100	110	120	130	140	150	160	170	180	190
n^{store}	144	171	190	211	236	252	267	278	283	295	301	302
n^{ICEV}	5	6	6	7	8	9	9	9	10	10	10	10
$n^{\text{driver,ICEV}}$	46	54	60	67	76	81	86	89	91	94	96	96
D^{ICEV}	5083	6687	8053	9933	12210	13825	15137	16007	16680	18227	19061	19115
$\overline{D}^{\text{ICEV}}$	110.5	123.8	134.2	148.3	160.7	170.7	176.0	179.9	183.3	193.9	198.6	199.1
Inv^{v}	0.302	0.362	0.362	0.422	0.482	0.543	0.543	0.543	0.603	0.603	0.603	0.603
Fix^{v}	0.012	0.014	0.014	0.016	0.018	0.021	0.021	0.021	0.023	0.023	0.023	0.023
$Oper^{\text{driver}}$	1.150	1.350	1.499	1.674	1.899	2.024	2.149	2.224	2.274	2.349	2.399	2.399
$Oper^{\text{dist}}$	0.254	0.335	0.403	0.497	0.611	0.692	0.757	0.801	0.834	0.912	0.954	0.956
TCO^{ICEV}	1.717	2.060	2.278	2.610	3.011	3.279	3.470	3.588	3.735	3.887	3.979	3.981

Abbreviations hold as follows: Cat. area [km] - catchment area, n^{store} - number of served stores, n^{ICEV} - number of ICEVs, $n^{\text{driver,ICEV}}$ - number of weekly driver shifts, D^{ICEV} [km] - weekly total distance, $\overline{D}^{\text{ICEV}}$ [km] - average tour distance, Inv^{v} [m€] - investment costs for vehicles, Fix^{v} [m€] - total annually costs for vehicles, $Oper^{\text{driver}}$ [m€] - total driver costs, $Oper^{\text{dist}}$ [m€] - total driving costs, TCO^{ICEV} [m€] - total costs of ownership ICEVs.

Table 6: Results for all investigated scenarios for the ECV vehicle fleet.

Scenario	I	II	III	IV	V	VI	VII	VIII	IX	X	XI	XII
Cat. area	80	90	100	110	120	130	140	150	160	170	180	190
n^{store}	144	171	190	211	236	252	267	278	283	295	301	302
n^{ECV}	5	6	6	7	8	9	9	9	10	10	10	10
$n^{\text{driver,ECV}}$	46	54	60	67	76	81	86	89	91	94	96	96
n^{stat}	0	0	0	4	14	17	25	29	32	37	44	44
D^{ECV}	5083	6687	8053	9933	12210	13825	15137	16007	16680	18227	19115	19115
\bar{D}^{ECV}	110.5	123.8	134.2	148.3	160.7	170.7	176.0	179.9	183.3	193.9	199.1	199.1
Inv^v	0.487	0.584	0.584	0.681	0.779	0.876	0.876	0.876	0.973	0.973	0.973	0.973
$Oper^{\text{driver}}$	1.150	1.350	1.499	1.674	1.899	2.024	2.149	2.224	2.274	2.349	2.399	2.399
$Oper^{\text{dist}}$	0.058	0.076	0.092	0.113	0.139	0.157	0.172	0.182	0.190	0.208	0.218	0.218
Inv^s	0.000	0.000	0.000	0.018	0.063	0.077	0.113	0.131	0.144	0.167	0.198	0.198
TCO^{ECV100l}	1.694	2.010	2.175	2.487	2.880	3.134	3.310	3.413	3.581	3.696	3.788	3.788
TCO^{ECV90l}	1.645	1.951	2.117	2.419	2.802	3.047	3.222	3.325	3.484	3.599	3.691	3.691
TCO^{ECV80l}	1.597	1.893	2.058	2.351	2.724	2.959	3.135	3.238	3.387	3.502	3.593	3.593
TCO^{ECV100h}	1.694	2.010	2.175	2.589	3.237	3.568	3.948	4.152	4.397	4.640	4.910	4.910
TCO^{ECV90h}	1.645	1.951	2.117	2.521	3.159	3.480	3.860	4.065	4.300	4.543	4.813	4.813
TCO^{ECV80h}	1.597	1.893	2.058	2.453	3.081	3.392	3.772	3.977	4.203	4.445	4.715	4.715

Abbreviations hold as follows: Cat. area [km] - catchment area, n^{store} - number of served stores, n^{ECV} - number of ECVs, $n^{\text{driver,ECV}}$ - number of weekly driver shifts, D^{ECV} [km] - weekly total distance, \bar{D}^{ECV} [km] - average tour distance, Inv^v [m€] - investment costs for vehicles, $Oper^{\text{driver}}$ [m€] - total driver costs, $Oper^{\text{dist}}$ [m€] - total driving costs, Inv^s [m€] - investment costs for stations TCO^{ECV} [m€] - total costs of ownership ECVs for different scenarios (cf. Section 5.2).

Table 7: Emissions for all investigated scenarios for ICEVs and ECVs.

Scenario	I	II	III	IV	V	VI	VII	VIII	IX	X	XI	XII
E^{ICEV}	2534.9	3335.1	4016.5	4954.1	6089.7	6895.1	7549.3	7983.1	8318.7	9090.1	9506.5	9533.1
E^{ECV}	1884.8	2479.8	2986.4	3683.5	4527.9	5126.7	5613.2	5935.7	6185.2	6758.8	7088.1	7088.1
ΔE	-25.65	-25.65	-25.65	-25.65	-25.65	-25.65	-25.65	-25.65	-25.65	-25.65	-25.44	-25.65

Abbreviations hold as follows: E^{ICEV} [kgCO_{2,eq}] - emissions operating the network with ICEVs, E^{ECV} [kgCO_{2,eq}] - emissions operating the network with ECVs, ΔE [%] - emission savings, operating the network with ECVs instead of ICEVs.

Table 8: Comparison for all scenarios between the ECV and ICEV results.

Scenario	I	II	III	IV	V	VI	VII	VIII	IX	X	XI	XII
$n^{\text{ECV}} - n^{\text{ICEV}}$	0	0	0	0	0	0	0	0	0	0	0	0
$n^{\text{driver,ECV}} - n^{\text{driver,ICEV}}$	0	0	0	0	0	0	0	0	0	0	0	0
$D^{\text{ECV}} - D^{\text{ICEV}}$ [%]	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.28	0.00
$\bar{D}^{\text{ECV}} - \bar{D}^{\text{ICEV}}$ [%]	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.28	0.00
$Inv^v, \text{ECV} - Inv^v, \text{ICEV}$ [%]	61.36	61.36	61.36	61.36	61.36	61.36	61.36	61.36	61.36	61.36	61.36	61.36
$Oper^{\text{driver,ECV}} - Oper^{\text{driver,ICEV}}$ [%]	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
$Oper^{\text{dist,ECV}} - Oper^{\text{dist,ICEV}}$ [%]	-77.23	-77.23	-77.23	-77.23	-77.23	-77.23	-77.23	-77.23	-77.23	-77.23	-77.17	-77.23
$TCO^{\text{ECV100l}} - TCO^{\text{ICEV}}$ [%]	-1.33	-2.43	-4.52	-4.71	-4.35	-4.43	-4.61	-4.89	-4.11	-4.90	-4.79	-4.86
$TCO^{\text{ECV90l}} - TCO^{\text{ICEV}}$ [%]	-4.16	-5.27	-7.08	-7.32	-6.94	-7.10	-7.13	-7.33	-6.71	-7.41	-7.24	-7.30
$TCO^{\text{ECV80l}} - TCO^{\text{ICEV}}$ [%]	-7.00	-8.10	-9.64	-9.93	-9.53	-9.77	-9.66	-9.77	-9.32	-9.91	-9.69	-9.75
$TCO^{\text{ECV100h}} - TCO^{\text{ICEV}}$ [%]	-1.33	-2.43	-4.52	-0.80	7.50	8.79	13.76	15.72	17.74	19.37	23.41	23.32
$TCO^{\text{ECV90h}} - TCO^{\text{ICEV}}$ [%]	-4.16	-5.27	-7.08	-3.41	4.92	6.12	11.24	13.28	15.14	16.87	20.96	20.88
$TCO^{\text{ECV80h}} - TCO^{\text{ICEV}}$ [%]	-7.00	-8.10	-9.64	-6.02	2.33	3.45	8.71	10.83	12.53	14.36	18.51	18.43

The table shows the differences between the quantities described in Table 5 and Table 6.

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