Are ECVs breaking even?
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Competitiveness of electric commercial vehicles in medium–duty logistics networks

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Abstract

Within this paper, the competitiveness of electric commercial vehicles in medium-duty mid-haul logistics is evaluated for a specific case study. This is done combining an aggregated total cost of ownership analysis with integrated vehicle routing and location routing model components for the routing of vehicles within the network and for locating charging stations at stores. Thus, a fair comparison of electric commercial vehicles and internal combustion engine vehicles is performed.

Results show that for this specific case study nearly no operational limitations arise with the electrification of the mid-haul logistics fleet. Moreover, electric commercial vehicles show clear advantages 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

1. Introduction

Transportation contributes significantly to climate change at a global level as well as to noxious air emissions, particulate matter and noise emissions at a local level. Therefore, a change towards environmentally friendly freight distribution is necessary. This can be achieved 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 gas, nor noxious emissions, nor particulate matter. If all energy used for charging of the 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 two major disadvantages of electric vehicles: limited driving range and long charging times. In addition, the portfolio of acquirable ECVs with sufficient load capacity is very sparse if 7.5 tonne and 12 tonne medium–duty ECVs are addressed.

However, first pilot projects on electric logistic fleets have been launched. For instance, DPDHL has launched a first electric fleet delivering letters and small packages for postal services in German cities. After a first fleet of 12 Renault Kangoo ZE was tested as early as 2011 (DPDHL, 2011), a larger pilot project has been launched in 2013 aiming at zero emission deliveries for a city region with 310,000 inhabitants (Pieringer, 2013; DPDHL, 2013, 2014b). Because of the positive project development, DPDHL eventually bought the company, which manufactured the ECVs that were used in the field tests (DPDHL, 2014a). However, it has to be stated that these and other projects (e.g. UPS, 2013) all focus on short haul applications, where range and charging times on routes as the main operational disadvantages of ECVs in mid-haul transportation play only a minor role. For mid-haul applications, logistics fleet operators still perceive ECVs as less (time) efficient and thus less competitive than ICEVs. Therefore, even pilot projects on medium duty ECVs are still sparse.

One extensive field test focusing on medium duty ECVs has been conducted in Germany within the research project ELMO 'Elektromobile urbane Wirtschaftsverkehre' ('electrified commercial transport in urban areas'). ELMO was initiated as a lighthouse project of the German federal government (co–funded by the German state), and managed by Fraunhofer IML. The objective of the project was to evaluate competitiveness of ECVs compared to ICEVs, and to assess how ECVs can be integrated in existing fleets and mid haul logistics operations. During the project period from 2011 to 2015, energy consumption and charging behaviour of twelve mid range electric utility vehicles 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. One of the key results of this project is that medium sized ECVs are on the verge of breaking even in (urban) mid-haul distribution. This holds especially, since ECVs become more competitive with increasing overall traveled distance (cf. Lee et al., 2013; Feng and Figliozzi, 2013; Davis and Figliozzi, 2013).

Based on such promising results, the question now is if and to what extend a further electrification of mid–haul logistics fleets is feasible and worthwhile. In order to answer this question, it is no longer sufficient to calculate costs based on the tracking results of single vehicles as it was so far done in ELMO. Instead, it has to be analyzed if and how medium sized ECVs can be integrated into logistics networks fulfilling all real–world demand and delivery requirements. Thereby, the aim must be to minimize operational disadvantages with regard to range limitations and charging times (Stütz et al., 2016). This requires that optimal routing decisions are taken considering the specific characteristics of ECVs. In addition, as the decision for integrating ECVs is taken for the first time, there is a need to design a cost efficient charging infrastructure in order to allow for a high utilization of the vehicles. As these decisions are interdependent (since routing decisions depend on charging station locations, and the locating of charging stations depends on underlying route patterns), integrated routing and network design aspects have to be regarded when comparing ECVs and ICEVs.

Against this background, the aim of this paper is to derive the first competitiveness analysis for the integration of medium duty ECVs in mid–haul transportation within real–world logistics networks considering network design and vehicle routing decisions. According to the specific planning situation, the following requirements have to be considered by this analysis:

- The specific characteristics of ECVs regarding range limitations and charging demand have to be regarded when determining routes within the logistics network.
- As the decision for an integration of ECVs is taken for the first time, we assume that there are no charging stations in the logistics network yet. Thus, optimal positions of charging stations have to be determined.
- As decisions on locating charging stations and designing future routes of ECVs are interdependent (cf. Schiffer and Walther, 2015), these decisions have to be taken simultaneously to warrant an optimal logistics network design.
- The approach must be able to regard real–world logistics requirements like service times as well as demand patterns and time windows for delivery at customers or stores.
- Also, real–world data available from field tests (like ELMO) should be used in order to avoid over- or underestimation of energy consumption rates and charging as well as

driving times. Thus, case specific real-world driving times and driving speed based on road types and traffic have to be considered. In addition, information on the real-world energy consumption of the vehicles has to be used if available from field tests.

- Based on discussions with fleet operators in ELMO, it is assumed that charging stations can be located at stores, and that service time can be used for charging.
- Also, partial recharging is allowed as technical analyses show that partial recharging does not lead to disadvantages with regard to the life time of the battery. On the contrary: As deep discharging is considered to contribute to an accelerated battery degradation, partial recharging and opportunity charging are regarded as a key success factor to prolong battery lifetime.

Taking those requirements into consideration, we provide an integrated planning apporoach which combines total cost of ownership (TCO) calculations based on real-world data of research projects like ELMO with Vehicle Routing Problem (VRP) and Location Routing Problem (LRP) planning components for ECV and ICEV fleets. Results are compared with respect to the overall cost for both fleets in order to assess the competitiveness of medium–duty ECVs within mid–haul transportation. Furthermore, we investigate the emission savings to quantify the ecological benefit of an electric logistics fleet. Based on those results, we provide managerial insights for logistics fleet operators as far as the cost efficiency and competitiveness of ECVs for medium–duty mid–haul transportation is concerned. In addition, the environmental benefit is discussed for political (and societal) decision makers following sustainability targets.

The remainder of this paper is structured as follows: In Section 2, an overview of recent literature on planning approaches for electric logistics fleets as well as on feasibility studies and cost analysis for ECVs is given. A mixed integer formulation of our integrated planning system as well as a solution method for large sized networks is introduced in Section 3. Our real world case study, based on empirical data, is derived in Section 4. In Section 5, results are presented, deriving insights on the competitiveness of ECVs compared to ICEVs from an economical as well as an ecological perspective. A conclusion of the main findings and an outlook on future research is given in Section 6.

2. Literature Review

Recent research on ECVs has been done focusing on either aggregated cost analysis (TCO calculations) to investigate the competitiveness of ECVs based on assumptions regarding the number of vehicles, charging times and range, or on VRPs with additional ECV specific constraints in order to provide operational decision support on routing and charging. Within this chapter, a brief overview on these two research streams is given in order to highlight the necessity of considering both components in a profound competitiveness analysis. For an extensive overview on research with respect to electric vehicles in goods distribution we refer to Pelletier et al. (2016).

Most approaches which try to evaluated the competitiveness of ECVs use aggregated TCO calculations. Those calculations are used to compare the life cycle costs of ECVs and ICEVs. TCOs are in general based on suppositions and assumptions regarding external and operational parameters, which are often discussed using a sensitivity analysis.

Lee et al. (2013) provide a TCO calculation for medium–duty ECVs, taking realistic energy consumption and realistic driving cycles within a range between 48 km and 96 km into consideration. The key findings are that ECVs become more competitive the higher the overall traveled kilometers are and the more the driving pattern is characterized by stops and low speeds. Feng and Figliozzi (2013) compare the TCO of ECVs and ICEVs focusing on different fleet and battery replacement scenarios. They find that ECVs become competitive in 3 out of 6 considered scenarios, if the total daily mileage per vehicle exceeds 129 kilometers. However, the competitiveness decreases significantly if battery replacement is taken into consideration. Davis and Figliozzi (2013) provide a TCO analysis taking fuel consumption, approximated routing constraints, battery replacement and real–world speed profiles into consideration. The analysis finds that a high vehicle utilization as well as certain route characteristics (frequent stops, congested streets, idling motors) increase the competitiveness of ECVs compared to ICEVs. Taefi et al. (2016) provide a TCO analysis of ECVs focusing on the cost-optimal balance between a high vehicle utilization and the resulting increase in required battery replacements due to battery degradation.

Concluding, recent research has been provided on the competitiveness of ECVs based on TCO calculations. Results show that the competitiveness of ECVs increases with higher overall driving distances and higher vehicle utilization because of low operational and high investment costs of ECVs. However, all of these calculations are focusing on short haul transportation with overall driving ranges of less than 125 kilometers. Charging on routes to extend the driving range as well as operational routing constraints are not considered within those analyses.

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 pick up or delivery routes for conventional logistics fleets. These models have recently been extended addressing additional constraints for logistics fleets with ECVs.

Conrad and Figliozzi (2011) present the Recharging VRP (RVRP), considering battery capacity limitations of ECVs and charging opportunities at customer vertices. The first model that considers additional vertices allowing for charging activities for any kind of alternative fuel vehicle (AFV) is introduced as the Green VRP (GVRP) by Erdoğan and Miller-Hooks (2012).

The first model that is explicity focusing on charging stations for ECVs has been introduced by Schneider et al. (2014) as the Electric VRP with Time Windows (EVRP-TW). This model has been extended for mixed fleets consisting of ECVs and ICEVs by Goeke and Schneider (2015), and for heterogeneous electric vehicles by Hiermann et al. (2016). Further extensions considering partial recharging and different charging technologies have been proposed by Felipe et al. (2014) and Keskin and Çatay (2016). However, all these approaches do not allow for siting of charging stations, since the general assumption is that locations for charging stations are already fixed and that only routing decisions have to be taken.

Only a few approaches have been published so far that address a charging station location decision and a vehicle routing decision simultaneously, and thus allow to consider the interdependencies between these decisions. Yang and Sun (2015) provide the Battery Swap Station Electric Vehicle LRP (BSS-EV-LRP) focusing on simultaneous routing and swapping station location decisions for ECVs with swappable batteries. Schiffer and Walther (2015) introduce the Electric LRP with Time Windows and Partial Recharges (ELRP-TWPR), focusing on simultaneous routing and location decisions taking time window constraints as well as partial recharging into consideration. A generalized model formulation and a generic solution method for the LRP with Intraroute Facilities (LRPIF) is presented by Schiffer and Walther (2016).

So far, the EVRP-TW and the ELRP-TWPR as well as the BSS-EV-LRP are mainly applied to test instances from literature, to show the applicability and competitiveness of the developed models and solution methods. Thus, their focus is not on applications to real–world case studies so far. As a result, instances often have a limited number of customers. Additionally, fictitious cost parameters or only ratios between fixed and variable costs are used for evaluation, since costs are not derived from real-world pilot projects or based on tracking of vehicles. Also, a detailed TCO calculation is not carried out. Simplifying assumptions are often taken, e.g. the energy consumption is assumed to be linear dependent on driven distance instead of depending on the topography, types of streets and traffic.

Concluding, several planning approaches for operational planning as well as strategic network design have been proposed recently, focusing on different charging options and different fleet types. However, none of these approaches evaluates the competitiveness of ECVs for a real–world case taking integrated locating and routing decisions with all real–world constraints as well as real–world TCO calculations into consideration. Against this background, 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 fictitious instances.

3. Methodological Background

This section introduces our integrated planning approach to assess the competitiveness of ECVs in mid–haul transportation compared to ICEVs. First, a short introduction into TCO calculations is given in Section 3.1. Thereby, we distinguish between data that can be derived from external sources, e.g. manufacturers of ECVs and tracking of vehicles, and data that can only be gathered after endogeneous decisions on network design and routing of vehicles within the logistics network have been taken. In order to gather this endogeneous information, a mixed integer formulation for the necessary strategical and operational planning tasks is given in Section 3.2. Since the resulting models are hard to solve in reasonable time for large real–world instances, an efficient metaheuristic solution approach to derive high quality results is briefly described in Section 3.3.

3.1. Total cost of ownership calculation

In order to assess the competitiveness of ECVs against ICEVs, a TCO calculation for the respective vehicles is necessary, considering costs over time as well as a time dependent discount. For both, ECVs as well as ICEVs, the TCO can be calculated with (3.1) in a general fashion.

$$TCO = \sum_{t=0}^{T} \frac{Inv_t}{(1+r)^t} + \sum_{t=0}^{T} \frac{Fix_t}{(1+r)^t} + \sum_{t=1}^{T} \frac{Var_t}{(1+r)^t} \tag{3.1}$$

We consider three cost components: While Inv_t represents one-time investments in period t (e.g. vehicle investment costs, investment costs for charging stations), Fix_t denotes periodically (annually) arising fixed costs (e.g. circulation tax, annual maintenance), and Var_t denotes distance dependent costs (e.g. costs for energy, distance dependent maintenance). The discount rate $(1+r)^{-t}$ is defined by the discount factor r.

Inv_t and Fix_t depend on structural network decisions, e.g. the number of vehicles (for ICEVs), respectively the number of vehicles and charging stations (for ECVs), utilized within the logistics network. A fixed cost parameter can be determined merging investment and annual fixed costs for vehicles (c^{v}) and for charging stations (c^{s}) based on manufacturers' and fleet operators' information on prices and maintenance costs for ECVs, ICEVs and charging stations. Note within this context, that suppliers of electric delivery trucks often sell their vehicles in combination with suitable charging infrastructure (cf. Stütz et al., 2016). This cost parameter can then be multiplied with the number of vehicles and charging stations needed for operating the logistics network.

Var_t represents the costs that result from the overall driven distance within the logistics network and thus can be expressed as $Var_t = c^o d_t$ with a distance dependent cost term (c^o) [€/km] and the overall driven distance within the network during a certain period d_t [km]. Again, the cost term for distance dependend variable costs can be derived externally, for instance based on manufacturers' information or by tracking the energy demand of vehicles as done in the ELMO project. However, the driven distance has to be determined depending on chosen routes within the logistics network.

In the following, we show how the endogenous variables, i.e. the number of vehicles and charging stations as well as the total distance driven in order to fulfill demand within the logistics network, can be determined by solving routing models or respectively integrated routing and charging station location models.

3.2. Vehicle routing and charging station locating planning components

To assess the number of vehicles and charging stations as well as the total driven distance, decisions on the network design and the network operation have to be taken. Thus, different VRP or LRP based modeling components are presented in the following depending on the specific fleet type. The required mixed integer program (MIP) planning components can be developed stepwise starting with the current planning situation.

Thus, we first derive a VRP component, which is sufficient for the current ICEV fleet since no siting of charging stations is needed. In this case it is sufficient to determine the number of vehicles needed and the routes driven (respective the total distance when aggregated) for operating the network. Afterwards, this model is extended in order to explicitly take range and charging limitations of ECVs into account. This allows to assess operational, distance dependent costs and vehicle costs for an ECV fleet in a given network configuration (i.e. where charging stations already exist). However, the locations of charging stations have to be determined when an ECV fleet is installed for the first time. Therefore, the planning model is further extended to a LRP approach to determine the number and locations of charging stations in case that a first-time investment decision has to be taken. Doing so, the total number and locations (and thus resulting costs) of charging stations is determined in case the network structure has to be established.

All three planning components can be modeled with a set of vertices $\mathcal{V}_{0,n+1}$ and a set of arcs $\mathcal{A}$ on a directed and complete Graph $G = (\mathcal{V}_{0,n+1}, \mathcal{A})$ as a mixed integer program as follows: 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. $\mathcal{F}$ is defined as a set of additional potential charging station vertices. To allow for multiple visits to charging stations a set of dummy vertices $\mathcal{S}$ is used and can be divided into subsets $\mathcal{S}_\kappa$, containing dummy vertices for each real vertex κ. The ingoing and the outgoing depot are represented by vertex 0 and $n+1$ respectively. Thus, sets indexed by 0, $n+1$ or $0, n+1$ include the respective depot vertices. To provide a concise model formulation, we define a cut set $\delta\left(\mathcal{B}\right)$ of any arbitrary subset $\mathcal{B}$ of $\mathcal{V}_{0,n+1}$ as $\delta\left(\mathcal{B}\right) = \{(i,j) \in \mathcal{A} : i \in \mathcal{B}, j \in \mathcal{B}\}$ as the set of all arcs with exactly both endpoints in $\mathcal{B}$. Analogously $\delta^+\left(\mathcal{B}\right) = \{(i,j) \in \mathcal{A} : i \in \mathcal{B}, j \notin \mathcal{B}\}$ defines all outgoing arcs of $\mathcal{B}$ and $\delta^-\left(\mathcal{B}\right) = \{(i,j) \in \mathcal{A} : i \notin \mathcal{B}, j \in \mathcal{B}\}$ defines all ingoing arcs of $\mathcal{B}$ respectively. In the following, those definitions are also used for singleton sets $\mathcal{B} = \{i\}$ by using $\delta^x\left(i\right) := \delta^x\left(\{i\}\right), \forall x \in \{+, \ , -\}$. In order to model time constraints, customer time windows $[e_i, l_i]$ are obtained to any vertex i, defining the earliest (e_i) and latest (l_i) time at which service is allowed to start at vertex i. The service time at any customer vertex i is given by s_i, while the driving time along arc (i,j) is given by t_{ij}. To estimate, if time windows remain feasible, the arrival time τ_i at any vertex i is used. In order to consider freight constraints, f_i depicts the amount of freight available within a vehicle at vertex i, while the demand of any customer i is given by p_i and each vehicles freight capacity is limited to F. The distance of arc (i,j) is given by d_{ij} Constraints on energy consumption are modeled using q_i as a vehicles state of charge at vertex i. Furthermore, the amount of energy recharged at vertex i is determined by w_i and a recharging rate r is used to calculate recharging times based on w_i. 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} is used to determine whether arc (i,j) is traveled or not. Since we match routes to vehicles during postprocessing, no additional vehicle index is needed. Binary y_i determines if a charging station is located at vertex i.

Routing component for ICEVs

To assess the overall costs of the ICEV vehicle fleet, fixed vehicle costs per route c^{v} and distance dependent operational costs c^{o} have to be considered. In this context, the number of routes is identified by the number of depot leaving arcs $(x_{0j} = 1)$ and the overall traveled distance is identified by the overall number of used arcs $(x_{ij} = 1)$. Thus, the TCO for the ICEV based logistic fleet is described by (3.2). Note within this context, that discount rates and other external factors are already included within c^{v} and c^{o}, and that costs are converted to the same period the network operation is optimized for (e.g. daily or weekly).

$$\min \quad TCO^{ICEV} = \sum_{j \in \delta^+(0)} c^{\mathrm{v}} x_{0j} + \sum_{(i,j) \in \delta(V_{0,n+1})} c^{\mathrm{o}} d_{ij} x_{ij} \tag{3.2}$$

Constraints for this planning component hold as follows: Constraints (3.3) enforce any customer to be visited exactly once. Flow conservation of vehicles is obtained by (3.4) and necessary to

Table 1: Decision variables and parameter definitions.

0	depot vertex departure
$n+1$	depot vertex arrival
$\mathcal{C}$	set of customer vertices
$\mathcal{F}$	set of potential recharging vertices
$\mathcal{S}_\kappa$	set of dummy vertices for vertex $\kappa \in \{\mathcal{C} \cup \mathcal{F}\}$
$\mathcal{S}$	set of all dummy vertices $(\bigcup_{\kappa \in \{\mathcal{C} \cup \mathcal{F}\}} \mathcal{S}_\kappa)$
$\mathcal{V}$	set of all vertices without depot vertices $(\mathcal{C} \cup \mathcal{F} \cup \mathcal{S})$
x_{ij}	binary: arc (i,j) is traveled
y_i	binary: recharging station is sited at vertex i
τ_i	arrival time at vertex i
w_i	amount of energy charged at vertex i
q_i	battery load at vertex i
f_i	freight load at vertex i
e_i	earliest time of arrival allowed at vertex i
l_i	latest time of arrival allowed at vertex i
s_i	service-time at vertex i
p_i	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

The table is subdivided as follows: indices and sets / decision variables / parameters / bounds.

create connected tours. Constraints obtaining time window feasibility are given by (3.5) and (3.6). Constraints (3.5) determines the arrival time at vertex j after departing from a customer vertex i, taking service and driving time into consideration. Time window feasibility is obtained by (3.6). Freight constraints are given by (3.7) and (3.8), obtaining a freight balance between any vertices and limiting the vehicles freight capacity. With those constraints, Miller-Tucker-Zemlin subtour elimination is used to avoid circles in tours. The definition range of binary variables x_{ij} is given by (3.9).

$$\sum_{j \in \delta^+(i)} x_{ij} = 1 \qquad \forall i \in \mathcal{C} \quad (3.3)$$

$$\sum_{j \in \delta^-(i)} x_{ji} - \sum_{j \in \delta^+(i)} x_{ij} = 0 \qquad \forall i \in \mathcal{V} \quad (3.4)$$

$$\tau_j \geq \tau_i + (t_{ij} + s_i)\, x_{ij} - l_0 \,(1 - x_{ij}) \qquad \forall i \in \mathcal{C}_0,\ \forall j \in \delta^+(i) \quad (3.5)$$

$$e_i \leq \tau_i \leq l_i \qquad \forall i \in \mathcal{V}_{0,n+1} \quad (3.6)$$

$$0 \leq f_j \leq f_i - p_i x_{ij} + F\,(1 - x_{ij}) \qquad \forall (i,j) \in \delta\,(\mathcal{V}_{0,n+1}) \quad (3.7)$$

$$0 \leq f_0 \leq F \quad (3.8)$$

$$x_{ij} \in \{0;1\} \quad \forall (i,j) \in \delta\,(\mathcal{V}_{0,n+1}) \qquad y_i \in \{0;1\} \quad \forall i \in \mathcal{V} \quad (3.9)$$

Routing component for ECVs

To assess the costs of an ECV fleet within an existing network configuration (i.e. charging stations are existing), an extended VRP component can be used. In this case, Objective (3.2) and constraints (3.3)–(3.9) remain equal, but additional constraints have to be added to model the charging and energy consumption behavior for ECVs. The single assignment constraint that is obtained for customers is relaxed for all other charging station vertices by (3.10). Even if a visit is only necessary if a recharge takes place, single assignment has to be secured in order to be capable of identifying arrival times at vertices, since we do not use a vehicle index in our MIPs. Charging times are integrated into the time window constraints for any vertex by Constraints (3.11). Constraints related to the energy consumption are added by (3.12)–(3.15). Energy consumption along arcs is modeled by constrains (3.12) and (3.13). Note that charging processes are only considered within (3.13), since vehicles are assumed to start with a full battery at the depot.

$$\sum_{j \in \delta^+(i)} x_{ij} \leq 1 \qquad \forall i \in \{\mathcal{V} \setminus \mathcal{C}\} \quad (3.10)$$

$$\tau_j \geq \tau_i + t_{ij} x_{ij} + r\ w_i - (l_0 + rQ)\,(1 - x_{ij}) \qquad \forall i \in \mathcal{V},\ \forall j \in \delta^+(i) \quad (3.11)$$

$$q_j \leq q_0 - h_{0j} x_{0j} + Q\,(1 - x_{0j}) \qquad \forall j \in \delta^+(0) \quad (3.12)$$

$$0 \leq q_j \leq q_i + w_i - h_{ij} x_{ij} + Q\,(1 - x_{ij}) \qquad \forall (i,j) \in \delta\,(\mathcal{V}_{n+1}) \quad (3.13)$$

$$0 \leq q_0 \leq Q \quad (3.14)$$

$$0 \leq q_i + w_i \leq Q \qquad \forall i \in \mathcal{V} \quad (3.15)$$

With those additional constraints, overall vehicle and operational costs of the ECV fleet can be estimated combining constraints (3.3)–(3.15) with objective (3.2). However, if an ECV fleet is installed for the first time, costs for installation of charging stations have to be considered as well.

Integrated routing and siting component for ECVs

Since the decision on the optimal number and position of charging stations within a logistics fleet network is interdependent with operational routing decisions (cf. Schiffer and Walther, 2015), the respective VRP component has to be extended even further. First, the objective function is extended to allow the consideration of costs for charging stations. Note within this context, that costs for charging stations may vary significantly due to construction work, which might be necessary to connect the charging station location to a higher level of the electric distribution grid. Doing so, the binary variable y_i, indicating if a charging station is located at vertex i or not, is multiplied by the cost term c^{s} for installation and maintenance of charging stations. Thus, in order to calculate the TCO for the ECV logistics network, (3.2) is substituted by (3.16).

$$\min \quad TCO^{ECV} = \sum_{i \in \mathcal{C} \cup \mathcal{F}} c^{\mathrm{s}} y_i + \sum_{j \in \delta^+(0)} c^{\mathrm{v}} x_{0j} + \sum_{(i,j) \in \delta(V_{0,n+1})} c^{\mathrm{o}} d_{ij} x_{ij} \tag{3.16}$$

In addition, charging station location decisions have to be integrated into the MIP by constraints (3.17)–(3.19). While (3.17) only allows for charging at vertex i if a charging station is located, (3.18) prevents 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 (3.19). The definition range of binary variables y_i is given by Constraints (3.20)

$$w_i \leq Q y_i \qquad \forall i \in \mathcal{V} \tag{3.17}$$

$$y_i \leq w_i \qquad \forall i \in \mathcal{S} \tag{3.18}$$

$$y_i \geq y_j \qquad \forall i \in \{\mathcal{V} \setminus \mathcal{S}\},\ \forall j \in \mathcal{S}_i \tag{3.19}$$

$$y_i \in \{0; 1\} \qquad \forall i \in \mathcal{V} \tag{3.20}$$

With those constraints, the charging station costs for the ECV fleet can be calculated using Objective (3.16) with constraints (3.3)–(3.20).

3.3. Solution method

Due to the computational complexity of the presented MIP formulations, only small sized instances can be solved to optimality within reasonable computational time using commercial solver packages. Algorithmic challenges especially exist for the routing and siting components of the ECVs. For instance, it is necessary to develop methods for time efficient evaluation of search moves for partial recharging. Also, efficient meta-heuristics are needed to determine appropriate configurations of charging stations and routes. Therefore, we use the solution

while $(\iota < \eta^{\max})$ **and** $(\iota - \iota_{\text{imp}} < \eta^{\max}_{\text{noi}})$ **do**
  if $\big($**modulo** $\left(\iota, \eta^{\text{lrg}}\right) = 0\big)$ **then**
    $\sigma' \leftarrow destroyAndRepair(\mathcal{D}_{\text{l}}, \mathcal{R}, \pi, \sigma)$
  else
    $\sigma' \leftarrow destroyAndRepair(\mathcal{D}_{\text{s}}, \mathcal{R}, \pi, \sigma)$
  if $\big(\lambda(\sigma')) < \lambda(\sigma^*)\left(1 + \delta^{\text{l}}\right)\big)$ **then**
    $\sigma' \leftarrow localSearch(\sigma')$
    if $\big(\lambda(\sigma') < \lambda(\sigma^*)\left(1 + \delta^{\text{d}}\right)\big)$ **then**
      $\sigma' \leftarrow dynamicProgramming(\sigma')$
  if $(\lambda(\sigma') < \lambda(\sigma^*))$ **then**
    $\sigma^* \leftarrow \sigma'$
    $\sigma'_{\text{f}} \leftarrow generateFeasibleSolution(\sigma')$
    if $feasible(\sigma'_{\text{f}})$ **and** $(\lambda(\sigma'_{\text{f}}) < \lambda(\sigma^*_{\text{f}}))$ **then**
      $\sigma^*_{\text{f}} \leftarrow \sigma'_{\text{f}}$
      $\iota_{\text{imp}} \leftarrow \iota$
  if $($**modulo** $(\iota, \eta^{\text{res}}) = 0)$ **then**
    $\sigma \leftarrow \sigma^*_{\text{f}}$
  $\iota \leftarrow \iota + 1$

Figure 1: Pseudo code of the used meta–heuristic presented in Schiffer and Walther (2016).

method developed in Schiffer and Walther (2016), since this method is able to provide high quality solutions for several LRPIF and equivalent VRP problems. The algorithm is a hybrid of Adaptive Large Neighborhood Search (ALNS), dynamic programming and local search using a generalized cost function with penalty terms to evaluate infeasible regions of the search space. In the following, we briefly describe the main idea of this meta–heuristic. Since the scope of this paper is to evaluate the competitiveness of ECVs, we refer to Schiffer and Walther (2016) for further algorithmic and mathematical explanations of the used algorithm.

Figure 1 shows a condensed pseudocode of the used algorithm. The core of the used meta-heuristic 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 operator choice in each search step.

Within the ALNS the current solution σ is destroyed in each search step by a destroy operator. The destroy operators are divided into two sets: Large destroy operators out of set $\mathcal{D}_{\text{l}}$ change the charging station configuration, while small destroy operators out of set $\mathcal{D}_{\text{s}}$ change only the route configurations. Afterwards, a new solution is created using a repair operator out of the set of all repair operators $\mathcal{R}$. If the temporary solution σ' obtained after a destroy and repair step is within a certain corridor δ^{l} to the best solution σ^*, an additional local search procedure is used for intensification. If the obtained solution is within a certain corridor δ^{d} to the best solution σ^* afterwards, an additional dynamic programming component is used to identify the optimal facility configuration on each route evaluating a limited search tree. During the search phase, the best as well as the best feasible (σ_{f}^*) solution are stored to overcome infeasible regions of the searching space. 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 $\eta_{\mathrm{noi}}^{\mathrm{max}}$ iterations. This method can be used to solve the LRP component for the ECV fleet. In addition, this algorithm has also proven to provide high quality results for VRP components (cf. Schiffer and Walther, 2016), and thus can also be used to solve the VRP components for ICEVs and ECVs by skipping the large destroy operators.

4. Case study

Within this section, the real–world case study as well as the the experimental design for the assessment of the competitiveness of ECVs are explained. First, we provide general information on the real-world logistics network and derive resulting planning tasks in Section 4.1. Second, we describe the experimental design which is used to evaluate the competitiveness of medium duty ECVs in mid–haul transportation systems in Section 4.2. Third, cost terms which are used within the integrated planning approach are derived in Section 4.3.

4.1. Logistics network and resulting planning tasks

Since the aim is to assess competitiveness of ECVs in real–world logistics networks, an application on a case study with real–world data and constraints is necessary to derive realistic results. To do so, we base our analysis on the integration of ECVs into the real–world logistics network of a company that participated in the ELMO project. The 'TEDi Logistik GmbH & Co. KG' (from here on referred to as 'TEDi Logistik') is a direct subsidiary of the German retail company 'TEDi' that operates about 1,400 stores all over Europe, selling a broad range of non-food articles (TEDi, 2016). Within each distribution area, TEDi Logistik's main purpose is to supply TEDi's stores with new goods, coming on pallets or roller containers from a central warehouse, and to collect empty pallets and roller containers from each store in order to haul them back to a central warehouse. Our real world case focuses on a distribution area (cf. Figure 2) within 'Northrine Westfalia', a federal state of Germany, which has also been the area of the ELMO field test. In this area, 302 stores are supplied from a central warehouse of about 42,000 square metres, which is located in Dortmund. The TEDi stores are located within a vicinity of 190 kilometers around a central warehouse, which is a typical range for mid–haul

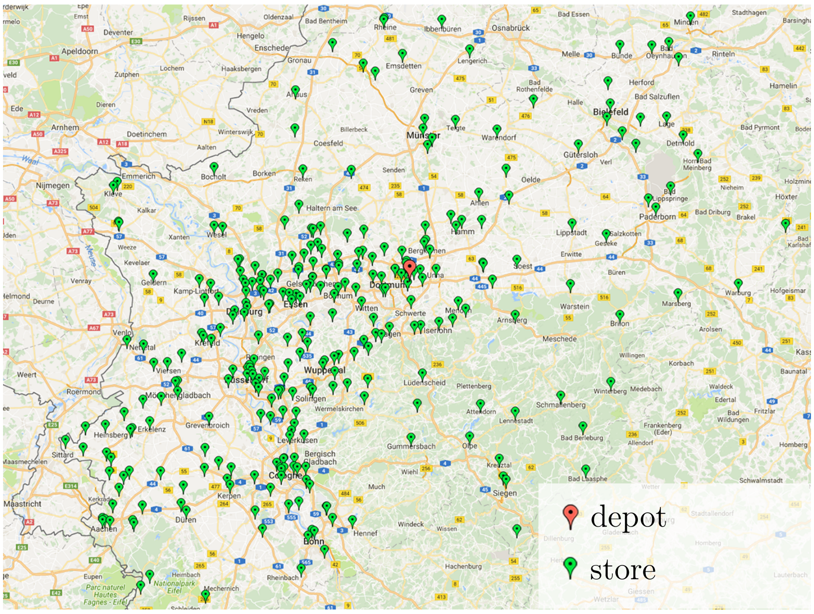

Figure 2: Logistics network structure of TEDi

transportation. Stores are usually served once or twice a week, whereby time windows for deliveries are given by the opening times of the stores on a working day. The average weekly demand of each store is derived from 2015 data. On average (median), each store receives six pallets per delivery stop (standard deviation=2.06, min=4, max=12). In contrast to package or general cargo companies, the network and demand structure at TEDi does not allow for an assignment of vehicles to fixed service areas. Instead, routing is necessary in order to calculate optimal delivery plans that allow for a high utilization of vehicles.

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. Usually, 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 second shift in order to allow for a change of drivers and for reloading. During the ELMO project, two of the medium duty trucks were replaced by battery-electric trucks converted by EMOSS. During the course of the ELMO-project, EMOSS developed the blueprints and the retrofit truck concept which eventually became the model CM1216, introduced by EMOSS in May 2014 (EMOSS, 2016). In a pilot phase, these trucks were used within a catchment area of 70 km around the central warehouse to replenish selected TEDi stores. The trucks had to drive back to the central warehouse once or twice a day in order to connect the battery to a quick charger for recharging. Data covering a total mileage of 33,000 km was gathered during the field test in the ELMO project. Based on this data, real charging rates as well as energy consumption rates and traveling times can be used when modeling the logistics network and the ECV behavior.

As mentioned above, the ECVs had to go back to the central warehouse for recharging due to driving range limitations (200 km at maximum) and the operation of ECVs was therefore limited to a vicinity of 70 km around the warehouse in the ELMO project. However, this was not the result of an optimal routing decision, but rather a fixed manual assignment of vehicles to customers and routes (based on assumptions on range and charging demand) that was taken at the beginning of the ELMO project. If an extensive integration of ECVs in the logistics network is pursued, optimal routing decisions for all vehicles considering range limitations and charging times have to be taken. Additionally, charging on routes (i.e. at TEDi stores), and thus the installation of charging stations within the network has to be considered to allow the ECVs to travel larger distances from the central warehouse. Thus, the competitiveness of ECVs in mid–haul transportation can only be determined if vehicle routing and charging station location decisions are taken in an optimal way. In the following, the experimental design is presented to analyze if and to what extend ECVs can be integrated in the logistics network of TEDi.

4.2. Experimental design

To evaluate the competitiveness of the two vehicle concepts, a TCO analysis as described in Section 3 is conducted for a pure ICEV as well as a pure ECV fleet. As already stated (see Section 3), cost factors merged over investment and fixed costs for vehicles (c^{v}) and for charging stations (c^{s}) are derived from literature and from manufacturers' information, while cost factors for operational driving costs (c^{o}) are determined based on the tracking data gathered in the ELMO project. The cost factors are presented in more detail in Table 3 in Section 4.3. However, the decision variables these cost factors have to be multiplied with, i.e. the number of vehicles, the number of charging stations and the total distance driven, have to be determined endogenously.

Decision stages

As depicted in Section 4.1, the planning tasks to estimate the overall costs vary with respect to the considered vehicle type. Therefore, we calculate results for both vehicle types using the following two stage solution approach:

Network structure: Within the first stage, the network structure has to be determined with regard to fueling/charging of vehicles. For the ICEV fleet, the network structure can be assumed to be sufficient as there are comprehensive filling stations (combined with a long range) and thus, fueling is not limiting the operation of the network. Therefore, no decisions have to be taken on this step for ICEVs. However, an appropriate charging station configuration has to be determined for ECVs, since there are currently no charging stations installed in the logistics network. Thus, the lack of charging infrastructure (combined with a limited range) is currently limiting the operation of the ECVs. Therefore, optimal locations of charging stations are determined using the LRP approach presented in Section 3.2. Using this integrated approach results in an optimal design of a medium–duty logistics network with charging stations allowing for an optimal operation of ECVs.

Network operation: On a second stage, the operation of the vehicles within the network is optimized, i.e. decisions on routes and the number of vehicles are taken. This is done using the VRP component for ICEVs and ECVs presented in Section 3.2. In order to allow for a fair comparison between the two vehicle types, the same algorithmic parameters as stated in Schiffer and Walther (2016) are used for applying the VRP to both vehicle types. Thus, the solution quality of the routing decisions is kept comparable (which is why we do not use the routing decisions that were determined in the network structure stage with the LRP component for the ECVs).

Electrification rate

So far, ECVs have only been used within a vicinity of 70 km around the central warehouse. In order to analyse an increasing electrification of the logistic fleet, we model a stepwise coverage of the network by ECVs. Thus, we assume customers which are closer to the depot to be served by ECVs first, which is a reasonable assumption due to driving range limitations. We investigate the competitiveness of ECVs for larger catchment areas by allowing for recharging on routes. In total, we derive 12 scenarios considering all stores within an catchment area with a radius between 80 km and 190 km around the central warehouse, using a step width of 10 km. The resulting instances contain between 144 and 302 stores (cf. Table 2). Doing so, a comparison of the TCO for the resulting network operated exlusivelyby ICEVs with the TCO for the resulting network operated exlusively by ECVs allows to assess competitiveness of ECVs for each scenario.

Table 2: Number of customers per instance.

scen.	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. store) for each scenario.

Emission evaluation

Since the overall political target is to reduce local and global emissions within the transportation sector, there is increasing pressure on the logistics fleet operators to implement emission reduction measures. Utilizing ECVs for mid–haul delivery might be an option for reducing the ecological impact. Therefore, we determine ecological performance as overall (i.e. well–to–wheel) CO_2 emissions that can be reduced by using ECVs instead of ICEVs. Thus, we evaluate the emission savings for each scenario, taking the TCO minimizing results on the overall traveled distance and thus fuel / energy consumption into consideration, in order to quantify the ecological impact of using ECVs instead of ICEVs. Note, that this calculation is done independent of our TCO analysis, i.e. emissions are calculated but not not minimized, since the focus is on an economic analysis.

4.3. Cost terms and technical data

Within the TCO analysis, we compare costs for a MAN TGL 12.250, a 12 tonne ICEV and chassis base model for EMOSS CM1216, to the EMOSS CM1216 12 tonne ECV that has been used within the ELMO field test. Table 3 shows all vehicle specific parameters. The purchase price of the MAN TGL as well as information on its energy consumption are taken from Taefi et al. (2016). For the EMOSS CM1216, the purchase price is chosen due to a personal communication with the EMOSS sales support, and the battery capacity as well as energy consumption are derived from the ELMO field test. For both vehicles, the price is considered without value added taxes. Annual taxes are taken due to the information given by the federal ministry of finance for the MAN TGL, while no annual taxes are considered for the EMOSS CM1216, since ECVs are freed from taxes for at least five years within the European Union. Energy prices for Diesel fuel and for electricity are taken as average price of the year 2015 from the Eurostat database and the EUs weekly oil bulletin. We consider an industrial electricity price for a company purchasing between 2,000 MWh and 20,000 MWh per year. Prices for charging stations are real prices that were paid within the ELMO project. Note that prices for charging stations are lower than estimated for other ECVs applications, since in the TEDi case, sockets are directly installed in the walls next to the loading ramps of the TEDi stores and strong current is already existing at the stores. The planning horizon is scheduled to 5 years, considering a discount rate of 5% (cf. Taefi et al., 2016).

With those parameters, cost coefficients are derived as in Table 3 on a per day basis. Note within this context, that the vehicle costs have to be divided by half to derive c^{v}, since each vehicle performs two trips per day, respectively is used in two shifts with the change of drivers taking place at the depot. Thus, the number of tours is twice as high as the total number of vehicles operated. The station costs and operational costs can directly be used as c^{s} and c^{v}

Table 3: Cost 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)
battery capacity	-	-	-	160	kWh	ELMO
energy consumption	0.19	l / km	Taefi et al. (2016)	0.73	kWh / km	ELMO
energy price	1.18	€/ l	EU (2016c)	0.07	€/ kWh	EU (2016b)
charging station	-	-	-	4500	€	ELMO
daily vehicle costs	26.66	€/ veh.		53.32	€/ veh.	
daily station costs	-	-		2.47	€/ stat	
operational costs	0.2233	€/ km		0.0508	€/ km	

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

within the respective planning components.

To calculate the respective emissions, we use carbon dioxide equivalent conversion factors as stated in Edwards et al. (2014), estimating 2624.89344 ${}^{gCO_{2,eq}}/_{l}$ for ICEVs and 507.97422 ${}^{gCO_{2,eq}}/_{kWh}$ for ECVs.

5. Computational Results

Results were calculated assuming that a homogenous ICEV respectively ECV fleet covers each of the 12 scenarios given in Table 2. In the following, results are presented regarding the network structure and operation (5.1), the resulting total costs and the cost structure (5.2), and the emission savings that can be achieved by ECVs (5.3). Concluding, managerial insights are derived for network operators and society/politics (5.4). All results which are shown in the figures are included in Appendix A in detail.

5.1. Network structure and operation

In Figure 3, results for the operation of the network are illustrated for each of the 12 considered scenarios. With respect to the coverage radius of each scenario, the number of served stores (n^{store}) and the number of charging stations (n^{stat}) needed for operating the network with ECVs is given. In addition, the total distance driven ($D^{\text{ICEV}}, D^{\text{ECV}}$), the average distance driven per tour ($\overline{D}^{\text{ICEV}}, \overline{D}^{\text{ECV}}$) and the total number of necessary vehicles ($n^{\text{ICEV}}, n^{\text{ICEV}}$) are illustrated for both, operating the network by ICEVs as well as ECVs. While continuous lines represent the results for the ICEV fleet, the dashed lines represent the results for the ECV fleet.

As can be seen, the number of stores, the total distance driven, the average distance per

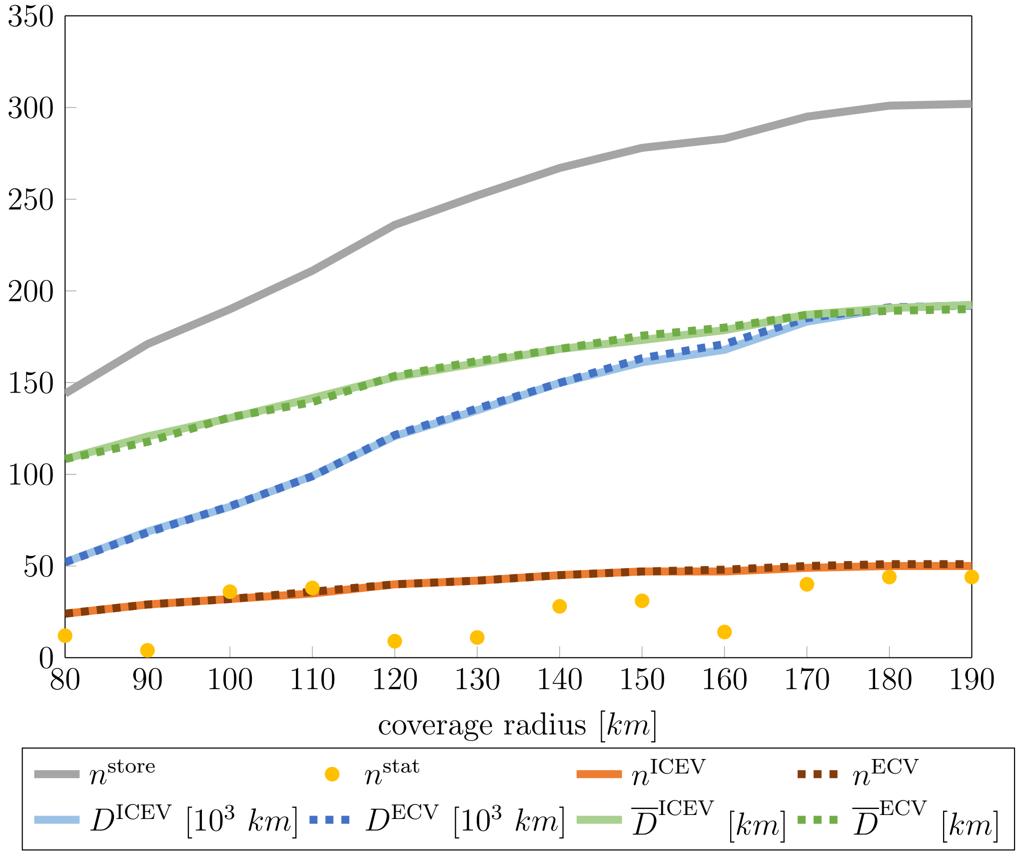

Figure 3: Results for the network operation structure for ICEVs and ECVs with respect to the coverage radius.

tour as well as the number of vehicles needed for the operation of the logistics network are monotonous increasing with an increasing coverage radius around the central warehouse from scenario 1 to 12. It can be noted that the total distance driven increases proportionally to the number of stores, while the average distance driven per tour as well as the total number of trucks needed for operating the network is increasing with a lower gradient for ICEVs as well as ECVs.

Contrary to that, the number of charging stations is not increasing monotonously, but is varying irregularly within a range of 4 and 44 stations. Thereby, the number of stations is rather independent from the distance around the warehouse or the number of stores, but related to the underlying scenario – especially the customer pattern. If an additional vehicle is needed due to freight capacity limitations, it also increases the initial overall available energy which can be used and thus, for additional customers which can only be served with more vehicles, the number of necessary charging stations might decrease. Therefore, even a small change in the number of vehicles and in the planned tours may result in completely different charging demand, due to varying route patterns. In addition, this points to a trade-off between vehicles and charging stations. With the current cost factors (i.e. relatively low costs for charging stations), charging stations are planned to fulfill charging demand for a certain number of vehicles. However, with other cost factors in a different application case (e.g. much higher costs for charging stations if set up costs for a higher voltage level arise or inductive chargers are purchased), charging stations might be increasing monotonously at the lowest number possible, while the number of vehicles needed would vary depending on the routes and distance to cover.

Focusing on the differences between operating the network with ICEVs or ECVs, it can be noted that the results for the ICEV fleet and the results for the ECV fleet are nearly matching, with respect to the number of necessary vehicles and the overall as well as the average driven distance. This shows that there are nearly no operational disadvantages arising from range limitations or required charging times for ECV within the investigated logistics network. These results reflect the expectations of TEDi Logistik's management at the beginning of the ELMO project.

Analyzing these results in detail, we figured out that there are some specific network characteristics that benefit the usage of ECVs for the investigated application case: First, vehicles go back to the depot at least once a day in order to allow for a change of the driver between the first and the second shift and for reloading of freight. Thus, ECVs can be recharged at least once a day at the depot (within two hours using fast charging) before they start for their second tour. In addition, vehicles often have to return to the depot in order to pick up palletized goods after only a few service stops. Thus, for a lot of trips, the traveled distance is roughly about 100 km which is substantially lower than the actual range of the EMOSS CM1216. Second, due to the vicinity of at most 190 km around the central warehouse most of the remaining tours show distances less than 200 km, which is still within the driving range that the ECVs can cover without recharging. Thus, operational disadvantages due to range limitations are significantly reduced in this application case. Third, charging stations can be installed at the TEDi stores and thus, installation and maintenance costs are lower than in other ECV applications. Also, service times can be used for recharging (in other networks, an installation of charging stations at customers might not be possible).

Note that the monotonously increasing results and the matching of the ECV and the ICEV curves also indicate that the meta heuristic presented in Section 3.3 delivers very robust and stable results.

5.2. Total costs and cost structure

Figure 4 shows results with regard to overall costs for ICEVs ($\hat{C}^{\text{ICEV}}$) as well as ECVs ($\hat{C}^{\text{ECV}}$), dependent on the coverage radius for all scenarios. As can be seen, total costs are lower for

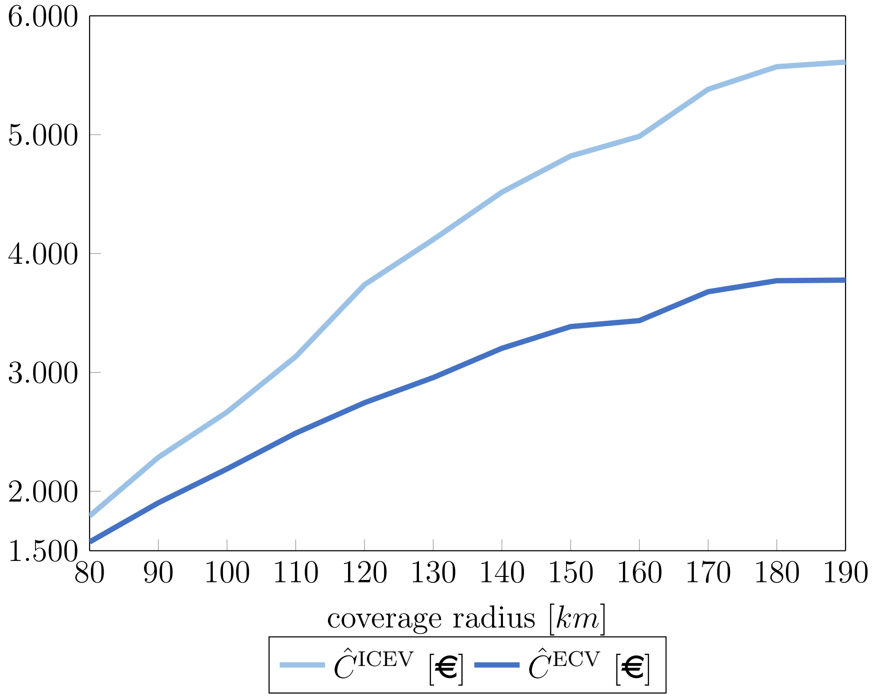

Figure 4: Overall costs for ICEVs and ECVs with respect to the coverage radius.

ECVs than for ICEVs within all scenarios resulting in cost savings from 12.21% to 32.31%, which increase monotonously with an increasing coverage radius (cf. Table 7). This means, that at least cost savings between 64.827 € per year and 542.882 € per year can be achieved based on the results given in Table 5 and Table 6, assuming deliveries on 296 days per year since deliveries are only interrupted on Sundays and public holidays.

In order to analyze those cost savings in more detail, Figure 5 shows a more detailed analysis of the overall costs and their single components for ICEVs as well as ECVs and the respective cost savings for selected scenarios. Within this context, the vehicle costs ($C^{\text{ICEV}}, C^{\text{ECV}}$) and the operational costs ($C^{\text{oper,ICEV}}, C^{\text{oper,ECV}}$) are illustrated for both, ICEVs as well as ECVs. For ECVs, additional costs for charging stations (C^{stat}) are depicted. In addition, the cost savings ΔC if ECVs are used instead of ICEVs are shown. With regard to total costs, higher investment costs arise for ECVs, but these are more than compensated by lower variable distance based operational costs. As a consequence, overall costs for ECVs are the lower, the higher the total distance driven respectively the utilization of the electric trucks is. In the TEDi logistics network, the distance driven by truck is the higher the higher the vicinity around the central warehouse is that has to be covered (i.e. the more stops have to be covered). Additional costs arising due to the installation of charging stations are negligibly low compared to vehicle and operational costs within every scenario, due to a high number of necessary vehicles and a high

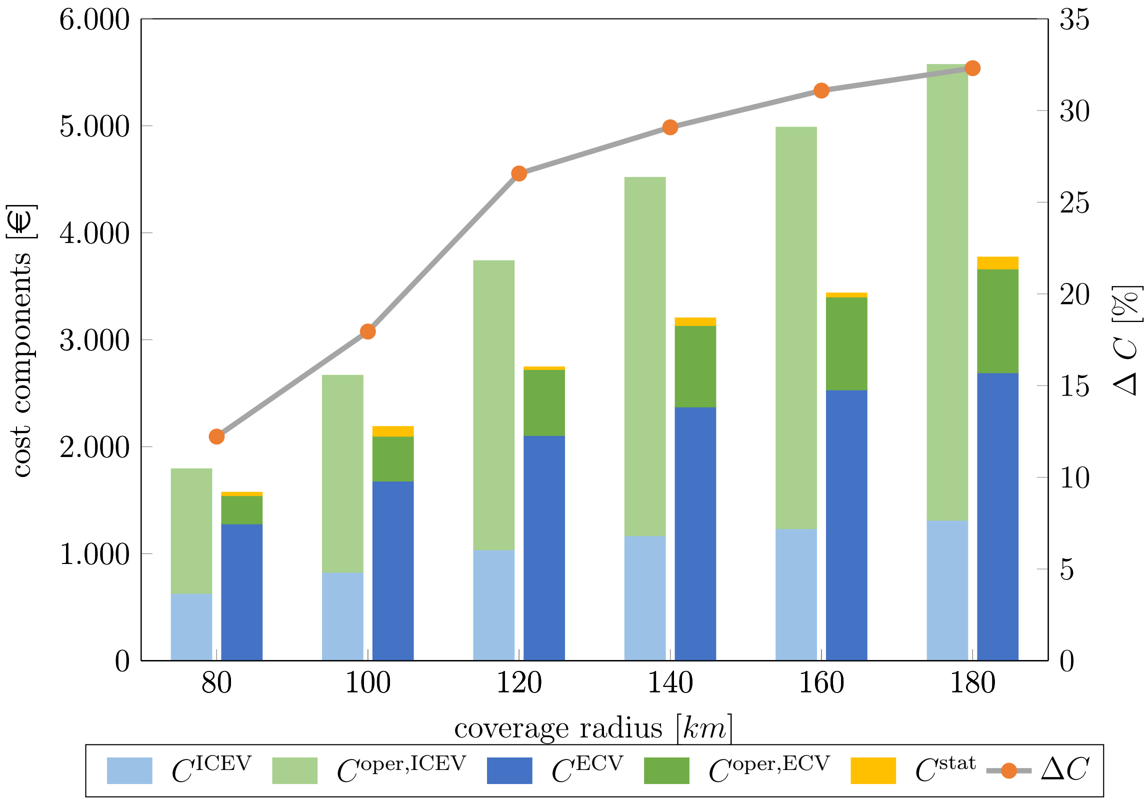

Figure 5: Overall costs for ICEVs and ECVs with respect to the coverage radius.

overall driven distance. Therefore, total cost savings for the ECV fleet compared to an ICEV fleet (shown by the continuous line that is corresponding to the left hand side axis in Figure 5) increase with an increasing vicinity around the central warehouse that has to be covered.

As can be seen in Figure 5, overall savings in cost up to 32.31% can be achieved if the whole fleet is electrified. However, the electrification of the whole fleet at once is not applicable in practice. To discuss the stepwise electrification of a fleet in practice and to identify good rates of electrification focusing on overall costs or a relative cost decrease is not sufficient. Instead, cost per delivered good is often used as a key performance indicator in practice. In our case, goods are delivered on palettes. Thus, we use 'euro per pallet' [€/pt] as a key performance indicator to discuss the respective results. Table 4 shows the costs per delivered pallet C_p^{ICEV} for ICEVs and the costs per delivered pallet C_p^{ECV} for ECVs for each scenario. In addition the relative change in costs per pallet between scenario j and the scenario with the next lower catchment area i is stated for ICEVs ($\Delta_{ij}C_p^{ICEV}$) and ECVs ($\Delta_{ij}C_p^{ECV}$). As can be seen, the costs per are significantly lower for ECVs than for ICEVs. The difference between C_p^{ICEV} and C_p^{ECV} reflects cost savings as illustrated in Figure 5 for each scenario. Focusing on $\Delta_{ij}C_p^{ICEV}$ and $\Delta_{ij}C_p^{ECV}$ the cost per pallet for ICEVs is constantly rising with an increasing catchment

Table 4: **Costs per pallet for ICEVs and ECVs**

scen.	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
C_p^{ICEV}	2.11	2.27	2.39	2.54	2.71	2.80	2.89	2.95	3.01	3.10	3.15	3.16
$\Delta_{ij}C_p^{ICEV}$	-	7.95	5.18	6.16	6.83	3.19	3.17	2.28	1.74	3.21	1.54	0.30
C_p^{ECV}	1.85	1.89	1.96	2.02	1.99	2.01	2.05	2.07	2.07	2.12	2.13	2.13
$\Delta_{ij}C_p^{ECV}$	-	2.41	3.64	2.79	**-1.25**	0.91	1.89	1.29	**-0.17**	2.38	0.56	**-0.26**

Abbreviations hold as follows: cat. area - catchment area [km], C_p^{ICEV} - cost per delivered pallet using ICEVs [€/pt], C_p^{ECV} - cost per delivered pallet using ICEVs [€/pt], $\Delta_{ij}C_p^{ICEV}$ [%] - relative change in costs per pallet (ICEVs), $\Delta_{ij}C_p^{ECV}$ [%] - relative change in costs per pallet (ECVs).

area, while negative $\Delta_{ij}C_p^{ECV}$ are derived for ECVs for certain catchment areas. Treating the different scenarios as different grades of electrification for the vehicle fleet this shows, that instead of raising the share of electrification linearly with respect to the catchment area, larger steps are beneficial at certain points. For instance, raising the catchment area of stores that are served by ECVs directly from 100 km to 120 km results in 1.29 % lower cost per pallet than an increase from 100 km to 110 km first. Further cost savings are achieved skipping a rollout to 150 km and 180 km, directly choosing the next higher roll out of ECVs.

When looking at these results, it should be noted that there are certain characteristics that work in favor for the ECVs fleet. For instance, the installation costs for charging stations are low compared to other applications and might vary significantly as pointed out in Section 3.2. The main reason for those low costs is that stations are allowed to be installed directly at the loading ramps of the TEDi stores (in other networks it might not be possible to install charging stations directly at the customer). At the ramps, heavy current infrastructure is already availabe and only a socket without chassis has to be installed next to the loading ramp. This is leading to rather low cost factors for charging infrastructure. Also, service times can be used for charging, which considerably decreases operational disadvantages of ECVs due to limited range and charging demand.

5.3. Emissions

Results on CO_2 emissions ($E^{\mathrm{ICEV}}, E^{\mathrm{ECV}}$) are illustrated in Figure 6 for ICEVs as well as ECVs for all analyzed scenarios, showing the total CO_2 emissions for the operation of each fleet. In addition emission savings (ΔE) if ECVs instead of ICEVs are used are depicted. Figure 6 shows that ECVs are advantageous with respect to emission savings since they emit around 25% less CO_2 emissions than ICEVs within a well-to-wheel system boundary (i.e. regarding all emissions from the well to the combustion respective from the well to the electricity generation

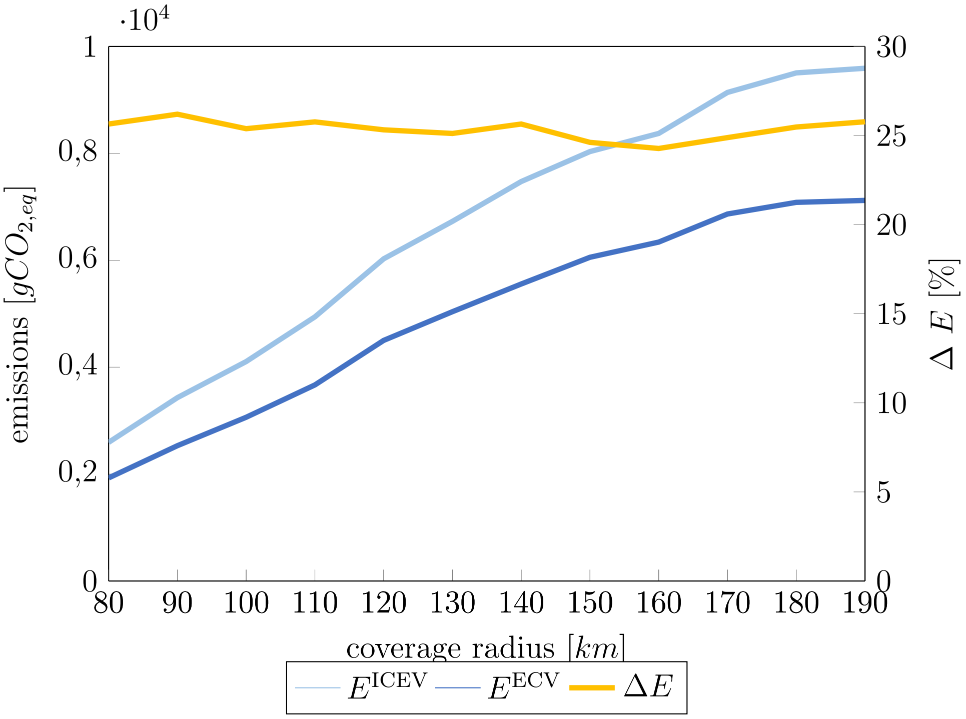

Figure 6: Overall costs for ICEVs and ECVs with respect to the coverage radius.

and transmission) for all scenarios. As the total distance driven by ECVs and ICEVs to cover the network demand is nearly identical (cf. Figure 3), the CO_2-saving is mainly resulting out of 25% less CO_2 resulting from electricity generation compared to Diesel production and combustion.

Even for companies that focus mainly on economic objectives, emission savings might be a very important asset for electrification of logistic fleets in the future. There are political targets aiming at saving more than 40% of total CO_2 emissions in the transportation sector until 2020 (cf. European Comission, 2014). Hence, many (larger) logistics companies already aim at significant short and long term emission reductions (cf. Green Freight Europe, 2014).

5.4. Managerial insights

Analyzing the derived results, several managerial insights can be drawn for logistics fleet and network operators. Those insights can be summed up in four key findings:

A detailed network analysis at an operational level is necessary to estimate the competitiveness of ECVs appropriately: Since route patterns as well as considered cost structures and charging possibilities might vary significantly with respect to the analyzed network, aggregated cost analysis are not sufficient to assess the competitiveness of ECVs. Instead, detailed analysis, taking operational as well as strategic network design aspects into consideration are necessary to assess each application case individually. In the TEDi/ELMO case, an aggregated TCO was not sufficient to evaluate the competitiveness of the ECVs in detail, since the network operator did not expect the results to be this positive for the ECVs. This shows that an integrated model for network design and operation using VRP and LRP components had to be applied. Using this approach avoids over- or underestimation of ECVs in logistics networks by individual case suitable competitiveness assessment. On the one hand, with this approach even more logistics networks which are competitive to be operated with ECVs might be identified, even though aggregated cost analysis show negative results. On the other hand, the presented approach is also suitable to prevent fleet operators from assessing ECVs to good for different applications with varying cost structures in case aggregated analysis overestimate the competitiveness of ECVs against ICEVs. 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.

For certain 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, assessing ECVs for logistics networks might be worthy, even under contemporary cost and technical conditions. Since positive results in this dimension have not been expected by the network operator, a detailed analysis of the TEDi case revealed characteristics that work in favor for the competitiveness of ECVs: For instance, the vicinity of stores of not more than 190 km around the central warehouse allows many routes to be covered by ECVs without charging (or charging only once per day). Also, the possibility to install sockets near the loading ramps of the TEDi stores favors ECVs as this results in low investments for charging infrastructure as well as in time efficient charging while providing service. Furthermore, in the TEDi case the vehicles go back to the depot once per day between the first and second shift. Thus, vehicles can charge at the depot while the drivers change and while the vehicle is reloaded for the second shift. Investigating logistics networks with similar characteristics might result in comparable results, revealing the underestimation of the competitiveness of ECVs, while investigating networks with adverse characteristics might reveal overestimations of aggregated analysis vice versa.

Besides economical, additional advantages can be realized: The utilization of ECVs also allowed for a reduction of CO_2 emissions as well as of local hazardous emissions (NO_x, particulate matter) and noise. This can especially be important in the future as politics is putting strong pressure on the logistics sector to decrease emissions. Besides mere altruism or corporate eco-targets, logistics companies serving urban areas (such as TEDi Logistik) are currently facing entry barriers for ICEVs in many European cities. Currently, about 500 European cities have established access restrictions with over 200 of these based on vehicle emissions (cf. EU, 2016a). Therefore, logistics companies are increasingly aiming at low– and zero–emission strategies in last mile deliveries.

Also, reduced noise emissions allow for delivery in city centers at times where ICEVs are not allowed to deliver freight. Low–noise transport is an important application for night time and off–hour delivery. Cases from around the world illustrate the benefits of this concept, especially for logistics companies. At the moment many countries lack legal certainty to ensure low noise transport, but first attempts like the dutch 'Piek-certificaat' are on the rise, making ECVs as a core component for low noise transport even more attractive (cf. Taniguchi and Thompson, 2014, p. 156 *ff.*). As a spin–off project of ELMO, Fraunhofer IML and TEDi Logistik (along with other partners) have initiated the research project "GeNaLog" focusing on low noise night time logistics, in which this aspect is going to be addressed.

Operational planning components affect strategic network structure decisions: Especially if intermediate stops are necessary, the integrated models presented in this (and related) papers give concrete 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 an strategical design is no longer possible.

6. Conclusion and Outlook

Within this paper, the competitiveness of ECVs in medium–duty mid–haul logistics is evaluated for a specific case study of a company delivering non-food goods from a central depot to 302 stores in Northrhine-Westfalia, a federal state of Germany. A TCO analysis is combined with integrated VRP and LRP model components that allow for an optimized routing of ECVs within the network as well as the locating of charging stations where needed. Doing so, the limited driving range and the need for charging ECVs on routes in mid–haul logistics is regarded. Thus, a fair assessment of advantages and disadvantages of an electrification of the logistics fleet is possible.

The results show that for the investigated application case, the electrification of the mid–haul 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 distance driven per tour are nearly identical to ICEVs. This holds even for a complete electrification of the logistics fleet delivering goods within a vicinity of up to 190 km around a 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 once a day as well as the limited vicinity of stores around the depot. Results were rather surprising for the network operator as well as for project partners that studied the utility of electric commercial vehicles within mid-haul logistics without VRP and LRP models, neglecting operational as well as network design aspects so far.

Even if the result of this case study is, that ECVs are already economically advantageous for the considered application case, mainly two 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. Within this context, low emission zones, which might be realized in several cities and result in high penalty costs or even a ban of ICEVs in certain areas, can be considered and might increase the benefit of using ECVs instead of ICEVs even further. Thereby, the future development of technological parameters (e.g. battery capacity, charging times) should be paid attention to. Second, as results of the case study show, the number (and thus also the locations) of charging stations vary irregularly with increasing distance (and thus varying customer patterns) around the central depot. Therefore, results can be used for a rough estimation of installation costs for charging stations. However, no decision support on the location and specific number of stations is possible, as soon as varying customer patterns have to be served within a network (and thus, the planning of milk-runs is no longer sufficient). Therefore, robust models must be applied to account for changing demand and resulting variations of routes in the network. Only based on such robust results a concrete investment decision for charging stations should be derived, designing the respective network structure in practice.

A. Computational results

In Tables 5–7, results calculated with the methods described in Section 3 and illustrated in Section 5 are provided in detail. While Table 5 contains results for operating the network with an ICEV logistics fleet, Table 6 shows results for operating an ECV logistics fleet. Differences between ICEVs and ECVs for the respective quantities are shown in Table 7. Table 8 contains results on the respective emissions produced operating an ICEV or ECV fleet.

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

scen.	I	II	III	IV	V	VI
cat. area [km]	80	90	100	110	120	130
n^{store}	144	171	190	211	236	252
n^{tour}	48	57	63	70	79	84
n^{ICEV}	24	29	32	35	40	42
D^{ICEV} $[km]$	5200	6877	8231	9908	12085	13490
C^{ICEV} [€]	630.72	748.98	827.82	919.8	1038.06	1103.76
$C^{\text{oper,ICEV}}$ [€]	1161.77	1536.26	1838.88	2213.42	2699.85	3013.66
$\hat{C}^{\text{ICEV}}$ [€]	1792.49	2285.24	2666.7	3133.22	3737.91	4117.42
$\overline{D}^{\text{ICEV}}$ $[km]$	108.3	120.6	130.7	141.5	153.0	160.6
scen.	VII	VIII	IX	X	XI	XII
cat. area [km]	140	150	160	170	180	190
n^{store}	267	278	283	295	301	302
n^{tour}	89	93	94	98	100	100
n^{ICEV}	45	47	47	49	50	50
D^{ICEV} $[km]$	14983	16108	16788	18326	19059	19233
C^{ICEV} [€]	1169.46	1222.02	1235.16	1287.72	1314	1314
$C^{\text{oper,ICEV}}$ [€]	3347.18	3598.52	3750.52	4093.92	4257.86	4296.76
$\hat{C}^{\text{ICEV}}$ [€]	4516.64	4820.54	4985.68	5381.64	5571.86	5610.76
$\overline{D}^{\text{ICEV}}$ $[km]$	168.3	173.2	178.6	187.0	190.6	192.3

Abbreviations hold as follows: cat. area - catchment area, n^{store} - number of served stores, n^{tour} - number of necessary delivery tours, n^{ICEV} - number of necessary ICEVs, D^{ICEV} - overall driven distance, C^{ICEV} - vehicle dependent costs, $C^{\text{oper,ICEV}}$ - operational costs, $\hat{C}^{\text{ICEV}}$ - overall costs, $\overline{D}^{\text{ICEV}}$ - average tour length.

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

scen.	I	II	III	IV	V	VI
cat. area $[km]$	80	90	100	110	120	130
n^{store}	144	171	190	211	236	252
n^{tour}	48	58	63	71	79	84
n^{ECV}	24	29	32	36	40	42
n^{stat}	12	4	36	38	9	11
D^{ECV} $[km]$	5200	6826	8260	9892	12138	13586
C^{ECV} [€]	1279.68	1546.28	1679.58	1892.86	2106.14	2239.44
$C^{\text{oper,ECV}}$ [€]	264.16	346.76	419.61	502.51	616.61	690.17
C^{stat} [€]	29.64	9.88	88.92	93.86	22.23	27.17
$\hat{C}^{\text{ECV}}$ [€]	1573.48	1902.92	2188.11	2489.23	2744.98	2956.78
$\overline{D}^{\text{ECV}}$ $[km]$	108.3	117.7	131.1	139.3	153.6	161.7
scen.	VII	VIII	IX	X	XI	XII
cat. area $[km]$	140	150	160	170	180	190
n^{store}	267	278	283	295	301	302
n^{tour}	89	93	95	99	101	101
n^{ECV}	45	47	48	50	51	51
n^{stat}	28	31	14	40	44	44
D^{ECV} $[km]$	14983	16331	17098	18514	19102	19200
C^{ECV} [€]	2372.74	2479.38	2532.70	2639.34	2692.66	2692.66
$C^{\text{oper,ECV}}$ [€]	761.14	829.61	868.58	940.51	970.38	975.36
C^{stat} [€]	69.16	76.57	34.58	98.80	108.68	108.68
$\hat{C}^{\text{ECV}}$ [€]	3203.04	3385.56	3435.86	3678.65	3771.72	3776.70
$\overline{D}^{\text{ECV}}$ $[km]$	168.3	175.6	180.0	187.0	189.1	190.1

Abbreviations hold as follows: cat. area - catchment area, n^{store} - number of served stores, n^{tour} - number of necessary delivery tours, n^{ECV} - number of necessary ECVs, D^{ECV} - overall driven distance, C^{ECV} - vehicle dependent costs, $C^{\text{oper,ECV}}$ - operational costs, C^{stat} - charging station dependent costs, $\hat{C}^{\text{ECV}}$ - overall costs, $\overline{D}^{\text{ICEV}}$ - average tour length.

Table 7: Comparison for all scenarios between the ECV and ICEV results.

scen.	I	II	III	IV	V	VI
$\Delta(n^{\text{ECV}} - n^{\text{ICEV}})$	0	0	0	1	0	0
$\Delta(D^{\text{ECV}} - D^{\text{ICEV}})$ [%]	0.00	-0.74	0.35	-0.16	0.44	0.71
$\Delta(C^{\text{ECV}} - C^{\text{ICEV}})$ [%]	102.89	106.45	102.89	105.79	102.89	102.89
$\Delta(C^{\text{oper,ECV}} - C^{\text{oper,ICEV}})$ [%]	-77.26	-77.43	-77.18	-77.30	-77.16	-77.10
$\Delta(\hat{C}^{\text{ECV}} - \hat{C}^{\text{ICEV}})$ [%]	-12.22	-16.73	-17.95	-20.55	-26.56	-28.19
$\Delta(\overline{D}^{\text{ECV}} - \overline{D}^{\text{ICEV}})$ [%]	0.00	-2.45	0.35	-1.57	0.44	0.71
scen.	VII	VIII	IX	X	XI	XII
$\Delta(n^{\text{ECV}} - n^{\text{ICEV}})$	0	0	1	1	1	1
$\Delta(D^{\text{ECV}} - D^{\text{ICEV}})$ [%]	0.00	1.38	1.85	1.03	0.23	-0.17
$\Delta(C^{\text{ECV}} - C^{\text{ICEV}})$ [%]	102.89	102.89	105.05	104.96	104.92	104.92
$\Delta(C^{\text{oper,ECV}} - C^{\text{oper,ICEV}})$ [%]	-77.26	-76.95	-76.84	-77.03	-77.21	-77.30
$\Delta(\hat{C}^{\text{ECV}} - \hat{C}^{\text{ICEV}})$ [%]	-29.08	-29.77	-31.09	-31.64	-32.31	-32.69
$\Delta(\overline{D}^{\text{ECV}} - \overline{D}^{\text{ICEV}})$ [%]	0.00	1.38	0.77	0.01	-0.77	-1.16

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

Table 8: Results for all investigated scenarios for the ICEV vehicle fleet.

scen.	I	II	III	IV	V	VI
E^{ICEV} $[gCO_{2,eq}]$	2593395	3429765	4105045	4941414	6027149	6727864
E^{ECV} $[gCO_{2,eq}]$	1928270	2531225	3062983	3668163	4501028	5037977
$\Delta(E^{\text{ECV}} - E^{\text{ICEV}})$ [%]	-25.65	-26.20	-25.38	-25.77	-25.32	-25.12
scen.	VII	VIII	IX	X	XI	XII
E^{ICEV} $[gCO_{2,eq}]$	7472468	8033539	8372675	9139722	9505290	9592069
E^{ECV} $[gCO_{2,eq}]$	5556014	6055881	6340301	6865383	7083426	7119767
$\Delta(E^{\text{ECV}} - E^{\text{ICEV}})$ [%]	-25.65	-24.62	-24.27	-24.88	-25.48	-25.77

Abbreviations hold as follows: E^{ICEV} - emissions operating the network with ICEVs, E^{ECV} - emissions operating the network with ECVs, $\Delta(E^{\text{ECV}} - E^{\text{ICEV}})$ - emission savings, operating thenetwork with ECVs instead of ICEVs.

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