Transportation Research Part C 139 (2022) 103628

Contents lists available at ScienceDirect

Transportation Research Part C

journal homepage: www.elsevier.com/locate/trc

# On the integration of battery electric buses into urban bus networks

Nicolas Dirks [a,*], Maximilian Schiffer [b], Grit Walther [a]

[a] Chair of Operations Management, School of Business and Economics, RWTH Aachen University, 52072 Aachen, Germany
[b] School of Management & Munich Data Science Institute, Technical University of Munich, 80333 Munich, Germany

ARTICLE INFO

*Keywords:*
Electric buses
Fleet transformation
Charging infrastructure design

ABSTRACT

Cities all around the world struggle with urban air quality due to transportation related emissions. In public transport networks, replacing internal combustion engine buses by electric buses provides an opportunity to improve air quality. Hence, many bus network operators currently ask for an optimal transformation plan to integrate battery electric buses into their fleet. Ideally, this plan also considers the installation of necessary charging infrastructure to ensure a fleet's operational feasibility. Against this background, we introduce an integrated modeling approach to determine a cost-optimal, long-term, multi-period transformation plan for integrating battery electric buses into urban bus networks. Our model connects central strategic and operational decisions. We minimize total cost of ownership and analyze potential reductions of nitrogen oxide emissions. Our results base on a case study of a real-world bus network and show that a comprehensive integration of battery electric buses is feasible and economically beneficial. By analyzing the impact of battery capacities and charging power on the optimal fleet transformation, we show that medium-power charging facilities combined with medium-capacity batteries are superior to networks with low-power or high-power charging facilities.

## 1. Introduction

Cities around the world struggle with low air quality, which is to a significant extend caused by transportation related emissions. In this course, the European Union issued inner-city emission thresholds to achieve a reduction of air pollutant concentrations (cf. European Comission 2008), which requires to curb transportation related emissions. Here, the utilization of battery electric vehicles (BEVs) that cause zero local emissions remains a viable option to meet these thresholds. Accordingly, for public transport, BEBs provide a promising alternative to internal combustion engine buses (ICEBs) with potential reductions of $NO_x$ emissions and savings in operational (fuel) costs. Known challenges of electric vehicles such as limited driving ranges and needs for recharging appear to be manageable for BEBs as their routes are predetermined and thus, fleet operators are able to consider these limitations a-priori. Accordingly, many public transport authorities aim at an integration of BEBs into their public bus fleet. Amongst others, the cities of Paris and Nottingham consider and test the partial (Paris) or full (Nottingham) electrification of their public bus network (see, e.g., ZeEUS 2017).

In this course, a transformation towards electrified bus fleets is a central task for many fleet operators resulting in the following planning tasks: At strategic level, operators must decide on the transformation of the bus fleet and the investment into sufficient charging infrastructure. Transforming the bus fleet over time requires strategic decisions on purchases and sales of buses linked to decisions on drivetrain technologies, battery capacities, and charging concepts. Installing charging infrastructure requires decisions on the timing of the installation as well as on the locations and characteristics of charging facilities. At operational level, operators

* Corresponding author.
*E-mail addresses:* nicolas.dirks@om.rwth-aachen.de (N. Dirks), schiffer@tum.de (M. Schiffer), walther@om.rwth-aachen.de (G. Walther).

https://doi.org/10.1016/j.trc.2022.103628
Received 16 December 2020; Received in revised form 16 September 2021; Accepted 26 February 2022
Available online 2 April 2022

need to ensure operational feasibility of the bus timetable, i.e., of service trips specified by bus lines and service times. To guarantee operational feasibility, the right buses need to get assigned to these service trips, while considering limited driving ranges of BEBs, and (partial) recharging operations. Accordingly, integrating BEBs into urban bus networks requires a transformation plan that links strategic bus network design decisions with operational feasibility constraints.

Against this background, we introduce an integrated modeling approach for a cost-optimal, long-term, multi-period transformation plan to integrate BEBs into urban bus networks. We minimize a fleet transformation's TCO based on a mixed integer problem (MIP) that considers strategic and operational decisions simultaneously: At strategic level, we provide a transformation plan with decisions on purchases and sales of buses, specified by drivetrain technologies, battery capacities, charging concepts, and decisions on charging infrastructure network design. At operational level, this transformation plan accounts for the assignment of buses to trip sequences of a vehicle schedule, while considering (partial) recharging operations to ensure operational feasibility. Our modeling approach constitutes a generic tool that can be applied to different bus networks by academics or practitioners as it remains solvable with of the shelf optimization software.

We apply our model to the real-world bus network of the city of Aachen, Germany. Our results allow to analyze the resulting transformation strategy as well as to conduct sensitivity analyzes for design-critical parameters, e.g., battery capacities and low- or high-charging power concepts. Moreover, we assess reductions of $NO_x$ emissions achieved by an integration of BEBs. Based on these results, we provide several managerial insights that point towards promising directions for future BEB applications.

The remainder of this paper is structured as follows. In Section 2, we give an overview of related literature, before we develop our methodology in Section 3. Section 4 describes our case study and experimental design. Section 5 discusses our results, and Section 6 concludes this paper.

## 2. Literature review

Our work relates to the broad field of electric vehicle routing and scheduling, and charging network design. To keep this paper concise, we point the interested reader to the recent surveys of Schiffer et al. (2019) and Shen et al. (2019), and focus only on BEB specific work in the following.

*TCO analysis.* TCO analyzes have widely been used for descriptive analyzes of the competitiveness of electric vehicles (see, e.g., Feng and Figliozzi 2013), incorporating different aspects such as investment, energy, operational, and maintenance cost; herein approximating vehicle operations and strategic decisions. In this field, only a few studies focused on TCO analysis for BEBs. Göhlich et al. (2014) focused on technology assessment for BEBs, while Pihlatie et al. (2014) proposed a TCO model including a component, vehicle, and traffic system analysis. Both studies found that the lowest TCOs are realized for buses with low-capacity batteries combined with high-power charging facilities. In contrast, Nurhadi et al. (2014) identified low-power charging facilities combined with high-capacity battery buses as the most beneficial combination using a similar methodology. Lajunen (2018) compared different charging concepts and found that opportunity charging buses show lower TCO than overnight charging buses.

Concluding, some TCO analyzes exist for BEBs but lack the explicit consideration of strategic network design decisions and operational constraints. Hence, their results depend heavily on the chosen approximations and parameters and may lead to conflicting outcomes (see, e.g., Pihlatie et al. 2014, Nurhadi et al. 2014).

*Strategic planning approaches.* Strategic planning approaches focus on cost-optimal decisions for bus fleet composition or charging infrastructure planning. Kunith et al. (2017) focused on locating charging facilities for an entire bus network, taking a decision for each bus line separately, while including decisions on the battery power of buses and the charging power of charging facilities. In a similar approach, Xylia et al. (2017) accounted for different drivetrain technologies, assigning one specific type to each bus line. Li et al. (2018) focused on determining an optimal bus fleet composition, including partial recharging considerations. Wei et al. (2018) focused on finding an optimal fleet composition including the installation of charging facilities for a single point in time, while considering a given vehicle schedule with dead-heading. Islam and Lownes (2019) minimized costs for vehicle investments, depot charging facilities, and external emissions for a fleet replacement process in which only a limited amount of vehicles can be replaced with ICEBs. Pelletier et al. (2019) proposed a multi-period fleet transformation model that minimizes total costs for depot and fast charging buses. They approximated daily operations for a given vehicle schedule as well as costs for charging infrastructure. This approximation does not ensure operational feasibility as specific charging facility locations as well as energy balances of BEBs along routes are neglected. Lin et al. (2019) proposed a model for locating charging facility parks that consist of multiple charging facilities and considered interdependencies with the electricity grid. Li et al. (2019) proposed a time–space–energy network to locate charging facilities while accounting for the bus fleet composition and external costs of emissions. An (2020) proposed a stochastic model to optimize charging facility locations and the bus fleet size while considering time-dependent electricity prices.

Concluding, several strategic planning approaches exist, but none of these approaches considers all necessary planning components. Most approaches do not guarantee operational feasibility for the identified solutions. The approaches that consider operational feasibility regard only limited settings (e.g., ignore dead-heading of buses) or do not account for a multi-period time horizon. The few approaches that account for strategic decisions and operational feasibility exist in the field of electric location-routing problems (see, e.g., Schiffer and Walther 2017) and cannot be applied to our planning problem as they neglect bus network specific characteristics.

**Table 1**
Overview of related modeling approaches.

| | Strategic | | | | | | | | | Operational | | | | | | | | This paper |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Kunith et al. (2017) | Xylia et al. (2017) | Li et al. (2018) | Islam and Lownes (2019) | Pelletier et al. (2019) | Lin et al. (2019) | An (2020) | Wei et al. (2018) | Li et al. (2019) | Li (2014) | Wen et al. (2016) | Adler and Mirchandani (2017) | Van Kooten Niekerk et al. (2017) | Tang et al. (2019) | Yao et al. (2020) | Rogge et al. (2018) | Liu and Ceder (2020) | |
| Total costs | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | – | – | – | – | – | ✓ | ✓ | – | ✓ |
| Multi-period | – | – | ✓ | ✓ | ✓ | ✓ | – | – | – | – | – | – | – | – | – | – | – | ✓ |
| Heterogeneous bus fleet | – | ✓ | ✓ | ✓ | ✓ | – | ✓ | ✓ | ✓ | – | ✓ | ✓ | ✓ | – | ✓ | ✓ | – | ✓ |
| Bus purchases and sales | – | – | ✓ | ✓ | ✓ | – | – | – | – | – | – | – | – | – | – | – | – | ✓ |
| Siting charging facilities | ✓ | ✓ | – | – | – | ✓ | ✓ | ✓ | ✓ | – | – | – | – | – | – | – | ✓ | ✓ |
| Operational feasibility | ✓ | ✓ | ✓ | – | – | – | – | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Partial recharging | ✓ | ✓ | ✓ | – | – | – | ✓ | – | – | – | ✓ | – | ✓ | – | – | – | ✓ | ✓ |
| Dead-heading | – | – | – | – | – | – | – | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |

*Operational planning approaches.* Operational planning approaches resemble electric vehicle scheduling problems and aim to determine an optimal vehicle schedule that requires a minimum number of buses for a given network and charging infrastructure. Li (2014) focused on a single-depot vehicle scheduling problem with full recharging or battery swapping for BEBs, while Adler and Mirchandani (2017) considered multiple depots but no consecutive recharging operations. Wen et al. (2016) considered multiple depots, consecutive recharging operations, as well as full and partial recharging. Van Kooten Niekerk et al. (2017) incorporated electricity prices, battery depreciation, and various recharging options. Recently, Tang et al. (2019) analyzed robust scheduling strategies to account for stochastic traffic conditions, and Yao et al. (2020) proposed a heuristic to minimize total costs of a bus network operated by depot charging buses.

Recently, first operational approaches started to integrate strategic decisions and focused on the integration of charging station network design decisions. Rogge et al. (2018) focused on determining a cost-minimal vehicle schedule while estimating the number of depot charging facilities that are necessary to recharge buses. Liu and Ceder (2020) proposed a bi-objective model to schedule buses and to install fast charging facilities at first or final stations of a bus line, herein accounting for both dead-heading and partial recharging.

Concluding, some operational planning approaches exist that determine or account for vehicle schedules. While some of them aim to integrate strategic decisions for the design of charging station infrastructure, none extends to integrate fleet transformation characteristics.

*Conclusion.* Table 1 shows the relation between our work and existing approaches that remain focused on either strategic or operational aspects of the planning problem. As can be seen, strategic modeling approaches so far lack either a multi-period time horizon, operational feasibility, or charging station infrastructure design decisions. In particular, first approaches that strive towards an integrated modeling approach (Wei et al. 2018, Li et al. 2019) lack a multi-period investment decision and partial recharging. Operational approaches lack among others strategic fleet transformation decisions, charging infrastructure design decisions, and often a total cost perspective. The only operational approach that strives towards an integrated model (Liu and Ceder 2020) integrates charging infrastructure design decisions but still neglects all fleet transformation decisions as well as a total cost perspective.

With this work, we present a comprehensive and realistic planning model that covers all requirements as listed in Table 1. Specifically, we: (i) perform a comprehensive TCO optimization that considers all decision relevant strategic costs as well as anticipated operational costs for using BEBs; (ii) develop an integrated approach that considers strategic and operational decisions simultaneously; (iii) derive a transformation plan to integrate BEBs in a heterogeneous bus fleet by regarding purchases and sales of buses with alternative drivetrain technologies, battery capacities, and charging concepts; (iv) optimize the time-dependent installation of charging infrastructure; and (v) approximate operational feasibility by considering a given vehicle schedule of a bus timetable including (partial) recharging decisions for BEBs. We apply this model to a real-world case study and present managerial insights, including the reductions of $NO_x$ emissions that result from the integration of BEBs.

## 3. Methodology

In this section, we introduce our methodology to determine an optimal transformation plan for integrating BEBs into urban bus networks. We first present our problem setting in Section 3.1, before we develop a corresponding mixed-integer linear model in Section 3.2.

### 3.1. Problem setting

We focus on the transformation of a bus fleet, which is used to operate a public urban bus network from the point of view of its fleet operator. Specifically, we decide on the sale and purchase of buses over time with respect to the bus type, its drivetrain, and in case of BEBs its battery capacity. Additionally, we decide on investments into necessary charging infrastructure to operate BEBs. Here, we decide on the required charging infrastructure, the location of charging facilities and on the used charging concept, i.e., if buses are only charged at the depot (overnight charging) or if partial recharging at bus stations (opportunity charging) is allowed. Moreover, we consider the operational requirements of the bus network and guarantee that the fleet is at any time able to operate according to the given bus timetable.

In this setting, we consider a heterogeneous bus fleet with different drivetrain technologies, namely ICEBs and BEBs with a homogeneous economic vehicle lifetime. We focus on a finite planning horizon during which the operator may sell ICEBs to replace them with buses of the same technology or with a BEB. Once an operator decides to replace an ICEB by a BEB, the BEB remains in the fleet until the end of its economic lifetime. We assume that the lifetimes of the BEBs' batteries are shorter than the economic lifetime of the BEBs. Thus, the operator has to account for battery replacements. To account for beginning and end of horizon effects in the planning time horizon, we account for an initial purchase of the initial bus fleet's value as well as for the salvage value of the bus fleet at the end of the planning horizon depending on the buses' age. To calculate discounted cash flows we use a linear depreciation rate.

While ICEBs do not require refueling during daily operations, BEBs may need to recharge while operating. Herein, the necessity to recharge depends on the bus line, the driving ranges, and the battery capacities of buses, respectively. Accordingly, we account for decisions on battery capacities.

We decide on the number and locations of two different types of charging facilities. While night charging facilities (NCFs) exclusively get installed at the central depot, we assume that the high-power, fast-charging opportunity charging facilities (OCFs) (e.g., pantographs) can be sited at initial and final stations of bus lines. Once installed, charging facilities cannot get uninstalled.

Accordingly, we differentiate buses into two different types, night charging buses (NCBs) and opportunity charging buses (OCBs). While NCBs exclusively recharge overnight at the depot, OCBs can additionally recharge during the day at OCFs during (short) dwell-times between operations. A distinction between NCBs and OCBs is necessary because OCBs must be equipped with special batteries and on-board charging devices to be able to recharge at OCFs.

In order to consider operational requirements, we embed a vehicle schedule that is feasible for ICEBs based on a given bus timetable. The bus timetable includes several service trips that must be operated. A service trip represents a driving activity with passengers on-board starting at an initial and ending at a final station of a bus line. Accordingly, a service trip is defined by start and end times at the respective initial and final bus stations.

As model input, we use trip sequences, which we determine based on a bus timetable. All trip sequences together create a vehicle schedule. A trip sequence denotes a specific order of service trip operations, dead-heading operations, and dwell-time operations that are performed by a single bus during one day. Herein, dead-heading operations constitute driving activities without passengers, which are used to transfer the bus from the final station of a trip to the initial station of the next trip. During dwell-time operations, buses pause at the first station of a trip in order to stay in line with the bus timetable. If such a station is equipped with a charging facility, an OCB may use available dwell-time to recharge its battery before departing to its next operation. Fig. 1 shows an example of one trip sequence containing four trips. Each trip sequence is operated by a dedicated bus, such that the number of trip sequences of the vehicle schedule indicates the number of buses required to operate the bus network. A bus starts and ends operating a specific trip sequence at the depot. We assume that any BEB starts with a full battery when leaving the depot in the morning, and model the amount of energy charged during a recharging process linear to the available recharging time.

As we aim at a conservative assessment of BEBs, we neglect potential additional revenue due to power grid services such as demand side management, vehicle to grid operations, and participation in the energy balancing market, as well as additional revenue due to a second life usage of batteries. We further neglect insurance and taxes as they typically do not differ between ICEBs and BEBs. Since the total number of buses and bus drivers is predetermined by the vehicle schedule and remains equal independent of the bus fleet composition, we do not account for labor costs.

Within this setting, we seek for a cost optimal transformation plan that indicates (i) which buses should be replaced in which time period and with which bus type, (ii) at which locations charging stations should be built in which time step, and (iii) which bus should operate which trip sequence in which time step, such that (iv) all bus to trip sequence allocations remain feasible over the planning horizon.

A few comments on this problem setting are in order. First, we assume the lifetime of BEBs and ICEBs to be equal. As BEBs are expected to have a higher lifetime than ICEBs due to less wearing parts (see, e.g., Davis and Figliozzi 2013), this assumption is in favor for ICEBs and represents a conservative estimate for BEBs. Second, we assume that we can always sell an ICEB, while a BEB remains in the fleet until the end of its lifetime once it is purchased. While this assumption clearly limits the decision space of the operator, it is in line with the scope of our study, which aims at analyzing the transformation towards an electrified bus fleet within a finite planning horizon. Third, we assume that charging facilities do not get uninstalled once they have been built. For charging facilities installed at the depot, no alternative locations exist, such that the assumption is not limiting in this case. For charging facilities at bus stations, the assumption is in line with current practice, where investments into charging facilities are treated as irrevocable strategic decisions, in particular since the placement of fast charging facilities may require significant additional investments for high voltage installations. Fourth, we assume that a bus starts with a fully charged battery in the morning. This does not affect the applicability of our results in practice as the buses usually have a sufficiently long break during the night such

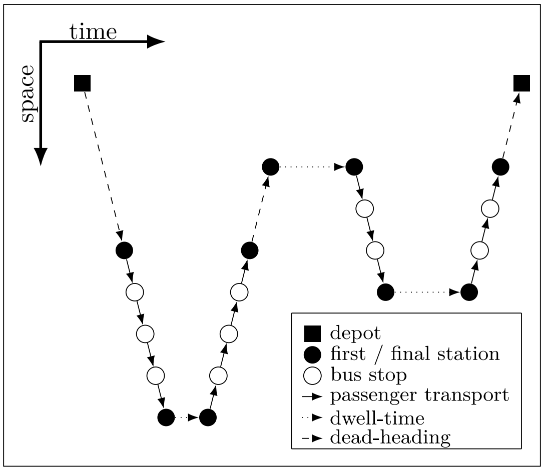



**Fig. 1.** Exemplary trip sequence of a vehicle schedule.

that they can be fully recharged. Fifth, we embed a predetermined vehicle schedule, which remains unchanged during the planning horizon, in our model. We make this assumption in order to keep the proposed modeling framework computationally efficient and note that using an ICEB-optimized schedule represents a conservative assumption for BEBs, as a more cost-efficient assignment for BEBs may exist. Integrating such an assignment decision into the modeling framework remains an interesting avenue for future research. Sixth, we assume a linear recharging function. We fit this function such that it yields a worst-case estimate for the original recharging function, which shows a concave shape. Since we consider only 80% of the nominal battery capacity to be usable when computing planning solutions, this worst-case estimate is sufficiently accurate. Nevertheless, the linear approximation would need to be replaced, e.g., by a piecewise linear function, when accounting for higher shares of usable battery capacity.

### *3.2. Model*

We now introduce a MIP to formalize the problem setting outlined above. This MIP accounts for discrete, time-dependent decisions over a finite time horizon $\overline{\mathcal{T}} = \{t_0, \dots, t_{\mathrm{n}+1}\}$, where $t_0$ and $t_{n+1}$ denote synthetic accounting periods in which the purchase costs of the original fleet and the salvage value of the transformed fleet are considered, but no decisions are taken. Subset $\mathcal{T} \subset \overline{\mathcal{T}} = \{t_1, \dots, t_{\mathrm{n}}\}$ denotes all time steps in which decisions are made. Set $\hat{\mathcal{T}}$ is an auxiliary set to define variables before the planning horizon, e.g., to account for purchase decisions that precede the planning horizon. Henceforth, we index time-dependent variables and parameters by $t$. In the following, we provide the notation of sets and decision variables. Table 2 summarizes our model parameters, sets, and decision variables.

We introduce different sets, one for each bus type, to avoid a complex tracking of individual buses: let $\mathcal{K}$ denote the set of all bus types, with $\mathcal{K}^{\mathrm{ICEB}} \subseteq \mathcal{K}$ being the set of all ICEB types and $\mathcal{K}^{\mathrm{BEB}} \subseteq \mathcal{K}$ being the set of all BEB types. We note that any set of bus types may contain several sub-types to account for different vehicle characteristics, e.g., heterogeneous battery capacities. Accordingly, we split the BEBs into NCB types $\mathcal{K}^{\mathrm{n}}$ and OCB types $\mathcal{K}^{\mathrm{o}}$ such that $\mathcal{K}^{\mathrm{BEB}} = \mathcal{K}^{\mathrm{n}} \cup \mathcal{K}^{\mathrm{o}}$.

Further, we denote with $\mathcal{F}$ the set of potential locations where a charging facility can be built. These locations must be initial stations of bus lines, i.e., stations at which a trip starts. We use $\lambda_i \in \mathcal{F}$ to denote the vertex that represents the initial station of trip $i$.

Let $\mathcal{S}$ be the set of all trip sequences $s \in \mathcal{S}$ for a given bus schedule. We note that all trips are uniquely identified by a label $l \in \mathcal{L}$ such that trip sequences are formally disjoint. Accordingly, we represent a trip sequence $s$ via two sets $\mathcal{N}_s$, $\mathcal{A}_s$. Here, $\mathcal{N}_s$ denotes the labels $l \in \mathcal{L}$ of all trips that belong to trip sequence $s$, while set $\mathcal{A}_s$ contains tuples $(i, j)$, which denote that trip $j$ succeeds trip $i$ after either some dwell-time or dead-heading. We note that formally, $\mathcal{A}_s$ allows to construct $\mathcal{N}_s$ and is thus sufficient to define $s$, but the additional use of $\mathcal{N}_s$ eases the notation of the MIP model significantly. For a detailed explanation of the computation of the sets $\mathcal{S}$, $\mathcal{N}_s$ and $\mathcal{A}_s$, which together define a vehicle schedule, we refer to Appendix A.

We use decision variables $n_{kt}$ to denote the number of buses of type $k$ in period $t$ in the bus fleet, and $Q_k$ to denote the battery capacity of a bus of type $k \in \mathcal{K}^{\mathrm{BEB}}$. Let $h_k$ be the holding period of a bus of type $k$, i.e., the time that a bus remains in the fleet before it is sold. Decision variables $p_{kt}$ define the number of buses of type $k$ that are purchased at the beginning of period $t$. Decision variables $a_t$ depict the number of installed depot charging facilities in period $t$. Binary decision variables $y_{ft}$ state whether an installed charging facility is located at bus station $f$ in period $t$. Binary decision variables $x_{skt}$ indicate which bus type $k$ is used to operate trip sequence $s$ in period $t$. We use variables $\Theta_{st}$ as an artificial delimiter that denotes the minimum battery capacity which is necessary to operate trip sequence $s$. For OCBs, $\Theta_{st}$ is limited by the net battery capacity $\mu Q_k$. In contrast, for NCBs, $\Theta_{st}$ is relaxed. With this delimiter, we formally decouple all energy balance constraints from being indexed to a specific bus type and keep the number of variables and constraints as small as possible. Finally, decision variables $q_{it}$ define the battery state of charge and $w_{it}$ denotes the amount of energy recharged before operating trip $i$ in period $t$. With this notation our model holds as follows.

**Table 2**
Notation of the model.

| | | |
|---|---|---|
| **Sets** | | |
| $\mathcal{K}$ | Set of bus types | $k \in \mathcal{K}$ |
| $\mathcal{K}^{\mathrm{ICEB}}$ | Set of ICEB types | $k \in \mathcal{K}^{\mathrm{ICEB}}$ |
| $\mathcal{K}^{\mathrm{BEB}}$ | Set of BEB types | $k \in \mathcal{K}^{\mathrm{BEB}}$ |
| $\mathcal{K}^{\mathrm{n}}$ | Set of night charging BEBs | $k \in \mathcal{K}^{\mathrm{n}}$ |
| $\mathcal{K}^{\mathrm{o}}$ | Set of opportunity charging BEBs | $k \in \mathcal{K}^{\mathrm{o}}$ |
| $\mathcal{F}$ | Set of potential charging facility locations | $f \in \mathcal{F}$ |
| $\mathcal{T}$ | Set of time periods | $t \in \mathcal{T}$ |
| $\mathcal{S}$ | Set of trip sequences | $s \in \mathcal{S}$ |
| $\mathcal{L}$ | Set of labels of all trips | $l \in \mathcal{L}$ |
| $\mathcal{N}_s$ | Set of labels $l \in \mathcal{L}$ of all trips that belong to trip sequence $s$ | $i \in \mathcal{N}_s$ |
| $\mathcal{A}_s$ | Set of tuples $(i, j)$ denoting that trip $j$ succeeds trip $i$ within sequence $s$ | $(i, j) \in \mathcal{A}_s$ |
| **Decision variables** | | |
| $n_{kt}$ | Integer: number of buses of type $k$ in fleet in period $t$ | – |
| $p_{kt}$ | Integer: number of buses of type $k$ purchased in period $t$ | – |
| $a_t$ | Integer: number of depot charging facilities in period $t$ | – |
| $y_{ft}$ | Binary: indicates if a charging facility is available at location $f$ in period $t$ | – |
| $x_{skt}$ | Binary: indicates if trip sequence $s$ is operated by a bus of type $k$ in period $t$ | – |
| $\Theta_{st}$ | Actual/fictional required battery capacity for operating trip sequence $s$ in period $t$ | kWh |
| $q_{it}$ | Battery state of charge before operating trip $i$ in period $t$ | kWh |
| $w_{it}$ | Amount of energy recharged before operating trip $i$ in period $t$ | kWh |
| **Parameters** | | |
| $c_k^{\mathrm{b}}$ | Costs for purchasing a bus of type $k$ | € |
| $c_{kt}^{\mathrm{q}}$ | Costs for purchasing a battery per unit for bus type $k$ in period $t$ | €/kWh |
| $C_0^{\mathrm{fleet}}$ | Value of the initial bus fleet | € |
| $v_k^{\mathrm{b}}$ | Salvage revenue due to selling a bus of type $k$ | € |
| $c_f^{\mathrm{o}}$ | Costs for installing an opportunity charging facility at location $f$ | € |
| $c_f^{\mathrm{hv}}$ | Additional costs for installing additional high-voltage equipment at location $f$ | € |
| $c^{\mathrm{n}}$ | Costs for installing a night charging facility | € |
| $c_f^{\mathrm{om}}$ | Annual costs for maintenance of an opportunity charging facility at location $f$ | €/a |
| $c^{\mathrm{nm}}$ | Annual costs for maintenance of a night charging facility | €/a |
| $\eta$ | Annual days of operation | d |
| $c_k^{\mathrm{bm}}$ | Costs for maintenance per distance covered by a bus of type $k$ | €/km |
| $c_k^{\mathrm{e}}$ | Costs for energy per unit consumed by a bus of type $k$ | €/kWh |
| $\beta_f$ | Number of potential opportunity charging points at location $f$ | – |
| $g$ | Discount rate | – |
| $e^b$ | Economic lifetime of a bus | a |
| $e^q$ | Economic lifetime of a battery | a |
| $h_k$ | Holding period of a bus of type $k$ | a |
| $Q_k$ | Installed battery capacity in BEB type $k$ | kWh |
| $\mu$ | Available percentage of battery capacity | – |
| $r$ | Charging power of an opportunity charging facility | kW |
| $\lambda_i$ | Denotes the vertex that represents the physical initial station of trip $i$ | – |
| $\gamma_i$ | Position of trip $i$ within a trip sequence | – |
| $o_k^{\mathrm{p}}$ | Energy consumption rate for a bus of type $k$ with passengers on-board | kWh/km |
| $o_k^{\mathrm{e}}$ | Energy consumption rate for an empty bus of type $k$ | kWh/km |
| $l_i$ | Covered distance of operating trip $i$ | km |
| $d_{ij}$ | Distance between end of trip $i$ and start of subsequent trip $j$ | km |
| $\tau_{ij}$ | Time between end of trip $i$ and start of subsequent trip $j$ | h |
| $\phi_{ij}$ | Travel time between end of trip $i$ and start of subsequent trip $j$ | h |

*Objective.* Objective (1) minimizes the (discounted) TCO associated with the integration of BEBs into urban bus networks. It includes costs for the bus fleet transformation ($C^{\mathrm{fleet}}$), the charging infrastructure installation ($C^{\mathrm{infr}}$), and the bus network operation ($C^{\mathrm{oper}}$). Each of these cost types occur on an annual basis: $C_t^{\mathrm{fleet}}$, $C_t^{\mathrm{infr}}$, $C_t^{\mathrm{oper}}$. Due to the finite planning horizon, the fleet operator needs to purchase the initial bus fleet for its initial value $C_0^{\mathrm{fleet}}$. To avoid unintended effects of the finite planning horizon, we account for the salvage value $V_{\mathrm{n+1}}^{\mathrm{fleet}}$ of the bus fleet at the end of the planning horizon.

$$\min\ Z = TCO = C^{\mathrm{fleet}} + C^{\mathrm{infr}} + C^{\mathrm{oper}} = C_0^{\mathrm{fleet}} + \sum_{t \in \mathcal{T}} \frac{C_t^{\mathrm{fleet}} + C_t^{\mathrm{infr}} + C_t^{\mathrm{oper}}}{(1+p)^t} - \frac{V_{\mathrm{n+1}}^{\mathrm{fleet}}}{(1+p)^{\mathrm{n+1}}} \tag{1}$$

The (annual) costs associated with the bus fleet transformation ($C_t^{\mathrm{fleet}}$) described in Eq. (2) consist of costs for purchasing new buses ($C_t^{\mathrm{bus.purch}}$), purchasing batteries and replacing them after their economic lifetime $e^q$ ($C_t^{\mathrm{bat.purch}}$), minus revenues ($V_t^{\mathrm{bus.sold}}$) due to selling buses for a salvage value at the end of the holding period $h_k$. The salvage value at the end of the planning period is determined by a linear depreciation of the purchase costs.

$$
\begin{aligned}
C_t^{\text{fleet}} &= C_t^{\text{bus.purch}} + C_t^{\text{bat.purch}} - V_t^{\text{bus.sold}} \\
&= \sum_{k\in\mathcal{K}} c_k^{\text{b}} p_{kt} + \sum_{k\in\mathcal{K}^{\text{BEB}}} c_{kt}^{\text{q}} Q_k \left(p_{kt} + p_{k,t-e^{\text{q}}}\right) - \sum_{k\in\mathcal{K}} \left(\left(c_k^{\text{b}} - v_k^{\text{b}}\right)\left(1 - \frac{h_k}{e^{\text{b}}}\right) + v_k^{\text{b}}\right) p_{k,t-h_k}
\end{aligned}
\tag{2}
$$

Costs for charging infrastructure ($C^{\text{infr}}$) consist of installation and maintenance costs, as described in Eq. (3). Costs for installing charging infrastructure ($C_t^{\text{infr.install}}$) only occur for newly installed charging facilities, i.e., if binary variable $y_{ft}$ changes its value from zero to one, or if integer variable $a_t$ increases. Herein, the costs for installing charging points as well as the maintenance costs depend on the number of charging points ($\beta_f$) to be installed at location $f$, which is exogenous to the model. Additionally, we consider additional investment costs for necessary high-voltage equipment ($c_f^{\text{hv}}$), e.g., if an additional transformer is necessary to operate a larger number of charging points in parallel.

$$
\begin{aligned}
C_t^{\text{infr}} &= C_t^{\text{infr.install}} + C_t^{\text{infr.maint}} \\
&= (\beta_f c_f^{\text{o}} + c_f^{\text{hv}}) \sum_{f\in\mathcal{F}} \left(y_{ft} - y_{f,t-1}\right) + c^{\text{n}}(a_t - a_{t-1}) + \beta_f c_f^{\text{om}} \sum_{f\in\mathcal{F}} y_{ft} + c^{\text{nm}} a_t
\end{aligned}
\tag{3}
$$

As described in Eq. (4), operational costs ($C^{\text{oper}}$) occur due to maintenance and repair of the bus fleet ($C_t^{\text{oper.maint}}$) as well as due to energy consumption ($C_t^{\text{oper.energy}}$), both depending on the selected bus type ($x_{skt}$) and the total distance covered. Herein, we consider heterogeneous energy consumption for service trips with passengers ($l_i$) and deadheading trips without passengers ($d_{ij}$).

$$
\begin{aligned}
C_t^{\text{oper}} &= \eta\left(C_t^{\text{oper.maint}} + C_t^{\text{oper.energy}}\right) \\
&= \eta\left(\sum_{k\in\mathcal{K}}\sum_{s\in\mathcal{S}} c_k^{\text{bm}}\left(\sum_{i\in\mathcal{N}_s} l_i + \sum_{(i,j)\in\mathcal{A}_s} d_{ij}\right) x_{skt} + \sum_{k\in\mathcal{K}}\sum_{s\in\mathcal{S}} c_k^{\text{e}}\left(o_k^{\text{p}} \sum_{i\in\mathcal{N}_s} l_i + o_k^{\text{e}} \sum_{(i,j)\in\mathcal{A}_s} d_{ij}\right) x_{skt}\right)
\end{aligned}
\tag{4}
$$

At the end of the planning horizon, we take a payment ($V_{\text{n+1}}^{\text{fleet}}$) equal to the total final salvage value of all buses ($V_{\text{n+1}}^{\text{bus.salv}}$) and batteries ($V_{\text{n+1}}^{\text{bat.salv}}$) into account. Again, the salvage value results from a linear depreciation, as described in Eq. (5).

$$
\begin{aligned}
V_{\text{n+1}}^{\text{fleet}} &= V_{\text{n+1}}^{\text{bus.salv}} + V_{\text{n+1}}^{\text{bat.salv}} \\
&= \sum_{k\in\mathcal{K},\ t\in\{\mathcal{T}|t\ge t_{\text{n+1}}-h_k\}} \left(\left(c_k^{\text{b}} - v_k^{\text{b}}\right)\left(1 - \frac{t_{\text{n+1}} - t}{e^{\text{b}}}\right) + v_k^{\text{b}}\right) p_{kt} + \sum_{k\in\mathcal{K}^{\text{BEB}},\ t\in\{\mathcal{T}|t\ge t_{\text{n+1}}-e^{\text{q}}\}} c_{kt}^{\text{q}} Q_k \left(1 - \frac{t_{\text{n+1}} - t}{e^{\text{q}}}\right)\left(p_{kt} + p_{k,t-e^{\text{q}}}\right)
\end{aligned}
\tag{5}
$$

*Constraints.* Our objective is subject to the following constraints.

$$n_{kt} = n_{k,t-1} + p_{kt} - p_{k,t-h_k} \qquad k \in \mathcal{K}, t \in \mathcal{T} \cup \hat{\mathcal{T}} \tag{6}$$

$$a_t \ge \sum_{k\in\mathcal{K}^{\text{BEB}}} n_{kt} \qquad t \in \mathcal{T} \tag{7}$$

$$a_t \ge a_{t-1} \qquad t \in \mathcal{T} \tag{8}$$

$$y_{ft} \ge y_{f,t-1} \qquad f \in \mathcal{F}, t \in \mathcal{T} \tag{9}$$

$$\sum_{k\in\mathcal{K}} x_{skt} = 1 \qquad s \in \mathcal{S}, t \in \mathcal{T} \tag{10}$$

$$n_{kt} \ge \sum_{s\in\mathcal{S}} x_{skt} \qquad k \in \mathcal{K}, t \in \mathcal{T} \tag{11}$$

$$\left(o_k^{\text{p}} \sum_{i\in\mathcal{N}_s} l_i + o_k^{\text{e}} \sum_{(i,j)\in\mathcal{A}_s} d_{ij}\right) x_{skt} \le \mu Q_k \qquad s \in \mathcal{S}, k \in \mathcal{K}^{\text{n}}, t \in \mathcal{T} \tag{12}$$

$$\Theta_{st} \le \mu Q_k + M(1 - x_{skt}) \qquad s \in \mathcal{S}, k \in \mathcal{K}^{\text{o}}, t \in \mathcal{T} \tag{13}$$

$$0 \le q_{it} \le \Theta_{st} - d_{0i} o_k^{\text{e}} \qquad s \in \mathcal{S}, i \in \{\mathcal{N}_s | \gamma_i = 0\}, k \in \mathcal{K}^{\text{BEB}}, t \in \mathcal{T} \tag{14}$$

$$0 \le q_{jt} \le q_{it} + w_{it} - l_i o_k^{\text{p}} - d_{ij} o_k^{\text{e}} \qquad s \in \mathcal{S}, (i,j) \in \{\mathcal{A}_s | \gamma_i \ne 0\}, k \in \mathcal{K}^{\text{BEB}}, t \in \mathcal{T} \tag{15}$$

$$0 \le w_{jt} \le r(\tau_{ij} - \phi_{ij}) y_{\lambda_j t} \qquad s \in \mathcal{S}, (i,j) \in \mathcal{A}_s, t \in \mathcal{T} \tag{16}$$

$$w_{it} \le \Theta_{st} - q_{it} \qquad s \in \mathcal{S}, i \in \mathcal{N}_s, t \in \mathcal{T} \tag{17}$$

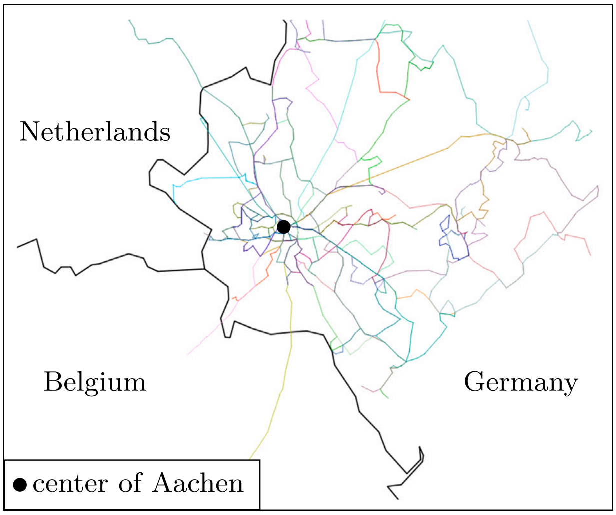



**Fig. 2.** Bus network in Aachen.

$$n_{kt}, p_{kt} \in \mathbb{N} \qquad k \in \mathcal{K}, t \in \mathcal{T} \tag{18}$$

$$a_t \in \mathbb{N} \qquad t \in \mathcal{T} \tag{19}$$

$$y_{ft} \in \{0; 1\} \qquad f \in \mathcal{F}, t \in \mathcal{T} \tag{20}$$

$$x_{skt} \in \{0; 1\} \qquad s \in \mathcal{S}, k \in \mathcal{K}, t \in \mathcal{T} \tag{21}$$

Constraints (6) define the holding balance for each bus type and thus the point in time when buses of a certain type must be sold. Constraints (7) ensure sufficient overnight charging facilities in the depot. Constraints (8) and (9) ensure that an installed charging facility cannot be uninstalled in a subsequent period. Constraints (10) ensure that any trip sequence $s$ is served by exactly one bus type $k$. To guarantee operational feasibility, Constraints (11) enforce that for each bus type $k$ the number of buses available is sufficient for the fleet's operation at any point in time. In order to ensure the bus network operation with limited driving ranges of BEBs, Constraints (12)–(17) preserve energy balance constraints and secure that a bus does not run out of energy during operations. Here, Constraints (12) ensure that the total energy consumption of a trip sequence does not exceed the net available battery capacity $\mu Q_k$ if an NCB is assigned to it. Constraints (13)–(17) ensure that an assigned OCB never runs out of energy, while accounting for (partial) recharging operations. Specifically, Constraints (13) limit the artificial delimiter $\Theta_{st}$ to the net available battery capacity $\mu Q_k$. By linking the artificial delimiter $\Theta_{st}$ with the binary sequence assignment variable $x_{skt}$ in Constraints (13), we formally decouple the assignment decisions from the following energy balance Constraints (14)–(17) to reduce the model complexity. Constraints (14) limit the battery state of charge $q_{it}$ before operating the first trip of a trip sequence, and Constraints (15) indicate the battery state of charge $q_{jt}$ ahead of all remaining trips and at depot arrival. Since the amount of recharged energy depends on recharging time and charging power, Constraints (16) limit the recharged energy $w_{it}$ to the product of net available time $\tau_{ij} - \phi_{ij}$ and the installed charging power $r$. Constraints (17) ensure that the recharged energy $w_{it}$ does not exceed the remaining battery capacity $Q_k - q_{it}$. We note that Constraints (13)–(17) only affect OCBs, since $\Theta_{st}$ has a dummy status if $x_{skt} = 1, k \notin \mathcal{K}^{o}$. Therefore, for NCBs, Constraints (13)–(17) do not apply as $\Theta_{st}$ remains a sufficiently high value so that the related energy balance constraints are relaxed. Finally, Constraints (18)–(21) state integer and binary domains.

## 4. Case study

We base our case study on the real-world bus network in the city of Aachen, Germany (see Fig. 2), which is one of the biggest European public transport systems that relies exclusively on bus transportation. Within one year, the buses of the network's operator "Aachener Straßenbahn und Energieversorgungs-AG" (ASEAG) cover a distance of 20 million kilometers and transport more than 71 million passengers resulting in a transport volume of 101 million passenger kilometers per year (ASEAG 2020). In total, 55.9 million Euros of bus fares were captured in 2019. To serve 108 bus lines, 498 buses are available and 600 bus drivers are employed. Besides regular bus lines, this includes school buses, night buses, express buses and dial-a-bus services. In total, the buses travel on average 56,000 km per day. The average distance of bus lines' respective trips is between 3.2 and 41 km, while the length of

**Table 3**
Technical data.

| Parameter | Description | Value | Unit | Reference |
|---|---|---|---|---|
| $e$ | Economic lifetime of any bus | 12 | Years | II, III, IV |
| $h_k$ | Holding period of a bus of type $k$ | $1, \dots, 12$ | Years | |
| $Q_k$ | Battery capacities | $100, 200, 300, 400$ | kWh | V |
| $\mu$ | Usable percentage of battery capacity | 80 | % | II, IV |
| $b$ | Economic lifetime of a battery | 6 | Years | II |
| $o^{\mathrm{p}}_{\mathrm{ICEB}}$ | Diesel consumed by an ICEB | 0.61 | l/km | I |
| $o^{\mathrm{p}}_{\mathrm{BEB}}$ | Electricity consumed by a BEB | 2.06 | kWh/km | III |

(I)–(V) refer to references as follows: (I) ASEAG (2020), (II) IKT für Elektromobilität (2015), (III) Lajunen (2018), (IV) Rogge et al. (2018), (V) Gao et al. (2017).

a sequence a bus is driving per day (i.e., the sum of all trips and dead-heading activities) lies between 40 km and 481 km. ASEAG operates this fleet with a single depot.

Currently, legal $NO_x$ concentration thresholds are exceeded in the city center of Aachen. Accordingly, local public transport authorities aim at operating public transport and thus the ASEAG's bus fleet mainly by BEBs in the future (Stadt Aachen 2018). As a result, the local bus operator ASEAG currently considers to comprehensively integrate BEBs into its fleet, herein facing the need to provide sufficient charging facilities and to ensure operational feasibility. Given the high heterogeneity of bus lines regarding their different lengths and number of bus stops, the ASEAG bus network constitutes a promising case study to observe a multitude of structural effects when applying an integrated planning approach.

Accordingly, we base our analysis on the transformation process of the ASEAG bus network towards BEBs. We analyze the underlying network with the regular bus lines, i.e., we omit the school, night, express, and dial-a-service lines. In total, we consider 60 regular bus lines with 5092 trips per workday serving 1018 bus stops (AVV 2019). In the following, we detail the used data and our methodology to evaluate $NO_x$ emissions in Section 4.1, before we describe our experimental design in Section 4.2.

### 4.1. Data

We consider a time horizon of 20 years, $\mathcal{T} = \{2020, 2021, \dots, 2039\}$ and a fleet size that equals the number of necessary trip sequences, such that one bus is available for each trip sequence. To cover the considered 60 bus lines, the fleet requires $|\mathcal{S}| = 357$ buses.

We assume a maximum holding period of buses, i.e., a vehicle lifetime, of 12 years. Accordingly, we introduce $|\mathcal{K}^{\mathrm{ICEB}}| = 12$ different ICEB classes, each with a specific holding period $h_k \in \{1, \dots, 12\}$, to allow for a heterogeneous age mix of ICEBs in the fleet. We assume that once BEBs are purchased, all vehicles are kept for the maximum holding period of 12 years.

We consider different battery capacities $Q_k \in \{100, 200, 300, 400\}$ kWh that reflect the range of technical specifications currently offered on the market (cf. Gao et al. 2017), with $Q_{\max} = 400$ kWh being the maximum available battery capacity. Note that we consider only $\mu = 80\%$ of the respective battery to be usable in our case study (cf. Table 3) to preserve the conservative perspective of our analysis and to keep our linear recharging assumption valid. Depending on the application case, one may consider even lower shares of usable battery capacity. We refer to Appendix C for a detailed discussion of this effect. Besides different battery capacities, we further distinguish between NCBs that are only charged overnight at the depot, and OCBs that can be additionally charged during operations. Combining the different battery capacity classes and charging concepts, we account for $|\mathcal{K}^{\mathrm{n}}| = 4$ types of NCBs and $|\mathcal{K}^{\mathrm{o}}| = 4$ types of OCBs.

We allow any initial bus station of a trip to serve as a potential opportunity charging facility location such that the set of potential opportunity charging facilities consists of $|\mathcal{R}| = 182$ locations. To install opportunity charging facilities, we consider two different setups. If an opportunity charging facility is installed at a normal bus stop, we consider the installation of a charging facility with $\beta_f = 2$ charging points to provide sufficient charging points for most parallel charging operations as hardly more than two buses arrive in parallel at normal, spatially distributed stations. If opportunity charging facilities are installed at centrally-located hub stations, we increase the number of charging points to $\beta_f = 8$, which reflects the maximum number of bus lines that arrive at one central hub in parallel in our case study and account for additional transformer cost. In our specific case study, three centrally located hub stations "Aachen Bushof", "Mühlener Bahnhof", and "Eschweiler Bushof" exist.

Table 3 details further technical data that is necessary to specify all parameters. If a bus performs a dead-heading operation without passengers on board, we reduce the energy that is consumed by 25% compared to the energy consumption with passengers on board.

One comment on this case study setup is in order. We exogenously set the number of charging points, which affects the optimality of our solution and does not necessarily ensure that two BEBs compete for a charging point during operations. To quantify the operational bottlenecks that result from competing charging operations, we applied an a-posteriori analysis on the solution and find that for our case study, 23 out of 666 charging operations (3,5%) are conflicting. We then analyzed how these conflicts could be resolved by a-posteriori increasing the number of charging points at the built stations. As in our case study the cost for building charging infrastructure is significantly smaller than the cost for transforming the fleet, a-posteriori increasing the number of charging points at locations with bottlenecks such that no charging conflicts remain, requires additional investment costs of 0.14% compared

**Table 4**
Cost terms.

| Parameter | Description | Value | Unit | Reference |
|---|---|---|---|---|
| $c^{b}_{ICEB}$ | Purchase costs of an ICEB | 330,000 | € | I |
| $c^{b}_{BEB}$ | Purchase costs of a BEB (w/o battery) | 350,000 | € | I[a] |
| $v^{b}_{k}$ | Salvage value of purchase costs of a bus | 7 | % of $c^{b}_{ICEB}$ | I |
| $c^{q}_{k0}$ | Initial battery costs (50 kW) | 487.5 | €/kWh | III[b] |
| $c^{q}_{k0}$ | Initial battery costs (350 kW) | 780 | €/kWh | III[b] |
| $c^{bm}_{ICEB}$ | Maintenance costs of an ICEB | 0.5 | €/km | I |
| $c^{bm}_{BEB}$ | Maintenance costs of a BEB | 0.44 | €/km | I |
| $c^{e}_{ICEB}$ | Diesel price | 0.97 | €/l | IV |
| $c^{e}_{BEB}$ | Electricity price | 0.13 | €/kWh | IV |
| $c^{o}_{f}$ | Costs of an opportunity charging facility (50 kW) | 30,000 | € | V |
| $c^{o}_{f}$ | Costs of an opportunity charging facility (150 kW) | 90,000 | € | VI |
| $c^{o}_{f}$ | Costs of an opportunity charging facility (350 kW) | 134,250 | € | VI |
| $c^{hv}_{f}$ | Costs for installing a transformer at a central hub station | 500,000 | € | VI |
| $c^{n}$ | Costs of a night charging facility (depot) | 5,000 | € | V |
| $c^{om/nm}_{f}$ | Maintenance costs of a charging facility | 1 | %/year of $c^{o/n}_{f}$ | V |
| $g$ | Interest rate | 5 | %/year | I |
| $\eta$ | Annual days of operation (fictional) | 307 | Days/year | |

(I) – (VI) characterize references as follows: (I) IKT für Elektromobilität (2015), (II) Kunith (2017), (III) Lajunen (2018), (IV) Destatis (2018), (V) NPE (2015), (VI) personal communication with a major bus manufacturer.
[a]Adapted based on specific bus type characteristics.
[b]Updated considering annual battery price reduction (2.5%).

to the optimized solution. Accordingly, exogenously fixing the charger capacity for each location remains a mild assumption for our case study.

However, for case studies that require significantly higher cost for charging facility infrastructure, this assumption might create a huge bias; in this case, the charging facility capacity should be incorporated into the optimization, e.g., by using an outer optimization routine to determine the best charging facility capacity for each potential location or by extending our modeling approach to directly account for blocking at charging facilities, thus implicitly selecting the right number of charging points for each location.

We base our cost term estimates on data from recent field projects and expert knowledge. Table 4 provides an overview of these cost terms and their references. We note that cost terms of opportunity charging facilities and batteries for OCBs depend on charging power. Here, the increased cost per kWh for OCBs that are amenable for 350 kW charging result from increased technical requirements. To determine cost values for battery capacities and charging facility technologies that are not listed in Table 4, we apply a linear interpolation between listed values. For night charging facilities and NCBs, we assume a charging power of 50 kW. We anticipate operational costs by calculating a number of workday equivalent days, i.e., we convert weekend and public holiday timetables into their workday equivalent.

Table 5 summarizes the initial bus fleet composition (see Stadt Aachen 2018) and the legal $NO_x$ emission thresholds (see European Union 2009) that these buses comply with. Regarding the fleet composition at the start of the planning horizon in $t_0$, we assume that all buses comply with the $NO_x$ threshold that was in force when the bus was purchased, i.e., emissions depend on the age of the bus.

When an ICEB is purchased during the planning horizon, we assume that it complies with the newest EU-VI standard. For BEBs, we assume zero local $NO_x$ emissions. Further, we assume that the operator replaces older ICEBs with high emissions first. We then calculate $NO_x$ emissions a-posteriori converting EURO emission thresholds ($E_{NO_x}$) for heavy-duty vehicles and buses that are defined in kWh to mass emissions per kilometer as

$$\widehat{E_{NO_x}}\left[\frac{g}{km}\right] = E_{NO_x}\left[\frac{g}{kWh}\right] o\left[\frac{m^3}{km}\right] \rho\left[\frac{kg}{m^3}\right] H\left[\frac{kWh}{kg}\right],$$

with $o = 0.00059$, $\rho = 832.5$, and $H = 11.9$.

### 4.2. Design of experiments

We split our experiments into two parts. We first perform an a-priori feasibility study to discuss structural characteristics of the case study. We then perform optimization-based analyzes by solving the MIP as introduced in Section 3.

*A-priori feasibility study:* We perform an a-priori feasibility study to analyze the minimum battery capacities that are necessary for an electrification of the bus network dependent on the available charging power. Additionally, we analyze the maximum share of BEBs that can be feasibly deployed for a specific battery capacity and charging power. These results allow for in-depth analyzes

**Table 5**
Emission factors.

| Number of buses[a] | Standard[b] | $E_{NO_x}$ [g/kWh] | $\widehat{E_{NO_x}}$ [g/km] |
|---|---|---|---|
| 109 | EU-III | 5.0 | 29.22 |
| 165 | EU-V / EEV | 2.0 | 11.69 |
| 83 | EU-VI | 0.4 | 2.38 |

[a]Stadt Aachen (2018).
[b]European Union (2009).

**Table 6**
Bus types per scenario.

| Scenario | Bus type | | |
|---|---|---|---|
| | ICEB | NCB | OCB |
| `all` | ✓ | ✓ | ✓ |
| `ic` | ✓ | | |
| `nc` | ✓ | ✓ | |
| `oc` | ✓ | | ✓ |

of the optimization-based analyzes with regard to its solution space, i.e., allow to quantify whether a certain share of BEBs results from economic conditions or technological limitations.

*Optimization-based analyzes:* We define each scenario by its purchasable bus types. Table 6 summarizes all possible scenarios, including a reference scenario in which all different bus types are available (`all`), a scenario in which only ICEBs are available (`ic`), as well as two scenarios in which either only ICEBs and NCBs (`nc`) or only ICEBs and OCBs (`oc`) are available.

For each scenario, we analyze different parameter settings for the available charging power ($r$) and annual battery price reductions ($b$). We vary the available charging power $r$ in $r \in \{50, 100, \dots, 500\}$ kW and consider battery price reductions $b \in \{0, 2.5, \dots, 12.5\}$ %/year. With these parameter variations, we capture an ongoing discussion between academics and practitioners whether high-capacity batteries should be favored over high-power charging facilities combined with low-capacity batteries or vice versa. Concluding, we consider four scenarios (`all`, `ic`, `nc`, `oc`) and 60 different parameter settings (`r50-500|b0-12.5`).

We identify each scenario by a unique identifier, stating (in this order) the bus type scenario, the available charging power, and the considered battery price reduction, e.g., our basic scenario (`all|r350|b2.5`) refers to a scenario where all bus types are available, the available charging power of charging facilities is $r = 350$ kW, and the annual battery price reduction is $b = 2.5$ %/year. We split our analyzes in two parts, first analyzing a base case, motivated from our a-priori feasibility studies, and a subsequent sensitivity analyzes over the stated parameter ranges.

## 5. Results

In the following, we first discuss our a-priori feasibility study in Section 5.1. Afterwards, we discuss results for the reference scenario in Section 5.2, before we detail the scenario analysis in Section 5.3, and derive managerial insights in Section 5.4. We solved the MIP to optimality for all cases within a computational time limit of 60 min, using a standard desktop computer with 16-GB-RAM and 3.6 GHz (Intel i7-4790) using Gurobi-8.1.0.

### 5.1. A-priori feasibility study

With this a-priori analysis we aim at identifying the space of operationally feasible solutions, i.e., we identify which sequences can be operated by a BEB dependent on the available power at opportunity charging facilities and dependent on the battery capacity of the BEBs. To do so, we determine for each sequence $s \in \mathcal{S}$ the minimum battery capacity that is necessary to operate a BEB on this sequence. For these analyzes, we consider the most optimistic scenario and assume that an OCF is available at any first or final station of a trip. To check the feasibility of a sequence, we then use Constraints (14)–(16). We repeat this analysis for different power levels at charging facilities to explore the interdependency between the available charging power level at opportunity charging facilities and the available battery capacity.

Fig. 3 shows a Box-Whisker-Plot that details the distribution of necessary battery capacities to operate all $|\mathcal{S}| = 357$ sequences with BEBs at a certain charging power level. Further, the figure indicates the maximum battery capacity $Q_{\max} = 400$ kWh with a dashed line. As can be seen, a complete fleet transformation that allows to operate all sequences with BEBs is only feasible with either battery capacities or charging power levels that exceed the current technological state of the art.

Fig. 4 shows the share of sequences $s \in \mathcal{S}$, which can be operated with a BEB at a certain charging power level, if we set the available battery capacity to its maximum value. As can be seen, an electrification of 62.5% to 93.3% of the total fleet can be realized with current status-quo charging power levels between 50 kW and 150 kW. For higher shares of electrification, one has to significantly increase the charging power level. High-power chargers of the latest generation with a charging power of 350 kW allow for the electrification of 99.72% of all trips. To achieve a full electrification, a charging power of at minimum 400 kW would be necessary. Concluding, we note that a maximum electrification of 99.72% can be reached in our reference scenario (`all|r350|b2.5`).

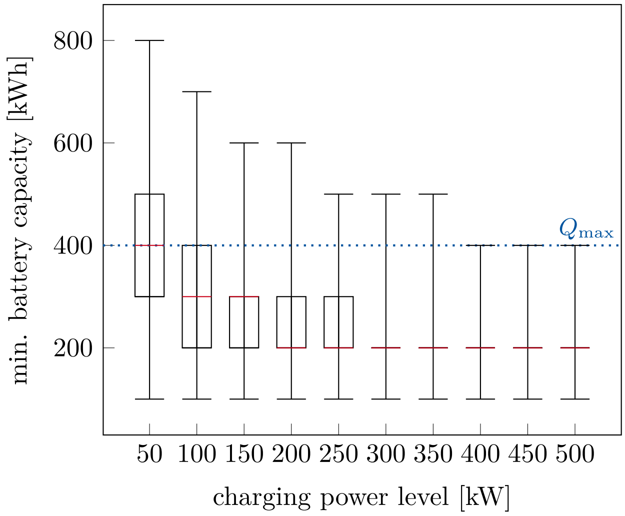



**Fig. 3.** Box-Whisker-Plot indicating minimum required battery capacity of any sequence for a variation of charging power (`r50-500|bX`).

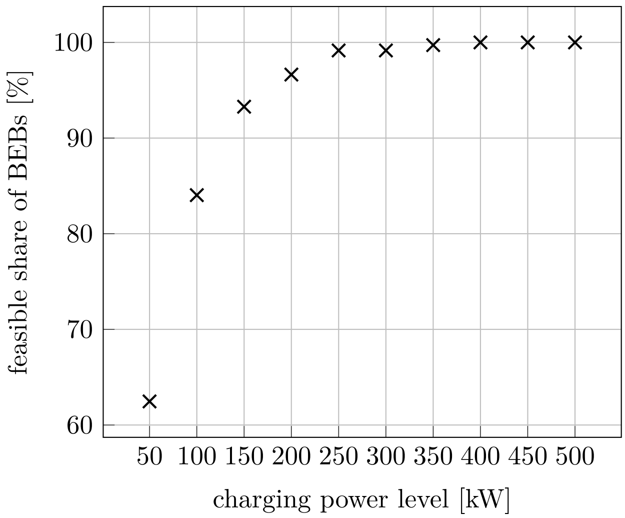


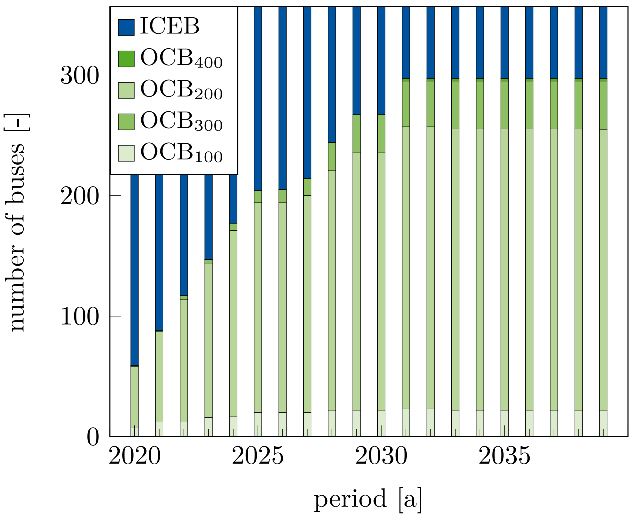

**Fig. 4.** Feasible share of BEBs for a variation of charging power (`r50-500|bX`), assuming a maximum battery capacity of 400 kWh.

### *5.2. Reference scenario*

Fig. 5 shows the cost-optimal bus fleet composition over the planning horizon $\mathcal{T} = \{2020, \ldots, 2039\}$ and its corresponding TCO balance that results from solving the MIP from Section 3 for the reference scenario (`all|r350|b2.5`). Here, the subscript of each BEB type indicates its battery capacity, e.g., $\mathrm{OCB}_{100}$ denotes OCBs with a battery capacity of 100 kWh. As can be seen, the fleet transformation evolves over time with a steadily increasing share of OCBs. Remarkably, only OCBs are integrated into the fleet, mostly with battery capacities of 100 kWh, 200 kWh or 300 kWh. Only two OCBs with the maximum capacity of 400 kWh are integrated in the year 2031. Overall, the realized deployment of BEBs falls short compared to its feasible maximum of 99.72% as only 84% of all buses are replaced by BEBs throughout the planning horizon. Obviously, the remaining buses are not replaced for economic reasons. This steady state is already reached after the first half of the planning horizon in 2031 such that the operational cost savings of the BEB can compensate the higher investment costs.

Our results show that the cost-optimal transformation takes place stepwise, which may appear counter-intuitive on the first glimpse. Analyzing this effect shows that each bus sequence has an individual break-even point that may differ over time due to additional effects, e.g., the annual battery price reduction. Still, the realized operational costs remain the critical parameter that determines whether a sequence breaks even for BEB deployment or not.

Fig. 6 analyzes the assignment of bus types with respect to the characteristics of trip sequences at the end of the planning horizon. It details the operational assignment of buses to sequences and shows which trip sequences are operated by which bus type. Each




| description | value | unit |
|---|---|---|
| TCO | 474.29 | €MM |
| initial bus fleet value | 54.37 | €MM |
| bus purchases | 210.18 | €MM |
| bus sales | -20.98 | €MM |
| final bus fleet value | -26.98 | €MM |
| charging infrastructure | 3.86 | €MM |
| operational costs | 253.84 | €MM |
| $NO_X$ emissions | 67.3 | t/year |

* Note that all costs are cumulated and discounted.

**Fig. 5.** Development of the bus fleet composition, TCO, and $NO_x$ emissions (all|r350|b2.5).

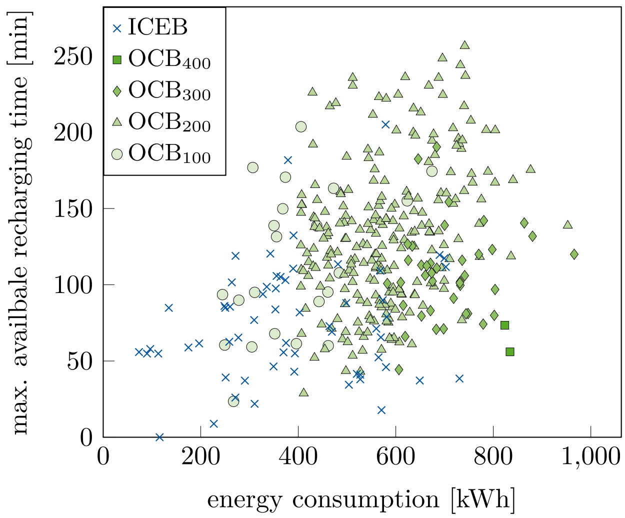



**Fig. 6.** Operational assignment of bus types to trip sequences at the end of the planning horizon (all|r350|b2.5).

data point represents one trip sequence $s$ of the input vehicle schedule $\mathcal{S}$, indicating its energy consumption and maximum available recharging time, as well as the bus type chosen to operate the sequence. Here, the maximum available recharging time is equal to the sum of available dwell-times between all trips of a sequence. As can be seen, the assignment of bus types depends on both energy consumption and potential recharging time. If feasible, OCBs are assigned to trip sequences with a high energy consumption to leverage the advantage of the BEBs' operational cost savings. Low-capacity OCBs are only assigned to trip sequences with a high energy consumption if sufficient recharging time is available; in case of small available recharging times, high-capacity OCBs are used to operate these sequences. In contrast, ICEBs are used to operate trip sequences with a low energy consumption. Thus, the missing electrification of these trip sequences does not result from range or charging limitations of BEBs, but for economic reasons. ICEBs are used to operate short sequences with a low energy consumption, as for these sequences the lower operational costs of a BEB cannot compensate for its higher investment costs.

Fig. 7 shows the charging infrastructure investments for the optimal fleet transformation. As can be seen, all charging infrastructure investments are taken in the first and fourth step of the planning horizon and only few bus stations are equipped with opportunity charging facilities. After 2023, no additional OCFs are installed in the network. These results show that our integrated planning approach allows to identify a network design that is able to operate a large share of a bus fleet via BEBs with only a few central opportunity charging facilities. Further, these results emphasize that the electrification of trip sequences that require not only investments into BEBs but also into opportunity charging facilities takes place at the beginning of the planning horizon such that the operational cost savings can compensate the investments over the planning horizon.

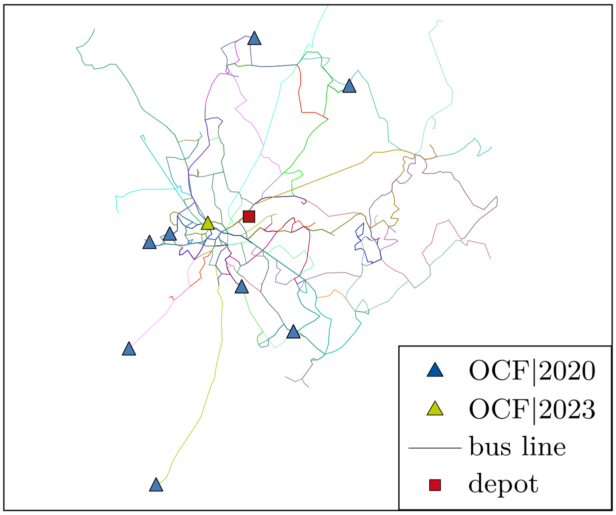



**Fig. 7.** Installation of opportunity charging facilities.

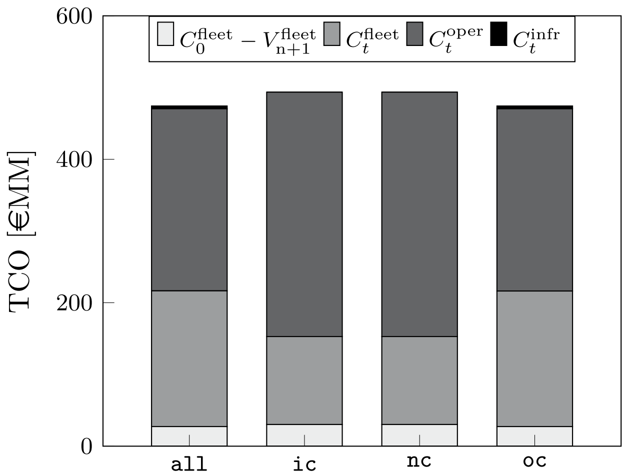



**Fig. 8.** TCO structure for each bus type scenario with $r = 350\,\text{kW}$ and $b = 2.5\,\%/\text{year}$.

### 5.3. Scenario analysis

In the following, we summarize the findings of our sensitivity analysis for both the different bus type scenarios and for the parameter sensitivities. For detailed results, we refer to Appendix B.

First, we discuss results on costs and $NO_x$ emissions for the four bus type scenarios `all`, `ic`, `nc`, and `oc`. Fig. 8 shows the TCO structure for each bus type scenario, with all other parameters remaining as in the base case setting. Herein, information can be derived on the difference between the initial and final fleet value ($C_0^{\text{fleet}} - V_{\text{n+1}}^{\text{fleet}}$), investment costs resulting from the bus fleet transformation ($C_t^{\text{fleet}}$), operational costs ($C_t^{\text{oper}}$), and costs for installing charging infrastructure ($C_t^{\text{infr}}$). As can be seen, operational costs account for the largest share of TCO in all scenarios. Scenarios `all` and `oc` show lower operational costs but higher investment costs compared to scenarios `ic` and `nc`. Herein, the decrease in operational costs offsets the increase in investment costs such that scenarios `all` and `oc` show total costs that are 3.9% lower than in scenarios `ic` and `nc`. Fig. 9 shows $NO_x$ emissions of all scenarios. As can be seen, scenarios `all` and `oc` result in 52.9% lower $NO_x$ emissions than the `ic` and `nc` scenario.

We note that for both figures, the `all` and the `oc` as well as the `ic` and `nc` scenarios show the same results. This is not surprising because the optimal transformation strategy of the `all` scenario is based solely on the deployment of OCBs. Accordingly, the `nc` scenario remains equal to a pure ICEB scenario.

Next, we discuss the impact of the charging power that is available for partial recharging at opportunity charging facilities during dwell-times between trips. Fig. 10 shows the TCO for all bus type scenarios depending on the charging power keeping the annual battery price reduction at 2.5%/year. Obviously, the results of the `all` and `oc` scenarios as well as the results of the `ic` and `nc`

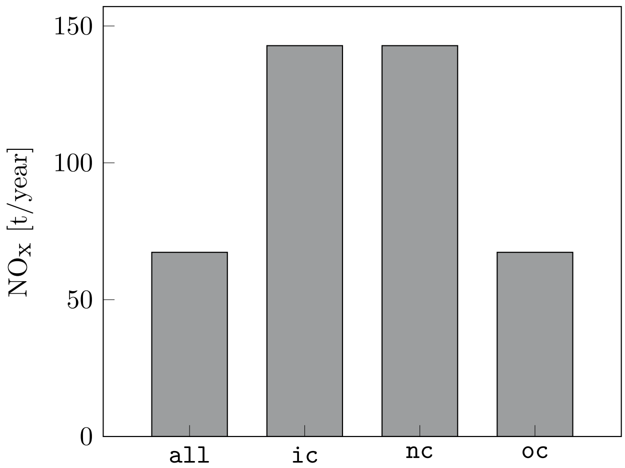



**Fig. 9.** $NO_x$ emissions for each bus type scenario with $r = 350\,kW$ and $b = 2.5\,\%/year$.

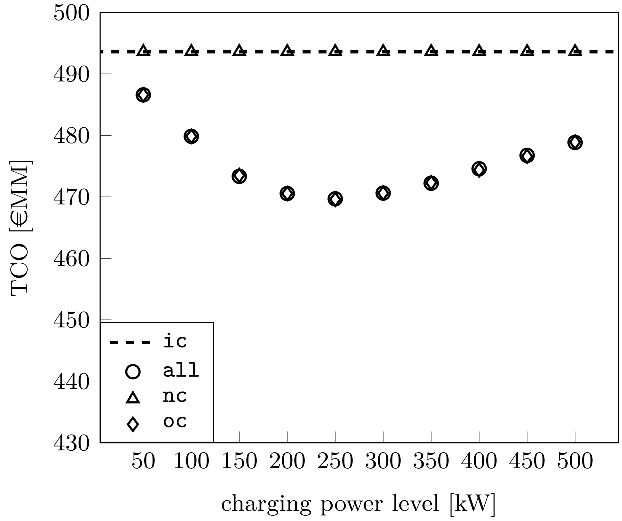



**Fig. 10.** TCO in scenarios `ic`, `all`, `nc`, `oc` for a variation of charging power (`X|r50-500|b2.5`).

scenarios are again equal as the charging power for intermediate charging does not affect the viability of NCBs. As can be seen, the minimum TCO with a reduction of 4.6% compared to the `ic` scenario can be achieved for the `all` and `oc` scenarios with a charging power of 250 kW. This setting allows for the best trade-off between higher investment costs, sufficient charging power, and reduced operational costs.

Fig. 11 shows the corresponding $NO_x$ emissions. As the cost savings correlate with the deployment of BEBs, a maximum reduction of $NO_x$ emissions by 56.2% for the `all` and `oc` scenarios is also realized for a charging power of 250 kW. This reduction exceeds the 52.9% savings of the reference scenario, which shows that the right balance between the available charging power and its cost does not only affect a fleet's overall TCO but also the viability of the electrification of single trip sequences.

We now analyze the impact of the annual battery price reduction on costs and emissions. Fig. 12 shows the TCO for all bus type scenarios depending on the annual battery price reduction while keeping the charging power at 350 kW. As can be seen, the deployment of OCBs (`all` / `oc`) improves the TCO compared to the `ic` scenario for any battery price reduction within a range of 1.8%/year to 11.2%/year. With a higher battery price reduction, more trip sequences break even for the OCB operations and thus the TCO savings increase. Contrary, for NCBs, only few trip sequences break even and the TCO remain close to the `ic` scenario. This holds even for annual battery price reductions equal or higher than 7.5%/year.

Fig. 13 shows the corresponding $NO_x$ emissions. The emission savings for the deployment of OCB ranges between 42.6% and 66.1%, while the emissions of the `nc` scenarios remain close or equal to the `ic` scenario.

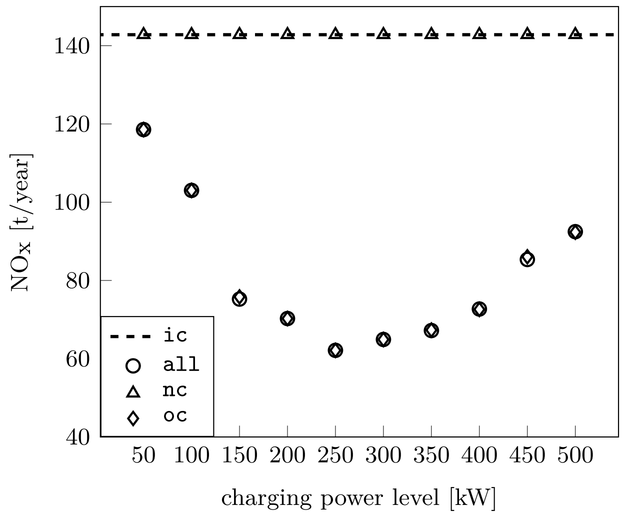



**Fig. 11.** $NO_x$ emissions in scenarios `ic`, `all`, `nc`, `oc` for a variation of charging power (`X|r50-500|b2.5`).

### 5.4. Managerial insights

The results of our case study allow to derive several managerial insights. We synthesize the findings of our study as follows:

**A comprehensive share of today's bus networks can be electrified with state-of-the-art technology:** Our a-priori feasibility study suggests that a large share of trip sequences in existing bus networks can already be operated by BEBs with available fast charging facilities and existing BEB specifications. Even for the ASEAG network as one of the biggest European public transport systems operated solely by buses, this share amounts to 99.72%.

**The deployment of BEBs is economically viable for a significant amount of potentially electrifiable trip sequences:** Our results show that in the cost optimal solution, BEBs are deployed on 84% out of the 99.72% of trip sequences that can potentially be electrified.

**Operated in mixed fleets, BEBs constitute a win-win-concept:** Our results show that, besides a significant reduction of $NO_x$ emissions, an appropriate deployment of BEBs in today's bus fleets may also yield economic savings with respect to a fleet's TCO.

**(Fast) opportunity charging concepts appear to be superior to depot-charging-only concepts:** While there is a controversial discussion whether one should (*i*) invest into additional fast charging infrastructure at bus stations to allow recharging during the day and decrease necessary battery capacities or (*ii*) compensate missing charging infrastructure by larger battery capacities and rely solely on depot charging, our results point towards a dominance of concepts that allow for additional (partial) fast recharging in between trips.

**A medium-power charging infrastructure combined with medium-sized battery capacities can offset the extremes of both technology ranges:** Our results show that instead of choosing an extreme combination of low charging power infrastructure and high battery capacities or vice versa, a balanced combination that chooses both characteristics within the middle of the two technology ranges results in a TCO and $NO_x$ optimal fleet transformation.

**Optimal fleet transformation strategies expand over a multi-period time horizon:** While most strategic planning approaches so far neglect a multi-period investment horizon, our results show that an optimal transformation strategy may indeed span over multiple time periods.

**Oversizing the power of charging infrastructure may decrease a fleet's cost-optimal share of BEBs:** Our results show that certain trip sequences do not break even, as the potential cost savings are not sufficient to compensate the additional costs of infrastructure.

One comment on these insights is in order. By design, no case study is generic and results for other applications or case studies may differ, e.g., in case of different characteristics of the bus network or for different technology options. Accordingly, one may see our findings as a first step towards integrated (electrified) bus network design that points to interesting aspects for practitioners and show further research directions for academics. Still, we suggest to rerun the proposed methodology in practice for each application case to validate our insights.

## 6. Conclusion

We presented an optimization-based model for the cost-optimal transformation of a public transport bus network towards a (partly) electrified fleet. Herein, we developed a MIP to identify a cost-optimal, long-term, multi-period transformation plan for integrating BEBs into urban bus networks while ensuring operational feasibility. We minimized the operator's TCO including costs

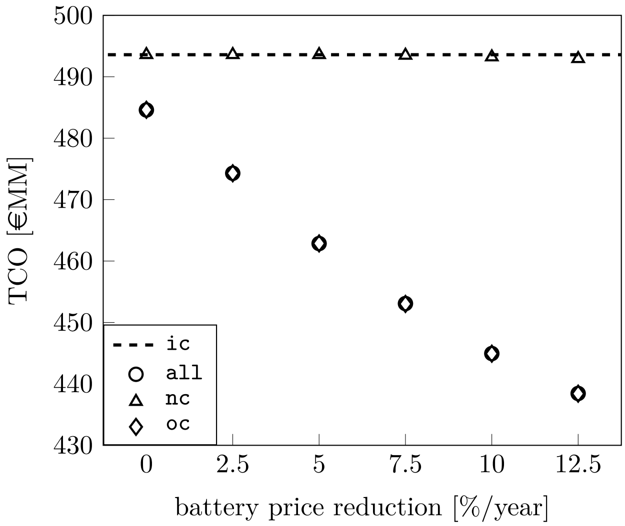



**Fig. 12.** TCO in scenarios `ic`, `all`, `nc`, `oc` for a variation of battery price reduction (`X|r350|b0-12.5`).

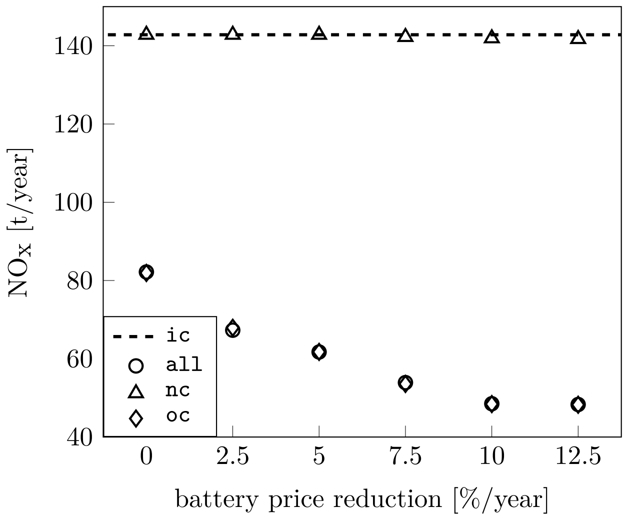



**Fig. 13.** $NO_x$ emissions in scenarios `ic`, `all`, `nc`, `oc` for a variation of battery price reduction (`X|r350|b0-12.5`).

for fleet investments, charging infrastructure installation, maintenance, and operations. To this end, we considered heterogeneous fleets of ICEBs and BEBs, different recharging concepts, and different battery capacities. We analyzed the transformation's impact on $NO_x$ emissions a-posteriori. This model is suitable for real-world applications and narrows the gap between strategic decisions and operational decisions.

We applied this modeling approach to a case study of a big European bus network in the city of Aachen, Germany, and performed additional sensitivity studies with respect to battery price reductions and charging power levels. Our results suggest that a large share of the bus network can be electrified resulting in a cost-optimal solution such that mixed fleets of BEBs and ICEBs constitute a win–win concept that reduces both the operator's TCO and the fleet's $NO_x$ emissions. Moreover, our results showed that a combination of medium-sized charging power infrastructure and medium-sized battery capacities may outperform extreme combinations of charging power and battery capacities.

Avenues for future research exist for a large-scale impact analysis based on multiple, structurally-different case studies. In the same vein, one may consider to develop a stochastic or robust modeling approach that allows to capture uncertain energy consumption or cost developments. A methodological direction for future research is given by integrating the simultaneous computation of vehicle schedules, which are precomputed in the current modeling approach.

```
Input  : N, τ^s, τ^e, t, d
Output: S
1  N* ← sortAsc(N, τ^s)
2  B ← [0]
3  S[0] ← N*[0]
4  N*.pop(0)
5  for j ∈ N* do
6  |  for b ∈ B do
7  |  |  i ← S[b][-1];
8  |  |  if τ^e[i] + t[i,j] < τ^s[j] then
9  |  |  |  π[b] ← t[i,j]
10 |  if π.length > 0 then
11 |  |  B* ← getShortest(π)
12 |  |  B** ← sortDesc(B*, S, τ^e)
13 |  |  B*** ← sortAsc(B**, S, d)
14 |  |  S[B***[0]].add(j)
15 |  else
16 |  |  B.add(B.length+1)
17 |  |  S[B[-1]] ← [j]
18 |  N*.pop(0)
```

**Fig. 14.** Modified concurrent scheduling algorithm.

## CRediT authorship contribution statement

**Nicolas Dirks:** Conceptualization, Data curation, Formal analysis, Methodology, Visualization, Writing – original draft, Writing – review & editing. **Maximilian Schiffer:** Conceptualization, Formal analysis, Methodology, Supervision, Validation, Writing – original draft, Writing – review & editing. **Grit Walther:** Conceptualization, Formal analysis, Methodology, Supervision, Writing – original draft, Writing – review & editing.

## Acknowledgments

We like to thank the associate editor Ola Jabali and three anonymous referees whose comments helped to improve this paper. This work was funded by the German North-Rhine-Westphalian Ministry of Culture and Science in the framework of the funding scheme "Forschungskollegs" (Grant No. 321-8.03.07-127598)

## Appendix A. Schedule computation

Our MIP in Section 3 requires a vehicle schedule as input. Creating such a schedule relates to the field of vehicle scheduling problems. To determine a vehicle schedule based on a given timetable, we use a modified form of the concurrent scheduling algorithm developed by Bodin et al. (1978), where trips, sorted by departure times, are assigned to buses under consideration of time feasibility constraints.

Fig. 14 shows a pseudo-code of the modified concurrent scheduling algorithm. Given an array of trips (N), departure ($\tau^s$) and end ($\tau^e$) times of all trips, and the distance (d) and duration (t) between any pair of trips, we create a vehicle schedule (S) as follows. We sort all trips in ascending order based on departure times (l. 1), create an initial bus (l. 2) to operate the very first trip (l. 3), and drop this trip (l. 4). For all remaining sorted trips (l. 5), we proceed as follows. For any created bus (l. 6), we check if the last operated trip (l. 7) is a feasible predecessor of the next trip (l. 8). If this is the case, it stores the duration of dead-heading (l.9). Unless no feasible bus exists (l. 10), we create a set of all buses with the shortest dead-heading duration (l. 11). Out of this set, we select all buses with the latest departure times of the last operated trip (l. 12). Out of this selection, the bus that so far covered the least distance (l. 13) is selected (l. 14). If there is no feasible bus at all (l. 15), we create a new bus (l. 16) and assign the next trip to this new bus (l. 17). Finally, we drop the assigned trip (l. 18).

**Table 7**
Detailed results of TCO and $NO_x$ emissions of scenarios `ic` and `all| r0-250| b0-12.5`.

| *r* | *b* | ICEBs | OCBs [-][a] | | | | NCBs [-][a] | | | | NCFs | OCFs | TCO | $NO_X$ |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| [kW] | [%] | [-] | 100 | 200 | 300 | 400 | 100 | 200 | 300 | 400 | [-] | [-] | [€MM] | [t/year] |
| – | – | 357 | – | – | – | – | – | – | – | – | – | – | 493.59 | 142.81 |
| 50 | 0 | 294 | 2 | 29 | 22 | 10 | 0 | 0 | 0 | 0 | 63 | 0 | 491.02 | 131.49 |
| 50 | 2.5 | 162 | 2 | 42 | 59 | 92 | 0 | 0 | 0 | 0 | 201 | 0 | 486.59 | 118.56 |
| 50 | 5.0 | 137 | 5 | 47 | 68 | 100 | 0 | 0 | 0 | 0 | 220 | 0 | 479.8 | 113.73 |
| 50 | 7.5 | 135 | 7 | 47 | 68 | 100 | 0 | 0 | 0 | 0 | 223 | 0 | 473.8 | 111.95 |
| 50 | 10.0 | 134 | 8 | 47 | 68 | 100 | 0 | 0 | 0 | 0 | 223 | 0 | 468.83 | 111.26 |
| 50 | 12.5 | 134 | 8 | 47 | 68 | 100 | 0 | 0 | 0 | 0 | 223 | 0 | 464.79 | 110.95 |
| 100 | 0 | 239 | 4 | 50 | 60 | 4 | 0 | 0 | 0 | 0 | 118 | 2 | 487.71 | 119.32 |
| 100 | 2.5 | 103 | 4 | 64 | 110 | 76 | 0 | 0 | 0 | 0 | 258 | 0 | 480.24 | 100.73 |
| 100 | 5.0 | 60 | 8 | 78 | 120 | 91 | 0 | 0 | 0 | 0 | 297 | 2 | 470.18 | 97.52 |
| 100 | 7.5 | 60 | 9 | 77 | 120 | 91 | 0 | 0 | 0 | 0 | 298 | 0 | 462.05 | 95.66 |
| 100 | 10.0 | 58 | 11 | 77 | 120 | 91 | 0 | 0 | 0 | 0 | 299 | 1 | 455.38 | 84.94 |
| 100 | 12.5 | 57 | 11 | 78 | 120 | 91 | 0 | 0 | 0 | 0 | 300 | 2 | 449.78 | 80.11 |
| 150 | 0 | 205 | 4 | 101 | 46 | 1 | 0 | 0 | 0 | 0 | 162 | 5 | 483.36 | 91.29 |
| 150 | 2.5 | 73 | 5 | 123 | 115 | 41 | 0 | 0 | 0 | 0 | 284 | 4 | 473.66 | 75.8 |
| 150 | 5.0 | 29 | 7 | 139 | 128 | 54 | 0 | 0 | 0 | 0 | 328 | 4 | 463.06 | 69.57 |
| 150 | 7.5 | 26 | 10 | 140 | 127 | 54 | 0 | 0 | 0 | 0 | 332 | 5 | 454.22 | 62.76 |
| 150 | 10.0 | 25 | 11 | 140 | 127 | 54 | 0 | 0 | 0 | 0 | 333 | 5 | 446.91 | 57.4 |
| 150 | 12.5 | 24 | 11 | 138 | 130 | 54 | 0 | 0 | 0 | 0 | 333 | 3 | 440.95 | 56.49 |
| 200 | 0 | 194 | 7 | 127 | 29 | 0 | 0 | 0 | 0 | 0 | 183 | 6 | 481.48 | 85.14 |
| 200 | 2.5 | 56 | 8 | 170 | 100 | 23 | 0 | 0 | 0 | 0 | 302 | 5 | 471.43 | 69.93 |
| 200 | 5.0 | 19 | 9 | 188 | 110 | 31 | 0 | 0 | 0 | 0 | 338 | 6 | 460.54 | 62.34 |
| 200 | 7.5 | 15 | 12 | 188 | 111 | 31 | 0 | 0 | 0 | 0 | 342 | 6 | 451.36 | 54.58 |
| 200 | 10.0 | 13 | 14 | 189 | 110 | 31 | 0 | 0 | 0 | 0 | 344 | 7 | 443.96 | 53.16 |
| 200 | 12.5 | 12 | 15 | 188 | 111 | 31 | 0 | 0 | 0 | 0 | 345 | 6 | 437.82 | 49.5 |
| 250 | 0 | 179 | 11 | 147 | 19 | 1 | 0 | 0 | 0 | 0 | 199 | 7 | 481.25 | 77.59 |
| 250 | 2.5 | 52 | 13 | 205 | 72 | 15 | 0 | 0 | 0 | 0 | 305 | 8 | 471.01 | 62.54 |
| 250 | 5.0 | 15 | 13 | 224 | 84 | 21 | 0 | 0 | 0 | 0 | 342 | 6 | 459.39 | 56.34 |
| 250 | 7.5 | 6 | 17 | 229 | 84 | 21 | 0 | 0 | 0 | 0 | 351 | 7 | 449.94 | 50.45 |
| 250 | 10.0 | 4 | 18 | 230 | 84 | 21 | 0 | 0 | 0 | 0 | 353 | 7 | 442.29 | 47.09 |
| 250 | 12.5 | 3 | 19 | 230 | 84 | 21 | 0 | 0 | 0 | 0 | 354 | 6 | 435.87 | 44.18 |

[a]Differentiated according to battery capacities (100, 200, 300, 400) in kWh.

We note that the proposed algorithm remains a rather standard approach to derive a vehicle schedule that disregards BEB specific characteristics. Apparently, one could design a schedule that is more favorable for BEB deployment by using a more sophisticated (electric) vehicle scheduling approach. To ensure transferability in practice, practitioners may replace the heuristically derived schedule by their real vehicle schedules. In our case, the heuristically derived, BEB insensitive schedule remains an approximation that does not bias our analysis in favor of BEBs.

## Appendix B. Detailed results

See Tables 7–12.

## Appendix C. Nominal battery capacity

Researchers and practitioners often reduce the nominal battery capacity for planning purposes by a factor of 0.2 to obtain a conservative planning solution that is not affected by unproportionally prolonged charging times for battery state-of-charge states above 80%, and thus allows to model a linearized recharging process. Moreover, such a battery capacity reduction helps to avoid planning solutions that cause deep discharging cycles for the battery. In our case study, we also made this assumption. Sometimes, researches even assume further reduced battery capacities to obtain even more conservative planning results. To analyze the impact of such a conservative assumption on our planning solution, Table 13 presents the results of further reducing the usable battery capacity from the 80% assumed in our case study by additional 10%–30%.

As can be seen, the number of deployed BEBs decreases only slightly with a further reduction of the usable battery capacity. While the number of BEBs with a battery capacity of 300 kWh remains constant or increases slightly, the number of BEBs with a battery capacity of 100 kWh or 200 kWh decreases slightly. The overall decrease amounts to at maximum 2% for an additional 30% reduction of the battery capacity. Analyzing the number of installed charging facilities, the number of NCFs implicitly decreases proportionally to the number of deployed BEBs. Contrarily, the number of installed opportunity charging facilities increases, such that more frequent charging operations allow to mitigate the impact of the reduced battery capacity.

**Table 8**
Detailed results of TCO and $NO_x$ emissions of scenarios all| r300-350| b0-12.5.

| *r* | *b* | ICEBs | OCBs [-][a] | | | | NCBs [-][a] | | | | NCFs | OCFs | TCO | $NO_X$ |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| [kW] | [%] | [-] | 100 | 200 | 300 | 400 | 100 | 200 | 300 | 400 | [-] | [-] | [€MM] | [t/year] |
| 300 | 0 | 187 | 14 | 147 | 9 | 0 | 0 | 0 | 0 | 0 | 193 | 8 | 482.63 | 80.76 |
| 300 | 2.5 | 54 | 16 | 225 | 58 | 4 | 0 | 0 | 0 | 0 | 302 | 9 | 472.4 | 65.85 |
| 300 | 5.0 | 19 | 17 | 243 | 69 | 9 | 0 | 0 | 0 | 0 | 338 | 8 | 460.92 | 56.83 |
| 300 | 7.5 | 8 | 18 | 251 | 71 | 9 | 0 | 0 | 0 | 0 | 349 | 8 | 451.51 | 51.41 |
| 300 | 10.0 | 4 | 22 | 252 | 70 | 9 | 0 | 0 | 0 | 0 | 353 | 8 | 443.45 | 48.52 |
| 300 | 12.5 | 3 | 24 | 250 | 71 | 9 | 0 | 0 | 0 | 0 | 354 | 8 | 437.17 | 44.94 |
| 350 | 0 | 196 | 18 | 140 | 3 | 0 | 0 | 0 | 0 | 0 | 180 | 9 | 484.59 | 82.18 |
| 350 | 2.5 | 60 | 22 | 233 | 40 | 2 | 0 | 0 | 0 | 0 | 297 | 9 | 474.29 | 67.3 |
| 350 | 5.0 | 19 | 23 | 252 | 56 | 7 | 0 | 0 | 0 | 0 | 338 | 9 | 462.85 | 61.73 |
| 350 | 7.5 | 6 | 24 | 263 | 57 | 7 | 0 | 0 | 0 | 0 | 351 | 9 | 453.08 | 53.91 |
| 350 | 10.0 | 3 | 28 | 262 | 57 | 7 | 0 | 0 | 0 | 0 | 354 | 9 | 444.94 | 48.51 |
| 350 | 12.5 | 1 | 28 | 263 | 58 | 7 | 0 | 0 | 0 | 0 | 355 | 8 | 438.44 | 48.31 |
| 400 | 0 | 209 | 24 | 122 | 2 | 0 | 0 | 0 | 0 | 0 | 161 | 10 | 486.83 | 93.02 |
| 400 | 2.5 | 68 | 27 | 235 | 26 | 1 | 0 | 0 | 0 | 0 | 289 | 9 | 476.59 | 76.98 |
| 400 | 5.0 | 19 | 29 | 259 | 44 | 6 | 0 | 0 | 0 | 0 | 338 | 9 | 465.09 | 67.13 |
| 400 | 7.5 | 5 | 30 | 271 | 45 | 6 | 0 | 0 | 0 | 0 | 352 | 8 | 454.85 | 58.65 |
| 400 | 10.0 | 3 | 32 | 272 | 44 | 6 | 0 | 0 | 0 | 0 | 354 | 8 | 446.5 | 51.39 |
| 400 | 12.5 | 1 | 32 | 274 | 44 | 6 | 0 | 0 | 0 | 0 | 356 | 8 | 439.86 | 47.33 |
| 450 | 0 | 231 | 26 | 99 | 1 | 0 | 0 | 0 | 0 | 0 | 131 | 10 | 488.83 | 108.32 |
| 450 | 2.5 | 74 | 32 | 231 | 20 | 0 | 0 | 0 | 0 | 0 | 283 | 10 | 479.1 | 88.98 |
| 450 | 5.0 | 19 | 30 | 275 | 29 | 4 | 0 | 0 | 0 | 0 | 338 | 9 | 467.26 | 80.15 |
| 450 | 7.5 | 6 | 32 | 284 | 30 | 5 | 0 | 0 | 0 | 0 | 350 | 9 | 457.1 | 66.32 |
| 450 | 10.0 | 3 | 36 | 280 | 33 | 5 | 0 | 0 | 0 | 0 | 354 | 8 | 448.56 | 57.62 |
| 450 | 12.5 | 1 | 37 | 283 | 31 | 5 | 0 | 0 | 0 | 0 | 356 | 8 | 441.62 | 53.5 |
| 500 | 0 | 258 | 26 | 73 | 0 | 0 | 0 | 0 | 0 | 0 | 104 | 8 | 489.9 | 114.44 |
| 500 | 2.5 | 90 | 37 | 214 | 16 | 0 | 0 | 0 | 0 | 0 | 266 | 11 | 481.45 | 92.65 |
| 500 | 5.0 | 23 | 40 | 263 | 28 | 3 | 0 | 0 | 0 | 0 | 334 | 10 | 469.7 | 83.18 |
| 500 | 7.5 | 7 | 39 | 277 | 30 | 4 | 0 | 0 | 0 | 0 | 350 | 9 | 459.25 | 77.5 |
| 500 | 10.0 | 3 | 39 | 280 | 31 | 4 | 0 | 0 | 0 | 0 | 354 | 8 | 450.54 | 67.33 |
| 500 | 12.5 | 1 | 43 | 276 | 33 | 4 | 0 | 0 | 0 | 0 | 356 | 8 | 443.42 | 62.77 |

[a]Differentiated according to battery capacities (100, 200, 300, 400) in kWh.

**Table 9**
Detailed results of TCO and $NO_x$ emissions of scenarios nc| r50-500| b2.5.

| *r* | *b* | ICEBs | OCBs [-][a] | | | | NCBs [-][a] | | | | NCFs | OCFs | TCO | $NO_X$ |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| [kW] | [%] | [-] | 100 | 200 | 300 | 400 | 100 | 200 | 300 | 400 | [-] | [-] | [€MM] | [t/year] |
| 50 | 2.5 | 357 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 493.59 | 142.81 |
| 100 | 2.5 | 357 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 493.59 | 142.81 |
| 150 | 2.5 | 357 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 493.59 | 142.81 |
| 200 | 2.5 | 357 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 493.59 | 142.81 |
| 250 | 2.5 | 357 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 493.59 | 142.81 |
| 300 | 2.5 | 357 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 493.59 | 142.81 |
| 350 | 2.5 | 357 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 493.59 | 142.81 |
| 400 | 2.5 | 357 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 493.59 | 142.81 |
| 450 | 2.5 | 357 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 493.59 | 142.81 |
| 500 | 2.5 | 357 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 493.59 | 142.81 |

[a]Differentiated according to battery capacities (100, 200, 300, 400) in kWh.

**Table 10**
Detailed results of TCO and $NO_x$ emissions of scenarios nc| r350| b0-12.5.

| *r* | *b* | ICEBs | OCBs [-][a] | | | | NCBs [-][a] | | | | NCFs | OCFs | TCO | $NO_X$ |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| [kW] | [%] | [-] | 100 | 200 | 300 | 400 | 100 | 200 | 300 | 400 | [-] | [-] | [€MM] | [t/year] |
| 350 | 0 | 357 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 493.59 | 142.81 |
| 350 | 2.5 | 357 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 493.59 | 142.81 |
| 350 | 5.0 | 357 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 493.59 | 142.81 |
| 350 | 7.5 | 338 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 19 | 19 | 0 | 493.48 | 142.24 |
| 350 | 10.0 | 335 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 22 | 22 | 0 | 493.22 | 141.91 |
| 350 | 12.5 | 332 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 25 | 25 | 0 | 492.94 | 141.72 |

[a]Differentiated according to battery capacities (100, 200, 300, 400) in kWh.

**Table 11**
Detailed results of TCO and $NO_x$ emissions of scenarios oc| r50-500| b2.5.

| $r$ | $b$ | ICEBs | OCBs [-][a] | | | | NCBs [-][a] | | | | NCFs | OCFs | TCO | $NO_X$ |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| [kW] | [%] | [-] | 100 | 200 | 300 | 400 | 100 | 200 | 300 | 400 | [-] | [-] | [€MM] | [t/year] |
| 50 | 2.5 | 357 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 493.59 | 142.81 |
| 100 | 2.5 | 357 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 493.59 | 142.81 |
| 150 | 2.5 | 357 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 493.59 | 142.81 |
| 200 | 2.5 | 357 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 493.59 | 142.81 |
| 250 | 2.5 | 357 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 493.59 | 142.81 |
| 300 | 2.5 | 357 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 493.59 | 142.81 |
| 350 | 2.5 | 357 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 493.59 | 142.81 |
| 400 | 2.5 | 357 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 493.59 | 142.81 |
| 450 | 2.5 | 357 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 493.59 | 142.81 |
| 500 | 2.5 | 357 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 493.59 | 142.81 |

[a]Differentiated according to battery capacities (100, 200, 300, 400) in kWh.

**Table 12**
Detailed results of TCO and $NO_x$ emissions of scenarios oc| r350| b0-12.5.

| $r$ | $b$ | ICEBs | OCBs [-][a] | | | | NCBs [-][a] | | | | NCFs | OCFs | TCO | $NO_X$ |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| [kW] | [%] | [-] | 100 | 200 | 300 | 400 | 100 | 200 | 300 | 400 | [-] | [-] | [€MM] | [t/year] |
| 350 | 0 | 357 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 493.59 | 142.81 |
| 350 | 2.5 | 357 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 493.59 | 142.81 |
| 350 | 5.0 | 357 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 493.59 | 142.81 |
| 350 | 7.5 | 338 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 19 | 19 | 0 | 493.48 | 142.24 |
| 350 | 10.0 | 335 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 22 | 22 | 0 | 493.22 | 141.91 |
| 350 | 12.5 | 332 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 25 | 25 | 0 | 492.94 | 141.72 |

[a]Differentiated according to battery capacities (100, 200, 300, 400) in kWh.

**Table 13**
Reduction of available battery capacity, $\mu = 0.8$ (all| r350| b2.5).

| – | $r$ | $b$ | ICEBs | OCBs [-][a] | | | | NCBs [-][a] | | | | NCFs | OCFs | TCO | $NO_X$ |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| [–] | [kW] | [%] | [-] | 100 | 200 | 300 | 400 | 100 | 200 | 300 | 400 | [-] | [-] | [€MM] | [t/year] |
| $1.0\mu$ | 350 | 2.5 | 60 | 22 | 233 | 40 | 2 | 0 | 0 | 0 | 0 | 297 | 9 | 474.29 | 67.30 |
| $0.9\mu$ | 350 | 2.5 | 63 | 21 | 231 | 40 | 0 | 0 | 0 | 0 | 0 | 294 | 11 | 474.98 | 68.31 |
| $0.8\mu$ | 350 | 2.5 | 63 | 20 | 231 | 41 | 0 | 0 | 0 | 0 | 0 | 294 | 14 | 475.93 | 70.07 |
| $0.7\mu$ | 350 | 2.5 | 66 | 18 | 231 | 40 | 2 | 0 | 0 | 0 | 0 | 291 | 17 | 476.78 | 72.08 |

[a]Differentiated according to battery capacities (100, 200, 300, 400) in kWh.

## References


Adler, J.D., Mirchandani, P.B., 2017. The vehicle scheduling problem for fleets with alternative-fuel vehicles. Transp. Sci. 51, 441–456.

An, K., 2020. Battery electric bus infrastructure planning under demand uncertainty. Transp. Res. C 111, 572–587.

ASEAG, 2020. Geschäftsbericht 2019. URL: https://www.aseag.de/fileadmin/user_upload/documents/Geschaeftsberichte/Geschaeftsbericht_2019.pdf. (Last Accessed May 2020).

AVV, 2019. OpenData AVV. URL: https://opendata.avv.de. (Last Accessed May 2020).

Bodin, L., Rosenfield, D., Kydes, A., 1978. Ucost: A micro approach to a transportation planning problem. J. Urban Anal. 5, 47–69.

Davis, B.A., Figliozzi, M.A., 2013. A methodology to evaluate the competitiveness of electric delivery trucks. Transp. Res. E: Logist. Transp. Rev. 49, 8–23.

Destatis, 2018. Data on energy price trends - long-time series. URL: https://www.destatis.de/EN/Themes/Economy/Prices/Publications/Downloads-Energy-Price-Trends/energy-price-trends-pdf-5619002.pdf?_blob=publicationFile&v=6. (Last Accessed May 2020).

European Comission, 2008. Directive 2008/50/ec of the european parliament and of the council of 21 may 2008 on ambient air quality and cleaner air for europe. URL: https://eur-lex.europa.eu/legal-content/EN/TXT/PDF/?uri=CELEX:32008L0050. (Last Accessed May 2020).

European Union, 2009. Regulation (ec) no 595/2009 of the european parliament and of the council of 18 june 2009 on type-approval of motor vehicles and engines with respect to emissions from heavy duty vehicles (euro vi) and on access to vehicle repair and maintenance information and amending regulation (ec) no 715/2007 and directive 2007/46/ec and repealing directives 80/1269/eec. URL: https://eur-lex.europa.eu/legal-content/EN/TXT/?uri=CELEX:32009R0595. (Last Accessed May 2020).

Feng, W., Figliozzi, M., 2013. An economic and technological analysis of the key factors affecting the competitiveness of electric commercial vehicles: A case study from the USA market. Transp. Res. C 26, 135–145.

Gao, Z., Lin, Z., LaClair, T., Liu, C., Li, J.-M., Birky, A., Ward, J., 2017. Battery capacity and recharging needs for electric buses in city transit service. Energy 122, 588–600.

Göhlich, D., Kunith, A., Ly, T.-A., 2014. Technology assessment of an electric urban bus system for berlin. WIT Trans. Built Environ. 138, 137–149.

IKT für Elektromobilität, 2015. Wirtschaftlichkeit von Elektromobilität in gewerblichen Anwendungen. URL: https://www.oeko.de/fileadmin/oekodoc/Gesamtbericht-Wirtschaftlichkeit-von-Elektromobilitaet.pdf. (Last Accessed May 2020).

Islam, A., Lownes, N., 2019. When to go electric? A parallel bus fleet replacement study. Transp. Res. D 72, 299–311.

Kunith, A., 2017. Elektrifizierung Des Urbanen öffentlichen Busverkehrs. Springer Fachmedien, Wiesbaden, Germany.

Kunith, A., Mendelevitch, R., Goehlich, D., 2017. Electrification of a city bus network — an optimization model for cost-effective placing of charging infrastructure and battery sizing of fast-charging electric bus systems. Int. J. Sustain. Transp. 11, 707–720.

Lajunen, A., 2018. Lifecycle costs and charging requirements of electric buses with different charging methods. J. Cleaner Prod. 172, 56–67.
Li, J.-Q., 2014. Transit bus scheduling with limited energy. Transp. Sci. 48, 521–539.
Li, L., Lo, H.K., Xiao, F., 2019. Mixed bus fleet scheduling under range and refueling constraints. Transp. Res. C 104, 443–462.
Li, L., Lo, H.K., Xiao, F., Cen, X., 2018. Mixed bus fleet management strategy for minimizing overall and emissions external costs. Transp. Res. D 60, 104–118.
Lin, Y., Zhang, K., Shen, Z.J.M., Ye, B., Miao, L., 2019. Multistage large-scale charging station planning for electric buses considering transportation network and power grid. Transp. Res. C 107, 423–443.
Liu, T., Ceder, A., 2020. Battery-electric transit vehicle scheduling with optimal number of stationary chargers. Transp. Res. C 114, 118–139.
NPE, 2015. Ladeinfrastruktur für Elektroautos in Deutschland – Statusbericht und Handlungsempfehlungen 2015. URL: http://nationale-plattform-elektromobilitaet.de/fileadmin/user_upload/Redaktion/NPE_AG3_Statusbericht_LIS_2015_barr_bf.pdf. (Last Accessed May 2020).
Nurhadi, L., Borén, S., Ny, H., 2014. A sensitivity analysis of total cost of ownership for electric public bus transport systems in swedish medium sized cities. Transp. Res. Procedia 3, 818–827.
Pelletier, S., Jabali, O., Mendoza, J.E., Laporte, G., 2019. The electric bus fleet transition problem. Transp. Res. C 109, 174–193.
Pihlatie, M., Kukkonen, S., Halmeaho, T., Karvonen, V., Nylund, N.O., 2014. Fully electric city buses - the viable option. In: 2014 IEEE International Electric Vehicle Conference. IEVC, vol. 138, pp. 1–8.
Rogge, M., van der Hurk, E., Larsen, A., Sauer, D.U., 2018. Electric bus fleet size and mix problem with optimization of charging infrastructure. Appl. Energy 211, 282–295.
Schiffer, M., Schneider, M., Walther, G., Laporte, G., 2019. Vehicle routing and location-routing with intermediate stops: A review. Transp. Sci. 53, 319–343.
Schiffer, M., Walther, G., 2017. The electric location routing problem with time windows and partial recharging. European J. Oper. Res. 260, 995–1013.
Shen, Z.-J.M., Feng, B., Mao, C., Ran, L., 2019. Optimization models for electric vehicle service operations: A literature review. Transp. Res. B 128, 462–477.
Stadt Aachen, 2018. Luftreinhalteplan Aachen - 1. Fortschreibung 2015 - Stand der letzten Bearbeitung 28. Mai 2018. URL: http://www.aachen.de/DE/stadt_buerger/umwelt/luft-stadtklima/luftreinhalteplan_umweltzone/pdf_materialien_fotos/LRP_2015_Bericht_2018_05_28.pdf. (Last Accessed May 2020).
Tang, X., Lin, X., He, F., 2019. Robust scheduling strategies of electric buses under stochastic traffic conditions. Transp. Res. C 105, 163–182.
Van Kooten Niekerk, M.E., van den Akker, J.M., Hoogeveen, J.A., 2017. Scheduling electric vehicles. Public Transp. 9, 155–176.
Wei, R., Liu, X., Ou, Y., Fayyaz, S.K., 2018. Optimizing the spatio-temporal deployment of battery electric bus system. Transp. Sci. 68, 160–168.
Wen, M., Linde, E., Ropke, S., Mirchandani, P., Larsen, A., 2016. An adaptive large neighborhood search heuristic for the electric vehicle scheduling problem. Comput. Oper. Res. 76, 73–83.
Xylia, M., Leduc, S., Patrizio, P., Kraxner, F., Silveira, S., 2017. Locating charging infrastructure for electric buses in stockholm. Transp. Res. C 78, 83–200.
Yao, E., Liu, T., Lu, T., Yang, Y., 2020. Optimization of electric vehicle scheduling with multiple vehicle types in public transport. Sustainable Cities Soc. 52, 101862.
ZeEUS, 2017. Zeeus ebus report #2. URL: https://zeeus.eu/uploads/publications/documents/zeeus-ebus-report-2.pdf. (Last Accessed May 2020).