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ORIGINAL RESEARCH

Planning a zero-emission mixed-fleet public bus system with minimal life cycle cost

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Abstract

The variety of available technology options for the operation of zero-emission bus systems gives rise to the problem of finding an optimal technology decision for bus operators. Among others, overnight charging, opportunity charging and hydrogen-based technology options are frequently pursued technological solutions. As their operating conditions are strongly influenced by the urban context, an optimal technology decision is far from trivial. In this paper, we propose an Integer Linear Programming (ILP) based optimization model that is built upon a broad input database, which allows a customized adaption to local circumstances. The ultimate goal is to determine an optimal technology decision for each bus line, considering its combined effects on charging and vehicle scheduling as well as infrastructural design. To this end, we develop technology-specific network representations for five distinct technologies. These networks can be viewed individually or as a multi-layered graph, which represents the input for the optimal technology mix. The proposed optimization framework is applied to a real-world instance with more than 4.000 timetabled trips. To study the sensitivity of solutions, parameter changes are tested in a comprehensive scenario design. The subsequent analysis produces valuable managerial insights for the bus operator and highlights the decisive role of certain planning assumptions. The results of our computations reveal that the deployment of a mixed fleet can indeed lead to financial benefits. The comparison of single technology system solutions provides a further basis for decision making and demonstrates relative superiorities between different technologies.

Keywords Electric bus network · Vehicle scheduling · Charging scheduling · Opportunity charging · Overnight charging · Mixed-fleet optimization

JEL Classification C44 · C61 · L92 · R42

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1 Introduction

Increasing ambitions to reduce - and ultimately eliminate - emissions in the transport sector have produced a number of different strategies and action plans in recent years. A central document, the European Strategy for Low-Emission Mobility, sets three goals to reach carbon neutrality by 2050: an increase in the efficiency of transport systems, an acceleration of the deployment of alternative fuels, and a transition toward zero-emission vehicles (European Commision 2016). These goals imply two prospective developments: (1) Public transportation is playing a crucial role in future transport solutions. (2) Public transportation is facing a major technological transition. Since 2019, the public sector of transportation is explicitly regulated by the revised Clean Vehicle Directive (CVD), a legislative act requiring that a specific share of procured vehicles must comply with the CVD's definition of *clean* and *zero-emission vehicles* (European Parliament 2019). Among other technology options, electric alternatives have raised particular interest, since they do not produce particulate emissions and fall into the more confined and sustainable definition of *zero-emission vehicles*.

Urban bus systems provide particularly interesting opportunities for electrification: passenger trips take place in a predictable, repetitive manner and are concentrated in a small geographic area, where electricity lines are usually found close to all bus routes. Moreover, urban congestion and short distances between bus stops result in stop-and-go traffic, which is particularly suited for electric propulsion. A major drawback, however, are limited driving ranges, as also short round trips accumulate to long driving distances in the course of a day. Therefore, the provision of charging and refueling infrastructure and their operational integration into current bus services presents a key challenge for bus operators. Within the CVD's regulated scope of zero-emission vehicles, multiple electric technology concepts exist to address this issue. Each of these technology options is based upon a different type of vehicle, which is characterized by a distinct type and size of battery or fuel cell.

The first type are pure battery electric buses, which are differentiated by their respective charging strategies. Based on the vehicles' technical configuration, buses mainly charge during the night or rely on fast charging at quickly accessible charging stations during the day. These recharging activities are either scheduled as longer, singular events, or on a short, but regular basis, for instance each time when a bus reaches a bus line's terminal station. The latter concept is often referred to as opportunity charging, a terminology that we keep using in the course of this paper. The second type of zero-emission vehicles are fuel cell buses, which use hydrogen as energy source and transform it into electrical energy. As hydrogen tanks are filled within relatively short time periods and provide sufficient energy for the routes of a whole day, the integration in present bus operations is, from an operational perspective, quite simple. The proper design of infrastructure, in contrast, causes major problems in the transition process, as delivery and storage of hazardous substances are accompanied by many legal and technical constraints.

Despite electric vehicles' general benefits concerning carbon emissions, air pollution, and noise levels, each alternative has distinct infrastructural requirements with regard to space, electricity, and storage systems. Moreover, operational factors, such as the vehicles' daily route lengths or dwelling times at bus stops have a significant influence on a technology's applicability. Many of these factors are dictated by the urban context and topology of a bus network and determine whether, and to what extent, a certain technology can be deployed. Moreover, hydrogen storage as well as large-scale charging facilities incur step-wise cost functions with huge cost increases when certain thresholds of demand are reached and larger infrastructure dimensions are required. For these reasons, a mix of technologies can well represent the most cost-efficient solution for a bus network and the optimal technology choice can only be derived with an integrated approach, considering local boundary conditions and synergies among bus lines.

In the present paper, we address this issue by providing a decision-support tool for determining the optimal technology choice for a given bus network from a broad set of zero-emission technology options. Specifically, we consider overnight charging, opportunity charging with supercapacitors or batteries, hydrogen fuelling, and overnight charging with hydrogen fuelling for range extension as possible technology concepts.

In order to gain structural insights into the decision problem, we conducted a thorough problem analysis with all relevant stakeholders of the conversion project. Once all major relationships and possible decisions were defined, we developed mathematical problem formulations that minimize the bus system's life cycle cost for each considered technology. The created Integer Linear Programming (ILP) models take strategic decisions by considering operational aspects such as vehicle and charging scheduling and are the core of our optimization framework. To derive the optimal technology mix, we combined these technology-specific ILP models into one large optimization model. Using this optimization framework, we generated solutions for each individual technology, as well as solutions for mixed-fleet bus systems, and analyzed them in a comprehensive scenario design.

Our contribution adds to the existing body of literature by considering a broader scope of technology options and a wider range of associated cost factors, thereby surpassing previous works (cf. Sect. 2). The incorporation of vehicle and charging schedules into our model formulation allows us to study a rarely addressed issue: the interdependence of a technology's vehicle numbers and infrastructural boundary conditions in a mixed-fleet context. The ultimate goal of our contribution is to determine the optimal technology mix for emission-free bus networks of medium-sized cities (in the range of 50.000–500.000 inhabitants). Included in our work is an extensive and unique database, which was filled in cooperation with practitioners and engineers from the involved transit agency, energy network providers and specialized consulting and research centers. To the best of our knowledge, such a comprehensive collection of cost categories was not used in literature before. Thereby, we try to overcome the often remaining gap between academic research and practical requirements (see Dirks et al. (2021)) and provide practicable solutions for decision makers.

In order to account for different technological settings and uncertain economic developments, more than a hundred different scenarios were compiled, solved, and analyzed in detail. The results of this sensitivity analysis are now being used as a basis for decision making and pave the way for an efficient zero-emission bus system. Our framework was developed as part of the project *move2zero* in Graz, Austria, which draws up a masterplan for a 100% conversion to zero-emission technologies by 2030. The huge collection of parameters in our framework allows a customized adaptation to local circumstances of other cities.

The rest of this paper is organized as follows. Related literature is reviewed in Sect. 2. A description of the studied technology options, the concrete problem declaration and an overview of economic and technical input parameters is given in Sect. 3. Section 4 presents the optimization framework, which builds on connection-based networks to model vehicle schedules. Besides the introduction of the underlying technology-specific graphs, this section includes the mathematical formulation of the proposed ILPs. Section 5 is devoted to the results of our real-world application case. It includes an analysis of the base-case scenario and an overview of the results of our scenario analysis. Final conclusions are drawn in Sect. 6.

2 Related literature

The provision of public transport services is accompanied by numerous decisions at the strategic, tactical, and operational level. Although strategic decisions are often dominated by political debates and the evaluation of a few, comparative scenarios, the use of mathematical optimization methods has increasingly become an industry-standard in public transportation planning. Due to its extensive nature, the planning process is usually divided into several sub-problems, each solved one after another: (1) network design, (2) setting of frequencies, (3) timetabling, (4) vehicle scheduling, (5) crew scheduling and (6) crew rostering. In the following section, we briefly discuss sub-problem (4), vehicle scheduling, which is the most relevant aspect for our study. A thorough overview of the above-introduced planning problems is provided in Ibarra-Rojas et al. (2015).

Given a line network and the timetables for one day, planning step (4) is concerned with the optimal deployment of operational resources, i.e., vehicles. In this planning step, each service trip of the provided timetable is assigned to a designated vehicle. The overall goal is to minimize the cost incurred by the vehicle fleet (size-dependent) and by daily operations (path-dependent). In its simplest form, the single depot case without further additions, called *vehicle scheduling problem* (VSP), can be solved in polynomial time. However, cost-optimal vehicle schedules may involve several line changes for buses throughout the day, which are not desirable from a practical point of view. Therefore, Kliewer et al. (2008) proposed several methods to reduce their occurrence. This and the introduction of other practical extensions (e.g. multiple depots, vehicle types or route constraints, see Bunte and Kliewer (2009) for an overview) give rise to increasingly challenging optimization problems.

In the context of electric bus systems, an additional aspect of operational scheduling concerns the planning of charging operations. The composition of vehicle schedules determines (1) route lengths and thus, recharging demand, and (2) dwelling times at terminal stations, which provide interesting opportunities to perform charging activities. The operational design of charging schedules, in turn, is closely intertwined with strategic aspects of infrastructure planning, e.g., the location and dimension of charging facilities. Questions of infrastructure design, charging scheduling and vehicle scheduling are therefore often addressed simultaneously.

An early study in the field of opportunity charging, for example, focused on the joint optimization of infrastructure decisions and charging schedules. Given predefined bus schedules, Wang et al. (2017) assumed that buses charge for a fixed recharging duration during layover times at transit centers and specifically addressed the interdependent nature of simultaneous charging activities and the number of required charges. Hu et al. (2022) studied a different setting and assumed that charging is allowed at terminal and intermediate stations. The provided model for the optimal selection of charging locations showed the benefits of locating charging stations at intermediate bus stops, especially when passenger boarding times are long or when dwelling times at terminal stops are short.

As the introduction of electric technologies already involves a wide range of accompanying measures, it is also common to intervene at an earlier level of the optimization process and lift the assumption of unchanged vehicle schedules. Liu and Ceder (2020), for example, used a lexicographic approach to address the interdependent nature of vehicle schedules and infrastructure dimensions and minimized (1) fleet size and (2) the number of required charging stations at terminal stops. Stumpe et al. (2021) took a different approach and jointly optimized strategic and operational aspects by determining vehicle schedules that minimize the sum of vehicle and infrastructure investments, as well as operational costs.

As operational adjustments are mainly induced by the vehicles' limited driving range, several studies include battery sizing decisions into their planning scope. An early study in this context is provided by Kunith et al. (2017), who optimized battery capacities and the number and location of charging stations within an opportunity charging bus network. Zhou et al. (2022) provided another model for the optimal number of deployed chargers, charging schedules and battery size. Besides the deterministic model with many practical considerations, they propose a number of robust variants to account for the uncertainty of energy consumption. In contrast to the latter two studies, which both built on simplified assumptions about vehicle schedules, a combined model for charger deployment, battery sizing and fleet scheduling is proposed by Wang et al. (2022). Further studies on opportunity charging networks focus on the technology's operational characteristics and address problems such as the uncertainty of energy consumption (e.g. Liu et al. (2022)) and reoptimization due to traffic delays (e.g. Abdelwahed et al. (2021)), peak power demand at charging stations (e.g. He et al. (2020)) or the role of battery degradation for different battery use limits (e.g. Zeng et al. (2022)). Summarizing, the existing studies often focus on very specific aspects of opportunity charging, assume that essential system variables are constant (e.g. vehicle schedules and charging duration), or fail to reflect the wide-ranging consequences of a fleet conversion on the cost of the overall bus system.

Opportunity charging is a relatively new concept and initial studies on range-limited technology options rather focus on the creation of shorter vehicle schedules, than on integrating regular recharging events to enhance the vehicles' driving range. In an early study in 1995, Freling and Paixão (1995) investigated the VSP with a maximum route time constraint, which may be used to represent technical restrictions such as a limited fuel capacity. Haghani and Banihashemi (2002) refined the problem formulation for a better adaption to fuel consumption concerns and considered only actual driving times in the maximum route time constraint, excluding interim time periods spend at the depot. An early study explicitly handling electric buses in the VSP was conducted by Wang and Shen (2007). The principal novelty of this paper is the formulation of a model that reintegrates vehicles into service operations when intermediate charging operations are completed. Specifically, vehicles were assumed to be recharged after a given driving time (420 min) and put into use again when a pre-defined charging time (180 min) is fulfilled. The above-mentioned models all make use of a very specific problem structure: the feasibility of a vehicle schedule is determined by the first trip's start time and the last trip's end time. A realistic depiction of a vehicle's energy consumption, however, does not depend on the total time a vehicle spends in operation, but on the accumulated path characteristics of the covered route. The VSP with distance, rather than time-dependent, route constraints cannot exploit the above-described problem structure and results in a large number of additional constraints. Li (2014) developed column-generation-based algorithms to address this issue and successfully solved large-size instances with more than 900 trips. In the upcoming years, the practical relevance of studies further advanced and more and more technical requirements were incorporated into the proposed frameworks. van Kooten Niekerk et al. (2017) investigated different methods to solve a model considering non-linear charging processes and depreciation cost of batteries, which are largely influenced by the batteries' depth of discharge. A more recent study on the non-linear nature of charging profiles and battery degradation was published by Zhang et al. (2021). For a detailed review and information on further aspects studied within the electric VSP, we refer to Perumal et al. (2022).

The above-described variants of the traditional VSP account for limited driving ranges and, in more recent studies, integrate occasional recharging operations into bus schedules. These operation-centered approaches often fail to reflect system-wide implications, such as increased fleet size and its effects on required depot infrastructure or personnel. Moreover, many results relate to selected bus lines participating in pilot tests but do not account for the conversion of a whole bus fleet. A fair comparison of different technologies, however, should be based on a long-term perspective and a comprehensive assessment of all related expenditures. Estrada et al. (2022), for example, performed a short-term cost analysis for two selected bus lines and focused on the additional number of needed vehicles and charging stations for two different charging schemes: charging at the bus depot and charging at on-street chargers. The cost comparison of both options showed that charging within the bus network is more cost-efficient if service trips are scheduled in a regular manner and when charging events can be skipped in demanding time periods. Though observations like these do not reflect the impact of a whole fleet conversion, they highlight the technology decisions' strong dependency on route-specific characteristics and have led to a growing body of research on electric transit designs with mixed bus fleets.

An early study in this context is provided by Fusco et al. (2013), who considered buses with internal combustion engines and electric buses with several charging concepts, including depot charging, terminal charging and charging at en-route bus stops. However, the aim of the study was not the optimal technology choice, but the comparison of technologies in predefined scenarios. Xylia et al. (2017) went a step further and optimized the composition of a bus fleet with opportunity charging and bio-fuel alternatives as potential technology options. In the investigated bus network, bus lines close to major public transport hubs were selected to be operated with electric buses. The resulting technology mix produced promising results with respect to emission, as well as cost reduction. Rogge et al. (2018) provided a formal problem description for a heterogeneous bus fleet with two depot-charging bus types: a lightweight bus with strictly limited energy and increased recharging demand and a long-range bus, mainly charged overnight. The proposed model was solved with heuristic and meta-heuristic methods and heterogeneous fleets proved to be beneficial in both tested scenarios. Janovec and Koháni (2019) later built on this work and developed a linear optimization model for the electric bus scheduling problem. The proposed model, however, is only suited for a single charging strategy, namely partial charging. Studies on other technology alternatives, such as a combination of diesel and electric buses (Li et al. 2019) or buses using fast charging and dynamic wireless power transfer (Yıldırım and Yıldız 2021) also exist. Technology options with hydrogen propulsion have received limited attention in the OR literature, as state-of-the-art hydrogen buses do not require intermediate fuelling. Although their adoption involves some combinatorial decisions, the vast amount of literature on this topic is directed towards engineering questions (e.g. Trattner et al. 2021).

This literature overview reveals that studies on the optimal technology choice of zero-emission public bus systems with minimal life cycle cost - potentially reached through mixed fleets - are still rare. Also, to evaluate the consequences of a full fleet conversion, the interdependent nature of charging and vehicle schedules, fleet size and infrastructure design must be addressed. In the present paper, we aim to fill this gap by providing a decision-making framework that considers multiple state-of-the-art technologies and solves the strategic technology decision problem by incorporating operational planning aspects into an optimization framework that minimizes a bus system's total life cycle cost.

3 Problem description

The ultimate goal of this research is to identify the optimal technology mix for a zero-emission bus system. In the following, we describe the relevant details of the investigated technologies, define the optimization task, and discuss the required specifications of vehicles and the bus network. We keep the technical details to a minimum and refer to engineering literature for further reading.

3.1 Technology options

The following emission-free technology concepts were considered as viable options:

3.1.1 Overnight charging (ONC)

The ONC concept assumes that charging activities of battery buses mainly take place overnight, when buses are out of operation. Each vehicle is provided with an individual charging point, where charging operations take place with smallest possible power levels. In spite of the low grid impact of each individual vehicle, simultaneously charging all ONC buses in one depot poses high requirements on the electricity grid.

Although ONC buses are usually equipped with large batteries, their limited driving range is usually not sufficient to ensure proper service operations for the whole day. Besides powertrain consumption, auxiliaries like heating or air-conditioning consume substantial amounts of energy. Depending on the operational conditions, buses might have to recharge their batteries after several hours of operation. Therefore, interim charging at the depots' charging facilities is incorporated into vehicle schedules. Additionally, the utilization of charging stations at closer, centrally located company-owned properties is considered as another recharging option, as the reduced availability of electric buses during travel and charging times can have profound effects on the required fleet size.

3.1.2 Opportunity charging with supercap buses (OPC + supercaps) or battery buses (OPC + batteries)

Opportunity charging is based on the idea of quickly increasing battery charge levels in short time slots, namely during dwelling and boarding times at terminal stations and commonly shared bus stops. As the construction of charging stations in public areas is associated with many legal constraints and considerable financial effort, the selection of suitable charging locations requires particular attention. As it is often done in literature, we consider terminal stations and bus line intersection points as candidate charging locations for OPC. At terminal stations, bus schedules usually contain pauses that are well-suited for charging operations. Since some terminal stations are located on the outskirts of a city and are only reached by isolated bus lines, synergies from joint use of charging infrastructure can also be achieved by locating charging stations at network intersection points. Therefore, centrally located intermediate bus stops used by more than one bus line can also present excellent charging options for OPC. An optimal charging schedule at shared charging stations can reduce the number of overall charging points considerably. The adaptation of vehicle schedules to extended stopping times, however, increases total circulation times and

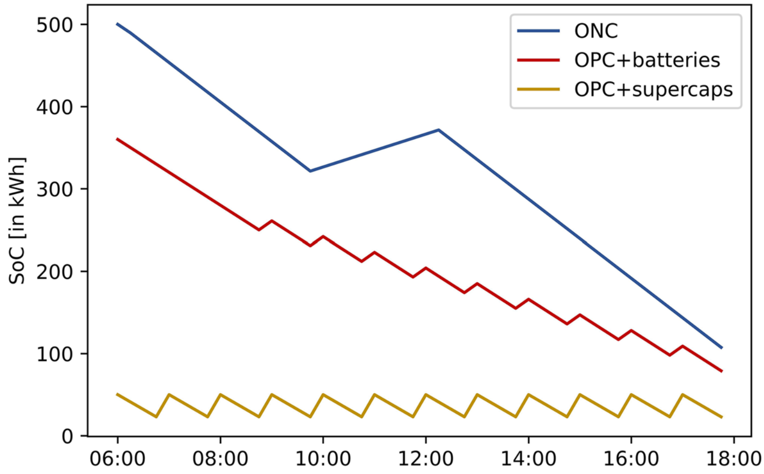


Fig. 1 Example of State of Charge (SoC) for different charging strategies

possibly affects fleet size. As compared to ONC, the effect on vehicle numbers is expected to be small.

For OPC, batteries and supercapacitors are available as energy storage systems. Supercapacitors can be charged with extremely high power levels, but have limited energy density and must be recharged in short time intervals. In contrast, buses with batteries provide longer driving ranges and thereby offer greater flexibility for bus operators (e.g. skipping charging activities in rush hours, as shown in Fig. 1, beginning of the red line). Yet, buses are usually recharged during night and therefore require individual charging points at the depot. Moreover, lower charging power levels result in longer charging activities during the day, reduce the availability of buses and can have a greater effect on the required fleet size.

3.1.3 Fuelling with hydrogen (FC) or overnight charging plus fuelling with hydrogen (FC-REX)

Similar to battery electric vehicles, hydrogen buses are equipped with electrical powertrains, batteries, and additionally, fuel cells (FC) and hydrogen tanks. Electricity generated by an electrochemical reaction of hydrogen and air is stored in small intermediate buffer batteries. As these propulsion systems offer high flexibility in terms of range, traditional bus schedules can be maintained. A great challenge, however, is the provision of hydrogen. For a zero-emission bus system, also production processes of hydrogen must be emission-free. This can currently only be reached by electrolysis from water. Depending on the market availability and fuel cell bus adoption levels, hydrogen demand can be fulfilled by purchases from third parties or an in-house production plant. In any case, hydrogen is intermediately stored at local filling stations. A limiting factor, however, is the SEVESO-III directive (European Parliament 2012), which requires that the stored amount of hydrogen at a given location must remain below 5 tons. In this context, a slightly modified concept, namely the use of fuel cells as range extenders (FC-REX) becomes attractive. Buses following this concept have larger batteries than traditional FC buses and are charged overnight. As opposed to ONC buses, which perform recharges when batteries are depleted, batteries of FC-REX buses are continuously recharged through hydrogen conversion in fuel cells. As hydrogen is not the primary source of energy in this concept, dimensions of storage and filling systems can be smaller as compared to FC.

3.2 Problem declaration

Given the range of technology options described in Sect. 3.1, the optimization problem consists of choosing a suitable set of technologies that minimize overall costs and allow the provision of all prescribed bus services. For each bus line, it is required to choose one single technology option. Clearly, the particular characteristics of a certain bus line, such as route length, topographic properties and availability of charging locations, apply for all buses operating on this line and yield the same influence factors on all of them. Also, an investment into OPC charging stations is less meaningful, if these are utilized only by a subset of buses serving a line. Additionally, operational planning for the bus operator benefits a lot from a strict partitioning of lines according to technologies.

In order to avoid adverse effects on service levels and to facilitate the stepwise integration of the new bus fleet, we retain the currently given timetables and concentrate our planning decisions on fleet composition, vehicle and charging scheduling, and the corresponding infrastructural layout. These problems relate to different planning levels (e.g. operational charging scheduling, strategic charger deployment, etc.), but a well-reasoned answer to the strategic question of the optimal technology choice can only be given in consideration of operational aspects. We use normal weekday schedules (having the highest travel demand) as a reference for our planning framework. If the bus operator does not plan major network adaptions in the future, using these plans can represent an adequate solution approach. To account for the increased staffing levels (see Jefferies and Göhlich 2020) we track the total number of working hours of drivers and price them by an average hourly rate. Clearly, including crew scheduling and rostering for decades ahead would be beyond the scope of a realistic planning scenario.

3.3 Economic and technical parameters

The objective of minimizing overall costs is captured by the concept of life cycle cost (LCC). LCC refers to all costs that are incurred through an investment, including acquisition, running and disposal costs. As these expenditures occur at different points in time, the present value of a system component, e.g. a bus, is calculated as discounted sum of procurement, maintenance and replacement costs within the planning horizon, i.e., 20 years in our application. Note that a component's service life, e.g. the operating lifetime of a bus, can be shorter than the overall planning horizon, but that we impose a direct replacement at forecasted market rates upon disposal.

In our framework, system components are divided into route-related, vehicle-related and infrastructure-related elements, whose LCC are calculated in an initial preprocessing step. Besides economic calculations, the preparation of technical input parameters is handled at this stage. Much of the required technical and economic information is subject to high uncertainty due to the ongoing technical development, and therefore highly debated among experts. We do not claim that our parameter choices give a definite answer to this problem, but they serve as a realistic example to be used in face of such an extensive decision-making problem. Clearly, values will change within the next few years and whenever more accurate data becomes available, this can be included in the optimization model. To account for the high degree of uncertainty at the current planning stage, an extensive scenario analysis was carried out. Major findings of this analysis are summarized in Sect. 5.3. We now discuss the details of the necessary input data and give precise values, wherever we are allowed to publish them. When not indicated otherwise, the assumed input parameters were gathered and agreed on within the consortium of the move2zero project in Graz.

3.3.1 Route data

The main determinants of route data are energy consumption and path-related cost factors, namely costs of electricity, hydrogen and driving personnel. Energy consumption is a crucial factor for system configuration and is influenced by a number of different parameters itself (e.g. driving profiles, number of stops, passenger load, vehicle weight, use of auxiliaries, ...). In our application, consumption values were estimated based on manufacturers' specifications, industry reports and experience from the local bus operator, who already had performed a one-year test phase of battery electric buses. For each bus line, the required passenger capacity, and thus the size of the bus, namely standard (12-m) or articulated (18-m) bus, was given in advance. In order to compile an accurate representation of route-specific consumption profiles, powertrain consumption was estimated based on the average speed attained for each bus line. As auxiliaries like heating or cooling consume substantial amounts of energy and the transportation system must be designed to operate on all days of a year, total energy consumption was calculated for a cold winter day, the most critical scenario in our latitudes. To account for an appropriate representation of energy costs in our objective function, different consumption factors, derived from power draw forecasts, based on monthly average temperatures, were used. The respective consumption values are given in Table 10. In contrast to battery electric buses, energy consumption of fuel cell buses is not expected to increase as much on critical winter days. Considering future efficiency gains, base values for hydrogen consumption were set to 6 and 9 kg/100 km for 12 and 18 m buses. With respect to cost-related parameters, i.e., electricity, hydrogen and driver cost, the specific unit values were gathered within the transit agency, forecasted into future values, transformed into LCC factors and aggregated into appropriate measurement units later used in the optimization model (see Tables 1, 2).

Table 1 Vehicle specifications and aggregated bus costs for different technologies

12 m/18 m bus	ONC	OPC+ batteries	OPC+ supercaps	FC	FC-REX
Fuel cell [kW]	–	-	–	64/80	80/100
Nominal battery capacity [kWh]	350/500	240/300	40/80	36/36	106/136
Battery type	NMC[2]	LTO[3]	supercapacitor	NMC	NMC
Charging power depot [kW]	100	100	–	–	50
Charging power network [kW]	100	300	600	–	–
Charging efficiency [%]	0.97	0.95	0.95	–	–
Lifetime [years]	8	10	10	10	10
PV[1] bus [Mio. €]	1.846/2.470	2.024/2.656	1.706/2.345	2.487/2.826	2.463/3.087

[1]PV = Present Value 2030

[2]NMC = Nickel Manganese Cobalt

[3]LTO = Lithium Titanium Oxide

3.3.2 Vehicle data

In order to compile representative bus purchasing costs we divide the total vehicle purchasing price for a technology into a common price for the base vehicle, and an additional price increase for technology-specific vehicle parts, i.e., the powertrain. To retrieve the total value for technology-specific powertrain costs, different configurations for battery, supercap and fuel cell buses were defined and multiplied with calculatory unit cost for the respective powertrain system. The technical specifications of our base scenario are listed in Table 1. Given average life expectancies of vehicles and exchangeable components, maintenance cost, and future price predictions, all subsequent costs of initial purchasing decisions were computed for the investigated planning horizon of 20 years and aggregated into a total number (assuming a discount rate of 3.3 %). Hence, the cost figures reported in Table 1 include initial acquisition, repair and maintenance costs as well as costs for vehicle replacement at the end of their respective operating life. To represent the declining costs of battery replacement, we applied a logarithmic learning curve, which was deduced from the data of a manufacturers' survey, conducted by TECHNOMA[1] (internal report, 22.09.2021). The yearly vehicle maintenance costs for each technology vary between 3 and 10 % of the initial purchasing costs, depending on the specific technology type and bus size. As henceforth calculated vehicle numbers do not include backup vehicles at the depot, a vehicle reserve of 10% was considered by including a corresponding markup in expected costs.

Vehicle configurations effect costs, but also lay down the technological framework for charging activities. In practice, many internal (e.g. depth of discharge) and external factors (e.g. temperature) have to be considered during charging processes, and complex battery management systems are used to ensure optimal battery

[1] TECHNOMA Technology Consulting & Marketing GmbH, www.technoma.at

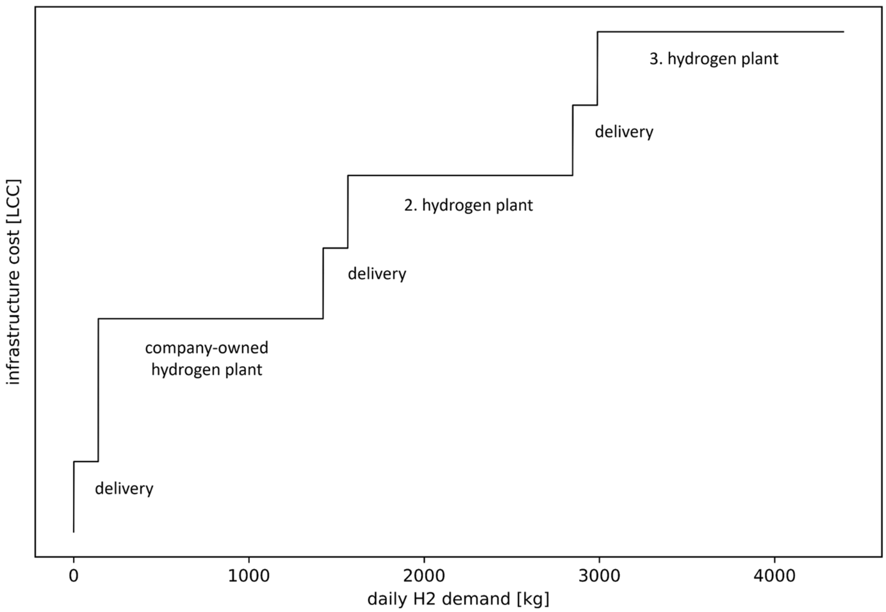


Fig. 2 Exemplary step function for H2 infrastructure cost

performance. In our framework, upper and lower bounds on nominal battery capacities confine the available range for operational planning. Within this reduced operating range, we assume a constant charging power. Thus, the amount of charged energy is proportional to charging time. This assumption is often found in literature (e.g. Olsen et al. 2020; Stumpe et al. 2021 or Wang et al. 2017).

3.3.3 Infrastructure data

The type and cost of the required hydrogen infrastructure heavily depend on the selected production and delivery concept. Hydrogen can be generated in an off-site production plant with subsequent delivery (via truck or pipeline), or in company-owned production plants. Depending on the amount of daily required hydrogen, one or the other concept can be regarded as the more economical solution. As we consider mixed fleets, the number of hydrogen buses and consequently, total hydrogen demand, are determined as part of the optimization model. Thus, different supply concepts must be provided at the input stage and costs for hydrogen infrastructure are considered in the form of a step function, with different total infrastructure costs for different expansion levels. Because of the SEVESO-III threshold on stored hydrogen, the establishment of several, smaller-dimensioned hydrogen stations at different locations can be considered to fulfill higher levels of hydrogen demand. An exemplary step function for infrastructure costs of hydrogen, with several production locations, is provided in Fig. 2. Numerical details of the hydrogen infrastructure concept considered for our problem will be given in Sect. 5.1.

Table 2 Introduced parameters

General	
$cost^{energy}_{(q,l)}$	Energy-related costs of technology q on bus line l
$cost^{energy}_{(s,t)}$	Energy-related costs of deadhead arc from s to t
$cost^{driver}$	Time-related costs of driving duties
$cost^{bus}_{(q,b)}$	Costs per bus of bus type b of technology q
$cost^{charger}_{(q,n,o)}$	Costs of charger o at station n for technology q
$cost^{\beta}_{(q,i)}$	Cost step i of fleet size dependent step cost function of technology q
$cost^{kW}_{i}$	Cost step i of kW dependent step cost function
$cost^{H2}_{i}$	Cost step i of H2 dependent step cost function
$step^{\beta}_{(q,i)}$	Step i of fleet size dependent step cost function of technology q
$step^{kW}_{i}$	Step i of kW dependent step cost function
$step^{H2}_{i}$	Step i of H2 dependent step cost function
$power_q$	Depot charging power for technology q
$start_t$	Start time of trip t
end_t	End time of trip t
$dur_{(s,t)}$	Duration of deadhead trip from s to t
$dur^{+trip}_{(s,t)}$	Duration of deadhead trip from s to t and service trip t
d^{out}_{b}	Source node of bus type b at the depot
$line_v$	Bus line of node v
$type_v$	Bus type of node v
loc_c	Location of charging event c
$\mathcal{M}$	Big-M
ONC-specific	
$Charge_c$	Energy amount charged at charging node c
$Cons_t$	Consumption of trip t
$Cons_{(s,t)}$	Consumption from source node s to target node t
SoC^{min}_{v}	Minimum state of charge at node v
SoC^{max}_{b}	Maximum state of charge at nodes of type b
$SoC^{discharge}_{b}$	Maximum state of charge at which recharging is allowed
OPC-specific	
$Chargetime^{q}_{l}$	Necessary charging duration per round of line l
$Start_c$	Start of charging event c
H2-specific	
$Cons^{kg}_{l}$	Hydrogen consumption of trips of line l
$Cons^{kg}_{(s,t)}$	Hydrogen consumption of deadhead arc from s to t
kW^{H2}_{i}	Power load of hydrogen infrastructure at step i

In contrast to LCC for hydrogen infrastructure, which depend on the total level of daily filled hydrogen, charging station costs and other depot-related costs (e.g. workshop staff) depend on the number of total buses per technology. Buses operating under the ONC, OPC+batteries, or FC-REX concept, for example, are fully charged overnight. The number of required chargers at the depot is therefore assumed to be equal to the number of deployed buses, the associated power loads and costs vary for each technology. Another relevant factor is grid access. The aggregated power loads of infrastructure at the depot, i.e. charging points and hydrogen plants, can become extremely high. As electrical infrastructure is not designed for large simultaneous power demands, substantial grid upgrades are required if certain power limits are exceeded. Similar to the above-described other elements of depot infrastructure, also grid connection costs take the form of a step function.

Besides depot charging, battery electric technology options also build on daytime charging at charging stations within the network. In order to find an optimal selection of charging infrastructure, an input list of candidate sites is required. The opening costs for additional charging stations within the network consist of land, grid, and charger costs and vary per number of charging points and total required power load. Together with yearly maintenance costs for charging and electricity infrastructure (approx. 3% of the initial investment costs), these values were added up to an incremental cost value per charging point. The concrete cost values for our application were gathered with the local bus operator, the local electricity grid operator and the consulting firm TECHNOMA, but are not available for publication. Typical assumptions for charger costs can be found in Kunith (2017).

4 Optimization model

The proposed problem formulation is based on different graph representations to model vehicle schedules that account for energy requirements of various technologies. The base network, a graph representation for hypothetical operations without range limitations, is used as a basis for the efficient design of technology-specific networks. Building upon the same optimal base network for the fulfillment of all trips, we add technology-specific adaptations and construct network layers that model the operational procedures of each potential technology. Besides the representation of each individual technology, these networks can be combined in a multi-layered graph, which represents the input for the optimal technology mix.

4.1 Base network

The underlying structure of our model consists of a network where every trip between two terminal stations is represented by a node and two nodes are joined by an arc if the two associated trips can be performed consecutively by the same vehicle. Other networks with nodes describing trips were used, e.g., in Freling and Paixão (1995).

Table 3 Introduced variables, sets and parameters for the base network

Variables	
$l_{(i,j)} \in \{0, 1\}$	1 if at least one trip-trip arc between lines i and j is used
	0 otherwise
$a_{(s,t)} \in \{0, 1\}$	1 if arc $(s, t) \in A$ is used
	0 otherwise
$x^{\beta} \in \mathbb{N}$	Number of required buses
Sets	
L	Set of bus lines l
A	Set of arcs from source node s to target node t
$A^{-}(v)$	Set of preceding nodes of node v
$A^{+}(v)$	Set of successive nodes of node v
A^{tt}	Subset of trip-trip connections
$A^{tt}_{(i,j)}$	Subset of trip-trip connections that connect bus lines i and j
V^{trips}	Set of trip nodes t
Parameters	
c^{β}	Penalty for buses
c^{tt}	Penalty for trip-trip connections
c^{ll}	Penalty for line-line connections
d^{out}	Source node at the depot
d^{in}	Sink node at the depot
$\mathcal{M}$	Big-M: total number of trips

The base network consists of a directed graph $G = (V, A)$ with nodes $V = V^{trips} \cup \{d^{out}\} \cup \{d^{in}\}$ and arc set $A \subseteq V \times V$. Each node $t \in V^{trips}$ represents a service trip, i.e., a trip which is obtained from predetermined timetables with a given start and end time and a given pair of terminal stops of a certain bus line l. d^{out} and d^{in} are source and sink nodes and represent the buses' presence at the depot at the beginning and end of the day. An arc $(s, t) \in A$ connects node s with node t and describes either idle times or deadhead trips. Idle times occur when a subsequent trip starts at the same location, but not immediately after the buses' arrival; deadhead trips occur between different terminal stations across the network and the bus depot and are usually carried out without passengers. The introduced variables, sets and paramters are listed in Table 3.

The arcs of the base network can be classified into pull-out trips, pull-in trips and trip-trip connections. Pull-out trips are outgoing arcs from the depot node d^{out} to each service trip t, pull-in trips connect each trip node t with the depot node d^{in}. Trip-trip connections are links between service trips that can be served consecutively by the same vehicle. To guarantee this feasibility, only trip nodes with departure times later than the preceding trips' arrival times are connected. Moreover, the bus type associated with each trip node presents a limitation for feasible trip-trip connections. Each trip node is characterized by a designated bus line, which is strictly operated by a standard or an articulated bus. As trip-trip arcs represent either idle times or deadheads between two consecutive trips served by one vehicle, only trip nodes characterized by the same bus type are connected in the network.

4.2 Network reduction

Since a full representation of all feasible arcs yields a network of excessive size, which cannot be solved within reasonable time, the following arc reduction strategies are applied:

1. **Restriction of waiting times**
   In order to avoid impractical turning times, lower and upper bounds are imposed on waiting times at terminal stations. In our tests, the lower bound was not used (set to 0) and the upper bound was set to 60 minutes. This restriction has no effect on the resulting number of necessary buses but reduces the number of potential trip-trip connections considerably.
2. **Optimization of trip-trip connections**
   We aim to identify a reduced subset of trip-trip connections and choose only those connections that are necessary to operate the network with a minimum number of buses. We identify these arcs by solving a technology-neutral single depot vehicle scheduling problem. It can be expected that the trip-trip connections used in this base network will be highly relevant also for our more general problem. Allowing line changes in a bus network can have a positive effect on the required fleet size, but complicates day-to-day operations. Therefore, our model minimizes not only the number of vehicles, but also considers a linear combination of the total number of line changes and the number of bus lines involved in any line changes. The latter is especially relevant in subsequent chapters since some bus lines cannot be operated with all technologies. In constraint (2) of the following formulation, the fleet size is determined by calculating the total number of depot-leaving arcs. Constraint (3) ensures that each service trip in V^{trips} is covered by a vehicle, thus the sum of incoming arcs must be 1. Constraint (4) preserves the vehicle flow by ensuring that each node has the same number of in- and outgoing arcs. Finally, in constraint (5) variable $l_{(i,j)}$ is determined, which indicates whether a trip-trip connection between two different lines i and j exists. This variable is not strictly necessary but was used to avoid extensive changes of vehicles between lines. A lower number of different line combinations in vehicle schedules simplifies the real-world implementation. Moreover, it can reduce potential effects on the technology decision of connected bus lines if certain lines cannot be operated with the cost-minimal technology and other possible trip-trip connections are not considered.

$$\min \quad x^{\beta} * c^{\beta} + \sum_{(s,t)\in A^{tt}} a_{(s,t)} * c^{tt} + \sum_{(i,j)\in L\times L|i\neq j} l_{(i,j)} * c^{ll} \tag{1}$$

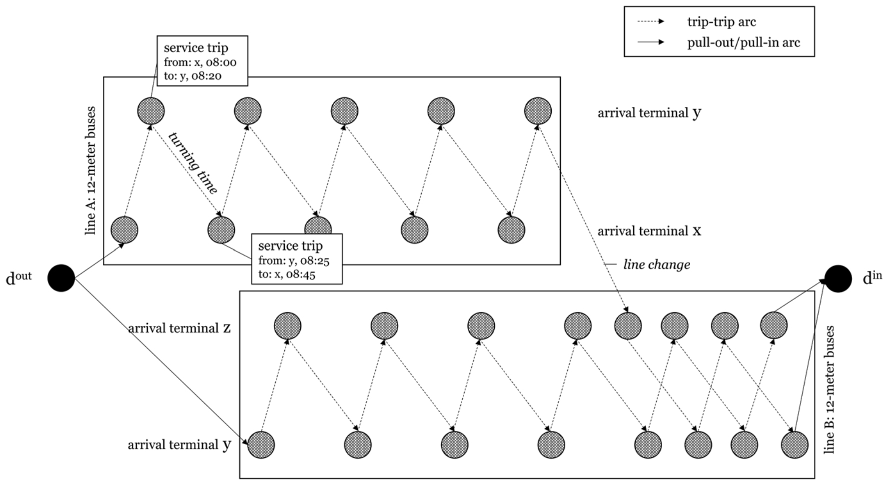


Fig. 3 Solution of a base network

$$x^{\beta} = \sum_{t \in A^{+}(d^{out})} a_{(d^{out},t)} \tag{2}$$

$$\sum_{s \in A^{-}(v)} a_{(s,v)} = 1 \qquad \forall v \in V^{trips} \tag{3}$$

$$\sum_{s \in A^{-}(v)} a_{(s,v)} = \sum_{t \in A^{+}(v)} a_{(v,t)} \qquad \forall v \in V^{trips} \tag{4}$$

$$\sum_{(v,t) \in A^{tt}_{(i,j)}} a_{(v,t)} \leq l_{(i,j)} * \mathcal{M} \qquad \forall (i,j) \in L \times L \mid i \neq j \tag{5}$$

The resulting vehicle schedules identify trip-trip connections that are prerequisites for bus operations with a minimum number of buses. For a graphical illustration, see Fig. 3. In the following sections, we use this reduced set of trip-trip arcs, as well as all pull-in and pull-out arcs as a basis for the construction of technology-specific networks. This collection of arcs is referred to as A^*.

If the considered bus network uses multiple depots, the described network formulation can be extended by additional depot nodes with pull-in and pull-out arcs to each service trip. Moreover, an additional index must be introduced for the decision variable x^{β}, such that the number of buses can be tracked for each depot individually.

4.3 Technology-specific networks

Building upon the results of the preceding subsections, each technology is modeled on the basis of the above-described base network $G = (V, A^*)$ and extended with technology-specific modifications. The resulting technology networks can be viewed individually or as a multi-layered graph, whereas each technology is represented by its individual graph layer, and graph layers are connected through converging arcs at depot nodes.

4.3.1 ONC

The ONC network is built as a directed graph $G^{ONC} = (V^{ONC}, A^{ONC})$, with $V^{ONC} = V^{trips} \cup V^c$ and $A^{ONC} = A^* \cup A^c$. V^c is a set of nodes representing potential charging activities, which are inserted after service trips. The amount of charged electricity during these interim charging activities is restricted to a discrete set of possible charging loads. As also power levels are predetermined, the duration of each available charging operation is known in advance. A charging node c is therefore characterized by a concrete start and end time as well as a charging location n. As the decision for building charging stations at different locations is not fixed beforehand, each bus line is provided with arcs from every trip node to all potential charging locations, i.e. the depot and strategically selected network sites. In order to reduce the set of these deadhead arcs, we chose for all trip nodes of line l only those trips, whose end terminal lies closer to the charging station's location than their starting terminal.

Charging activities are assumed to start immediately after the buses' arrival: Going from a trip node t to a charging node c the start time is defined as end_t plus deadhead time $dur_{(t,c)}$. As the duration of charging events is discretized, also the end time of charging node c is available in advance. In order to continue vehicle deployment after charging, deadhead arcs to service trips of all bus lines are introduced, if nodes are characterized by the same bus type and departure times of subsequent trips are reachable. As a prompt reintegration in service operations is desirable, a maximum idle time after charging limits the set of possible connections. The set of additional arcs leaving and entering charging events is summarized in A^c.

The number of timetabled trips varies by time of the day and usually takes a form as depicted in Fig. 4, in transportation planning also referred to as *camel curve* (Kliewer et al. 2008). The peak number of simultaneous trips provides a lower bound for the minimum fleet size. As ONC buses start their operations with fully charged batteries and premature recharges are unlikely to be optimal, charging events in early rush hours are dismissed. Towards the end of the day, when more and more buses return from daily operations and occupy chargers to charge their batteries overnight, interim charging events at the depot are also dismissed. An exemplary vehicle schedule of a solved ONC network is depicted in Fig. 5.

4.3.2 OPC + supercaps and OPC + batteries

In order to account for charging opportunities at intermediate bus stops, trips of the base network are further divided into two or several partial trip nodes. A trip starting at terminal station v, passing potential charging station n and ending at terminal station w is partitioned into a trip node from v to n and another trip node from n to w. At potential charging location n, a possible charging event is represented through the

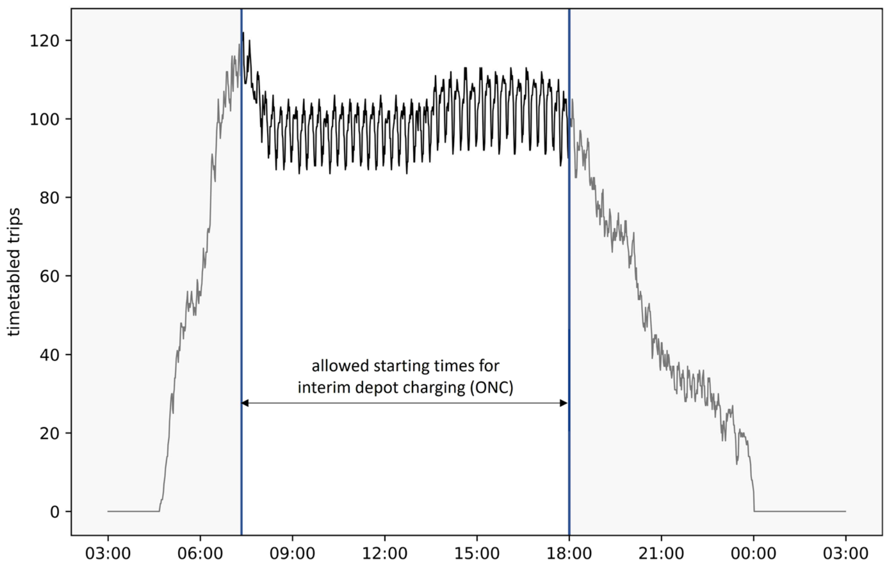


Fig. 4 Number of service trips by time of the day

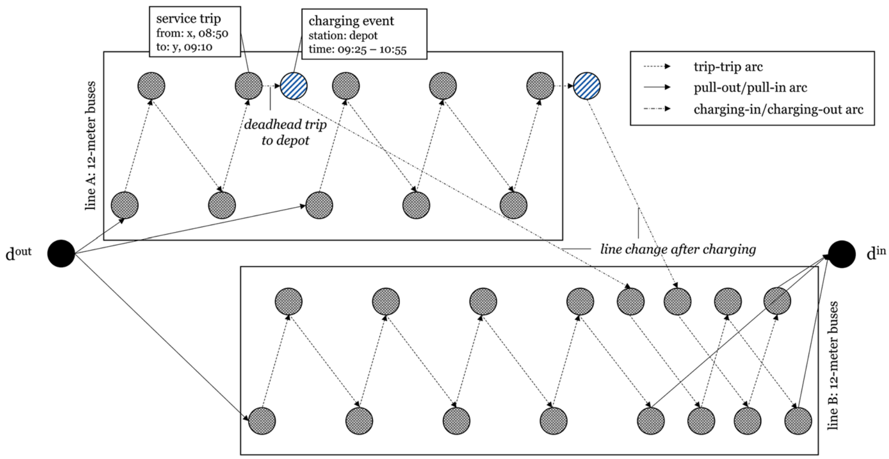


Fig. 5 Solution of an ONC network

insertion of charging node c. Each charging node c is characterized by its' specific location, the earliest possible start time $start_c$, and a maximum charging duration $chargetime_l$. We assume that the sum of all charging operations along a line must fully compensate the amount of consumed energy in each rotation. This assumption seems legitimate, as supercapacitors are characterized by very small storage capacities and buses highly depend on frequent recharges. Based on this assumption, we can derive a prescribed charging duration from a bus line's consumption profile. As

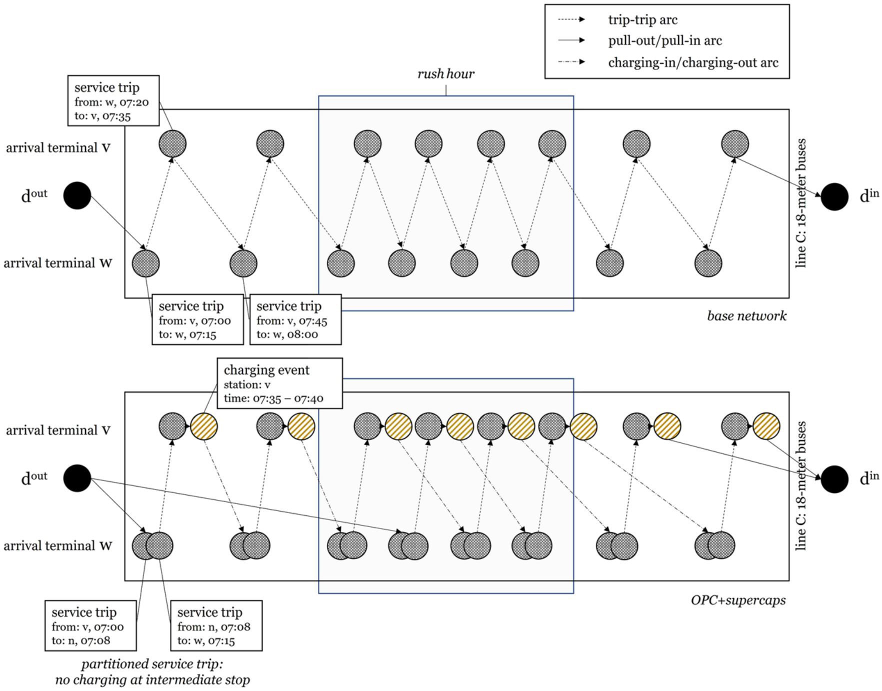


Fig. 6 Solution of an OPC + supercaps network

charging activities can be split over several stations along a route, the length of individual charging activities is not explicitly defined in advance. Overall, the total duration of performed charging events must meet the predefined $chargetime_l$ per rotation. To enter a charging node c, so-called charging-in arcs, which connect the end of trip nodes with the respective charging node are inserted. As some of the potential charging sites provide room for several chargers at a station, duplicated nodes and charging-in arcs are created for each potential charger at a station. Moreover, arcs leaving charging nodes, called charging-out arcs, are added between the charging event and subsequent trips on the same bus line, if they start within a certain time limit after charging. Additionally, new arc connections between partial trips of previously unified trips (e.g. the trip from v to w) are inserted, to allow a direct trip connection without intermediate charging. All newly inserted network arcs represent waiting arcs with zero duration, i.e., they do not occupy any time, as the location of buses does not change. As leaving charging nodes via connecting trips is not possible at all times, additional pull-in arcs to the depot are added from each potential charging node. A network solution of exemplary bus line C operated with OPC+supercaps is provided in Fig. 6.

The OPC+batteries network is defined in a similar manner as OPC+supercaps. The original trip nodes are divided into partial trips and provided with additional trip-trip connections. Charging nodes are inserted after trip nodes ending at potential charging locations. As the maximum charging duration depends on the respective technology, a non-identical set of charging-out arcs is produced for OPC+batteries.

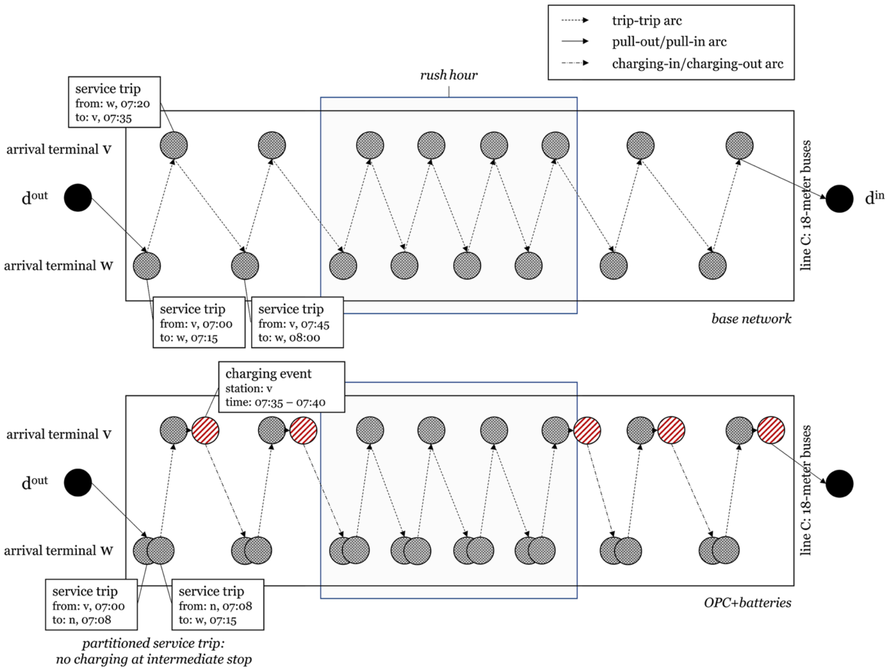


Fig. 7 Solution of an OPC + batteries network

Another distinction originates in the size of deployed battery capacities. In many cities, rush hours bring the capacities of bus networks to their limits. The generally larger energy buffer of conventional traction batteries used in the OPC+batteries concept allows to omit charging events during time periods, where bus frequencies are high and an enforced charger occupation at every circulation would result in the need for additional charging stations; see Fig. 7.

4.3.3 FC and FC-REX

Hydrogen-based technologies do not require special considerations during operations throughout the day. Batteries of FC-REX buses are assumed to be charged during the night. Thus, they require charging infrastructure at the depot, but no charging events must be scheduled during the day. Therefore, FC and FC-REX networks are simply based on the directed graph of the base network presented in Sect. 4.1. If the hydrogen filling station is not located directly at the depot and buses must make a detour for their daily hydrogen refilling, pull-in trips can be adapted to account for longer traveling distances.

4.4 ILP representation

The developed ILP builds upon the described networks and can be structured into a general part, represented by constraints (6)–(18) and technology-specific parts, represented by constraints (19)–(45). The major decision variables $t_{(q,l)}$, $a_{(s,t)}$ and z^* are defined in the general model constraints. The binary variable $t_{(q,l)}$ indicates whether technology q is chosen for bus line l. Variables of type $a_{(s,t)}$ are used to model the selection of arcs in the underlying technology networks. z^* variables indicate the level of bus numbers per technology ($z^{\beta}_{(q,i)}$) and infrastructure requirements at the depot (z_i^{kW}, z_i^{H2}). The full list of decision variables and used sets is provided in Tables 4 and 5. A preliminary version of the following model was described in Frieß and Pferschy (2021).

$$\begin{aligned} \min \sum_{q\in Q}\sum_{l\in L} t_{(q,l)} * cost^{energy}_{(q,l)} + \sum_{(s,t)\in A} a_{(s,t)} * cost^{energy}_{(s,t)} + \sum_{q\in Q} d_q * cost^{driver} \\ + \sum_{q\in Q}\sum_{b\in B} \beta_{(q,b)} * cost^{bus}_{(q,b)} + \sum_{q\in Q}\sum_{i\in I^{\beta}_q} z^{\beta}_{(q,i)} * cost^{\beta}_{(q,i)} + \sum_{i\in I^{kW}} z^{kW}_i * cost^{kW}_i \\ + \sum_{i\in I^{H2}} z^{H2}_i * cost^{H2}_i + \sum_{q\in Q}\sum_{n\in N^q}\sum_{o\in O_n} v^q_{(n,o)} * cost^{charger}_{(q,n,o)} \end{aligned} \tag{6}$$

$$\sum_{q\in Q} t_{(q,l)} = 1 \qquad \forall l \in L \tag{7}$$

$$\sum_{v\in A^-(t)} a_{(v,t)} = t_{(q,l)} \qquad \forall q \in Q, l \in L, t \in V_l \tag{8}$$

$$\sum_{s\in A^-(v)} a_{(s,v)} = \sum_{t\in A^+(v)} a_{(v,t)} \qquad \forall v \in V \mid v \notin \{d^{out}, d^{in}\} \tag{9}$$

$$\beta_{(q,b)} = \sum_{t\in A^+(d^{out}_b)} a_{(d^{out},t)} \qquad \forall q \in Q, b \in B \tag{10}$$

$$x^{\beta}_q = \sum_{b\in B} \beta_{(q,b)} \qquad \forall q \in Q \tag{11}$$

$$x^{kW}_q = x^{\beta}_q * power_q \qquad \forall q \in Q^{kW} \tag{12}$$

$$\sum_{i\in I} z^{\beta}_{(q,i)} * step^{\beta}_{(q,i)} = x^{\beta}_q \qquad \forall q \in Q \tag{13}$$

$$\sum_{i\in I} z^{kW}_i * step^{kW}_i = \sum_{q\in Q} x^{kW}_q + x^{kW}_{H2} \tag{14}$$

$$\sum_{i\in I} z^{H2}_i * step^{H2}_i = \sum_{q\in\{\text{FC,FC-REX}\}} x^{H2}_q \tag{15}$$

Table 4 Introduced variables

General	
$a_{(s,t)} \in \{0, 1\}$	1 if arc from source s to target t is used
	0 otherwise
$t_{(q,l)} \in \{0, 1\}$	1 if technology q is chosen for line l
	0 otherwise
$\beta_{(q,b)} \in \mathbb{N}$	Number of buses of bus type b of technology q
$x_q^{\beta} \in \mathbb{N}$	Total number of buses of technology q
$x_q^{H2} \in \mathbb{N}$	Total hydrogen demand of technology q
$x_q^{kW} \in \mathbb{N}$	Total depot power demand of technology q
$x_{H2}^{kW} \in \mathbb{N}$	Total depot power demand of hydrogen infrastructure
$z_{(q,i)}^{\beta} \in \{0, 1\}$	1 if cost step i of β cost function of technology q is chosen
	0 otherwise
$z_i^{H2} \in \{0, 1\}$	1 if cost step i of $H2$ cost function is chosen
	0 otherwise
$z_i^{kW} \in \{0, 1\}$	1 if cost step i of kW cost function is chosen
	0 otherwise
$d_q \in \mathbb{N}$	Duty hours of technology q
ONC-specific	
$\varepsilon_v^+ \in \mathbb{N}$	Remaining charge when leaving node v
$\varepsilon_v \in \{0, 1\}$	1 if remaining charge at node v forbids charging
	0 otherwise
$v_{(n,o)}^q \in \{0, 1\}$	1 if charger o at station n is built
	0 otherwise
OPC-specific	
$b_{(l,n)}^q \in \mathbb{N}$	Charging time at charging station n at line l
$b_c^{start} \in \mathbb{N}$	Start of charging at charging node c
$b_c^{end} \in \mathbb{N}$	End of charging at charging node c
$g_{(c,m)}^{start} \in \{0, 1\}$	1 if charging event c already started at time step m
	0 otherwise
$f_{(c,m)}^{end} \in \{0, 1\}$	1 if charging event c did not end by time step m
	0 otherwise
$u_{(c,m)} \in \{0, 1\}$	1 if charging event c is taking place in time step m
	0 otherwise
$v_{(n,o)}^q \in \{0, 1\}$	1 if charger o at station n is built for technology q,
	0 otherwise
$w_{(c,t)} \in \mathbb{N}$	Time between start of charging event c and start of preceding trip t

Table 5 Introduced sets

Q	Set of technology options q
Q^{kW}	Set of overnight-charging options {ONC, OPC+batteries, FC-REX}
Q^{OPC}	Set of OPC-based options {OPC+supercaps, OPC+batteries}
Q^{H2}	Set of hydrogen-based options {FC, FC-REX}
B	Set of bus lengths b
I_q	Set of cost intervals i of step-wise cost function of technology option q
I^{kW}	Set of cost intervals i of kW-dependent step-wise cost function
I^{H2}	Set of cost intervals i of H2-dependent step-wise cost function
L	Set of bus lines l
A^*	Subset of arcs from the base network:
	All pull-in and pull-out arcs, optimized trip-trip arcs
A	Set of all network arcs from source s to target t
$A_n \subseteq A$	Set of incoming arcs of simultaneous charging events at station n
$A^-(v)$	Set of preceding nodes of node v
$A^+(v)$	Set of successive nodes of node v
N	Set of potential OPC charging stations n
N^q	Set of potential charging stations n of technology q
$N_l^q \subseteq N^q$	Set of potential charging stations n of technology q along bus line l
O_n	Set of potential chargers o at charging station n
M	Set of discrete time steps m
V	Set of network nodes v
V^c	Set of charging nodes c
V^{trips}	Set of trip nodes t
V^l	Set of trip nodes of bus line l

$$\sum_{i \in I_q} z^{\beta}_{(q,i)} = 1 \qquad \forall q \in Q \tag{16}$$

$$\sum_{i \in I^{kW}} z_i^{kW} = 1 \tag{17}$$

$$\sum_{i \in I^{H2}} z_i^{H2} = 1 \tag{18}$$

The overall objective of our model is to minimize LCC of the electric bus network. LCC are composed of route-dependent ($cost^{energy}$, $cost^{driver}$), vehicle-dependent ($cost^{bus}$) and infrastructure-dependent cost drivers ($cost^{\beta}$, $cost^{kW}$, $cost^{H2}$, $cost^{charger}$). In constraint (7), each bus line l is assigned to exactly one electric technology option. Constraints (8)–(10) are similar to constraints (2)–(4) and specify network flow and vehicle numbers per technology option and bus length. As infrastructure-related costs depend on total vehicle numbers, the sum of differently sized buses per technology is calculated in (11). In (12), the power load at the depot is calculated for technologies that charge overnight. Constraints (13)–(15) take the total number of buses per technology, the total power load over all technologies, and the total hydrogen demand and translate these figures into binary variables z_i^*, which indicate the related step of the step-wise cost function for the objective function. Constraints (16)–(18) assure that only one level of the step-wise cost function can be chosen.

The ONC concept assumes that charging activities only take place occasionally. In order to determine the charging demand between trips, the batteries' state of charge is explicitly recorded at each network node. In constraint (19), the start values at d_{out} are set to the maximum SoC of each bus type b, as batteries of both 12- and 18-meter buses are fully charged during nights. Constraint (20) requires that the remaining SoC is constantly kept above a minimum level SoC^{min}. In (21) and (22), the most recent SoC is calculated for each trip- and service node. (21) assures that the SoC of a trip node t is set to a value lower than the SoC of the preceding node v minus the consumption of the deadhead trip from v to t and the consumption of trip t itself. When the arc connection between v and t is not being used, node t is simply bounded by SoC^{max}. In constraint (22), analogous updates are made for charging nodes v. The SoC when leaving a charging node v is calculated by subtracting the energy consumption of deadhead trip (s, v) and adding the amount of charged energy at charging node v to the SoC of the preceding node s. Constraints (23) and (24) forbid deadhead trips to charging stations shortly after charging, but only when a certain level $SoC^{discharge}$ is reached. Moreover, the scheduling of simultaneous charging events at a station is limited to the maximum number of available chargers in (25). Constraint (26) assures that the use of an additional charger o is only considered when charger $o-1$ is already occupied. The lexicographic usage of chargers also breaks symmetries. Finally, in (27), the amount of duty hours of driving personnel is calculated as the sum of all deadhead and service trips. As daytime charging of ONC buses takes considerable time and does not have to be monitored, time spent at charging stations is not included in staffing costs.

$$\varepsilon^+_{d_b^{out}} = SoC_b^{max} \qquad \forall b \in B \tag{19}$$

$$\varepsilon^+_v \geq SoC_v^{min} \qquad \forall v \in V^{trips} \cup d^{in} \tag{20}$$

$$\begin{aligned} \varepsilon^+_t \leq\ & \varepsilon^+_v - a_{(v,t)} * (cons_{(v,t)} + cons_t) \\ & + (1 - a_{(v,t)}) * SoC^{max} \qquad \forall t \in V^{trips}, v \in A^-(t) \end{aligned} \tag{21}$$

$$\begin{aligned} \varepsilon^+_c \leq\ & \varepsilon^+_s - a_{(s,c)} * (cons_{(s,c)} - charge_c) \\ & + (1 - a_{(s,c)}) * SoC^{max} \qquad \forall c \in V^c, s \in A^-(c) \end{aligned} \tag{22}$$

$$SoC_v^{max} * \varepsilon_t \geq \varepsilon^+_t - SoC_b^{discharge} \qquad \forall t \in V^{trips}, b = type_t \tag{23}$$

$$a_{(t,c)} \leq 1 - \varepsilon_t \qquad \forall t \in V^{trips}, c \in A^+(t) \tag{24}$$

$$\sum_{o \in O_n} v^{ONC}_{(n,o)} \geq \sum_{(t,c) \in A_n} a_{(t,c)} \qquad \forall n \in N^{ONC} \tag{25}$$

$$v^{ONC}_{(n,o)} \leq v^{ONC}_{(n,o-1)} \qquad \forall n \in N^{ONC}, o \in O_n \mid o \neq 1 \tag{26}$$

$$\sum_{(s,t) \in A} dur^{+trip}_{(s,t)} * a_{(s,t)} \leq d_{ONC} \tag{27}$$

The model constraints for OPC+supercaps and OPC+batteries technologies are almost identical. For each bus line l, a predetermined total $chargetime_l$ has to be fulfilled in each rotation through charging at either one or more potential charging stations along the line. Therefore, the total sum of charging times $b^q_{(l,n)}$ across different stations n has to equal $chargetime^q_l$, if technology q is chosen for a line. A positive charge time at a station n requires incoming arcs for the respective charging events of each rotation, as stated in (29). As the duration of charging activities at a given station is not set beforehand, charging stops of zero length are forbidden in (30). The set of potential subsequent trips is further confined in (31), such that only connection trips with start times greater or equal than the charging node's end time b^{end}_c can be used. Constraints (32) and (33) are used to determine the concrete start and end times of charging activities in natural numbers. The binary auxiliary variables g^{start} and f^{end} set in (34) and (35) translate this information into a binary vector created in (36), which indicates whether a charging spot has to be reserved for charging event c at time step m. If a charger o at station n is occupied by any charging event, the charger has to be established and binary variable $v_{(n,o)}$ is set to 1. Constraint (38) simply controls the order in which chargers are considered, similarly to (26). Constraint (39) ensures that a station can only be used for one technology, either OPC+supercaps or OPC+batteries. This was required in our application for practical reasons, but may be dropped wherever dual charging stations are technically feasible. As charging activities of OPC buses take place in the presence of bus drivers, duty hours of driving personnel include trip durations, charging times, and waiting periods, which arise between charging operations and trip connections. The sum of the latter two is defined in (40) and is calculated as the difference between the start of charging event c and the start of successive trip t. The total sum of duty hours is calculated in (41). As buses with supercapacitors are fully charged within minutes and buses leave the depot over a longer time period, the scheduling of precharging processes does not constitute a bottleneck and can be handled by an informal scheme. The demand for simultaneous chargers for supercapacitors at the depot is approximated by the total number of supercapacitor charging stations distributed within the network. The total power load for precharging OPC+supercaps at the depot is therefore calculated in (42) as product of the number of charging stations within the network and the maximum charging power.

$$\sum_{n \in N_l^q} b_{(l,n)}^q = chargetime_l^q * t_{(q,l)} \qquad \forall q \in Q^{OPC}, l \in L \tag{28}$$

$$a_{(t,c)} * chargetime_{line_c}^q \geq b_{(line_c, loc_n)}^q \qquad \forall q \in Q^{OPC}, c \in V^c, t = A^-(c) \tag{29}$$

$$b_{(line_c, loc_n)}^q \geq \sum_{t \in A^-(c)} a_{(t,c)} \qquad \forall q \in Q^{OPC}, c \in V^c \tag{30}$$

$$b_c^{end} \leq start_t * a_{(c,t)} + (1 - a_{(c,t)}) * \mathcal{M} \qquad \forall q \in Q^{OPC}, c \in V^c, t \in A^+(c) \tag{31}$$

$$b_c^{start} = a_{(t,c)} * start_c \qquad \forall q \in Q^{OPC}, c \in V^c, t = A^-(c) \tag{32}$$

$$b_c^{end} = b_c^{start} + b_{(line_c, loc_n)}^q \qquad \forall q \in Q^{OPC}, c \in V^c \tag{33}$$

$$b_c^{start} \geq (1 - g_{(c,m)}^{start}) * (m + 1) \qquad \forall q \in Q^{OPC}, c \in V^c, m \in M \tag{34}$$

$$m - 1 \geq b_c^{end} - \mathcal{M} * f_{(c,m)}^{end} \qquad \forall q \in Q^{OPC}, c \in V^c, m \in M \tag{35}$$

$$u_{(c,m)} = f_{(c,m)}^{end} + g_{(c,m)}^{start} - 1 \qquad \forall q \in Q^{OPC}, c \in V^c, m \in M \tag{36}$$

$$v_{(n,o)}^q * \mathcal{M} \geq \sum_{c \in V_{no}} \sum_{m \in M} u_{(c,m)} \qquad \forall q \in Q^{OPC}, n \in N^q, o \in O_n, m \in M \tag{37}$$

$$v_{(n,o)}^q \leq v_{(n,o-1)}^q \qquad \forall q \in Q^{OPC}, n \in N^q, o \in O_n \mid o \neq 1 \tag{38}$$

$$\sum_{q \in Q^{OPC}} v_{(n,1)}^q \leq 1 \qquad \forall n \in N \tag{39}$$

$$w_{(c,t)} = start_t * a_{(c,t)} - start_c * a_{(c,t)} \qquad \forall q \in Q^{OPC}, c \in V^c, t \in A^+(c) \tag{40}$$

$$\begin{aligned} &\sum_{c \in V^c} \sum_{t \in A^+(c)} w_{(c,t)} \\ &\quad + \sum_{(s,t) \in A} a_{(s,t)} * dur_{(s,t)} \leq d_q \qquad \forall q \in Q^{OPC} \end{aligned} \tag{41}$$

$$x_q^{kW} = \sum_{n \in N^q} v_{(n,1)}^q * power_q \qquad \forall q \in \{\text{OPC} + \text{supercaps}\} \tag{42}$$

The two hydrogen-based technologies FC and FC-REX require only little technology-specific adaptions. In (43), the total hydrogen demand of each technology is calculated as hydrogen consumption of all operated service and deadhead trips, whereas the former is substituted by accumulated consumption figures for whole bus lines. While the dimension of required hydrogen infrastructure was defined in (15), the corresponding power load x_{H2}^{kW} of hydrogen infrastructure is specified in (44). The power load for nightly charging operations of FC-REX buses was specified in (12). Finally, in (45), the drivers' duty hours of hydrogen-based operations are calculated as the sum of deadhead and service trip durations.

$$x_q^{H2} = \sum_{l \in L} t_{(q,l)} * cons_l^{kg} + \sum_{(s,t) \in A} a_{(s,t)} * cons_{(s,t)}^{kg} \qquad \forall q \in Q^{H2} \tag{43}$$

$$x_{H2}^{kW} = \sum_{i \in I} z_i^{H2} * kW_i^{H2} \tag{44}$$

$$d_q \geq \sum_{(s,t) \in A} dur_{(s,t)}^{+trip} * a_{(s,t)} \qquad \forall q \in Q^{H2} \tag{45}$$

In the proposed solution framework, the initial step is solving an ILP for each individual technology. To this end, five distinctive models, each composed of the described general model part (6)–(18) and the respective technology-specific constraints, are set up and computed. Since practical considerations might give preference to a uniform bus fleet to simplify procurement and maintenance operations, also these results provide valuable information for the decision maker. Ultimately, the full optimization model (6)–(45), which considers an arbitrary mix of technologies, is created and solved.

5 Results

The presented framework was applied to determine the optimal technology split for the bus system in Graz, Austria. In the investigated setting, the commercial solver Gurobi generated good-quality solutions within acceptable computation times (Gurobi Optimization, LLC 2022). The calculations were run on a 64-bit operating system with an Intel® Core™ i5-9500 CPU @3.00GHz processor and with 32 GB RAM. The proposed ILPs were implemented in Python and solved with Gurobi 9.0. In order to reduce the computational burden for the calculation of the optimal technology mix, the solver was provided with an incumbent solution from the previously computed most cost-efficient individual technology, as this technology is likely to appear also in the optimal technology mix. Moreover, we stopped the computation when the LP-gap reported by Gurobi reached 2%, which required roughly 10 h of computation time.

Table 6 Hydrogen infrastructure concept A–hydrogen storage at several locations

Exp. stage	Location	LB H2[1] [kg]	UB H2[2] [kg]	infrastructure cost [LCC in Mio. €]	production cost [€/kg]
0	Depot	0	0	–	–
1	Depot	1	140	9.47	3.44
2	Site 1	141	1564	28.72	3.44
3	Site 2	1565	2988	47.98	3.44
4	Site 3	2989	4392	67.34	3.44

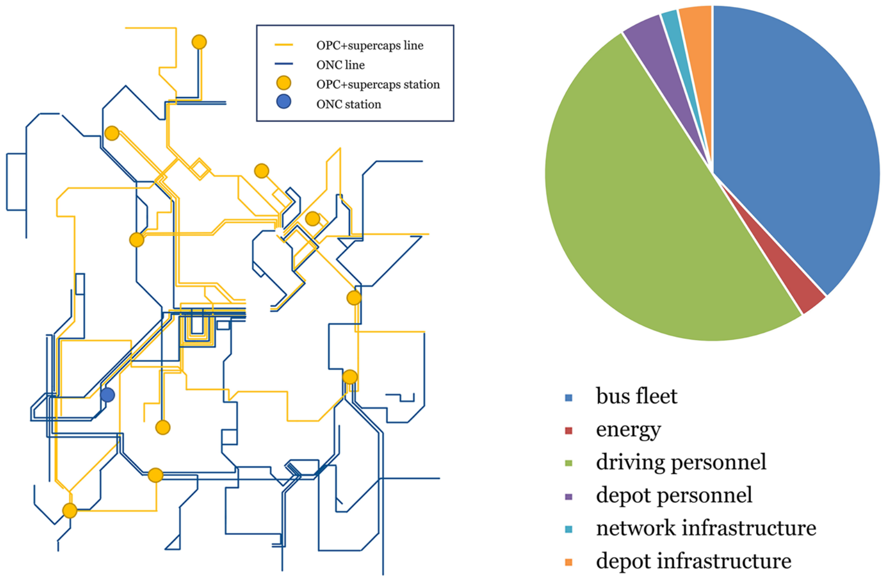
[1] Lower bound of daily filled hydrogen

[2] Upper bound of daily filled hydrogen

5.1 Real-world application

The current bus fleet of Graz is composed of 170 Diesel buses, which cover more than 33.500 km per day. In light of minor future network adaptions, it is planned to fulfill more than 4.000 service trips on 41 bus routes on a regular working day. The henceforth reported computational results are based on the timetables of a regular working day. Geographically, the city is situated in a basin region. An early adoption of zero-emission buses provides not only benefits with respect to carbon emissions, but also in view of local air quality. With a first demonstration phase of fuel cell and battery electric buses beginning in 2024, the full fleet conversion is planned to be completed in 2030. As we only consider electric technology options in the technology mix, our calculations relate to a 20-year planning horizon, starting in 2030 and ending in 2050. The results of our calculations are based on currently applicable planning assumptions, which may be updated when new information becomes available in the course of the demonstration phase.

For the deployment of hydrogen-based technologies, various city-specific infrastructure concepts have been designed by HyCentA (Hydrogen Center Austria). Infrastructure concept A, as presented in Table 6, serves as input for the base-case scenario. In the first expansion stage, hydrogen is bought from a third-party vendor and delivered to the depot. If daily hydrogen demand exceeds the upper bound of 140 kg, hydrogen is produced in company-owned production plants. In each additional expansion stage, a new production plant with 1.4 tons of daily filling capacity is established at a separate location. The respective total costs of infrastructure are given in Table 6. The associated hydrogen production costs of 3.44 €/kg of each expansion stage arise in addition to the total infrastructure cost and are not to be mistaken with production costs usually found in manufacturer's specifications, as these prices typically include proportional costs of infrastructure. As we attribute hydrogen costs to routes, rather than infrastructure, different production costs for different expansion stages, as specified in initial concept drafts, were not considered in the given setting and cost differences among expansion stages were counted up on infrastructure costs.



(a) Line network with charging stations (b) Cost structure of system components

Fig. 8 Optimal technology mix of the baseline scenario

5.2 Base scenario

The results of our computations suggest that a mixed electric bus fleet can indeed lead to monetary advantages. The optimal technology mix of the baseline scenario consists of 12 OPC+supercaps and 29 ONC bus lines, as represented in Fig. 8a. Bus lines operating under the OPC + supercaps concept are generally highly frequented and have circulation times above the average. Overall, 90 vehicles and 10 charging stations, equipped with 14 chargers in total, are required to operate these lines. In comparison, buses operated under the ONC concept perform recharges exclusively at the depot and no additional charging locations are utilized, which can be well explained by their high fixed costs. Coincidentally, also ONC-operated bus lines require the deployment of 90 vehicles, and a total of 180 buses is needed to guarantee smooth bus operations on all working days throughout the year.

A comparative cost breakdown in individual cost drivers is provided in Table 7. In the optimized technology mix, bus fleet LCC (life cycle cost) make up 38.08% of the total costs. With 56.85%, daily operation has turned out to be the largest cost driver. The major part originates from personnel costs, which differ only slightly between technologies. Personnel costs are directly proportional to driving hours (including short-term charging for OPC + supercaps and OPC + batteries, but excluding nightly charging as well as daytime recharging at the depot). Clearly, aspects of crew scheduling for a 20-year planning horizon are beyond the scope of our framework. The other part of daily operations stems from energy costs, which vary significantly between different technologies but make up only small shares of

Table 7 Comparison of LCC in Mio. € of different technologies of the base scenario

	MIX		FC		FC-REX		ONC	
	LCC	%	LCC	%	LCC	%	LCC	%
Total bus fleet	**385**	**38.08**	**430**	**40.04**	**453**	**40.81**	**416**	**40.54**
Energy	29	2.87	45	4.23	44	3.96	30	2.97
Driving personnel	505	49.95	503	46.92	503	45.37	505	49.19
Depot personnel	40	4.03	40	3.79	40	3.67	42	4.16
Total daily operation	**574**	**56.85**	**590**	**54.94**	**588**	**53.00**	**578**	**56.33**
Network infrastructure	17	1.72	0	0.00	0	0.00	0	0.00
Depot infrastructure	33	3.36	53	5.01	68	6.19	32	3.13
Total infrastructure	**51**	**5.07**	**53**	**5.01**	**68**	**6.19**	**32**	**3.13**
Total LCC	**1011**	**100.00**	**1074**	**100.00**	**1110**	**100.00**	**1026**	**100.00**
Cost comparison			+ 6.20 %		+ 9.83 %		+ 1.53 %	
			OPC+batteries		OPC+supercaps			
			LCC	%	LCC	%		
Total bus fleet			**418**	**41.40**	**367**	**36.32**		
Energy			26	2.60	25	2.56		
Driving personnel			468	46.27	471	47.87		
Depot personnel			42	4.16	41	4.20		
Total daily operation			**536**	**53.03**	**538**	**54.63**		
Network infrastructure			25	2.55	44	4.56		
Depot infrastructure			39	3.02	44	4.49		
Total infrastructure			**56**	**5.57**	**89**	**9.05**		
Total LCC			**1011**	**100.00**	**985**	**100.00**		

total LCC (note that all cost values were forecasted in 2021). Also infrastructure investments, which can be very high in the first place, vary significantly between technologies. In the optimized technology mix, total infrastructure costs make up 5.07% of total LCC.

A comparison among technologies shows that a network purely operated by FC buses results in a 6.20% increase in LCC in comparison to the optimal technology split. A pure FC-REX network exceeds LCC of the optimal MIX by 9.83%. Hydrogen and overall energy costs are lower for FC-REX, as compared to FC, but vehicle, as well as infrastructure costs, are considerably higher. While greater vehicle costs result from exogenous input parameters, higher infrastructure costs arise from an additional need for charging stations and an insufficient reduction of hydrogen demand, which fails to permit a downsizing of infrastructure. The smallest achievable fleet size for the given bus network consists of 160 vehicles (without backup) and is reached by hydrogen-based technologies. A network purely operated by ONC, in comparison, requires 188 vehicles per day. Total LCC, however, are only 1.53% higher than total LCC of the optimal technology mix and upfront infrastructure costs are reduced by approx. 20 Mio. €.

Solutions for OPC+batteries and OPC+supercaps are hardly comparable with other alternatives and are therefore shown separately. A limited list of potential charging locations can make a purely electric system operation under the OPC concept impossible. As this was the case for the bus network in Graz, a high penalty for non-electric bus lines was introduced in the objective function to retrieve the highest possible coverage of OPC. The resulting cost tables (without penalties) account for a varying subset of electric bus lines in each scenario, namely 38 for OPC+batteries and OPC+supercaps in the base case.

5.3 Scenario analysis

The results described in Sect. 5.2 depend on a large set of input assumptions concerning technical data, cost values and system parameters. As we are dealing with a long-term planning problem for technologies still under development, many of these input values remain uncertain. With roughly 40 different types of parameters at hand, a study with three levels (low, middle, high) per factor would result in $3^{40} = 1.2 * 10^{19}$ scenarios, if all combinations were tested in a full factorial design. Therefore, only a carefully chosen subset of scenarios was studied. Altogether, we assembled 104 scenarios, partitioned into four runs, each of which pertaining to a specific topic.

At first, in run 1, sensitivity tests with respect to changes in single input parameters were performed. Runs 2, 3 and 4 were then created to gain a deeper understanding of hydrogen-, charging- and energy-related factors, respectively. An overview of the most relevant scenarios and main findings is provided in Table 8. A detailed discussion of our scenario analysis is available in an extended online version of this article.[2] The computation of each scenario consists in solving an ILP for each

[2] https://optimization-online.org/?p=23502.

Table 8 Overview of scenarios and main findings

Run	Topic	Scenario description	Results	Take-aways
1	Variation of single parameters	Vehicle prices FC and FC-REX: cost reduction up to 30 %	Reduction of 3.66 % of total LCC with 150 FC and 10 FC-REX buses	Development of acquisition costs of fuel-cell vehicles crucial
		Vehicle configuration FC-REX: 80:20 electricity:H2 ratio	Reduction of 0.60 % of total LCC with a majority of FC-REX buses, pure FC-REX surpasses orginal MIX	Battery and fuel cell size greatly influence vehicle acquisition costs and thus, optimal solutions
		Available charging sites OPC: charging only at end stations	OPC+supercaps is totally omitted, LCC of MIX increase by 1.53 %	Only small financial advantage of OPC+supercaps over ONC
		Charging parameters ONC: see Table 10 in appendix	Reduction of parameters leads to higher shares of OPC, increase vice versa, no significant change of LCC	ONC benefits from larger batteries, higher charging power, lower energy consumption
		Energy consumption ONC/OPC: see Table 10 in appendix	Reduced consumption increases share of ONC, increase vice versa	
2	H2 costs & H2 consumption in different cost environments	H2 production costs: 2.00–4.50 €/kg H2 consumption: 12 m: 4.8–7.8 kg/100 km 18 m: 7.2–11.7 kg/100 km low-cost environment: infrastructure concept B, low vehicle prices	Low-cost env. and H2 prices below 3.50 €/kg make FC/FC-REX cost-competitive, solutions with prices $\geq$ 3.50 €/kg include ONC/OPC in MIX, low-cost env. and high consumption still results in largely H2-based MIX	Reduction of H2 consumption or cost is not sufficient to make hydrogen-based technologies competitive, low vehicle and infrastructure costs are decisive
3	Factor combinations of charging parameters ONC & OPC	Standard and increased battery & charging power levels under low/average/high consumption: see Table 10 in appendix	Combination of both ONC factors yields best results (see Figs. 9 and 10 for details)	None of the studied scenarios made OPC+batteries cost-competitive, cost advantage of MIX over ONC can shrink to $\leq$ 1%
4	Changing energy cost	Electricity (net) price: 0,06 €/kWh - 0,17 €/kWh hydrogen price: 3,89 €/kg - 9,94 €/kg	Fleet composition of MIX is not sensitive to different energy cost, LCC of MIX/ONC/FC/FC-REX can increase up to 3/3/7/8%	Lower energy efficiency of hydrogen-powered systems makes them more vulnerable to increasing energy cost (see Fig. 11)

affected individual technology, as well as solving the ILP for the optimal technology mix. The respective running times heavily depend on the specific input setting and may take from several hours up to one day (on a standard PC as described before) to reach an acceptable solution quality. A remarkable observation is that scenarios become more difficult to solve when the ONC network becomes more constrained, either through lower battery capacities or higher consumption values. Whenever possible, we used the feature of multi-scenario models in Gurobi, which allows to solve several scenarios simultaneously, rather than formulating and solving separate models for each individual scenario.

6 Conclusion

In this paper we developed an optimization model for determining a mix of emission-free technologies covering all lines of an urban bus network in a medium-sized city. The set of available technologies consists of overnight charging, different variants of opportunity charging, hydrogen fuelling, and overnight charging with hydrogen fuelling for range extension. The objective was the minimization of life cycle costs over a 20-year planning horizon, taking into account acquisition, running, and personnel costs as well as costs for the necessary charging and refueling infrastructure. As an input to our ILP model an extensive data set was collected, comprising technical parameters and cost values for all relevant components of the urban bus system in the city of Graz, Austria. By an appropriate modification of this input data set the derived framework will be applicable for other cities with little effort.

Our results suggest that the deployment of a mixed bus fleet can indeed lead to monetary advantages in comparison to single-technology solutions. Specifically, a mix of ONC and OPC+supercaps turned out to be optimal for the investigated bus network. A critical assumption, however, was that charging operations are allowed to take place at intermediate bus stops along the lines. When charging is restricted to end stations, the cost advantage of OPC declines and a pure ONC network constitutes the optimal technology choice. Other influential parameter assumptions are battery capacity and charging power of ONC buses, as they have a major impact on the necessary fleet size. Although these parameters changed the share of ONC and OPC buses in the optimal fleet composition, improved vehicle specifications only achieved small reductions of LCC. Besides these external parameter settings, diverging energy consumption assumptions produced technological shifts in the optimal fleet composition. Lower energy consumption values resulted in higher shares of ONC buses, while higher energy consumption increased the share of OPC+supercaps in the bus fleet. A full system operation by OPC, however, turned out to be infeasible with the given set of available charging sites.

The results for hydrogen-based alternatives showed that in the base-case scenario, FC and FC-REX are not competitive with battery-electric alternatives. When life cycle costs of fuel cell buses align to its battery-electric counterparts, network LCC improve considerably and a mix of FC and FC-REX surpasses all other technology options. A similarly significant effect is reached when vehicle configurations of

FC-REX buses are changed to larger batteries and smaller fuel cells, as vehicle LCC are directly decreased and additional cost advantages are realized through infrastructure and energy cost savings. Overall, this indicates that low vehicle prices are a major requirement for the technologies' competitiveness. The results of hydrogen-related input variations support this view, as neither cheaper hydrogen prices nor lower consumption values were sufficient to make hydrogen-based technologies competitive in scenarios with standard vehicle prices.

The analysis of altering energy costs showed that the original technology mix remains stable within a wide range of electricity prices and also the ranking among single technologies does not change. Solutions of hydrogen-based technologies generally react stronger to increased electricity prices, which can be explained by the lower energy efficiency of hydrogen-powered systems.

Overall, our results indicate that the optimal technology mix is a truly individual decision, which depends on an interplay of (1) internal operating conditions and (2) external market trends, i.e. prices and technical solutions. With the proposed optimization procedure we pursue a systematic approach to reveal the impact of relevant input assumptions and point out critical factors for a technology's effective performance. Together with a detailed, easy-to-handle data interface, the decision-support tool can also be transferred to other, medium-sized cities. With approx. 4.000 timetabled trips a day, solutions for the bus system in Graz are retrieved within acceptable computation times. For larger instances, however, running time requirements become prohibitively large and advanced decomposition approaches might be considered for solving the investigated planning problem.

A shortcoming of the proposed optimization model is that the timing of bus purchases is not explicitly considered. The bus fleet transition problem, as investigated by Pelletier et al. (2019) or Islam and Lownes (2019), provides clear replacement strategies for the transition phase, but usually adopts more aggregated approaches with respect to daily operations and resource requirements. Considering lengthy and politically sensitive public procurement processes as well as difficulties in timely deliveries and price uncertainties, we suggest to develop exact replacement plans once the long-term pursued technology choice is known.

The technology options investigated in this paper were selected together with experts of the bus operator in consideration of local circumstances. Other clean technology concepts, such as trolleybuses, natural gas or bio-fuel buses, might be additional options. Since the operational aspects of these technologies coincide to a large extent with hydrogen buses (high infrastructure cost but no refueling during the day), they could be included in our model with minor adaptations.

As a comprehensive evaluation of different technologies requires a systematic comparison on various levels, a further problem is the incorporation of the environmental impact in investment decisions. Though all investigated technology options are locally emission-free, their deployment gives rise to further processes down the value chain, which cannot be ignored on a global scale. As environmental effects are a multi-criteria concept in itself and compete with monetary arguments, a future research direction is to embed multi-objective optimization methods in the optimal technology choice.

Appendix A Additional material

See Tables 9, 10.

Table 9 Hydrogen infrastructure concept B - hydrogen storage at one location

Exp. stage	Location	LB H2[1] [kg]	UB H2[2] [kg]	Infrastructure costs [Mio. €]	Production costs [€/kg]
0	Depot	0	0	–	–
1	Depot	1	999	11.41	3.24
2	Depot	1000	1998	20.65	3.24
3	Depot	1999	2997	29.52	3.24
4	Depot	2998	3996	38.40	3.24
5	Depot	3997	4392	44.13	3.24

[1] lower bound of daily filled hydrogen

[2] upper bound of daily filled hydrogen

Table 10 Charging-related parameters used in the base scenario, Run 1 & 3

Parameters for 12 m/18 m buses	Decrease	Standard	Increase	Unit
ONC battery capacities	200/350	350/500	500/650	kWh
ONC charging power	50	100	150	kW
OPC+batteries battery capacities	–	240/300	480/600	kWh
OPC+batteries charging power	–	300	450	kW
Avg. energy consumption values[3] for system configuration	1.71/2.22	1.99/2.58	2.26/2.94	kWh/km
Avg. energy consumption values[3] for cost calculations	1.41/1.76	1.64/2.04	1.82/2.37	kWh/km

[3] As the considered technologies require different battery types and sizes, which have different weights and thereby influence consumption values, an additional adaption is made with regard to vehicle weight. Based on the results of a local e-bus study (Holding Graz, AVL List GmbH, internal report, 26.03.2021), 0.05 kWh/km energy consumption are added to above-mentioned base values for each extra ton of battery weight compared to the light-weight OPC+supercaps option

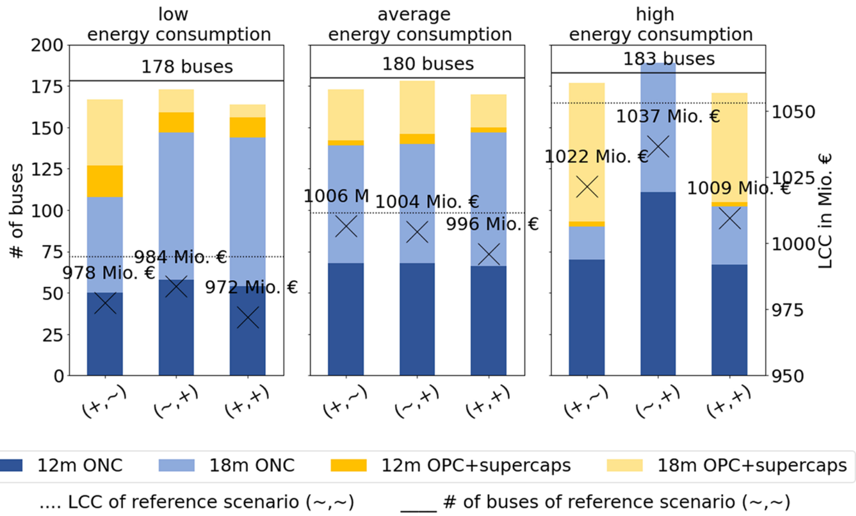


Fig. 9 Comparison of LCC and fleet composition of the technology mix for different ONC factor combinations. Each charging factor combination is signified by a tuple (battery capacity, charging power), which indicates the respective state of battery capacity and charging power. ~ stands for standard factor levels, a + represents an increase in battery capacity or charging power

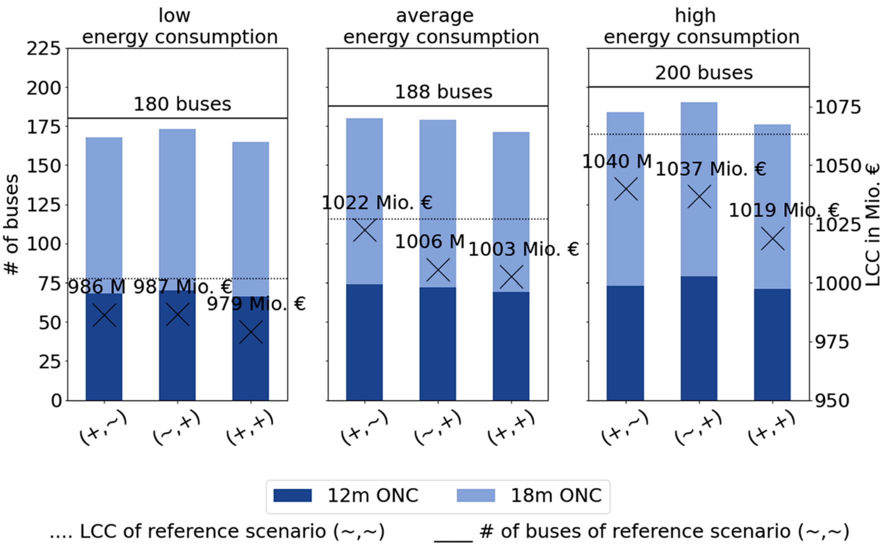


Fig. 10 Comparison of LCC and fleet composition of ONC networks for different charging factor combinations. Each charging factor combination is signified by a tuple (battery capacity, charging power), which indicates the respective state of battery capacity and charging power. ~ stands for standard factor levels, a + represents an increase in battery capacity or charging power

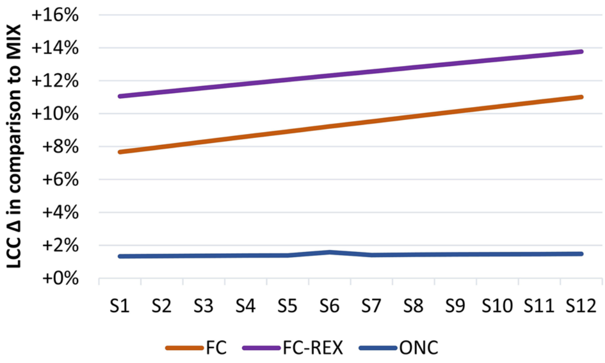


Fig. 11 LCC surplus of FC, FC-REX and ONC with increasing energy prices

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Declarations

Conflict of interest None.

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