THESIS FOR THE DEGREE OF DOCTOR OF PHILOSOPHY

Towards electric bus system: planning, operating and evaluating

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Abstract

The green transformation of public transportation is an indispensable way to achieve carbon neutrality. Governments and authorities are vigorously implementing electric bus procurement and charging infrastructure deployment programs. At this primary but urgent stage, how to reasonably plan the procurement of electric buses, how to arrange the operation of the heterogeneous fleet, and how to locate and scale the infrastructure are urgent issues to be solved. For a smooth transition to full electrification, this thesis aims to propose systematic guidance for the fleet and charging facilities, to ensure life-cycle efficiency and energy conservation from the planning to the operational phase.

One of the most important issues in the operational phase is the charge scheduling for electric buses, a new issue that is not present in the conventional transit system. How to take into account the charging location and time duration in bus scheduling and not cause additional load peaks to the grid is the first issue being addressed. A charging schedule optimization model is constructed for opportunity charging with battery wear and charging costs as optimization objectives. Besides, the uncertainty in energy consumption poses new challenges to daily operations. This thesis further specifies the daily charging schedules with the consideration of energy consumption uncertainty while safeguarding the punctuality of bus services.

In the context of e-mobility systems, battery sizing, charging station deployment, and bus scheduling emerge as crucial factors. Traditionally these elements have been approached and organized separately with battery sizing and charging facility deployment termed planning phase problems and bus scheduling belonging to operational phase issues. However, the integrated optimization of the three problems has advantages in terms of life-cycle costs and emissions. Therefore, a consolidated optimization model is proposed to collaboratively optimize the three problems and a life-cycle costs analysis framework is developed to examine the performance of the system from both economic and environmental aspects.

To improve the attractiveness and utilization of electric public transportation resources, two new solutions have been proposed in terms of charging strategy (vehicle-to-vehicle charging) and operational efficiency (mixed-flow transport). Vehicle-to-vehicle charging allows energy to be continuously transmitted along the road, reducing reliance on the accessibility and deployment of charging facilities. Mixed flow transport mode balances the directional travel demands and facilities the parcel delivery while ensuring the punctuality and safety of passenger transport.

Keywords: bus electrification, bus scheduling, charging station deployment, battery sizing, charge scheduling

List of publication

This thesis consists of an extended summary and the following appended papers:

Paper I: Zeng, Z., Wang, S. and Qu, X., 2022a. On the role of battery degradation in en-route charge scheduling for an electric bus system. Transportation Research Part E: Logistics and Transportation Review, 161, 102727. DOI: 10.1016/j.tre.2022.102727

Paper II: Zeng, Z., Wang, T., Qu, X., 2023. Optimizing en-route charging schedule for an electric bus network: Stochasticity and Real-world Practice. Transportation Research Part D: Transport and Environment (under first-round revision)

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Paper IV: Zeng, Z. and Qu, X., 2023. What's next for battery-electric bus charging systems. Communications in Transportation Research, 3, 100094. DOI: 10.1016/j.commtr.2023.100094

Paper V: Zeng, Z. and Qu, X., 2022c. Optimization of Electric Bus Scheduling for Mixed Passenger and Freight Flow in an Urban-Rural Transit System. IEEE Transactions on Intelligent Transportation Systems 24, 1288-1298. DOI: 10.1109/TITS.2022.3221332

For all papers, Ziling Zeng contributed to the conceptual design of the research, performed the literature review, collected and analyzed the data, developed the optimization model as well as interpreted the results, and drew the conclusions. Prof. Xiaobo Qu contributed with insights on the conceptual design of the research and acted as a mentor and reviewer of all five papers. Prof Tingsong Wang participated in the conceptual design and acted as a reviewer of Paper II. Prof Shuaian Wang contributed to the development and embellishment of the optimization models presented in Papers I and III. Paper IV is a peer-reviewed editoria.

Earlier versions of PAPER II have been presented at the 14th International Conference on Applied Energy (ICAE2022), Bochum, Germany, 8-12 August 2022.

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Zeng, Z., Cao, D. and Qu, X., 2020. Existing and Future Investigation of Charging Technology for Electric Bus. In Smart Transportation Systems 2020: Proceedings of 3rd KES-STS International Symposium, 19-27. Springer Singapore.

Zhang, L., **Zeng, Z.**, Gao, K., 2022. A bi-level optimization framework for charging station design problem considering heterogeneous charging modes. Journal of Intelligent and Connected Vehicles 5(1), 8-16.

Zhang, L., **Zeng, Z.**, Qu, X., 2020. On the role of battery capacity fading mechanism in the lifecycle cost of electric bus fleet. IEEE Transactions on Intelligent Transportation Systems 22(4), 2371-2380.

Qu, X., Zhong, L., **Zeng, Z.**, Tu, H. and Li, X., 2022. Automation and connectivity of electric vehicles: Energy boon or bane? Cell Reports Physical Science, 3(8), p.101002.

Ji, J., Bie, Y., **Zeng, Z.**, Wang, L., 2022. Trip energy consumption estimation for electric buses. Communications in Transportation Research 2, 100069.

Liu, Y., Wang, L., **Zeng, Z**., Bie, Y., 2022. Optimal charging plan for electric bus considering time-of-day electricity tariff. Journal of Intelligent and Connected Vehicles 5(2), 123-137.

Shang, P., Yang, L., **Zeng, Z**.*, Tong, L., 2021. Solving school bus routing problem with mixed-load allowance for multiple schools. Computers & Industrial Engineering 151, 106916.

Yang, L., Shang, P., Yao, Y., **Zeng, Z**., 2022. A dynamic scheduling process and methodology using route deviations and synchronized passenger transfers for flexible feeder transit services. Computers & Operations Research 146, 105917.

To my family

and

my loved ones

Acknowledgments

As I write the acknowledgments, my thoughts wander back to my Ph.D. journey, like a movie reel, gazing back and rolling over the people who have supported me. This journey would not have been possible without the support of my family, professors, and friends.

It is a tradition in China for a baby to crawl around a dazzling table toward an item that foretells his/her future interest. At that time I grabbed my mother's doctoral hat. It was an unspeakable coincidence, and in hindsight, it is all heartwarming and comforting. I am grateful to my mother for her encouragement and assistance during my entire education, her positive attitude, and her belief that there is no difficulty that cannot be solved, which has influenced me greatly and become my most solid spiritual strength.

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Contents

List of Tables

List of Figures

List of Abbreviations and Acronyms

DB	Diesel bus
DOD	Depth of discharge
EB	Electric bus
MFURT	Mixed-flow rural-urban transit
MILP	Mixed integer linear programming
LCC	Life cycle cost
LR	Lagrangian relaxation
PAPR	Peak-to-average power ratio
PCD	Portable charging devices
RO	Robust optimization
SOC	State of charge
TOU	Time of use
WTT	Well to tank

CHAPTER 1 Introduction

1.1 Why electrification?

Transportation is a fundamental aspect of modern society, providing essential mobility to people and goods alike. However, this sector accounts for a significant portion of total greenhouse gas emissions, with oil-derived fuels accounting for approximately 95% of transportation energy usage (ACEA, 2021; Liang et al., 2019). This indicates that it is imperative to explore and adopt sustainable transportation alternatives.

Transportation electrification has long been seen as an efficient and dependable method of reducing global warming and attaining carbon neutrality in the transportation industry. According to research by the Union of Concerned Scientists (Union of Concerned Scientists., 2019), a 40-foot electric bus (EB) produces just 347 g/mile of CO2, while a comparable diesel bus (DB)emits up to 2,680 g/mile and a natural gas-powered bus releases 2,364 g/mile. Since more and more renewable resources can create power instead of burning fossil fuels, the usage of electric buses is lowering reliance on fossil fuels. (Majumder et al., 2021). Besides, the exhaust from diesel buses contains a range of harmful pollutants, including particulate matter, nitrogen oxides, and sulfur dioxide, which contribute to respiratory and cardiovascular diseases (Chan et al., 2013). By contrast, EBs emit no tailpipe pollutants and are significantly quieter than diesel buses, making them an ideal solution for reducing noise pollution in urban areas. This significant reduction in emissions makes EBs an attractive option for local governments and transportation companies looking to reduce their carbon footprint and meet environmental targets.

In addition to reducing emissions, EBs also demonstrate greater energy efficiency compared to DBs. On a well-to-wheel basis, electric motors are more efficient at converting energy into motion than combustion engines, which lose energy through heat (Chan et al., 2013; Ribau et al., 2014). Regarding the overall energy efficiency, researchers estimated the instantaneous energy consumption of EBs and DBs. By factoring in vehicle speed, acceleration/deceleration, and ridership fluctuation, they arrive at average fuel consumption for DBs of 43.5 ± 9.5 L/100 km and average energy consumption for BEBs of 1.42 ± 0.32 kWh/100 km (Ma et al., 2021). Therefore, EBs are considered to be a viable alternative to traditional DBs, as they offer an efficient, cost-effective, and eco-friendly mode of transportation.

The Conference of the Parties to the United Nations Framework Convention on Climate Change in December 2015 resulted in Paris Agreement among 195 countries to limit global temperature increase to well below 2°C above pre-industrial level (Paris Agreemen., 2015). Building on the agreement objective of completely fossil-free transport by 2050, governments have been advocating the large-scale procurement and implementation of electric buses.

International Energy Agency reported that electric bus stock has expanded in major markets as shown in Figure 1.1 (IEA, 2021). Various worldwide programs and initiatives have been implemented to support the adoption of electric buses.

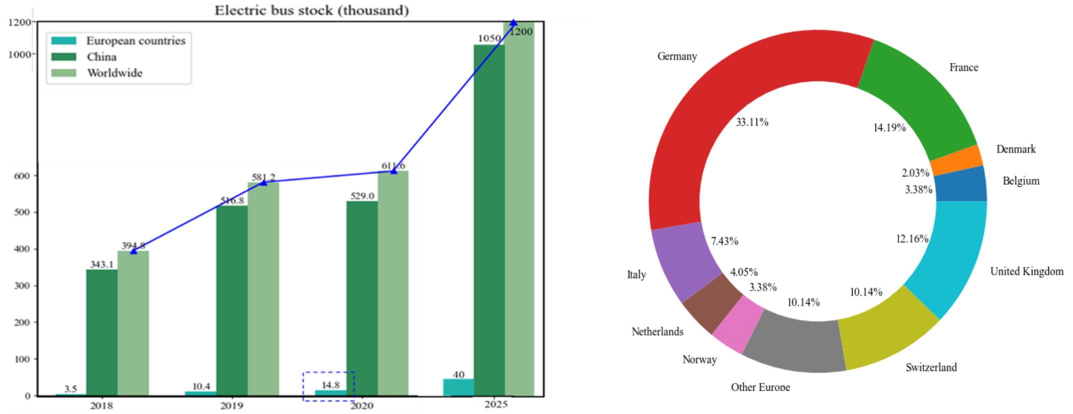
- China - China continues to dominate the electric bus market accounting for approximately 95% in 2021and has launched guidance in 2018 to replace the entire bus fleet with renewable vehicles in key areas such as provincial capitals by the end of 2020. The government has already invested heavily in electric bus infrastructure, with thousands of charging stations and battery swapping facilities already in operation. According to the Shenzhen Municipal Transportation Commission, the city's electric buses used 72.9% less energy in 2016 than diesel buses, which resulted in the replacement of 366,000 tons of coal with 345,000 tons of alternative fuels (Institute for Transportation and Development Policy., 2018).

- Germany - Germany is in a leading position in Europe and has set a goal of having entire public transport powered by renewable energy sources by 2050, and EBs are expected to play a major role in achieving this goal. Currently, the country has already made significant progress towards this goal, with 1,884 EBs in use. Germany has planned for longer-term purchases of around 8500 electrically powered buses before 2030.
- United Kingdom - The UK government has announced a commitment to end the sale of new petrol and diesel petrol and diesel vehicles by 2030, and committed to phasing out petrol and diesel cars and vans by 2035. Besides, they launched several programs to support the deployment of EBs across the country, including a £30 million Clean Bus Technology Fund and the Ultra Low Emission Bus Scheme.
- Norway - Norway has a target of phasing out sales of all new fossil-fuel vehicles by 2025, and EBs are expected to make up the majority of new bus purchases going forward. The government set a goal of obtaining a 100 percent EV share of urban bus sales by 2025. The country has already made significant progress towards this goal, with its share of EB sales skyrocketing from 9% in 2021 to 44% in 2022.
- France - France has set a goal of having 100% clean buses in dense areas by 2025 and 100% by 2029 in the suburbs. The government has launched several initiatives to support the adoption of EBs, including the Bus2025 Programme, which aims to invest €1.8 billion in 4,700 buses.
- Sweden - Sweden has the largest electric bus fleet in Northern Europe. More than 3% of the passenger car fleet and bus fleet is plug-in electric vehicles. The government has approved an investment of 11 million USD annually during 2018-2020, to support hardware and installation cost of electric vehicle charging stations. Västtrafik, a public transport service

agency, has formulated a target of electrifying 30 percent of the bus fleet by 2025 with a 100% EB fleet in Gothenburg city by 2030.

- United States - The United States has set a goal of achieving 100% zero-emission bus and truck sales by the year 2040. The federal government has launched several initiatives to support the adoption of EBs, including the $1.7 billion Low or No Emission Vehicle Program in 2023 and the Clean Cities Program.
- India - India has set a target of having 30% of all wheels electrified by 2030 and the National Electric Bus Program aims to deploy 50,000 electric buses nationwide. The government has launched several initiatives to provide financial incentives for the purchase of EBs and other electric vehicles, including the e-Sawaari, India Electric Bus Coalition, and the National Electric Mobility Mission Plan 2020.
- Canada - Canada has set a goal of having a fully electrified bus fleet by 2040, with a target of having 5,000 EBs on the road by 2025 nationally. The government has launched several initiatives to support the adoption of EBs, including the $2.75 billion Zero-Emission Transit Fund.

As illustrated in Figure 1.1, the global electric bus market is projected to double in size, reaching 1,200,000 units by 2025, with approximately 40% of new city buses registered in Europe expected to be battery electric (International Energy Agency, 2021). The European Investment Bank has launched a lending program to support the development of electric bus infrastructure. The program aims to provide up to €2 billion in financing for the deployment of EBs, charging infrastructure, and related projects. They also launched a Green Bus Fund, which provides financing for the purchase of electric and low-emission buses by public transport operators. These developments show that EBs are increasingly becoming a viable alternative to traditional diesel buses.



(a) EB market size development 2018 - 2025

(b) 2020 European countries' market size breakdown

Figure 1.1: Global electric bus market size (from Zeng et al., 2022b)

1.2 Scope and objectives

To ensure a stable transition from conventional buses to electric ones, systematic arrangements are needed from the planning to the operation phase. Compared with traditional fuel vehicles, the planning and operation of EBs is a more complex system engineering, and more parameters and indicators need to be considered. The vehicle characteristics of EBs (such as bus type, battery type, capacity, battery degradation, etc.), local climate, charging facilities, and charging plans will all affect the development of operating plans and operational benefits. Usually, when cities undertake an electric bus program, they can proceed in the order described in Figure 1.2. From start to end, all components have a common goal of reducing expenses. This allows for good operational performance with reduced budgetary pressure. During the planning stage, decision-makers are required to determine the type and size of the EB fleet to be purchased (Rogge et al., 2015), as well as the location and scale of charging facilities for energy replenishment (Zhang et al., 2018). Since electrification is now in its early stages, the timetable remains conventional. But when the era of mass or full-electric fleet comes, the timetable will also be redesigned in this phase. In the scheduling stage, the EB routing and dispatching are considered in detail (van Kooten Niekerk et al., 2017), to fully utilize the available resources to cover the timetable trips. However, from the previous literature, it was found that studies on the scheduling of EB charging are lacking, especially for opportunity charging. This problem however is an important issue in the operational phase, determining whether the fleet size is sufficient to complete the scheduled trips. At the same time, the charging schedule of electric vehicles is related to the depth of discharge of the battery, which determines the cycle life, and therefore the maintenance and replacement of the battery.

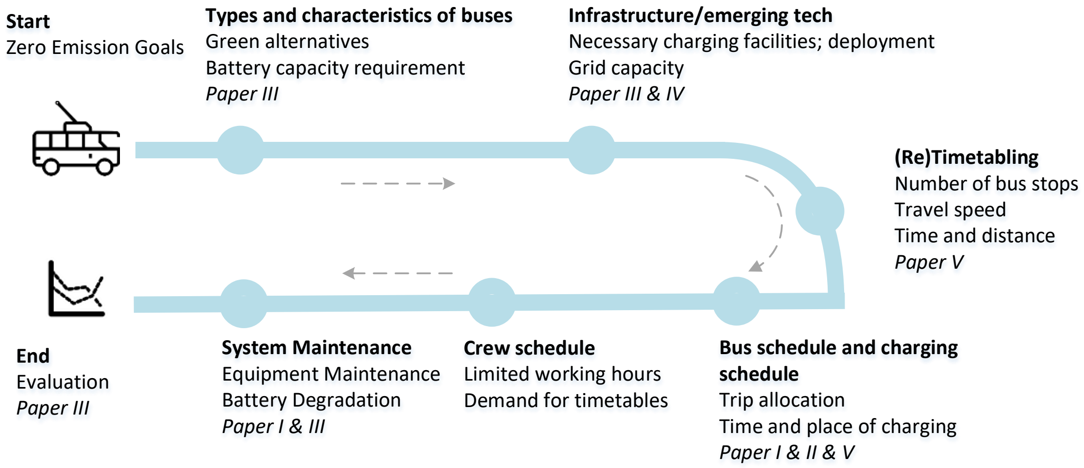


Figure 1.2: The roadmap of electric bus system planning

Therefore, this thesis builds on existing research to further plan, optimize, and evaluate the bus system from the planning to operation stage and focuses on the integration of emerging technologies in the system. Bus electrification is explored in terms of planning considerations: battery capacity, and charging station deployment, as well as in terms of operational applications: charge scheduling, and bus scheduling. The aim is to address the challenges of transport electrification at the system level in the specific context of public transport. Further, the possible purchase and operating solutions are evaluated in a full life-cycle cost analysis framework. In view of the charging characteristics of electric buses and the characteristics of passenger flow, the mixed transport model is proposed to further improve service efficiency and resource utilization to maximize the attractiveness of the green alternative.

The purpose of the thesis is to provide practical decision support to managers and to complement current research gaps. Specifically, this study is committed to answering the following research questions:

- Modeling and Validation. As electric buses are gradually replacing conventional vehicles, how can we provide quality decision support for each of these issues in the transportation system?
- Charging. As the biggest challenge for electric buses, how to schedule the charging events for the entire fleet while ensuring the feasibility of the plans and how to quantify the impact of different charging behavior on battery state-of-health?
- Evaluation and improvement. How to verify the environmental and economic advantages and disadvantages of the plans developed in different stages? How to improve operational efficiency accordingly?

The first aspect examined by the thesis is the description of the real-world problem and then the construction of an optimization model. They are expected to be in the form of mixed-integer linear programming, which can be easily solved using commercial solvers such as GAMS, CPLEX, and GRUBI. The models use total cost as the optimization objective, which usually includes several items such as ownership cost, maintenance cost, operation cost, and emission cost, where an emission tax is innovatively incorporated to calculate the whole life cycle emission expenses.

The second aspect of this thesis is the implementation of fast charging and to provide insights into the benefits of en-route fast charging technologies, as well as the optimal charge scheduling for systems that perform without compromising service quality in real-world operational settings. The impact of time-of-use electricity pricing, battery aging, battery properties, and energy consumption uncertainties on the charging schedule is thoroughly examined.

The third aspect focuses on evaluation and improvement. Based on a full life cycle perspective, we bring together both economic and environmental aspects to analyze the performance of the bus system in terms of vehicle acquisition, charging facility configuration, operation and maintenance, and emissions.

Regarding improvement, targeted practical solutions are proposed to facilitate charging opportunities and improve operational efficiency.

1.3 Methods, limitations, and delimitations

As mentioned earlier, the study design was descriptive and exploratory. The study was inspired by traditional systems theory approaches. Systems theory is an interdisciplinary form of systems research. A system is defined by boundaries (i.e., the delineation of the system) that represent more than the sum of its parts (subsystems). The goal of systems theory is to model the dynamics, constraints, and conditions of a system and to articulate principles (e.g., purposes, measures, methods, tools) that can be discerned and applied to other systems at each level of nesting and to achieve optimal equivalence across a wide range of domains (Ashby, 1961).

Research questions are explored through a quantitative method. To better provide decision support, quantitative simulation results of an optimization model are presented, and the results are analyzed and compared to historical operation data. In this way, causal statements are generated about the causality between the various influencing factors and the objectives, statements that can even go beyond the specific problem under study to inspire the potential and future directions of bus electrification. The various components and methodological tools used to develop the model are explained and discussed in detail in Chapter 3.

The analysis is limited to the specific sector chosen (bus transportation) and the charging technology chosen (opportunity charging). The term ‘electric buses’ in this release refers to battery-electric buses, not to hybrid models with both electric and internal combustion engines. The choice of charging power and location is for en-route fast charging, therefore slow charging in the depot is not the main focus.

When discussing life-cycle emissions, carbon dioxide equivalent (CO2eq) is used as the unit of measurement. The full life cycle is simplified into four parts: Glider powertrain, well-to-tank, and tank-to-wheel. In addition, some simplifications were made to build the optimization model. For example, the estimation of energy consumption is based on the average energy consumption of the type of bus and does not take into account temperature altitude, etc.

The bus network data (spatial and temporal) retrieved from Västtrafik, a bus operator in Gothenburg, may include discrepancies in the timetable and route reporting. These discrepancies have been corrected, but some uncertainties still exist. In addition, in determining the location of in-station chargers, we only considered the entire station level without specifying which platform.

1.4 State-of-the-art

1.4.1 Infrastructure deployment

The electric transit systems require comprehensive infrastructure planning since the bus networks have to be equipped with sufficient charging points to support daily operation (El-Taweel et al., 2020). Based on the way of charging electric buses, two technologies are emphasized: en-route charging and depot charging (He et al., 2020).

Depot charging is the most time-consuming charging strategy for electric buses. When buses finish their scheduled routes or stay in the depot during the shift. This charging is usually overnight or sometimes within the dwell time with slow chargers (typically 40–120 kW). The full charge process for depot charging takes around 4 hours. From the grid network aspect, this strategy avoids peak hour charging, where the subscribed power and the maximum charging power delivered by the charger are rather stable. Some optimization algorithms (Houbbadi et al., 2019) can attribute an optimal charging power for each bus.

Compared with depot charging, deploying charging piles along bus lines offers convenience and improves charging accessibility. A smaller battery package results in lighter bus weight, higher passenger capacity, and lower investment costs for battery ownership, but a higher price for infrastructure procurement.

(Lin et al., 2019). Supported by ABB (Wang et al., 2017a), a power technology group, the bus can be recharged at en-route charging stations with a 15-second energy boost while passengers are boarding and alighting. Based on the fast charging concept, the applications assume that en-route charging has no significant impact on existing timetables (Miles and Potter, 2014).

En-route charging can be realized through conductive (plug-in) and inductive (wireless) energy transfer. Inductive charging provides a lighter onboard battery that gets charged from magnetic fields, which requires an underground coil system and an onboard one. (Machura and Li, 2019) The charging power can reach 200 kW. However, due to the air gap between the coil system, the efficiency is relatively low (Lempidis et al., 2014). The maturity of the conductive charging technology enables a maximum of 600 kW charging power through either overhead or ground/underground infrastructures, which can be easily installed with little impact on the existing road networks. In this transitional phase, conductive fast-changing technology is widely used in European countries such as France, Germany, Italy, the UK, and Sweden, while only a few projects with inductive charging are presently being implemented (Nils Hooftman, 2020; Pamuła and Krawiec).

Due to the relatively high cost of en-route chargers, arranging the location and quantity of charging piles has become a challenge in the procurement and planning process. The optimal planning policies must seek to take into consideration as much as possible availability, effectiveness, and efficiency. Availability in charging station deployment could be achieved by setting the constraint that energy consumption should not exceed battery capacity (Xie et al., 2018). The optimal deployment of en-route charging stations fundamentally results from the efficient replenishment of real-time energy consumption. Thus, to ensure effectiveness, especially to extend the battery lifespan, the battery state of charge (SOC) must be kept within an optimal range (Zhang et al., 2020a) and be balanced with the charging station deployment plan (Xu and Meng, 2019). When the SOC is approaching the minimum level, a charging activity is required (Xie et al., 2020). Objectives are set to minimize the number of charging stations, maximize the charging demand coverage and reduce delays stemming from bus charging (Sebastiani et al., 2016). Although several studies have investigated charging station deployment for electric buses, the majority adopted fixed bus routes and schedules as input (Kunith et al., 2017b). Thus, homogeneous fleets are usually considered (Xu et al., 2015), and the fleet size is either empirical (Xylia et al., 2017) or assumed (Bi et al., 2018). It creates a large gap between the optimization results at the planning level and the optimal practical operation goals.

1.4.2 Battery sizing

The battery sizing problem assigns a bus (battery) type to an electrified bus line, fundamentally based on energy consumption (Rogge et al., 2015). In a battery-electric bus transit system, the charging stations and the onboard battery have the highest bearing on the ownership cost. For instance, the cost of the onboard battery accounts for at least 20% of the total expenses depending on the size of the battery (Nils Hooftman, 2019). If a homogenous bus fleet with the same battery capacity is considered to serve the transit network, it would inevitably lead to an oversizing and avoidable investment cost. Thus, the battery capacity of the bus is recommended to be determined individually for each bus line, thereby reducing required investments.

To determine the battery capacity, an adequate description of energy consumption is crucial. The state-of-the-art has been focusing on estimating and modeling the energy consumption of buses under real-world traffic conditions or based on different scenario settings (Basso et al., 2019; De Cauwer et al., 2015; Vepsäläinen et al., 2019). They reported that factors such as bus weight, the topography of the transit network, and energy efficiency could influence line-specific energy consumption and result in different charging demands. These charging demands that can be satisfied at charging stations depend on the dwelling time, the availability of charging infrastructures, and the battery state of charge (SOC) (Millner, 2010). Due to the interdependence of the energy supply through fast charging and battery capacity, a joint examination is necessary. Thus, some joint consideration has been taken of charging station deployment and battery sizing to minimize the cost of electrification, which includes a trade-off between battery capacity and charging infrastructure. Their model determines the minimum number of charging stations and the respective locations, as well as the optimal battery capacity for each bus route in the bus network while ensuring adequate energy supply for daily operations. (De Filippo et al., 2014; Kunith et al., 2017b; Rogge et al., 2015).

Another branch in terms of battery sizing is mainly focused on the co-optimization of battery size and energy distribution for EBs. To simultaneously optimize battery size and energy management for EB, combined optimization loops where one loop is used to size the battery and the other implements energy distribution (Du et al., 2017; Murgovski et al., 2011).

1.4.3 Bus scheduling

The bus scheduling problem extends the traditional vehicle routing problem to the handling of deadheading trips connecting, where a trip refers to bus service in a timetable and is characterized by the arrival and departure time at origin, destination, and some intermediate stops (Wang et al., 2020b). Unlike in the VRP, the station sequence of each trip is fixed, while range limitation and recharging possibilities should be taken into account to guarantee the service.

The methodologies of problem-solving differ according to different charging strategies as the required charging time varies. In the field of en-route charging, partial charging is allowed, and the capacity of the charging station is strictly limited. Li (2014) defined the bus scheduling problem with limited energy as the vehicle-scheduling problem with route constrain, where he considered charging stations with limited capacity and limited fleet size. A column-generation-based algorithm to solve the proposed optimization problem. van Kooten Niekerk et al. (2017) proposed a mathematical optimization model to address the homogenous fleet scheduling problems, with consideration of both linear and non-linear charging time. A column generation algorithm is proposed to solve the problem. Tang et al. (2019) developed the dynamic scheduling strategies of electric buses considering battery range limitation and the recharging plans of vehicles to deal with the problem brought by the stochasticity of urban traffic conditions. A branch-and-price framework is extended to effectively solve the proposed model. Wen et al. (2016) proposed a mixed-integer programming formulation of homogeneous electric vehicle fleet scheduling and developed an adaptive large neighborhood search method heuristic to solve the problem. A post-optimization phase is implemented to further improve the solution. Besides, the simulation method is widely used for bus scheduling based on operational data to acquire an adequate number of electric buses and to ensure the bus right on time (Teoh et al., 2018).

For depot charging, the deadhead trip between terminals and depots and the relatively high charging time should be carefully considered. Rogge et al. (2018) proposed a mixed-integer-linear programming method with heuristic and metaheuristic solving algorithms. They reported that a lightweight bus offers a more energy-efficient mode of transportation, although the deadheading mileage increases due to the frequency of charging. A heterogeneous fleet can offer 5% extra energy savings. Ke et al. (2016) developed a framework to simulate the operation and battery charging schedule of electric buses in Penghu to minimize the costs of an electric bus system including the expenses of EBs, batteries, chargers, and electricity. The genetic algorithm was used as an optimization tool. some recent works integrate depot charging and bus scheduling (An, 2020; Li et al., 2021; Rogge et al., 2018). Rogge et al. (2018) are the first to consider mixed-fleet scheduling in depot charging optimization, while some practical factors are not mentioned, such as battery type allocation, battery SOC management, and life cycle emissions. Li et al. (2021) followed up by considering charging scheduling and passenger demand uncertainty. An (2020) focused on the charging station coverage to support the daily operation with the minimized bus fleet.

1.4.4 Charge scheduling

The electric bus charge scheduling (EBCS) problem focuses on scheduling the EB charging events in time and space based on their access to different charging alternatives Since the EBCS problem is still in a novel stage and the number of studies in the literature is small, this section illustrates the approaches to solve the charging planning problem from different perspectives and summarizes their drawbacks.

Considering the EBCS in the centralized depot, Gao et al. (2018) planned to generate the lowest cost charging scheme for an EB fleet considering time-of-use (TOU) electricity price. An integer programming model was presented and was solved by a Genetic Algorithm Integer Programming Toolbox. Ke et al. (2016) simulate the battery charging schedule with both daytime and night-time charging alternatives. A genetic algorithm is introduced to jointly optimize the charging time and size of the bus fleet. These two studies overlooked the impact of EB charging demand on the grid, which may result in overloading the distribution transformer. Thus, Arif et al. (2020) proposed a mixed-integer linear programming model for depot charge schedule under a feed-in-tariff scheme to reduce the overloading on the low voltage feeder while maximizing the profit of the depot operator. The premise that the depot charging strategy can solve the mileage anxiety is that the bus is equipped with a sufficiently large battery pack. However, the battery still remains a significant cost component of EB, and this strategy would result in over-budgeted bus procurement.

The emerging technology of en-route fast charging provides promising potential to replenish the energy consumed during bus dwell time. Buses charging on the road usually benefit from this frequent replenishment and are equipped with smaller batteries to achieve lighter weight and higher efficiency (Aamodt et al., 2021). However, the en-route charging demand may overlap with the electricity demand peak, which results in expensive energy costs and pressures on the grid. Without an effective strategy to address the TOU rate and the impact on the grid, the advantages and reliability of EBs may be compromised. Therefore, the issue of charge scheduling for EBs has raised interesting challenges. Recent studies approached the problem through mathematical models of simulation methods.

Three related studies are in the context of mathematical optimization of en-route charge scheduling. Abdelwahed et al. (2020) modeled terminal station charging schedules for EBs. Two mixed-integer programming formulations are constructed based on discrete-time and discrete-event with minimized charging costs. The case study assumed that any arriving EB finds a free charging slot to avoid conflict. The proposed models were solved by a Cplex solver. The impact on the grid network is not considered in their models. Yang et al. (2018) explored an optimal charging scheme for wirelessly charged bus fleet on one route. The model innovatively considers two en-route charging alternatives: charging at bus stops and terminals. They introduced a peak-to-average ratio to reflect the impact on the grid. The 'Day-ahead RWED' and 'Optimal Actual CS' algorithms are presented for problem-solving without considering route interlining. Regarding the simulation method, Wang et al. (2020a) designed a price-aware terminal charging scheduling problem based on the Markov Decision Process. The model aims to maximize collected passenger fares while minimizing the charging costs. A full charging policy is adopted in the model. A large-scale simulation in Shenzhen City was conducted based on a policy iteration algorithm. Chen and Liang (2020) described the EB charging event as a Simi-Markov decision process without transition probability consideration. As in Yang et al. (2018), charging at bus stops and terminals are both available when considering a single route. The average reward reinforcement learning method is introduced for problem-solving. Qin et al. (2016) formulated an en-route charging strategy according to the battery SOC threshold based on the full charging policy. The numerical analyses explored the impact of different SOC charging thresholds on the cost of electricity and demand charges. They believe that charging the battery with a SOC of 60–64% is the most economical strategy and has the least impact on the grid.

In addition, charge scheduling is also applicable to dedicated charging stations around terminals. Zhou et al. (2020) constructed a Bi-level programming model for collaborative bus fleet and charge scheduling. The charging event is connected to the terminals through a dead-head trip. The TOU price policy is used to determine the charging slot. The charge scheduling problem was solved by a greedy dynamic selection strategy based on the multi-stage decision. However, this model does not take into account the conflicts of charging events caused by route interlining. Wang et al. (2017b) presented an optimization model for EB charge schedules. They focused on allocating buses to chargers at transit centers shared by several routes. The method aims at minimizing the total operational cost consisting of dead-head travel cost, charging price, and charging waiting cost. In their mixed-integer linear model, the charging duration is assumed to be fixed.

Recent studies also have approached the charge scheduling problem in an infrastructure deployment context. Sebastiani et al. (2016) proposed a simulation optimization method to minimize the number of on-route chargers and the average extra stop time caused by charging. They assumed that if the remaining energy plus the energy consumption within passenger boarding is insufficient to reach the next station, extra stop time is required. NSGA-II algorithm is introduced to solve the bi-objective problem. For joint consideration of charging station locating and battery sizing, Kunith et al. (2017a) described the problem as a capacitated set covering problem. They assumed that the bus charging time equals the dwell time. The influence of charging power, climate, and changing operating conditions are assessed. Besides, Liu et al. (2018b) developed a mixed-integer linear program to solve the charging station deployment problem. They assumed that a fast charger could be installed at bus stops and terminals, and the charging time equals bus dwell time. All these studies greatly simplify the charging behavior and do not take into account the interactions in practice, while ignoring the impact of the charging strategy on the battery.

1.5 Thesis structure

This thesis is based on five papers. Following the introductory chapter, the next chapter presents existing and emerging charging technologies. The advantages and disadvantages of each method are also presented. In Chapter 3, the description, formulation, and implementation of the EB charge scheduling problem are presented. The optimization model for charging plan generation is discussed in detail and related to the literature in the field. The first sub-topic focuses on static charge scheduling with battery degradation as one of the main optimization objectives. The second part pays attention to the uncertainties in real-world option and generate a robust optimization model accordingly. In Chapter 4, a joint optimization model is constructed to deal with battery sizing, charging station deployment, and bus scheduling. A life-cycle cost analysis framework is presented to evaluate the system performance in both economic and environmental aspects. Chapter 5 introduces three emerging charging solutions to provide more flexible charging alternatives to electric bus systems. Chapter 6 deals with operational efficiency improvement. An innovative mixed-flow transport mode is introduced to increase the utilization of transport resources. The thesis closes with Chapter 7, with main conclusions, result impacts and suggestions for future research on the topic.

The order of the appended papers moves from a presentation of the emerging charging technologies to the systematic optimization of charge scheduling for bus electrification, with a focus on en-route fast charging (PAPER I & II). With this knowledge, the evaluation of the transportation system is conducted on a life cycle cost analysis framework (PAPER III). To further increase the attractivity of the green alternatives, vehicle-to-vehicle charging technologies are discussed to better support the operation in the near future (PAPER IV) and a mixed-flow transport mode is presented to improve the utilization of transport resources (PAPER V). These papers address the issues faced by electrification from the planning phase to the assessment stage covering environmental aspects (energy efficiency, lifecycle emissions) and financial aspects (ownership costs, operational costs, maintenance costs).

CHAPTER 2 Charging technologies

Although there are reasons to be positive about the potential formation of an EB market, significant difficulties remain in the way of large-scale EB adoption. One possible key impediment to the widespread deployment of EBs is their short driving range. Although the advances in battery technology have theoretically increased the driving range similar to a full-tanked DB, yet, several factors such as temperature, humidity, and battery degradation impact real EB battery capacity(Pelletier et al., 2017), and capacity will be considerably decreased under particular harsh weather situations. As a result, EBs must be recharged on a regular basis to ensure the quality of operating service, and more EBs are required to accomplish a given number of trips than DBs.

Moreover, because an EB's driving range is constrained, a particular charging strategy is needed to maintain the BEB operational during the day. In order to offer dependable and effective charging behaviour, this section provides an overview of the current charging principles and chargers.

EBs exclusively employ off-board chargers. Because they are not constrained by restrictions on size and weight, these chargers may provide higher charging power levels. Regular charging is required for EBs' on-board battery. A BEB has a charging interface that can be linked to the necessary charging infrastructure in order to use grid power to charge the battery.

- Pantograph charging: a frequent method of charging EBs is to use a pantograph, which automatically connects the bus to the charging infrastructure. There are now two methods for making this contact. When charging is required, the pantograph can be put on top of the EB's roof and elevated, or it can be mounted on the charging infrastructure and moved downwards. The latter is preferable since it requires fewer pantographs and adds less weight to the BEB. Additionally, the pantograph is not subjected to bus vibrations.
- Plug-in charging: EBs can also be charged by plugging in a connection from the charging infrastructure. Currently, the connector must be manually plugged in, making this form of charging interface less appealing for big BEB fleets. But, in the near future, this procedure will be automated by robotization.
- Ground-based charging: Certain EBs are charged via a ground-based charging mechanism. This can be accomplished in two ways. A current collector, similar to pantograph charging, can be dropped from the bus to make contact with a conductive device embedded in the road surface. Another method is to use an electromagnetic field to transfer charging power wirelessly between a transmitter coil on the road surface and a receiving coil on the BEB. The primary benefit of wireless charging is that it allows EBs to charge while in motion.

Depot charging, opportunity charging, and dynamic wireless charging are the three most promising charging approaches as shown in Figure 2.1. Depending on the features and specifications of the bus network in cities, each of them fills a distinct demand and has pros and cons.

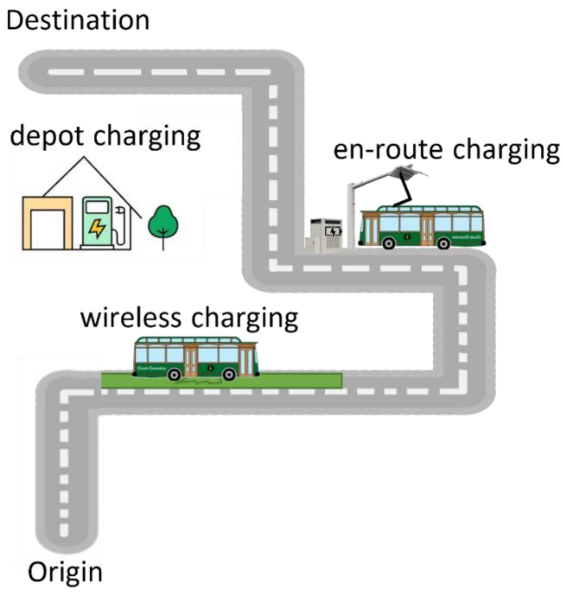


Figure 2.1: Illustration of different charging technologies

2.1 Depot charging

The name of depot charging is self-explanatory. Operators of electric buses charge their fleets overnight at the hub or depot where they park. This strategy implies that the vehicle does only one shift per day and stays idle all night (or for a longer period at the depot), and that the battery is large enough to sustain the daily needed range when completely charged.

Depot charging is typically plug-in charging with wall cabinets or mobile chargers with an output of 30-50 kW. The full charge process for depot charging takes around 4 hours. It is rare (or there is no real need) to go for a higher capacity (>100 kW) or via induction charging at a depot. That is why overnight charging is often referred as 'slow charging'. However, if necessary, fast chargers can also be adapted for overnight charging, sharing the same infrastructures as station charging technology.

Centralized and decentralized depot charging scheduling research raised recently for small, medium, or large-scale EBs considering different constraints, such as battery aging cost, grid distribution, and battery electro-thermal(Schoch et al., 2018). A centralized charging process is managed by a central controller, while decentralized charging process is operated by individual providers considering personal charging profiles. Figure 2.2 illustrates a centralized charging system, where the AC/DC module converts input alternating current power into adjustable output direct current power, DC/DC module converts a source of direct current from a high voltage level to a low level which is suitable for an electric bus. These two modules are monitored by the center controller maintaining the conversion infrastructure and communicating with the electric buses to perform the charging plan according to a standardized communication protocol.

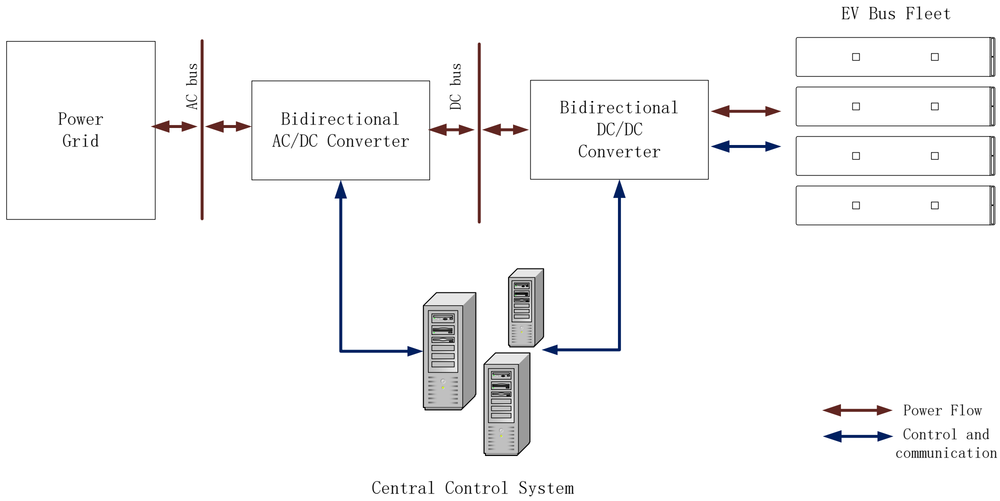


Figure 2.2 Centralized Depot Charging System (from Zeng et al., 2020)

Overnight charging is also perceived as the most cost-effective option for medium and heavy-duty vehicles which requires the least amount of infrastructure, as no other equipment is needed except the depot charger. With the long idle duration, buses can use less expensive, slower chargers, allowing fleet managers to cut their initial capital commitment. Furthermore, with overnight charging, electric fleets can benefit from cheaper electricity at night. But a large battery capacity is highly concerned, since electric buses need to serve a scheduled route during the daytime without being recharged. However, in some daily operational cases, it is difficult to complete the entire trip without charging. In order to increase the battery capacity, turning bigger and heavier is inevitable, which accordingly increases the overall consumption and reduces the maximum payload of the bus. Although the cost of infrastructure is the least, a large expenditure is required for large capacity batteries.

In terms of operational optimization, the depot charging strategy has little impact on the current electric bus schedule, and the dominant role will continue to be battery size. Because buses should arrive at the depot after completing their entire trip, there will be no delays in the scheduling process due to charging. Regarding the charging events, there are directions for operators to improve, for example, by proposing ways to manage night-time charging of the electric bus fleet and determining the best charging strategy to minimize battery aging, charging costs, or maintenance costs (Houbbadi et al., 2019).

From the grid aspect, this strategy avoids peak hour charging, where the subscribed power and the maximum charging power delivered by the charger are rather stable. Some optimization algorithms (Houbbadi et al., 2019) can therefore attribute an optimal charging power for each bus and each time slot.

2.2 Opportunity charging

Opportunity charging refers to bus charging at a certain station within its operational time. Opportunity charging can give EBs with charging chances while on the road, partially substitute centralized charging, and help reduce deadhead miles and fleet size buffer caused by empty driving. It covers two main charging strategies: terminal charging and en-route charging.

Terminal charging

Terminal charging is a charging method with chargers placed in bus terminals. Buses use mainly the regular turn-over time to replenish the energy. It usually implements conductive charging, which typically fully charges EBs in minutes. Conductive charging for terminals entails installing pantographs off-board and connecting the vehicle to a particular energy source. Off-board chargers, such as pantographs located on poles, promise cheaper infrastructure costs because a single charger may charge numerous buses, lowering vehicle weight. Conductive chargers capable of transmitting up to 600 kW are now on the market (ABB EV Charging Infrastructure 2015).

Terminal charging, as opposed to depot charging, is typically done during the daytime and is used to charge one bus several times throughout a day. There are no common charging units for different lines because it is located at the end of the line. As a result, the utilization rate is directly proportional to the battery capacity, battery management strategy, departure interval, and route length. Furthermore, the charging plan based on terminal charging is a strong linkage between the electric bus scheduling and the charging infrastructure planning. The battery capacity of the bus should be sufficient to allow several missed charges, to avoid the bus running out of energy due to external factors such as congestion, emergency or dense charging request. Although vehicle purchase costs can be lowered since the required battery capacity is significantly lower than depot charging, the high cost of fast chargers will increase station infrastructure expenditures.

When utilizing terminal charging, transit authorities must optimize both the battery capacity and the recharging procedure for EBs to ensure the economy and effectiveness of deployed EBs and charging facilities. The combination of battery capacity and charging approach should first ensure that EBs function normally. As a result, total capital and operational expenditures should be kept to a minimum. A big on-board battery, as previously discussed, can greatly raise the cost of EBs. EBs can carry a modest battery thanks to fast charging technology, which can regularly recharge EBs during their customary terminal layovers. But terminal fast charging stations incur significant capital expenses. For instance, a 500-kW on-route overhead rapid charging station costs round $500,000 to install. Also, en-route fast charging may result in high electricity power demand charges as well as increased energy expenditures due to charging.

As for the charge scheduling, one of the main aspects that need to be considered in this strategy is the impact that charging events may have on the bus schedule. Such as, the charging time should not exceed the next trip's departure time to avoid trip delay. For terminal charge scheduling, some solving algorithms such as genetic algorithm(Lee et al., 2013), dynamic programming (Lan et al., 2013), exponential smoothing model (Aabrandt et al., 2012) have been widely implemented.

En-route charging

En-route charging strategy provides EBs with prompt energy replenishment at several intermediate stations during passengers' boarding and alighting times. En-route charging incorporates fast charging activities within service trips. This is in contrast to the traditional charging time, which is at night (depot charging), end of the service trip (terminal charging). By increasing reliance on external charging infrastructure, en-route charging lessens the requirement for a big on-board battery. In general, increasing battery capacity increases EB weights greatly, resulting in higher energy consumption. Weiss et al. (2020) discovered that a 10 kWh battery upgrade will acquire a 15 kg mass of EB, resulting in an additional energy consumption of 0.7-1.0 kWh/100 km. Besides, this charging method efficiently reduces the required driving range from the daily driving distance to the distances between two planned charging operations. The next recharging opportunity is determined by the extent and availability of charging infrastructure, the type of equipment required on the vehicle, and the pattern of vehicle usage (in time and within the transport network).

Two main problems in this system are the deployment of chargers and the charge scheduling for electric buses. Both operations are complicated due to numerous influential aspects, for example, route characteristics, vehicles used, available places, and grid accessibility.

For charging infrastructure deployment, the major question is how to plan the location and type of charging facilities along the routes to meet the ever-growing electric bus demand in a systematic way, and how to couple the traffic and power gird networks. A pantograph fast charger installed at a bus stop also has substantially higher applicable purchasing, installation, and maintenance costs than a standard plug-in charger installed at a depot or charging station. As a result, it's critical to accomplish the best possible deployment of fast chargers at a chosen few bus stops, rather than all of them, in order to meet the demand for charging while minimizing capital expenditure or preserving financial viability.

When design charging plan, the charging cost, charging facility availability, energy density, power density, and battery lifetime should be considered [21]. En-route fast chargers usually have a higher charging power which will bring tremendous pressure on the grid, and it may be overloaded, especially for the peak-hour period when the EB charging demand is high. For example, ABB EV Charging Infrastructure (2015), which is a pioneering technology manufacturer in the industry, provided 20 single-deck EBs and four 450 kW faster chargers. A 450 kW rapid charger will provide a load that is similar to the load produced by 410 1.5 horsepower air conditioners working simultaneously. The bus transit operators shall make sure the total charging power cannot exceed the maximum charger power in order to lessen the burden of EB charging on the grid and maintain a stable environment of the power transmission system.

Additionally, the inevitably occurring battery aging also has an impact on how efficiently electric buses operate. For instance, reduced capacity results in decreased bus mileage and necessitates battery replacement when the capacity reaches the battery's end of life. Electric bus batteries typically deteriorate over time in two ways. One is the cyclic capacity loss, which is based on the quantity of charge-discharge cycles for batteries and is primarily brought on by the expansion of the internal solid electrolyte interphase layer. The other is the calendar capacity loss, which is related to self-discharge and side reactions of the battery during the energy storage process. Uncontrolled charging and discharging can have a substantial influence on battery aging, necessitate more frequent battery replacements, and raise expenditures without proper planning.

State of charge (SOC) is a measurement of the level of charge of the battery. A fully loaded battery has a SOC of 100 percent, while a fully discharged battery has 0 percent. To generate an efficient charging plan, the difference between the allowed maximal and the minimal SOC should be kept at a certain optimal level as shown in Figure 2.3.

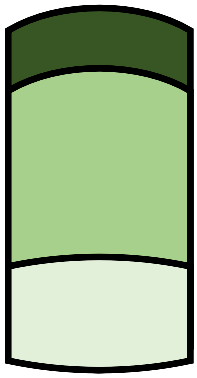


Figure 2.3: Battery State of Charge (SOC) (from Zeng et al., 2020)

In the en-route charging strategy, EB will be charged according to the current SOC. A frequent charging plan allows smaller batteries while higher power is needed along the route

To sum up, the main benefit of en-route charging is the possibility of partially charging the bus without any interruption during the daily operation. An optimal charging plan will maintain the battery in a certain SOC without letting the batteries deplete completely. Therefore, with this charging strategy, electric bus operation resembles the current DB operation, and some existing operational strategies can be easily adapted to manage the electric bus fleet. In general, the disadvantages of en-route charging include reliance on charging infrastructure availability and changes to electrical infrastructure to accommodate rapid charging, quicker battery deterioration, and worse overall energy efficiency.

2.3 Wireless charging

Wireless charging is a charging method using wireless power transfer technology. The first development of wireless charging can be traced back to the year 1905 when Nicola Tesla presented near-field coupling of two loop resonators based on magnetic resonance (Tesla, 1905). Wireless electric energy transmission is possible between two coil plates that are implanted in the pavement and loaded on the bottom of the vehicle, respectively and can provide powers of up to 300 kW with a charging efficiency of more than 80%. In general, wireless charging can be categorized as either static or dynamic. Operators may use stationary wireless charging equipment at a bus stop, parking lot, or garage. With dynamic charging, a variety of sets of embedded coils and accessories allow the vehicle to be charged while it is moving.

Regarding the environmental aspects, comparatively to plug-in charging, the usage-phase power consumption may be lowered, and there may be a reduction in energy use and emissions during battery manufacture. However, extensive wireless charging infrastructure may result in increased environmental issues.

As for the investment, the cost of wireless charging infrastructure is much higher than conductive chargers. A reasonable cost for an inductive charger with a capacity to transfer up to 200 kW can be estimated at 3 million SEK, including an onboard pick-up system and power electronics. The corresponding cost for a 300-kW conductive charger, according to the same reference, is estimated to be 1.5 million SEK. Besides, inductive wireless charging systems require ferrite cores for magnetic flux guidance and shielding, which are bulky and costly. Also, to control the minimum loss in the ferrites, the charging system is kept under 100 kHz. In this situation, larger coils are needed, and lower power transfer densities occur. The high cost and low power transfer density are particularly problematic for implementing dynamic wireless charging, especially for dynamic charging, as the charger should be equipped with a high-power capability to deliver enough energy to the electric bus during its very brief time passing over a charging coil. Therefore, this charging strategy has not yet been commercially implemented. For future development, it is sense to examine the tradeoffs and provide guidance for the future design of wireless charging bus systems.

2.4 Summary

There are mainly two concepts for the charging of batteries, standard and fast charging. Standard charging (typically 40 to 120 kW) is adapted mainly in the bus depot overnight and during longer brakes with moderate charging power. This causes a high battery capacity and a high weight of the bus system. Fast charging at bus stops (up to 600 kW), at terminals (usually between 150 to 500 kW) or beneath the road (up to 300 kW) can reduce the battery capacity and more importantly reduce the weight significantly.

To compare these charging methods from an economic standpoint, Chen et al. (2018) examined the cost-competitiveness of stationary charging (at depots) and dynamic charging in the EB operation (wireless charging). They stated that dynamic charging was anticipated to result in greater operational and maintenance expenses. Based on a life-cycle cost analysis framework, Bi et al. (2017) concluded that a wireless charger deployment can reduce the size of the battery and the cost of the battery and use-phase energy for an all-electric bus system. In contrast, the infrastructure for wireless charging adds additional expenses for the purchase and installation of chargers. The price of the battery unit, the effectiveness of wireless charging, and the purchase, installation, and maintenance costs of wireless chargers all have a significant role in the life-cycle cost differences between plug-in charging and wireless charging. Additionally, Lajunen and Lipman (2016) showed that opportunity charging was more economical than overnight charging for EB operation.

To sum up, wireless charging requires the costliest infrastructure and has the lowest power transfer density while it enjoys the least requirement of battery capacity and the highest guarantee of battery health. However, recently wireless charging is yet to become commercially viable, although a few experimental systems have been demonstrated.

Similar to wireless charging, en-route charging also lowers the EB purchase cost, preserves operational capability (i.e., driving range and payload capacity), and does not disrupt the existing operation schedules and is widely commercialized. Therefore, the focus of our thesis is on the deployment of en-route charging in public transportation systems, the development of charging plans, and the synergy with other transit resources.

CHAPTER 3 En-route Charge scheduling

3.1 On the role of battery degradation in charge scheduling

3.1.1 Motivation

Although in previous work, the charge scheduling models have meaningful results and important contributions, they all have a key weakness, the neglect of battery aging. This ignorance leaves completely unaccounted for the huge operational cost of battery replacement, which can be of the same order of magnitude as, or even many times, the cost of charging (Pelletier et al., 2018). But among other EB operation optimization issues, the consideration of battery aging is showing an increasingly important trend (Du et al., 2018; Zhang et al., 2021; Zhang et al., 2020b).

Paper I aims to model and analyze charging schedules of EBs that have access to chargers at bus stops and terminals in a route interlining context. For operational decision support, the schedule is supposed to determine when to charge, where to charge, and how long to charge. With this goal in mind, a mixed-integer linear programming method is proposed to optimize EB charging schedules with minimized energy cost and battery wear costs. The model explicitly accounts for the TOU rate, peak-to-average ratio, and battery degradation.

3.1.2 Problem description

The aim of this section is to introduce what we refer to as the electric bus charge scheduling problem (EB-CSP). The description of the parameters and variables discussed in this section can refer to Appendix A.

The EB-CSP is designed to solve the charge scheduling problem for a bus fleet which is defined in the set $N = \{1, \ldots, n, \ldots, |N|\}$ consisting of $|N|$ EBs, in which bus n is equipped with a Q_n kWh battery. According to the bus schedule, bus n is required to visit a total of L_n charging stations, where m_{nl} denotes the station ID of the l-th stop of bus n's schedule, $l = 1, \ldots, L_n$. The arrival time at the l-th stop of bus n, denoted by a_{nl}, and the departure time, denoted by b_{nl}, are predefined parameters. The time resolution in the proposed model is 1 minute. Set $T_{nl} = \{a_{nl}, a_{nl} + 1, \ldots, b_{nl} - 1\}$ is introduced to enumerate the available charging time during the bus dwell time. We assume that the bus will not charge at the first station, thus $a_{n1} = b_{n1}$.

Usually, bus stop m is equipped with one charging pile with a charging power of P_m kW, $k_m = 1$. For terminal stations, $k_m > 1$. When all the charging piles are occupied, the newly arrived bus cannot be connected to the grid. The specific charging start time will be determined by the charging end time of the buses occupying the charging piles.

As the scheduling strategy is designed for en-route fast charging, we assume that the battery is charged at constant current under a linear charging process where SOC rises linearly with time. The maximum energy that a bus can obtain in this phase is denoted as E_n^{max}. For the convenience of modeling, it is assumed that the initial energy and the maximum allowed energy for batteries are both E_n^{max}, for example, 90% of Q_n.

We define a charge event as connecting a charger to a bus and disconnecting it later. The next section seeks to generate the optimal en-route charging schedules in an EB network with minimized charging and battery wear costs while guaranteeing the PAPR of the grid within an acceptable range.

3.1.3 Method

The following mixed-integer linear programming formulation then represents the EB-CSP.

$$\text{minimize } \sum_{t\in T}\sum_{i\in I} f_{it}\cdot\Phi_{it}+\sum_{n\in N}\sum_{l\in R_n}\Delta q_n\cdot v_l^n \tag{1.1}$$

The objective function minimizes the daily charging costs of the bus fleet and the wear cost. The first term corresponds to the charging costs, where we aggregate the energy recharged in the battery at time i from group i by introducing variable Φ_{it}. Parameter f_{it} denotes the energy price of group i at time t. The second term in the objective function corresponds to the battery wear costs of the bus running on a predetermined schedule. The variable v_l^n decides the accumulated unit wear cost from the departure of $(l-1)$-th station to the departure of l-th stations. The unit wear cost is closely related to the SOC value and will be explained later. Parameter Δq_n indicates the quantity of energy transferred in the unit interval of SOC (e.g., ΔSOC).

$$soc_1^n=\frac{E_n^{max}}{Q_n}\quad n\in N \tag{1.2}$$

Constraint (1.2) defines the initial battery SOC as E_n^{max}/Q_n when the bus starts to serve the first station. It is assumed that only the linear charging behavior of the CC stage is considered, so the maximum energy E_n^{max} of this stage is introduced.

$$e_{lt}^n=\frac{\eta_{m_{nl}}P_{m_{nl}}}{60}x_{lt}^n\qquad n\in N,l\in R_n,t\in T_{nl} \tag{1.3}$$

$$Q_n\cdot\overline{soc}_l^n=Q_n\cdot soc_l^n+\sum_{t\in T_{nl}}e_{lt}^n\qquad n\in N,l\in R_n \tag{1.4}$$

$$Q_n\cdot soc_{l+1}^n=Q_n\cdot\overline{soc}_l^n-F_{nl}\qquad n\in N,l\in\{1,\dots,L_n-1\} \tag{1.5}$$

Constraint (1.3) depicts the energy retrieved from the station m_{nl} in unit time (e.g., from t to $t+1$). Note that the energy recharged in the battery is linear with respect to charging time during the constant current charging process. When the bus is connected to the charging pile, the decision variable x_{lt}^{n} is set to 1; otherwise, it is 0. Assume that the chargers installed in the same station are homogenous. Parameter $P_{m_{nl}}$ indicated the charging power of chargers at the station m_{nl}, $\eta_{m_{nl}}$ represents the charging efficiency of chargers at the station m_{nl}.

Constraint (1.4) recurs the battery energy change from bus arrival to the next departure at l-th station. $\sum_{t\in T_{nl}} e_{lt}^{n}$ specifies the battery energy increase when it is charged at lth station of bus n's schedule.

Constraint (1.5) describes the energy change from bus departure to the next arrival of bus n. We assume that the SOC only changes when the bus arrives at the next station instead of changing while driving. Therefore, the real-time energy consumption between stations is accumulated until reaching the next stop. The accumulative energy consumption F_{nl} between the l-th and $(l+1)$-th stations is calculated as $F_{nl} = \rho \cdot \theta_{nl} \cdot D_{nl}$. Parameter θ_{nl} indicates the efficiency coefficient, which is inversely proportional to the road condition. Parameter ρ represents the primary energy consumption rate.

$$\overline{soc}_{L_n}^{n} = \frac{E_n^{max}}{Q_n} \quad n \in N \tag{1.6}$$

The boundary condition of battery SOC before beginning the next day's schedule is defined in Constraint (1.6). It shows that when bus n arrives at the last station L_n, a charge event is required to ensure that the energy level reaches E_n^{max}.

$$Q_n \cdot soc_l^n \geq E_n^{min} \quad n \in N, l \in R_n \tag{1.7}$$

$$Q_n \cdot \overline{soc}_l^n \leq E_n^{max} \quad n \in N, l \in R_n \tag{1.8}$$

Constraints (1.7) and (1.8) appropriately defined the upper and lower bound of battery SOC. They ensure that the energy would not exceed the maximum level after charging and is above the minimum value before charging. The parameter E_n^{min} represents the minimum remaining energy allowed when not charging bus n. This parameter determines the battery depth of discharge, which in turn determines the cycle life of the battery.

$$\sum_{n\in N}\sum_{l=1,m_{nl}=m,t\in T_{nl}}^{L_n} x_{lt}^{n} \leq k_m \quad m \in M,\ t \in T \tag{1.9}$$

$$z_{lt}^{n} \geq x_{lt}^{n} - x_{l,t-1}^{n} \quad n \in N, l \in R_n, t \in \{a_{nl}+1, \dots, b_{nl}-1\} \tag{1.10}$$

$$z_{la_{nl}}^{n} = x_{la_{nl}}^{n} \quad n \in N, l \in R_n \tag{1.11}$$

$$\sum_{t\in T_{nl}} z_{lt}^{n} \leq 1 \quad n \in N, l \in R_n \tag{1.12}$$

$$x_{lt}^{n} = \{0,1\} \quad n \in N, l \in R_n, t \in T_{nl} \tag{1.13}$$

$$z_{lt}^{n} = \{0,1\} \quad n \in N, l \in R_n, t \in T_{nl} \tag{1.14}$$

Constraint (1.9) restricts that the sum of charging events carried out at the same time in the charging station m should be less than the number of chargers installed in the charging station. Constraint (1.10) and Constraint (1.11) denote the start time of the charging event. If the bus is being charged at the current time point and has not been charged at the previous time point, the present time is considered the charging start time. Constraint (1.12) defines that at most, one charging event takes place between each arrival and departure to avoid the infeasible solution caused by constantly moving buses from one charger to another. Constraint (1.13) determines whether bus n is being charged at station m on trip l at time point t. Constraint (1.14) indicates whether bus n starts charging at station m on trip l at time point t.

$$\Phi_{i,t} \leq \frac{1}{|I||T|} \cdot \Psi \cdot \Gamma_{max} \quad i \in I, t \in T \tag{1.15}$$

$$\Phi_{it} = \sum_{n\in N}\sum_{l=1,m_{nl}\in G_i,t\in T_{nl}}^{L_n} e_{lt}^{n} \quad i \in I, t \in T \tag{1.16}$$

Since $\Phi_{i,t} \leq max_{\{i\in I,t\in T\}}\Phi_{i,t}$, Constraint (1.15) introduces the maximum allowed peak-to-average ratio to restrict the load balance. Parameter Ψ indicates the total energy charged by the entire bus fleet. Variable $\Phi_{i,t}$ specifies the total charged energy of group i at the time t, which is calculated in Constraint (1.16).

To incorporate the unit wear cost in our model the decision variable v_l^n is then introduced to depict the cumulative unit wear cost between the departure of $(l-$

1)-th station and the departure of l-th station. Referring to (Han et al., 2014), $w_n(SOC)$ can be defined. The accumulated unit wear cost can be formulated as follows:

$$v_l^n = \sum_{SOC=soc_l^n}^{\overline{soc}_{l-1}^n-\Delta SOC} w_n(SOC) + \sum_{SOC=soc_l^n+\Delta\mathrm{soc}}^{\overline{soc}_l^n} w_n(SOC) \quad l \in R_n/\{l\}, \quad n \in N \tag{1.17}$$

$$v_1^n = w_n\left(\frac{E_n^{max}}{Q_n}\right) \quad n \in N \tag{1.18}$$

The first term in Constraint (1.17) corresponds to the discharge-related wear cost between two stations. Since we assume that the discharge process is a linear function of time, the corresponding SOC-related unit wear costs are sequentially accumulated until the next stop is reached. It adds up each SOC-related unit wear cost $w_n(SOC)$ in the interval $[soc_l^n, \overline{soc}_{l-1}^n - \Delta SOC]$ with unit interval as ΔSOC. The upper limit is set to $\overline{soc}_{l-1}^n - \Delta SOC$ instead of $\overline{soc}_{l-1}^n$ is because $w_n(\overline{soc}_{l-1}^n)$ is considered in the second term. In this work, the unit wear cost before departing from the first station is defined as $v_1^n = w_n\left(\frac{E_n^{max}}{Q_n}\right)$.

3.1.4 Case study

In this section, a numerical study is presented based on the e-bus network planned by Västtrafik as shown in Figure 3.1. The detailed input can refer to Appendix A.

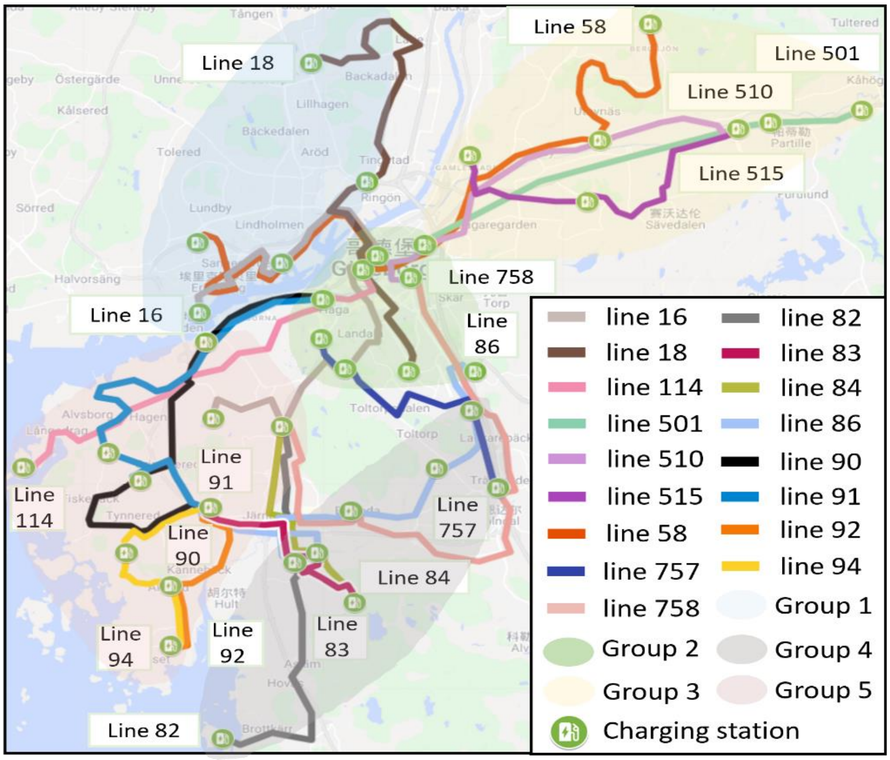


Figure 3.1: The electrified bus network in Västra Götaland (from Zeng et al., 2022a)

The minimum total amortized daily operational cost for the bus network is 8575.44 USD, which consists of 1092.05 USD energy cost and 7483.39 USD battery wear cost. The battery aging cost accounts for 87.26% of the total cost and is 6.85 times the cost of charging, and that's when we consider the small battery with a low battery price. Obviously, when larger capacity batteries are considered, the unit cost of battery wear increases and its share of the total cost increases further. The PAPR is 1.736, approximately 92.3% of the maximum limit value. Figure 3.2 shows the battery SOC profile of the 154 buses under the optimal charge schedule. In general, only 12 out of 154 vehicles reached the minimum energy threshold of 30% of battery capacity, while 67 buses maintained their DOD above 0.4.

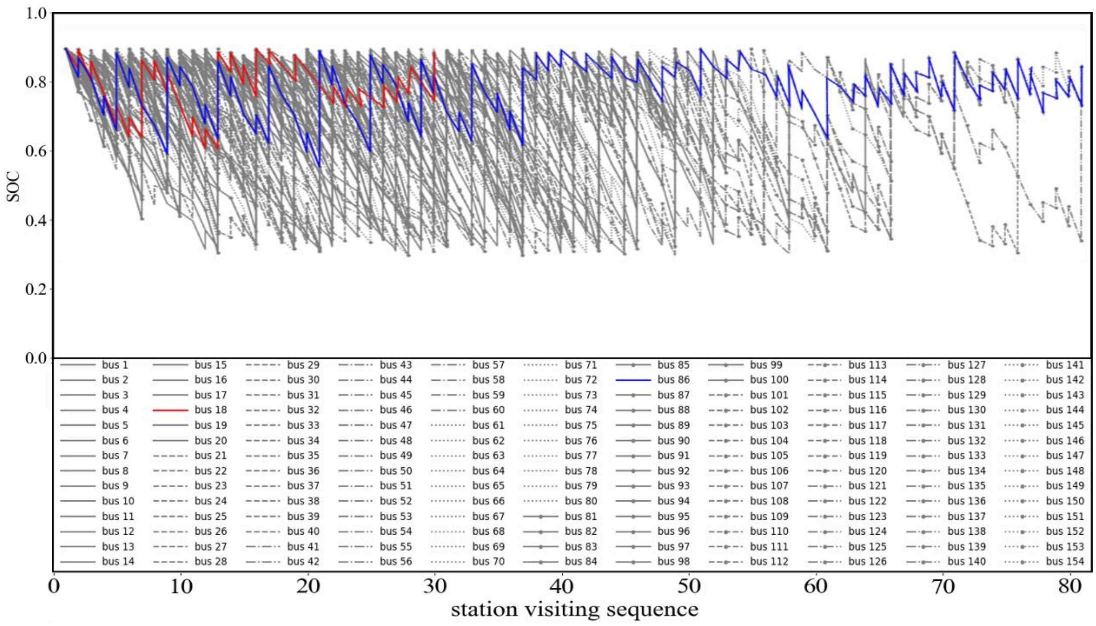


Figure 3.2 Battery SOC profile in the optimal charging schedule (from Zeng et al., 2022a)

The charging start time for each bus is shown in Figure 3.3, where the horizontal axis is the time index in hours, and the vertical axis is the sequence of stations visited by the buses. The upper square bar graph depicts the temporal distribution of charging demand requests over the whole network. Between 7:00 and 8:00 a.m., the demand is higher since there is generally a high frequency of bus service during the morning rush, resulting in a higher need for charging. Besides, it is also an excellent opportunity to avoid paying peak electricity rates. In general, the number of demands in each time slot does not change much, indicating that the charging demand is evenly dispersed throughout the day. The bar chart on the right depicts the station sequence distribution of the charging stations where the vehicles are charged.

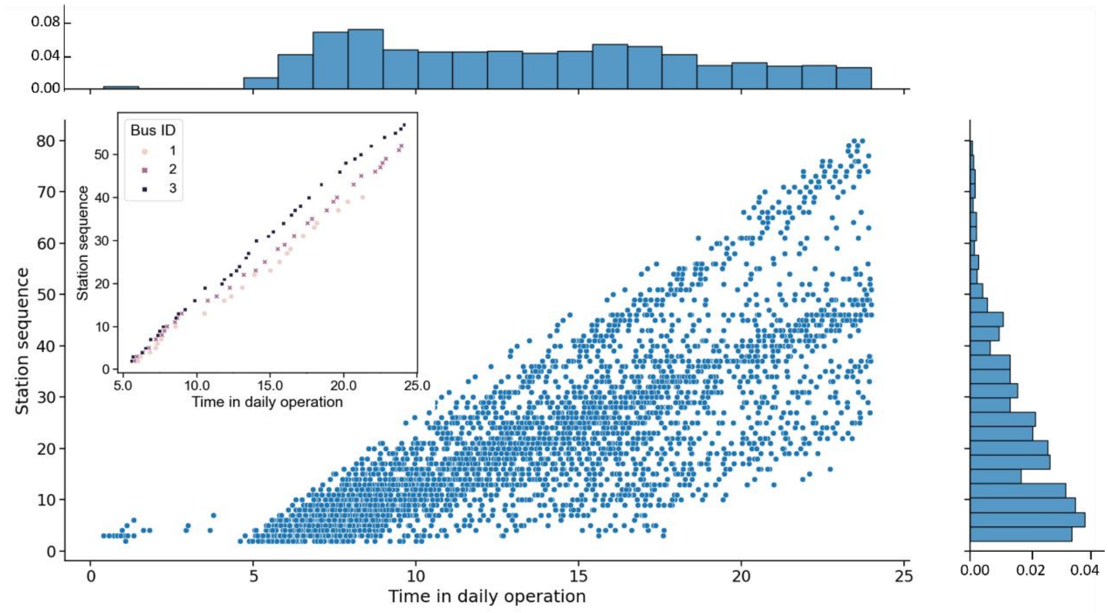


Figure 3.3: Bus charging start time (from Zeng et al., 2022a)

Without introducing PAPR in the model, the total cost is then reduced to 802.87 USD, with a charging cost of 1366.75 USD and a battery wear cost of 6661.94 USD. The actual PARP increased from 1.736 to 2.035, which may result in lower stability of the power system. The frequency of charging in the plan increases, thus reducing the wear cost of the battery. Without considering battery wear in the objective function, the wear cost increases by 4.2%. However, when the upper and lower boundaries of SOC are further relaxed, the battery wear cost increases by 25.6%, which is ten times the charging expenses even with a 10.89% drop in charging costs.

The numerical studies indicate that battery wear costs are a significant component of EB operation and maintenance expenses, which are at least six times the cost of charging under the optimal schedule. In the example study, small-capacity batteries with low overall cost were employed, and the unit wear cost would be significantly greater if a larger-capacity fleet was examined. Furthermore, we discovered that an acceptable upper and lower boundary setting for the battery SOC greatly reduced the expense of battery wear. This might be useful in EB-CSP modeling, where the design of boundaries is required for charge scheduling.

From a grid perspective, not only does it greatly reduce charging peaks, spreading charging demand, but it also attempts to balance charging demand from various groups at different times as much as feasible. Because we do not enable overnight charging at terminals, the degree of peak shaving is also limited. Furthermore, the introduction of TOU prices more directly limits fleets from having reduced charging demands during peak hours, therefore balancing charging demand in the time dimension. More findings and discussion are available in Appendix A.

3.2 Robust optimization of en-route charge scheduling

3.2.1 Motivation

In the previous section, we discussed the charge scheduling problem on the premise that the energy consumption is known and proportional to the distance traveled, resulting in a deterministic bus charging scheduling problem. In this section, we still focused on wired charging technologies, intending to consider energy consumption uncertainty and prevent charging conflicts at the network scale. The robust plan helps policymakers make informed decisions when developing policies and incentives aimed at promoting sustainable transportation solutions and improving operational efficiency.

3.2.2 Deterministic model

Based on the model proposed in Section 3.1.3, we explicitly describe the relationship between lines and stations in the bus route, allowing the possibility of articulating timetabled trips with more complex situations, while providing a detailed description of the energy consumption. In this model, the EB network can be abstracted with only en-route charging stations, represented by the set M. Each station is covered by one or more bus lines. The all-day service of one bus line is divided into multiple timetabled trips $R_n = \{l_0, \dots, l, l+1, \dots l_{end}\}$. The stations passed by each trip l are enumerated in Set $M_l = \{m_0, \dots, m, m + 1, \dots m_{end}\}$ in the order of arrival. The assumptions are the same as in Section 3.1.2. The introduction of sets, parameters, and variables used in the deterministic model can be found in Appendix B.

The deterministic model designs a charging schedule based on TOU electricity price to find the best time and place to charge the EB fleet. The following MILP formulation then represents the EB charge scheduling problem.

$$\text{minimize} \sum_{n \in N} \sum_{l \in R_n} \sum_{m \in M_{n,l}} \sum_{t \in T_{n,l,m}} c_{m,t}^{n,l} \cdot x_{m,t}^{n,l} \tag{2.1}$$

The objective function (2.1) minimizes the charging cost of the bus fleet. We aggregate the energy recharged in the battery at time $t \in T$ from station $m \in M$ by using the decision variable· $x_{m,t}^{n,l}$. Parameter $c_{m,t}^{n,l}$ denotes the TOU energy price for each station.

$$E_{m_0, b_{n,l_0,m_0}}^{n,l_0} = E_n^{max} \quad \forall n \in N \tag{2.2}$$

Constraint (2.2) defines the initial battery energy as E_n^{max} when the bus $n \in N$ started to serve the first station m_0 of the first timetable trip l_0. Parameter b_{l_0,m_0} denotes the departure time at the station m_0 on trip l_0.

$$e_{m,t}^{n,l} = \frac{\eta_m^{n,l} P_m^{n,l}}{60} x_{m,t}^{n,l}, \forall t \in T_{n,l,m}, \forall m \in M_{n,l}, \forall l \in R_n, \forall n \in N \tag{2.3}$$

Constraint (2.3) depicts the energy charged from station m in unit time (e.g., from t to $t + 1$). When the bus is connected to the charging pile, the decision variable $x_{m,t}^{n,l}$ is set to 1; otherwise, it is 0. Parameter $P_m^{n,l}$ indicates the charging power of each charger at station m, $\eta_m^{n,l}$ represents the charging efficiency of chargers at station m.

$$E_{m,b_{n,l,m}}^{n,l} = E_n^{max} + \sum_{\Upsilon \in A^{n,l,m}} \left(\sum_{t \in T_{n,\Upsilon}} e_{\Upsilon,t}^{n} - F_{\Upsilon}^{n} \right) + \sum_{t \in T_{n,l,m}} e_{m,t}^{n,l}, \tag{2.4}$$

$$\forall m \in M_{n,l}/\{m_0\}, \forall l \in R_n, \forall n \in N$$

$$E^{n,l}_{m,a_{n,l,m}} = E^{max}_{n} + \sum_{\Upsilon \in A^{n,l,m}} \left(\sum_{t \in T_{n,\Upsilon}} e^{n}_{\Upsilon,t} - F^{n}_{\Upsilon} \right), \tag{2.5}$$

$m \in M_{n,l}/\{m_0\}, \forall l \in R_n, \forall n \in N$

$$F^{n,l}_{m} = \left[\frac{1}{\delta} \left(\frac{\rho}{2} \cdot \varrho \cdot \iota \cdot \left(v^{n,l}_{m} \right)^2 + \mu \cdot \left(W^n + w \cdot \phi^{n,l}_{m} \right) \cdot g \cdot cos\theta^{n,l}_{m} + \left(W^n + w \cdot \phi^{n,l}_{m} \right) \cdot g \cdot sin\theta^{n,l}_{m} + \left(W^n + w \cdot \phi^{n,l}_{m} \right) \cdot \frac{v^{n,l}_{m}}{\Delta t^{n,l}_{m}} \right) \right] \cdot v^{n,l}_{m} + \frac{\zeta \cdot D^{n,l}_{m}}{v^{n,l}_{m}}, \forall m \in M_{n,l}/\{m_{\text{end}}\}, \forall l \in R_n, \forall n \in N \tag{2.6}$$

The residual energy when the bus departs from m-th station is calculated in Constraint (2.4). The energy change is formulated cumulatively in Constraint (2.4). $\sum_{t \in T_{n,l,m}} e^{n,l}_{m,t}$ specifies the battery energy increase when it is charged at station m and F^{n}_{Υ} indicates the energy consumption between two sequential stations. Constraint (2.5) recurs the energy level change from its first departure to the arrival at m-th station along the l-th trip. The energy consumption $F^{n,l}_{m}$ between two stations is calculated in Constraint (2.6).

$$E^{n,l}_{m,b_{n,l,m}} \leq E^{max}_{n} \quad \forall m \in M_{n,l}, \forall l \in R_n, \forall n \in N \tag{2.7}$$

$$E^{n,l}_{m,a_{n,l,m}} \geq E^{min}_{n} \quad \forall m \in M_{n,l}, \forall l \in R_n, \forall n \in N \tag{2.8}$$

Constraints (2.7) and (2.8) defined the upper and lower bound of battery energy.

$$\sum_{n \in N} \sum_{l \in R_n} x^{n,l}_{m,t} \leq k_m \quad m \in M, t \in T \tag{2.9}$$

$$\sum_{m \in M} x^{n,l}_{m,t} \leq 1 \qquad n \in N, l \in R_n, t \in T_{n,l,m} \tag{2.10}$$

$$z^{n,l}_{m,t} \geq x^{n,l}_{m,t} - x^{n,l}_{m,t-1} \qquad m \in M_{n,l}, l \in R_n, n \in N, t \in T_{n,l,m}/\{a_{n,l,m}\} \tag{2.11}$$

$$z^{n,l}_{m,a_{n,l,m}} = x^{n,l}_{m,a_{n,l,m}} \qquad m \in M_{n,l}, l \in R_n, n \in N \tag{2.12}$$

$$\sum_{t\in T_{n,l,m}} z_{m,t}^{n,l} \leq 1 \qquad m \in M_{n,l}, l \in R_n, n \in N \tag{2.13}$$

$$x_{m,t}^{n,l} = \{0,1\} \qquad m \in M_{n,l}, l \in R_n, n \in N, t \in T_{n,l,m} \tag{2.14}$$

$$z_{m,t}^{n,l} = \{0,1\} \qquad m \in M_{n,l}, l \in R_n, n \in N, t \in T_{n,l,m} \tag{2.15}$$

Constraint (2.9) restricts that the sum of charging events carried out at the same time at m-th station should be less than the number of chargers k_m installed in the charging station. Constraint (2.10) forces each bus to use only one charger per time unit. Constraints (2.11-2.12) denote the start time of the charging event. If the bus is being charged at the current time point and it has not been charged at the previous one, the present time is defined as the charging start time. Constraint (2.13) defines that, at most, one charging event takes place between each arrival and departure. Constraint (2.14) determines whether bus n is being charged at m-th station on l-th trip at time point t. Constraint (2.15) indicates whether bus n starts charging m-th station on l-th trip at time point t.

3.2.3 Robust optimization model

The energy consumption parameter $F_m^{n,l}$ in the robust model is expected to be uncertain. This uncertainty parameter is constrained by lower and upper bounds in interval sets. To restrict the total number of uncertain parameters, a budgeted uncertainty set is implemented. The introduction of symbols that are utilized in the robust reformulation can be found in Appendix B.

In this section, $\widehat{F_m^{n,l}} = \alpha\, \overline{F_m^{n,l}}$ is introduced to represent the energy consumption deviation, where $\overline{F_m^{n,l}}$ denotes the nominal values and $0 \leq \alpha \leq 1$. We further introduce the positive deviation $\xi_{n,\Upsilon}^{+}$ and the negative deviation $\xi_{n,\Upsilon}^{-}$ to rearrange Constraints (2.4-2.5).

$$\sum_{\Upsilon\in A^{n,l,m}} \left(\sum_{t\in T_{n,\Upsilon}} e_{\Upsilon,t}^{n} - \overline{F_\Upsilon^n} - \left(\xi_{n,\Upsilon}^{+} - \xi_{n,\Upsilon}^{-}\right) \cdot \widehat{F_\Upsilon^n}\right) + \sum_{t\in T_{n,l,m}} e_{m,t}^{n,l} \leq 0 \tag{2.16}$$

$$\forall m \in M_{n,l}/\{m_0\}, \forall l \in R_n, \forall n \in N$$

$$\sum_{\Upsilon \in A^{n,l,m}} \left(\sum_{t \in T_{n,\Upsilon}} e^{n}_{\Upsilon,t} - \overline{F^{n}_{\Upsilon}} - \left(\xi^{+}_{n,\Upsilon} - \xi^{-}_{n,\Upsilon} \right) \cdot \widehat{F^{n}_{\Upsilon}} \right) \geq E^{\min}_{n} - E^{\max}_{n}$$
$$\forall m \in M_{n,l}/\{m_0\}, \forall l \in R_n, \forall n \in N \quad (2.17)$$

However, Constraints (2.16-2.17) contain an unlimited number of constraints and the finite number of variables due to uncertainty parameters $\xi^{+}_{n,\Upsilon}$ and $\xi^{-}_{n,\Upsilon}$, making them unsolvable.

For Constraint (2.16), we have the robust counterpart deviation:

$$\left(\sum_{\Upsilon \in A^{n,l,m}} \left(\sum_{t \in T_{\Upsilon}} e^{n}_{\Upsilon,t} - \overline{F^{n}_{\Upsilon}} \right) + \sum_{t \in T_{n,l,m}} e^{n,l}_{m,t} \right) + \left(\Gamma_{n,l,m} \cdot U_{n,l,m} + \sum_{\Upsilon \in A^{n,l,m}} \left(V^{+}_{n,l,m,\Upsilon} + V^{-}_{n,l,m,\Upsilon} \right) \right) \leq 0 \;\; \forall m \in M_{n,l}/\{m_0\} \;\; \forall l \in R_n, \forall n \in N \quad (2.18)$$

$$U_{n,l,m} + V^{+}_{n,l,m,\Upsilon} \geq -\widehat{F^{n}_{\Upsilon}} \qquad \forall m \in M_l, \forall l \in R_n, \forall n \in N, \Upsilon \in A^{n,l,m} \quad (2.19)$$

$$U_{n,l,m} + V^{-}_{n,l,m,\Upsilon} \geq \widehat{F^{n}_{\Upsilon}} \qquad \forall m \in M_l, \forall l \in R_n, \forall n \in N, \Upsilon \in A^{n,l,m} \quad (2.20)$$

$$U_{n,l,m}, V^{+}_{n,l,m,\Upsilon}, V^{-}_{n,l,m,\Upsilon} \geq 0 \qquad \forall m \in M_l, \forall l \in R_n, \forall n \in N, \Upsilon \in A^{n,l,m} \quad (2.21)$$

Similarly, we can convert the Constraint (2.17) to its robust counterpart deviation:

$$\left(\Gamma_{n,l,m} \cdot \mathcal{U}_{n,l,m} + \sum_{\Upsilon \in A^{n,l,m}} \left(\mathcal{V}^{+}_{n,l,m,\Upsilon} + \mathcal{V}^{-}_{n,l,m,\Upsilon} \right) \right) + E^{\min}_{n} - E^{\max}_{n} - \sum_{\Upsilon \in A^{n,l,m}} \left(\sum_{t \in T_{\Upsilon}} e^{n}_{\Upsilon,t} - \overline{F^{n}_{\Upsilon}} \right) \leq 0 \; \forall m \in M_{n,l}/\{m_0\}, \forall l \in R_n, \forall n \in N \quad (2.22)$$

$$U_{n,l,m} + \mathcal{V}^{+}_{n,l,m,\Upsilon} \geq \widehat{F^{n,l}_{m}} \quad \forall m \in M_l, \forall l \in R_n, \forall n \in N, \Upsilon \in A^{n,l,m} \quad (2.23)$$

$$U_{n,l,m} + \mathcal{V}^{-}_{n,l,m,\Upsilon} \geq \widehat{-F^{n,l}_{m}} \quad \forall m \in M_l, \forall l \in R_n, \forall n \in N, \Upsilon \in A^{n,l,m} \quad (2.24)$$

$$\mathcal{U}_{n}, \mathcal{V}^{+}_{n,l,m,\Upsilon}, \mathcal{V}^{-}_{n,l,m,\Upsilon} \geq 0 \qquad m \in M_l, \forall l \in R_n, \forall n \in N, \Upsilon \in A^{n,l,m} \quad (2.25)$$

3.2.4 Results

Deterministic model results

The deterministic model consists of 175,924 binary variables and 336,150 single variables. The execution time is 24.5 seconds with no optimality gap. The optimal result shows that to maintain the daily operation of 154 EBs, the minimal charging cost is 3194.48 USD per day. The fleet receives a total of 26014.5 kWh of energy from the grid per day, with an average of 168.93 kWh per vehicle with a daily GHG emission of 30987.86 kg-CO2e. Figure 3.4 depicts the occupancy of each charging station. It indicates that terminal charging becomes the most dominant charging option. Although some intermediate stations are low in utilization, these charging opportunities ensure that the battery's SOC does not go below 30% to shorten the depth of discharge and further extend the battery's state of health.

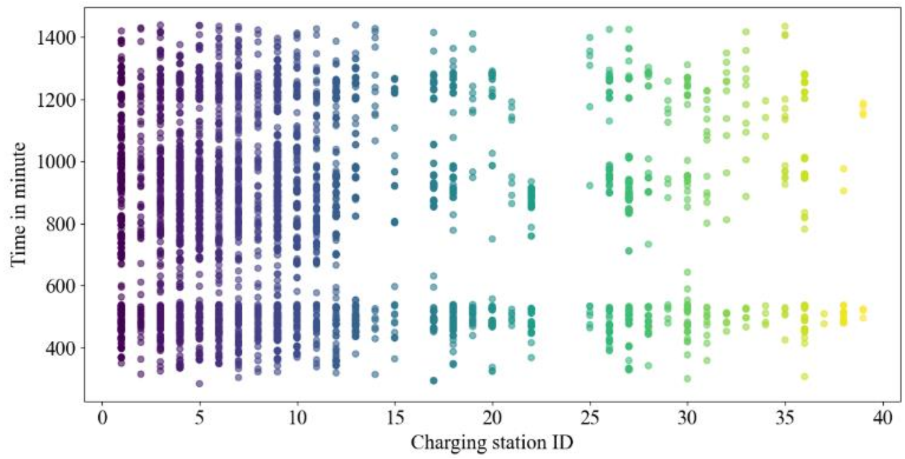


Figure 3.4: Charging station occupancy in time

Fig. 3.5 illustrates the distribution of bus charging demand and its Kernel density estimation. It can be observed that, of the 154 buses, 52 needed to be recharged above their battery capacity. Furthermore, 34 EBs do not require charging and are assured of returning to the depot with a battery level of more than 30%. This also explains why a few charging stations in Figure 3.4 have no occupants.

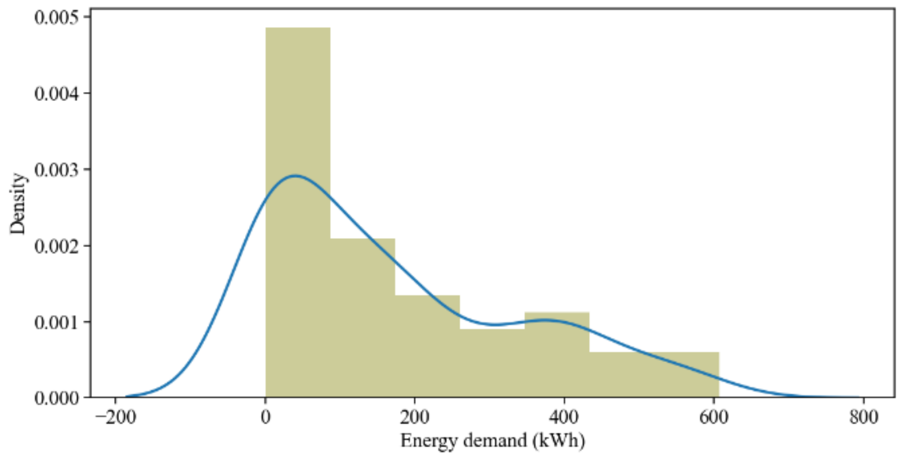


Figure 3.5: Daily charging demand distribution of the deterministic model

RO model results

The RO model consists of 175,924 binary variables and 792,886 single variables. The execution time is 42.54 seconds with no optimality gap. The optimal result shows that to maintain the daily operation of 154 EBs, the minimal charging cost is 3372.05 USD per day, with a 5.57% increase compared with the deterministic model. The fleet receives a total of 27141.75 kWh of energy from the grid per day, with an average of 176.25 kWh per vehicle. The estimated daily GHG emission is 32330.61 kg-CO2e. In terms of the average price per unit of energy spent on electricity, there is a 0.9% increase. Figure 3.6 illustrates the distribution of bus charging demand and its Kernel density estimation. Comparing with Figure 3.5, we find that the general trend is broadly consistent, with the number of vehicles with greater charging demand than battery capacity increasing by 1 unit and those with no charging demand decreasing by 2 units.

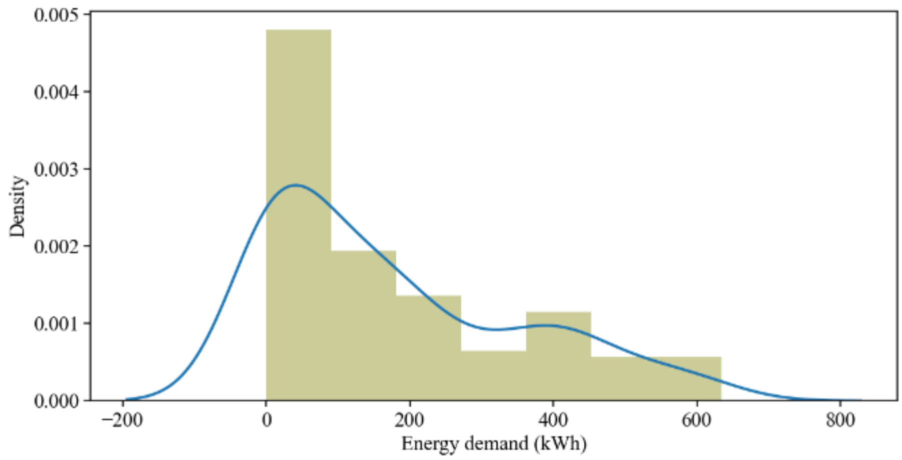


Figure 3.6: Daily charging demand distribution of RO model

To understand the behaviour of the EB system in response to different battery capacities, fleet compositions, and DODs, a sensitivity analysis is conducted. Based on the results, we conclude that, first, systems with larger batteries tend to request less en-route energy replenishment than systems with smaller ones. However, even if the battery capacity is large enough, it relies on opportunity charging to keep the energy level above the minimum allowable value. Second, a mixed fleet, i.e., assigning different battery capacities to different roads, is more cost-effective and can further improve the utilization of charging infrastructure. The advantages of a heterogeneous fleet will be more apparent if the battery size and charging schedule can be optimized in an integrated way. Third, reasonable charge/discharge limits will assist extend the cycle life of the battery. A battery under a [0%,100%] complete charge/discharge plan will last half as long as under a [30%,90%] plan. Setting strong DOD limitations in charge scheduling is therefore useful for controlling system maintenance costs, particularly when pack prices are still high.

In general, a robust electric bus charging schedule can improve the accessibility of public transportation by ensuring that electric buses can operate at full capacity, without any significant interruptions due to battery depletion. By providing reliable and frequent service, a robust electric bus charging schedule can also enhance the efficiency of public transportation systems by minimizing downtime and ensuring optimal performance of electric buses. A strong electric bus charging schedule may be supported by transportation policy via investing in electric public transportation infrastructure, such as charging stations and battery technology, and ensuring that they are situated in convenient and accessible areas for electric bus operators. Furthermore, policymakers should emphasize electric public transportation adoption in transportation planning and financing, as well as promote research and development in new technologies that can increase the performance and efficiency of electric buses. More findings and discussion are available in Appendix B.

CHAPTER 4 Life cycle cost analysis

4.1 Motivation

When evaluating the operational performance of EBs, the majority of previous studies were limited to one aspect, such as ownership costs or charging charges, and failed to provide a more comprehensive framework. Further consideration of lifecycle emissions would be of great benefit both in terms of evaluating the potential of e-mobility systems for carbon neutrality and in finding insights to specify the path for further improvement. Besides, previous studies for en-route charging mainly focused on the strategic level when locating the bus chargers instead of incorporating the operational level by considering bus scheduling. This poses difficulties for operating EBs under large-scale networks. In this context, a consolidated optimization model is proposed in this work to evaluate the en-route charging station deployment, battery sizing, and bus scheduling problem under a life cycle cost (LCC) analysis framework.

4.2 Problem description

The suggested LCC analysis framework aims to assess the performance of the electric bus transit system from the economic and environmental aspects. Figure. 4.1 provides the evaluation framework that outputs the bus fleet composition, the deployment of charging stations, and the bus schedule. The objective function is set as the annual equivalent LCC (with interest rate). It includes the infrastructure ownership fee, external cost of emissions, operational cost of charging, maintenance cost of battery changes, and other repairing work. The inputs consist of the bus lines (red lines) and related service trips based on the pre-defined timetable (grey and blue blocks in step 3), the dwell time at each stop, and a set of available battery capacities (e.g., 50 kWh, 100 kWh, 150 kWh). Under this evaluation criteria, the first step is to size the battery for each line to ensure that the battery of a bus is sufficient to serve the line. The second step is to set up charging stations by setting constraints. Constraints are for managing the battery SOC range, ensuring that, when the battery is approaching the minimum allowed SOC, a charger is installed at the next stop. For the bus scheduling part, the available route choices after finishing each service trip are provided, referring to time constraints and bus type compatibility constraints determining the availability of connections between two trips. Thus, when the bus arrives at the destination, the current trip of line 16 (8:00-8:40) is completed, and the block is marked in gray. Then, the bus scheduling process starts where alternatives are chosen based on a certain criterion, such as deadhead distance.

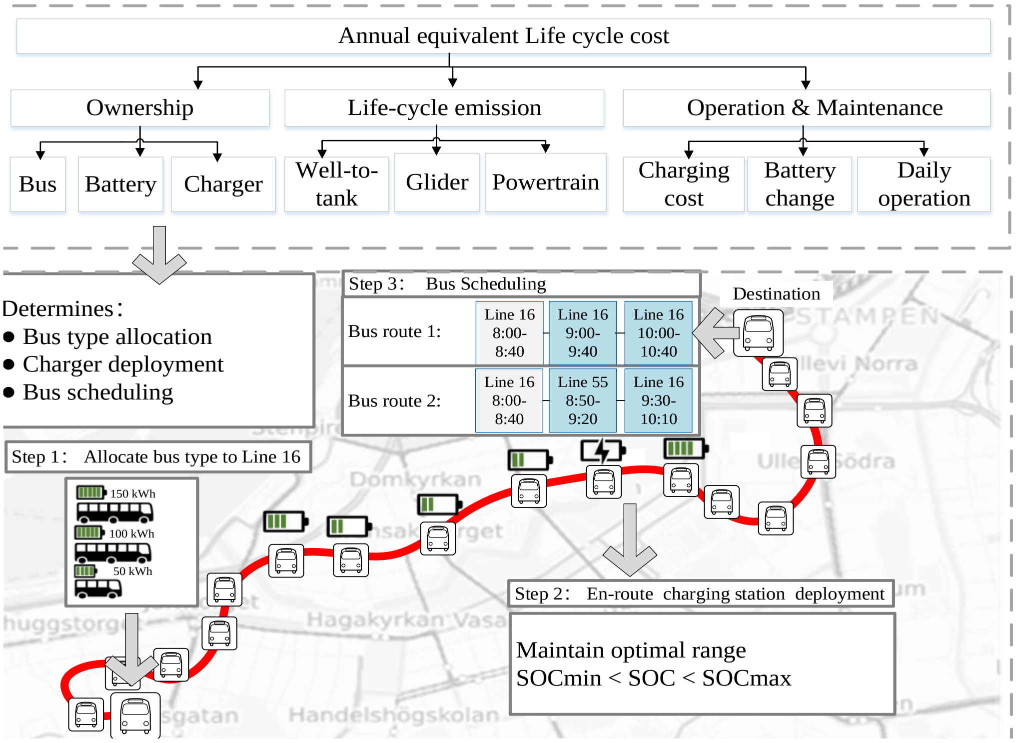


Figure 4.1: Overview of the life cycle optimization model (from Zeng et al., 2022b)

4.3 Consolidated optimization model

The model features will be detailed in the following sections: (1) life cycle cost and (2) constraints. Different from sequential optimization problems, the integrated model makes the variables that restrict each other between the sub-problems. The description of the sets, parameters, and variables discussed in this section are illustrated in Appendix C.

Life cycle cost

In this section, we describe the formulation of the objective function, which calculates the annual equivalent life cycle cost of an electric transit system from production to elimination.

$$\min C_{EAC} = C_{OWN} + C_{EM} + C_{OM} \tag{4.1}$$

The objective function defined in Constraint (4.1) aims at minimizing the sum of the infrastructure ownership cost C_{OWN}, the external cost of emissions C_{EM}, and annual operational and maintenance cost C_{OM}.

$$C_{OWN} = \left(\sum_{p\in P}\sum_{v\in V_p}(C_{BUC}^{p}+C_{BAC}^{p} - C_{BAS}^{p}) \cdot \vartheta_v + \sum_{i\epsilon S} C_{CHS} \cdot x_i\right) \cdot \frac{\gamma}{1-(1+\gamma)^{-n}} \tag{4.2}$$

$$C_{EM} = \sum_{v\epsilon V}(a_{WTT}^{v} + a_{PT}^{v} + a_{GL}^{v}) \cdot \xi \cdot n \cdot DIS_v \cdot \frac{\gamma}{1-(1+\gamma)^{-n}} \tag{4.3}$$

$$C_{OM} = \left(\sum_{p\in P}\left(\sum_{v\in V_p} C_{BUM}^{p} \cdot \vartheta_v + u \cdot n \cdot b_v \cdot DIS_v + C_{BAR}^{v} \cdot \omega_v\right) + \sum_{i\in S} C_{CSM} \cdot x_i\right) \cdot \frac{\gamma}{1-(1+\gamma)^{-n}} \tag{4.4}$$

$$\omega_v = \left\lceil \frac{n \cdot DIS_v \cdot b_v}{\left(\frac{1-SOC_{min}}{145.71}\right)^{-1/0.6844} \cdot q_v \cdot (SOC_{max} - SOC_{min})} \right\rceil \quad \forall v \in V \tag{4.5}$$

Constraint (4.2) calculates the annual equivalent infrastructure ownership cost. It consists of two parts: the capital cost for buses and that for the charging stations. The first part of Constraint (4.2) equals the cost of battery and bus purchases minus the residual value of the batteries. The decision variable ϑ_v indicates whether bus v is in use, which is the key object for optimizing bus schedules, as shown in Constraint (4.15). The second part sums up the cost of installing chargers at bus stops. Constraint (4.3) is for calculating the annual equivalent life cycle emissions from well-to-tank (WTT), glider, and powertrain based on yearly travel distance DIS_v which is calculated in Constraint (4.20). After that, a monetary scalar ξ is designed to convert the emissions into external cost. The annual operation and maintenance costs in Constraint (4.4) include four components: bus maintenance expenses, fleet charging costs, battery replacement costs, and station maintenance costs. The frequency of battery change for bus v within the entire life cycle is calculated in Constraint (4.5), based on a calibrated fatigue model.

Constraints

We then illustrate the formulation for battery sizing (e.g., Constraints (4.6—4.8, 4.14)), charger deployment (e.g., Constraints (4.9—4.13)), and bus scheduling (e.g., Constraints (4.15—4.20)). We then reformulate the problem as a set covering model as shown in Appendix C. Following the convention of daily operations, we assume that the bus will be fully charged before it departs from

$$\varphi_{i+1}^r = \varphi_i^r + \theta \cdot d_{i,i+1}^r - \varepsilon \cdot \frac{T_i^r}{60} \cdot x_i \qquad \forall i \in S, \forall r \in R \tag{4.6}$$

$$\sum_{p \in P} \beta \cdot Q_p \cdot y_p^r \geq \frac{max\ \varphi_i^r}{SOC_{max} - SOC_{min}} \qquad \forall i \in S, \forall r \in R \tag{4.7}$$

$$\sum_{p \in P} y_p^r = 1 \qquad \forall r \in R \tag{4.8}$$

$$e_{i+1}^r = e_i^r - \sum_{p \in P} B_p \cdot d_{i,i+1}^r \cdot y_p^r + \varepsilon \cdot \frac{T_i^r}{60} \cdot x_i \qquad \forall i \in S, \forall r \in R \tag{4.9}$$

$$e_i^r + \frac{\varepsilon \cdot T_i^r}{60} \cdot x_i - \sum_{p \in P} B_p \cdot d_{i,i+1}^r \cdot y_p^r \geq SOC_{min} \cdot \sum_{p \in P} Q_p \cdot y_p^r \quad \forall i \in S, \forall r \in R \tag{4.10}$$

$$e_i^r \leq SOC_{max} \cdot \sum_{p \in P} Q_p \cdot y_p^r \qquad \forall i \in S, \forall r \in R \tag{4.11}$$

$$SOC_i^r = \frac{e_i^r}{\sum_{p \in P} Q_p \cdot y_p^r} \qquad \forall i \in S, \forall r \in R \tag{4.12}$$

$$x_i \in \{0, 1\} \qquad \forall i \in S \tag{4.13}$$

$$y_p^r \in \{0, 1\} \qquad \forall p \in P, \forall r \in R \tag{4.14}$$

the depot and set SOC to SOC_{max} at the beginning of the day.

Constraint(4.6) calculates the estimated energy storage requirement for a bus to serve station $i+1$ with the maximum energy consumption rate θ. The parameter θ refers to the maximum energy consumption per unit among all available bus types. When a charger is provided, this requirement decreases by $\varepsilon \cdot T_i^r$ where ε is the charging power and T_i^r is the bus dwell time minus the charger connecting time. Constraint (4.7) determines the battery sizing from an inventory P. The battery applicability level β indicates the percentage of battery capacity after degradation, the degraded battery capacity $\beta \cdot Q_p$ should be applicable to the bus route. Constraint (4.8) further ensures that one bus type should be assigned to each line. Constraint (4.9) calculates the energy left when a bus arrives at stop $i + 1$, with an updated energy consumption rate B_p and charging station layout x_i. To keep the battery's SOC in the optimal range, we set Constraint (4.10) to constrain the remaining energy such that, when a bus leaves stop i, it is larger than the summation of the traveling consumption between two adjacent stops and the lowest allowed energy level. Constraint (4.11) defines the upper bound of the battery energy, which should not exceed the maximum allowed SOC times the battery capacity. Constraint (4.12) calculates the battery SOC when the bus arrives at stop i of line r. Two decision variables for charging station layout and battery sizing to the route are defined in Constraints (4.13–4.14) respectively. Constraint (4.13) introduces the binary decision variable x_i, representing whether stop i is a charging station. Constraint (4.14) defines the binary decision variable y_p^r indicating the battery sizing for line r.

To further manage the heterogeneous bus fleet, we formulate an integer network flow sub-model [P1] based on a node-arc framework, which decides the bus fleet size $\sum_{v \in V} \vartheta_v$ and further decides the value of C_{OWN} and C_{OM} *in* Constraints (4.2) and (4.4) respectively. To facilitate the use of algorithms to solve this problem, we describe the following sub-model as [P1].

Bus scheduling sub-model [P1]

$$min \sum_{v \in V} \vartheta_v = min \sum_{v \in V} \sum_{h \in G} z_{0h}^v \tag{4.15}$$

Subject to:

$$\sum_{v \in V_p} \sum_{h \in G_r} z_{0h}^v = y_p^r \qquad \forall p \in P, \forall r \in R \tag{4.16}$$

$$\sum_{h \in \mathrm{In}\,(g,p)} z_{hg}^v = \sum_{h \in \mathrm{Out}\,(g,p)} z_{gh}^v \qquad \forall v \in V_p, \forall p \in P, \forall g \in G \tag{4.17}$$

$$\sum_{p \in P} \sum_{v \in V_p} \sum_{h \in \mathrm{Out}(g,p)} z_{gh}^v = 1 \qquad \forall g \in G \tag{4.18}$$

$$z_{gh}^{v} \in \{0,1\} \qquad \forall v \in V, \forall g \in G, \forall h \in G \tag{4.19}$$

The objective function described in Constraint (4.15) does not exist independently but is the specific description of $\sum_{v\in V} \vartheta_v$ in Constraint (4.2) representing that minimizing the bus fleet equals minimizing the number of buses departing from the depot.

Constraint (4.16) depicts the relation between variables y_p^r and z_{gh}^v. It ensures that when the bus type p is assigned to line r, there should be one bus v of this bus type to serve the trips running on line r. Constraint (4.17) ensures the conservation of bus flow. Constraint (18) represents that there must be exactly one bus serving every trip node. Constraint (19) defines a binary decision variable z_{gh}^v. When it equals 1, the bus v serves trips g and h sequentially, and otherwise, it is set to 0. Note that z_{gh}^v records the daily service route of bus v.

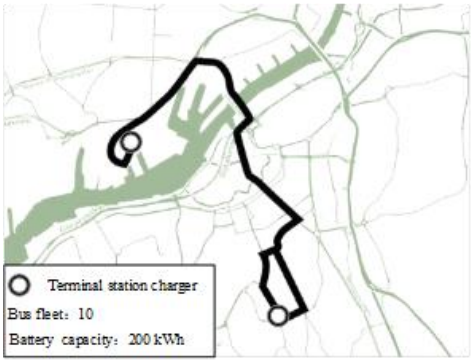
4.4 Case study

All instances in this section are implemented in the General Algebraic Modeling System (GAMS) 25.1.3 and were solved with CPLEX 12.0 on a Dell laptop with a 1.9 GHz Intel Core i7 CPU and 8 GB running on Windows 10.

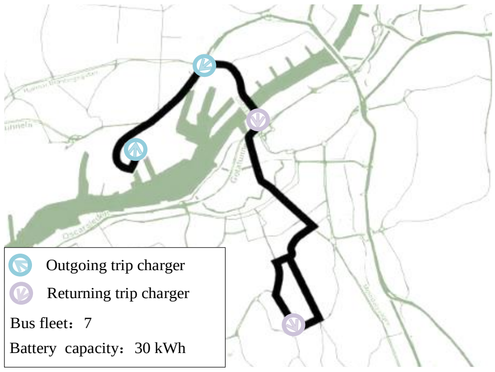
Existing Electrified Bus Line Optimization

This scenario is designed for optimizing the existing electrified bus line in Gothenburg (Line 55), which is the first venture of Volvo Buses for the purpose of developing, demonstrating, and evaluating next-generation sustainable public transport.

The current operational strategy is shown in Figure 4.2(a). It depicts an existing electrified line 55 with a distance of about 7.6 km. This line is equipped with two terminal charging stations. The bus schedules have been served by 10 pure EBs with 200 kWh battery capacity. The operational data is provided by Vasttrafik. The proposed optimal solution is illustrated in Figure 4.2(b). In contrast to the current plan, the charger deployment is considered separately for each direction in this scenario, with two chargers provided for outgoing trips (blue circle) and two for returning trips (purple circle). The increase in the number of chargers is caused by the compensation of downsizing in battery capacity. The bus fleet size in the proposed plan reduces from 10 to 7, and the battery capacity reduces from 200 kWh to 30 kWh. In keeping with current operating conditions (Volvo 7900).



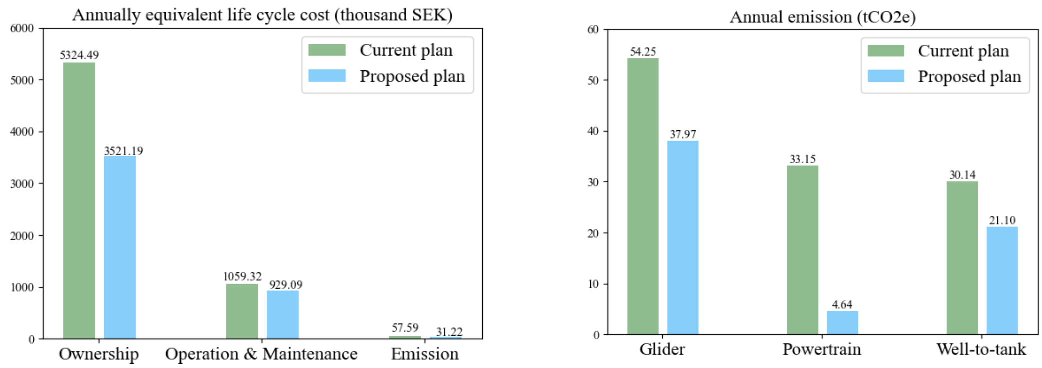
(a) The current plan



(b) The optimized plan

Figure 4.2: Operational strategies of existing setting and optimized plan

Figure 4.3(a) describes the breakdown of the annual equivalent LCC, which reveals the improvement delivered by the proposed plan. In the battery sizing module, a suitable battery capacity (30 kWh) is allocated for the short line (7.6 km). We find that the 30 kWh of battery capacity is sufficient to support a single trip operation under the optimal charging station configuration. More specifically, the annual equivalent LCC decreases by 1.96 million SEK, achieving a 30.4% reduction in comparison to the current plan. The individual measures, namely, the ownership cost, emission, and operational maintenance, are reduced by 1.8, 0.13, and 0.03 million SEK, respectively, with the external cost of emissions falling to around half that in the current plan. Figure 4.3(b) compares the optimized breakdown of annual equivalent life cycle emissions with the real-world operating plan. The results indicate that the annual emissions reduction in the glider, powertrain, and WTT stages is 16.28, 28.51, and 9.04 tCO2e, respectively, with the highest mitigation level in the powertrain, achieving an 86% reduction through a lower-capacity battery.



(a) Breakdown of annually equivalent life cycle cost

(b) Breakdown of annual emission

Figure 4.3: Performance of the current and proposed plans (from Zeng et al., 2022b)

Future Multi-line Planning

This scenario focuses on a near-future electrified bus line planning, with one existing electrified line and one planned line. For more information regarding the characteristics of the two lines, including the length, travel time, serving time, number of trips, and number of stops please refer to appendix C.

Figure 4.4 shows the optimal charger deployment for this network, with the existing line in solid black and the planned line in dashed brown. The battery sizing module assigns buses with 30 kWh battery capacity to both lines. The charger deployment module selects eight stops as charging stations from the available station set.

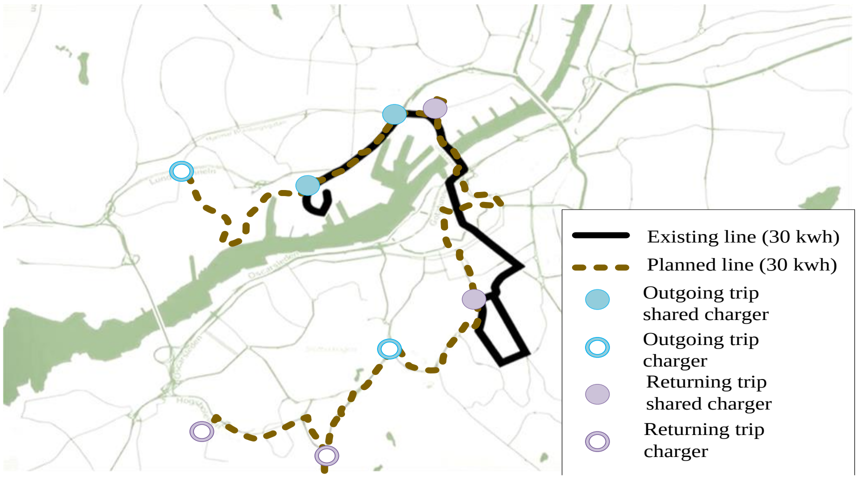


Figure 4.4: Optimal charger deployment for multi-line bus service (from Zeng et al., 2022b)

By analyzing the bus schedule, we can see that the strategy of sharing lines is advantageous because of the increased trip coverage of a bus when a tolerable bus deadhead mileage is allowed. The bus with the smallest number of trips has the longest deadheading distance. The average operational time is around 15 h per bus, while the longest is 24 h for the planned line. The average deadhead length is around 12 km, while the longest is 50 km when a bus travels between two lines or serves a single direction for one line.

To further evaluate the performance, the breakdown of the annual equivalent LCC. Same as the conclusion in the previous section, the investment in the ownership of infrastructures accounts for the largest share, at 62.5%. This is followed by the cost of operation and maintenance, namely the battery changes and energy consumption, accounting for 36.9%. Green electricity production in Sweden makes the external cost of emissions much lower than the other costs by only 0.56% of the total LCC. The emissions delivered by the glider, powertrain, and WTT elements are less than 200 tCO2e per year. Note that the emissions of WTT, powertrain, and glider in the network-scale electric bus system have a consistent pattern with the single line scenario, the glider accounts for the largest share, followed by WTT and finally powertrain.

To sum up, in this work, a novel optimization approach is proposed to consolidate the charging station deployment, battery sizing, and bus scheduling problem. An LCC analysis framework is introduced to evaluate the performance of the electrification infrastructure investment decisions. To make the problem tractable with a low computational burden, the tailored branch-and-price algorithm is suggested. The assessment results show that the integration of the planning and operational layers dramatically reduces the LCC. By comparing actual operations, and optimization results for one line and multi-line, it is large-scale road networks will tend to rely more on efficient daily operation strategies. The proposed method offers a wide range of applications due to the joint consideration of the strategic and operational layers. It is suitable for existing plan evaluation and adjustment and feasibility analysis of future planning as well.

CHAPTER 5 New charging solutions: V2V charging

The range anxiety of EBs is now being tackled by 1) high energy density and 2) the opportunity for fast charging. We are optimistic about battery technology, but the current experiments are still a long way from becoming commercially viable. Besides, the author argues that the utilization of the pricey charging station/lane will be unexpectedly low. With two terminal chargers available for energy replenishment, the author approximated the daily charging requirement for sixteen EBs on the fully electrified bus line 16 in Gothenburg, Sweden. The result in Figure 5.1(a) indicates that the average daily occupancy was 10.3%, with Terminals 1 and 2 seeing 10% and 10.76%, respectively.

The motivation for this work is the unsolved problems of existing strategies, such as insufficiency and underutilization of chargers. As shown in Figure 5.1, we propose three charging technologies that outlook the global trend to grapple with the problems.

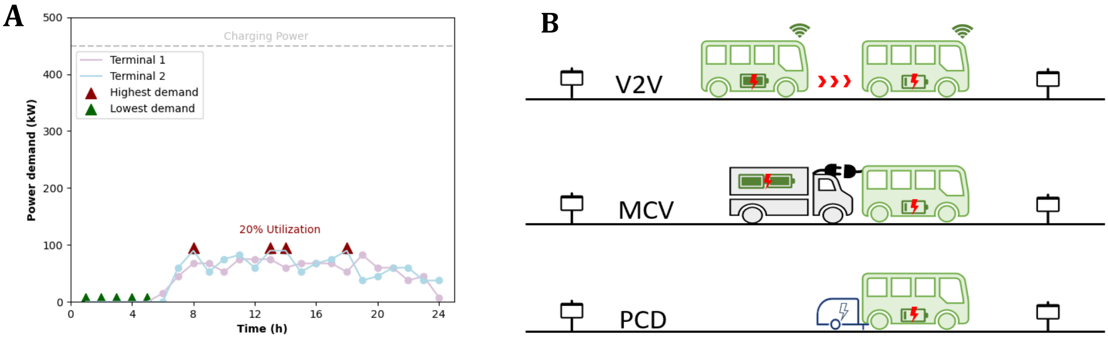


Figure 5.1: EB system shortcomings and solutions (from Zeng et al., 2023)

(A) Low usage of terminal chargers for bus line 16 in Gothenburg, Sweden. Note that the energy demands between time points t and t+1 are aggregated in time point t+1. (B) Three charging strategies for future EB system

5.1 Vehicle-to-vehicle wireless charging

Vehicle-to-vehicle (V2V) charging allows buses to recharge each other. This technology expands the transport network into two interdependent dimensions, the flow of vehicles and the flow of energy. When a safe distance for energy transmission between EBs is established, energy transfer is feasible in a dynamic wireless V2V charging system. Since the energy source is always entering the network and sustaining the energy transfer, in an ideal system, no EB on the road network would experience mileage anxiety. When one EB is ready to finish the last timetabled trip, it distributes the leftover energy as far as possible around the road network while reserving a little amount of power for getting to the depot. This strategy, in theory, maximizes energy efficiency, provided that transmission losses are insignificant. However, due to the added dimension of energy flow, the complexity of the system operations becomes substantially increased.

Technically, the magnetic resonant coupling wireless power transmission technique is a potential option for V2V charging due to its high-power transfer efficiency and long transmission distance. The transmitter and receiver coils are embedded in the front and back of the EB, respectively. With this approach, power is wirelessly delivered with high efficiency across large air gaps. Efficiencies are estimated to be above 90% when the distance is smaller than one meter at a standstill (Kurs et al., 2007). However, a long-distance energy transfer with dynamic lateral shifts is a game-changer. Assuming a distance of 5–8 meters between two EBs (one-second headway), the predicted power efficiency is next to none(Imura and Hori, 2011). To stimulate the development, the challenge would be: 1) meeting safety regulations (e.g., IEEE safety criteria for broad public exposure, and 2) maintaining effective power transfer under dynamic high-power requirements.

Given this, we believe that V2V wireless transmission will be appealing when power efficiency reaches roughly 45% (Kurs et al., 2007), i.e., slightly below the average value for dynamic charging lanes.

5.2 Mobile charging vehicle

Mobile charging vehicles (MCVs) are designed to deliver energy across a local grid via bidirectional chargers and then distribute it to EBs via a specialized aggregator. The aggregator oversees the interaction of MCV and EB, as well as the communication with the grid for energy replenishment. We speculate that an MCV may be wired for energy transfer and connected to the target EB, drawing inspiration from the architecture of the modular bus.

According to this technology, the bus charging station changes from being fixed to active, with MCVs following the EB on a timetabled trip and replenishing it with sufficient energy during the journey. As a result, buses will be freed from reliance on fixed charging locations; instead, all charging tasks could be completed en route. Besides, MCVs can also provide charging services at night if the schedule is more intensive than the fleet size of the MCV. Thus, the original EB charge scheduling problem is transformed into an MCV routing problem and an MCV charging problem.

In general, the cost of MCV energy supply is determined by the total battery degradation costs, electricity prices, energy delivery expenses, and the value of time savings. Taking the example of line 16 in Gothenburg city, we consider a typical EB with a 200kWh battery capacity serving 10 timetabled trips running back and forth with an average energy usage of 22.12 kWh per trip. With the MCV providing an output of 400kW and carrying a 700kWh high-power battery to charge the EB, we conclude that this approach would hardly be profitable unless the energy delivery cost for one EB is less than $0.63 when we exclude the $221.2 from the battery wear. Reduced output power makes this technique more cost-effective and lowers MCV development expenses but results in a considerable rise in the demand ratio between MCVs and EBs. In addition, the results show that the charging efficiency is set to 95%, which is currently only suitable for the lower output such as 2-level chargers (e.g., 6.6 kW). The calculation details are illustrated in Appendix.

5.3 Portable charging devices

The portable charging device (PCD) further reduces the dependence on energy replenishment from other vehicles. It can be seen as a backup battery with sufficient energy to power an EB for at least one timetabled trip. Large interchange stations, therefore, are set up as 'battery banks' in this system, where EBs with charging needs arrive and are connected to one or more PCD(s), which are then unloaded to the next en-route 'battery banks' when the PCD battery is depleted.

Weight, energy transfer efficiency, ownership cost, and lifespan of PCD are all key factors to consider. To avoid putting an extra burden on the EB, the PCD may be designed in the shape of a trailer, moving with the EB rather than being attached to the body. PCD differs from MCV in that it cannot be actively suspended on or disengaged from the EB, and it usually has a smaller battery aimed at serving one EB. On the other hand, this technique requires little initial outlay and is adaptable to several uses. PCD is therefore seen as the measure that can be commercialized the fastest for the EB system. There are already commercially viable applications aimed at light-duty electric vehicles that provide an emergency rescue service, and the battery capacity ranges from 3 kWh to 8 kWh with an efficiency of up to 85%(Memari et al., 2020).

It is worth noting, however, that the energy density of PCDs will still not push the technical limits of Li-ion batteries. Although neither the price nor the capacity of the PCD can be broken in a short amount of time, it is possible to add and remove tiny batteries for continuous energy delivery in the early stages. This concept can therefore be employed as a temporary rather than a long-term fix until high-capacity batteries are developed.

CHAPTER 6 New solutions for operational efficiency: mixed flow

6.1 Motivation

The important urban function of the EB is commuter service which has an asymmetric passenger flow (Kraus et al., 1976). When focusing on urban-rural regions, traffic is considerable heavier toward than away from the urban district during the morning peak, and this phenomenon is reversed during the afternoon peak. This results in a high directional disequilibrium factor, which poses a challenge for traffic planning (White, 2016). But even if operational efficiency can be improved, the nature of commuting is doomed to imbalances. The high urban-rural operating costs, along with low and moderate bus fares, place a significant strain on bus revenue.

The mobility and logistics across urban-rural regions confront comparable challenges: limited transportation resources and sparse demand. Bus networks connect numerous stations in rural regions to metropolitan hubs while presenting extreme asymmetry in passenger flow. If the spare capacity of public transit is implemented to carry freight for short-haul operations, the loss of empty trips can be offset by the profitability of transporting goods. For logistics, this approach promotes the accessibility and robustness of shipments. Not only does it reach remote rural areas, but it also rationalizes the parcel delivery time through the bus schedule, which dramatically improves the service level.

In this work, a practical business mode is provided for mixed passenger and freight flow based on the current public transit network. First, a standard is set when mixed traffic is permitted. For public transportation, a hybrid of planned and on-demand techniques is recommended, with scheduled timetables in high-traffic directions and on-demand services in low-traffic ones. Only low-traffic direction is assumed to be utilized for parcel delivery. To flexibly schedule the bus, EB is allowed to deadhead to the cargo distribution center for loading before returning to the origin to service the pre-booked passengers. Based on such a novel transportation mode, a reliable scheduling method is designed to optimize the electric bus schedules and charging plans with minimized operational costs while avoiding transportation interruptions due to energy shortages.

6.2 Problem description

In this section, we define the mixed-flow rural-urban transit (MFURT) problem. Notations mentioned in this section are summarized in Appendix E.

The MFURT problem is defined at the operational level and proposes to optimize EB scheduling and charging schedules. In this problem, bus timetables, bus fleet size, charger deployment, and passenger and cargo demand are the input conditions (Barabino, 2009). Figure 6.1 presents an exemplary MFURT service. We consider an MFURT network of two distribution centers with several charging piles, one bus route, and a collection of passengers and goods. EBs in this system offer passengers a scheduled service with predefined departure and arrival times (e.g., 7:00 and 7:50) during peak hours in one direction and on-demand service in the other due to passenger flow asymmetry. We are targeting low-frequency bus routes with departure intervals of up to one hour. Freight transport is only allowed to use vehicle resources in that direction where passengers are scarce. Before being transferred (e.g., from urban to rural area), we assume that all progressing products are gathered and stored at the distribution center. When the EB has completed a scheduled timetable trip, it might deadhead to the nearest distribution center to load multiple palettes or sets of parcels, and the time window for cargo picking up is relatively generous (e.g., 8:00-12:00). During the loading/unloading process, EBs have access to the chargers to refill their energy consumption. When the unloading is complete, the bus returns to the terminal to serve the next scheduled trip.

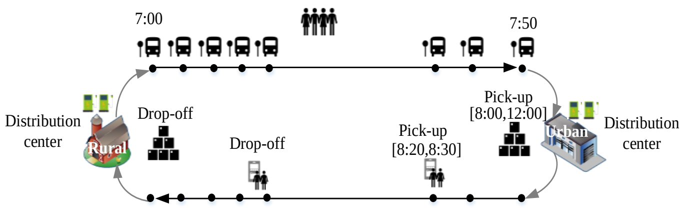
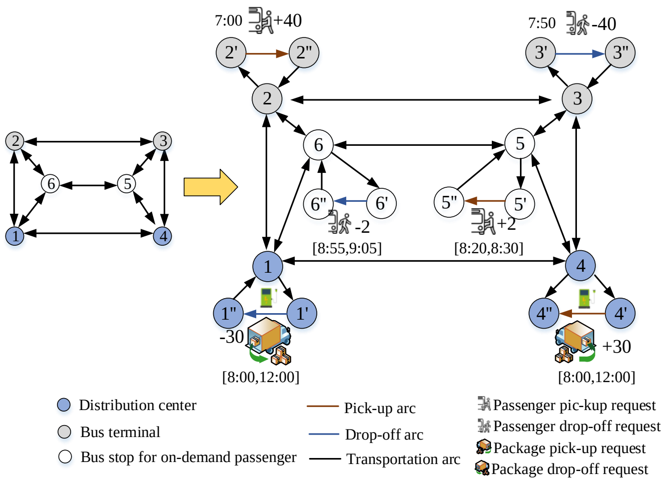


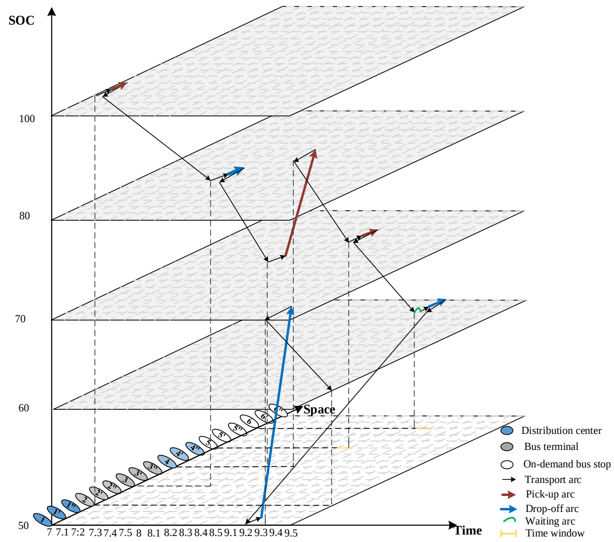
Figure 6.1: Graphical representation of the MFURT system (from Zeng et al., 2022c)

A three-dimensional network is then presented to represent the problem. The six-node physical network is first constructed in Figure 6.2(a). For the on-scheduled timetable trip, only the terminals (node 1 and node 2) remain, and the demand is concentrated on terminals, as the travel times and stop patterns are fixed in this mode of operation. The network is further extended, where each requesting node for pick-up or delivery is expanded to include three nodes. The main node *i* stands for the physical node. Similar to (Liu et al., 2018a), two dummy nodes *i'* and *i''* are introduced to denote the starting and ending of each service, respectively. The time duration for each service is denoted by the link between dummy nodes *i'* and *i''*. For distribution centers (nodes 3 and 4), the bus charging time is predefined and is included in this service duration time. When a bus is planned to cover the request, the arc between *i'* and *i''* must be visited for both pick-up and drop-off.

A standard time-discretized space-time network can be constructed through the procedure proposed in the papers with a minimum feasible space-time prism (Liu et al., 2018a; Tong et al., 2015; Yang et al., 2022). Figure 6.2(b) shows the corresponding spatial and temporal variations in battery state-of-charge to demonstrate both the state transition and bus route in the space-time-state network for a round trip. The bus, according to the timetable, travels from the starting point at 7:00 and picks up 40 people via the arc (2’, 2’’) with a fully charged battery. It arrives at the last stop after 50 minutes and passes through (3’, 3’’) for passenger alighting. The bus then deadheads to the urban distribution center with a SOC of 70% and is loaded and recharged for 15 minutes by an arc (4’, 4’’). The bus left station 4 with SOC at 80%. Based on the on-demand passenger request and their preferred time window, the bus arrives at the passenger pick-up point 5 at 8:30 and takes these two passengers to drop-off point 6 at 8:55 after waiting for 2 mins. To finish the unloading operation, the bus arrives at the rural distribution center at 9:20 and completes 15-minute unloading and charging activities through arcs (1’, 1’’), with the SOC climbing from 50% to 70% before returning to station 2.



(a) The physical and modified transportation network



(b) Illustrative bus schedule for a round trip

Figure 6.2: A toy example of the time-space-state network (from Zeng et al., 2022c)

6.3 Method

The optimization model for the MFURT network is presented in this section, which aims to optimize bus schedules, ensure passenger and cargo services and arrange the charging events for the electric bus fleet so as to minimize the total operational cost.

Primal problem:

Objective function,

$$\text{minimize} \sum_{k\in(K\cup K^*)} \sum_{(i,j,t,t',s,s')\in A} c^k_{i,j,t,t',s,s'} x^k_{i,j,t,t',s,s'} \tag{6.1}$$

Subject to,

(1) Flow balance constraint for each bus k:

$$\sum_{(o_k,j,t_o^k,t',s_o^k,s')\in A} x_{i,j,t,t',s,s'}^k = 1, \qquad \forall k \in (K \cup K^*) \tag{6.2}$$

$$\sum_{(i,d_k,t,t_d^k,s,s_o^k)\in A} x_{i,j,t,t',s,s'}^k = 1, \qquad \forall k \in (K \cup K^*) \tag{6.3}$$

$$\sum_{i,t,s:(i,j,t,t',s,s')\in A} x_{i,j,t,t',s,s'}^k = \sum_{i,t,s:(i,j,t,t',s,s')\in A} x_{j,i,t',t,s',s}^k \tag{6.4}$$

$\forall k \in (K \cup K^*), \forall (j,t,s') \notin \{(o_k, t_o^k, s_o^k), (d_k, t_d^k, s_o^k)\}$

(2) Pick-up and delivery coupling constraint for each bus k and each request r:

$$\sum_{(i,j,t,t',s,s')\in P_r} x_{i,j,t,t',s,s'}^k = \sum_{(i,j,t,t',s,s')\in D_r} x_{i,j,t,t',s,s'}^k \tag{6.5}$$

$\forall k \in (K \cup K^*), \forall r \in R$

(3) Mandatory visiting constraint for pick-up of request r:

$$\sum_{k\in(K\cup K^*)} \sum_{(i,j,t,t',s,s')\in P_r} x_{i,j,t,t',s,s'}^k = 1, \qquad \forall r \in R \tag{6.6}$$

(4) Capacity limitation for each bus:

$$\sum_{r\in R} \sum_{(i,j,t,t',s,s')\in\{P_r\cup D_r\}} d_{i,j,t,t',s,s'}^r \cdot x_{i,j,t,t',s,s'}^k \le V_k \tag{6.7}$$

$\forall k \in (K \cup K^*)$

(5) Binary decision variable:

$$x^k_{i,j,t,t',s,s'} \in \{0,1\} \tag{6.8}$$

The objective function in Constraint (1) is designed to minimize the total costs of all types of selected arcs, including travel costs, waiting expenses, and service revenue. Constraints (2-4) are the standard vehicle-based traffic balance constraints with a given initial departure state (o_k, t^k_o, s^k_o) and end-of-service state (d_k, t^k_d, s^k_o) for each vehicle. The possible traveling arcs are enumerated in the space-time-state arc sets A with proper SOC limitation and specification of the flow direction. Constraint (5) ensures that each demand r containing both pick-up and delivery needs to be served by the same vehicle within a given time window. Constraint (6) indicates that the pick-up and delivery arcs for each demand should be visited by exactly one bus. Constraint (7) ensures that the capacity limitation is respected. The decision variable $x^k_{i,j,t,t',s,s'}$ defined in Constraint (8) is a binary variable indicating whether the arc (i, j, t, t', s, s') is selected in the 3D route of bus k. Finally, our proposed model is a 0-1 integer linear programming model, which can be solved directly in a commercial solver.

The 3D structure of the decision variable would raise the computational complexity, which should be properly addressed by dedicated procedures and innovative solution frameworks. Next, the prime model is related by relaxing the Constraints (5-7) with two lagrangian multipliers $\lambda_{k,r}$ and $\bar{\lambda}_r$ in the objective function to reduce the number of constraints in the primal problem. Let parameter a represents the link (i, j, t, t', s, s').

Lagrangian dual problem:

Objective function,

$$Z = \sum_{k \in (K \cup K^*)} \sum_{a \in A} \tilde{c}^k_a x^k_a - \sum_{r \in R} \bar{\lambda}_r \tag{6.9}$$

where,

$$\tilde{c}_a^k = \begin{cases} c_a^k + \lambda_{k,r} + \bar{\lambda}_r, & (i,j,t,t',s,s') \in P_r \\ c_a^k - \lambda_{k,r}, & (i,j,t,t',s,s') \in D_r \\ c_a^k, & \text{otherwise} \end{cases}$$

Subject to,

Constraints (6.2)− (6.4) and Constraint (6.7)

Solving Algorithm

The LR-based Algorithm 1 is presented as the main algorithm. The optimum value generated by the Lagrangian dual problem can be seen as the lower bound to the primal problem. This strategy calls algorithm 2 and updates the arc cost $\tilde{c}_a^k$. By calculating the path cost for each vehicle, the solution is generated. If the optimal solution of the Lagrangian dual problem is feasible for the primal problem, we have certainly got the optimal solution for the primal problem. If this is not the case, we use a heuristic to determine an upper bound for the primal solution based on the solution of the lower bound. In the heuristic, the demand satisfaction would be checked, and virtual EBs would be dispatched to provide services for requests not accessed by physical EBs.

Algorithm 1: LR procedure

// Initialization
  Ser iteration number $v = 0$;
  Ser LR multipliers $\lambda_{k,r}$, $\bar{\lambda}_r$ to base value;
  Initialize upper and lower bound solutions $\{x_{UB}^0\}$, $\{x_{LB}^0\}$;
  Initialize upper bound $UB^* = +\infty$, lower bound $LB^* = -\infty$;
  Define a termination condition, a gap between UB^* and LB^*
  While termination condition is false, for each iteration v
  Do
    Reset the visit count for each arc $a \in \{P_r \cup D_r\}$ to 0;
    // Step 1. Calculate LB^v
    Initialize $LB^v = 0$
    For each bus $k \in (K \cup K^*)$
    Do
      //input: $\tilde{c}_a^k$
      Call Algorithm 1 based on arc cost $\tilde{c}_a^k$;
      Update the visit count for each arc $a \in \{P_r \cup D_r\}$;
      //Output LB^v
    End For
    // Update LB^*
    Substituting solution vector LB^v in Eq. (10);
    Update $LB^* = \max(LB^*, LB^v)$ and x^*;
    // Step 2. Update LR multipliers
    Calculate the visit of each request arc in P_r :

$\sum_{k\in(K\cup K^*)}\sum_{a\in P_r} x_a^k$

//Update arc multipliers $\bar{\lambda}_r^{\,v+1}$ and sub-gradient $\nabla L_{\bar{\lambda}_r}^v$ for each request with the following equations:

$\nabla L_{\bar{\lambda}_r}^v = \sum_{k\in(K\cup K^*)}\sum_{a\in P_r} x_a^k - 1$,

LR multiplier: $\bar{\lambda}_r^{\,v+1} = \bar{\lambda}_r^{\,v} + \bar{\theta}_r^v \cdot \nabla L_{\bar{\lambda}_r}^v$,

Step size: $\bar{\theta}_r^v = \frac{\bar{\theta}_r^0}{v+1}$

Checking the pairing between bus k and request r:

$\sum_{a\in P_r} x_a^k$

$\sum_{a\in D_r} x_a^k$

Update arc multipliers $\lambda_{k,r}^{\,v+1}$ and sub-gradient $\nabla L_{\lambda_{k,r}}^v$ for each bus and each request with the following equations:

$\nabla L_{\lambda_{k,r}}^v$=$\sum_{a\in P_r} x_a^k - \sum_{a\in D_r} x_a^k$

LR multiplier: $\lambda_{k,r}^{\,v+1} = \lambda_{k,r}^{\,v} + \theta_r^v \cdot \nabla L_{\lambda_{k,r}}^v$

Step size: $\theta_{k,r}^v = \frac{\theta_{k,r}^0}{v+1}$

Update the arc cost for $a \in \{P_r \cup D_r\}$

$$\tilde{c}_a^k = \begin{cases} c_a^k + \lambda_{k,r}^{\,v+1} + \bar{\lambda}_r^{\,v+1}, & a \in P_r \\ c_a^k - \lambda_{k,r}^{\,v+1}, & a \in D_r \end{cases}$$

// Step 3. Generate UB^v

Find a feasible solution for the primal problem with the result in Step 1.

For each request r:

If the pick-up requests are being served by more than one EB, then designate one of the EBs for the request.

If both the pick-up and drop-off requests are not being served by any EB, then assign a backup EB for both requests.

If the pick-up and drop-off requests are partially served, then designate the original EB and assign a backup EB for both requests.

End For

Calculate the upper bound UB^v based on the feasible solution $\{x_{UB}^v\}$

Update the upper bound $UB^* = \min\{UB^*,\ UB^{(k)}\}$

// Step 4: Evaluate the solution quality

Calculate the relative gap percentage by $\frac{UB^*-LB^*}{UB^*} \times 100\%$

$v = v + 1$

End while

we design Algorithm 1 uses dynamic programming to generate the time-space-state path for each EB, in which a label correction algorithm is coded to manipulate unprocessed and useful paths.

Algorithm 1: Time- and state- dependent forward dynamic programming algorithm

For each bus $k \in (K \cup K^*)$ **Do**

// Initialization

Label cost $L(.,.,.) \coloneqq +\infty$;

Node predecessor of vertex $(.,.,.) \coloneqq -1$;

Space predecessor of vertex $(.,.,.) \coloneqq -1$;

State predecessor of vertex $(.,.,.) \coloneqq -1$;

Set load d_k for bus $k \in (K \cup K^*)$ to 0;

// Bus k starts from depot with $L(o_v, t_o^v, s_o^v)$=0

For the entire operating period $t \in (t_o^v, t_d^v)$ **Do**

For each link (i, j) **Do**
For each state s **Do**
derive downstream state $s' = s \pm e(i, j, t)$;
derive arrival time $t' = t + TT(i, j, t)$;
If $d_k + d_{i,j,t,t',s,s'} \leq V_k$ **and** $L(i, t, s) + \tilde{c}^k_{i,j,t,t',s,s'} < L(j, t', s')$ **and** $s' \in [SOC_{min}, SOC_{max}]$ **Then**
$d_k = d_k + d_{i,j,t,t',s,s'}$ //load update
$L(j, t', s') = L(i, t, s) + \tilde{c}^k_{i,j,t,t',s,s'}$ //label update
Node predecessor of vertex $(j, t', s') \coloneqq i$;
Node predecessor of vertex $(j, t', s') \coloneqq t$;
State predecessor of vertex $(j, t', s') \coloneqq s$;
End If;
End For;
End For;
End For;
End For;

Output: Space-time-state path for each vehicle

6.4 Case Study

Two urban-rural bus routes in Shanxi Province, China, are used as an example to show how to integrate passenger and freight transport. Both the rural and urban terminals are close to a distribution center, at distances of 3 km and 2 km, respectively. Energy replenishment is planned at the distribution center with a charging power of 450 kW and a charging efficiency of 0.95. We are targeting two bus lines with lengths of 40.2 km and 37.3 km, as shown in Figure 6.3. They share the same city terminal and cover 8 and 7 rural stations, respectively. The one-way operating time is 70 minutes for line 1 and 65 minutes for line 2. The distance between stations, timetabled trips and on-demand requests can refer to Appendix E.

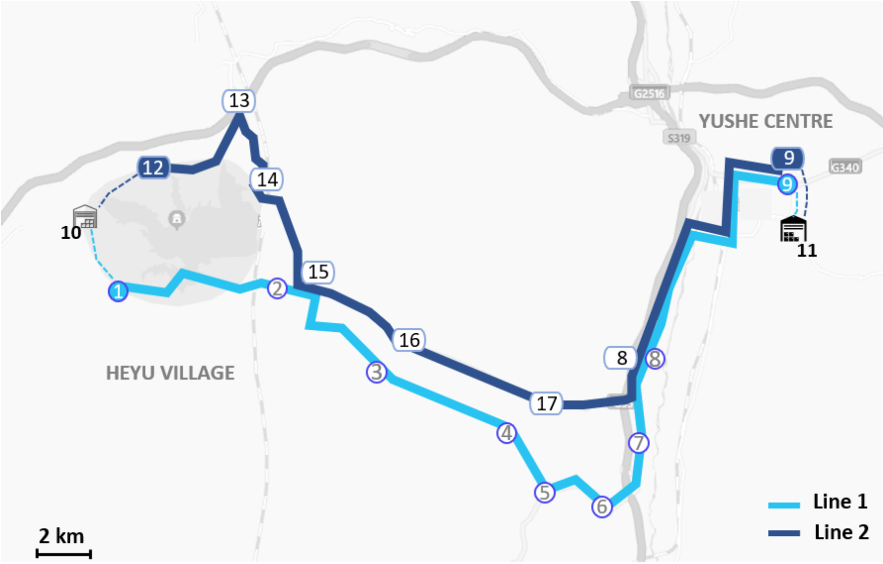


Figure 6.3: Urban-rural bus routes (from Zeng et al., 2022c)

Referring to Mahmoudi and Zhou (2016), the operational cost of a transportation arc traversed by a physical bus is assumed to be $22/h, while the expenses for a virtual one are $50/h. Besides, the waiting cost of a physical bus is $15/h, while waiting at depots is assumed to cost $0/h. The revenue of passenger service is assumed to be $10. Because the transit system focuses primarily on passenger service, the service allowance for goods is set at half the passenger rate. The initial value for LR multipliers is 2.

For mixed passenger and cargo journeys, we specify the number of passengers or cargo per requirement and ensure that the load on board is less than the capacity (for example, 20 passengers and 20 containers). Four EBs are available for daily operation, each with a 300-kWh battery capacity. A unit consumption of 1.8 kWh/km is assumed for the EB fleet. We assume that it takes 10 minutes to load and unload 20 containers and less than 1 minute to board and alight passengers. During the container loading/unloading time, the energy replenishment would achieve 7.125 kWh per minute under the linear charging procedure. We offer a variety of charging time (dwell time) options on the virtual arcs (e.g., (10', 10'') and (11', 11'')) to ensure that the goods can be loaded while having enough power to support subsequent journeys.

The optimized result is shown in Table 6.1. It indicates that all passenger and cargo demands can be met within the time window and that there are three sets of passenger demands combined with cargo movements. Furthermore, we discovered that no EBs were operating on empty. Suppose the EB is unable to pick up a passenger within the time window after performing the scheduled trip. In that case, it will choose to carry the cargo exclusively to improve transport efficiency.

Due to the long rural-urban bus routes, each EB is charged at least twice, while bus 3 has four charges. We assume that the EB does not have the opportunity to be charged during the midday break. The specific charging schedule, charging duration, charging start times, and SOC fluctuations are shown in Table 6.2. Thanks to the high-power charger, the EB can be replenished with 50% of its energy in 21 minutes, making a full charge the ideal alternative while loading and unloading freight.

Table 6.1: Optimized schedule for each EB

Bus	Bus route	SOC (%) profile
1	1-(21&13)-9-4-18-12	76-100-76-53-29-6
2	2-(14&15)-23-10-17-6	76-53-100-77-54-30
3	7-22-3-5-(25&19)	77-100-75-52-100
4	8-20-(24&16)-11	77-52-100-77

Table 6.2: Charging strategy for each EB

Bus	Charging location	Charging start time	Charging duration (min)	From SOC (%)	To SOC (%)
1	11	7:16	11	75	100

	10	9:06	12	73	100
2	10	10:21	20	52	100
	11	11:52	9	77	100
3	11	7:28	9	77	100
	10	8:41	9	77	100
	10	17:46	21	50	100
	11	19:41	11	75	100
4	10	10:56	20	52	100
	11	16:06	11	75	100

The results show that the LR algorithm can converge in fourth iterations and achieve the upper bound solution without a gap. This is due to the fact that our upper bound is derived from the lower bound solution, which is consistent with Shang et al. (2021). For an extended case study, please refer to Appendix E.

In general, MFURT services offer an innovative and cost-effective solution for public transportation providers, logistics providers, and authorities to improve the coverage of logistics services and balance the directional transportation demands. In places with scattered freight demand, the use of buses for freight transport has the potential to enhance on-time performance by displacing the usage of logistics transport vehicles. Focusing on minimizing operational costs, this paper describes the MFURT design problem within a space-time framework. The methods presented provide systematic technical direction and have important methodological implications.

CHAPTER 7 Conclusion

In this final chapter, the research questions are answered by bringing together the knowledge compiled in this thesis. The main implications and contribution of this work are discussed, together with directions for future research.

As shown in Figure 7.1, what contributions have been made at different stages of the development of the EB system against the road map are summarized.

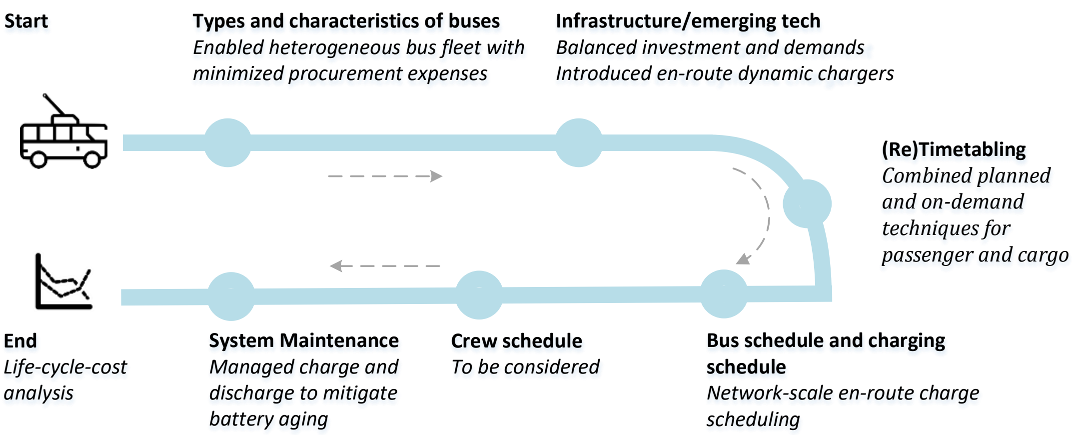


Figure 7.1: The contribution in electric bus system

The research behind this thesis confirms the characteristics of EBs have played a huge restriction in the process of planning and operation, affecting operational efficiency and life-cycle costs. Additionally, it is shown that the trade-offs associated with electrification should be captured and evaluated when generating plans and schedules.

The main conclusions are presented below in relation to the research questions initially posed in Chapter 1. In order to ensure a successful transition to electric buses and electric vehicles overall, a systems approach is needed. Thus, the research questions focused on the different stages of electrification.

As electric buses are gradually replacing conventional vehicles, how can we provide quality decision support for each of these issues in the transportation system?

As introduced in paper III, integrated optimization methods are conducive to generating practical and feasible plans. We coordinated and optimized the battery size, charging station deployment, and vehicle scheduling to achieve a 30.4% reduction in lifecycle costs compared to the current operational plan. In addition, it is suggested to provide an exact optimization model for offline plans, which can generate optimal solutions in a short time. The proposed models in the thesis can be easily solved by commercial solvers.

As the biggest challenge for electric buses, how to schedule the charging events for the entire fleet while ensuring the feasibility of the plans and how to quantify the impact of different charging behavior on battery state-of-health?

The charging problem is described and tackled in different ways depending on the charging method. This thesis constructs two optimization models to find the charging solution with the lowest operating cost for the opportunity charging strategy. One model has battery aging as the main optimization objective by quantifying the impact of battery wear (Paper I), while one focuses on the robustness of the scheme i.e., considering the uncertainty of energy consumption (Paper II). To avoid the problems in the description, battery management constraints, charging conflict avoidance constraints, and arrival time constraints are designed in the models.

Evaluation and improvement. How to verify the environmental and economic advantages and disadvantages of the plans developed in different stages? How to improve operational efficiency accordingly?

In order to systematically describe the advantages and disadvantages of the generated plans, a life-cycle cost analysis framework was constructed to consider the costs and emissions during the production to retirement process from both economic and environmental perspectives as shown in Paper III.

To further improve the efficiency of EB operations, new V2V charging technology and the corresponding charging methods are introduced in Paper IV. The main idea is to transform the traditional charging devices with fixed locations into charging banks operating on the road, completely replacing traditional charging activities that take up operational time.

In addition, improvement can also be made in terms of resource utilization. In response to the directional passenger flow, Paper V proposed a mixed-flow transport mode for passengers and cargo. The bus utilization rate is greatly enhanced by running on a schedule in the direction of high passenger flow and adopting an on-demand system in the opposite direction to flexibly adjust the vehicle route.

Overall, the main contribution of the thesis is to the research field of electric bus system planning, operating, and evaluating and can be summarised as follows:

1. Development of a systematic evaluation model of battery sizing, charging station deployment, and bus scheduling to assess the life-cycle performance of the bus system. Development of compelling scenarios and recommendations from an economic and environmental perspective.
2. Development of two optimization models for en-route charge scheduling model in large-scale networks. A case study in Sweden contextualizes and reinforces the relevance of the proposed model and results.
3. A thorough analysis of the further improvement of the public transport sector regarding operational efficiency, the service mode and optimization models are tailored for the public transport sector and can be adapted to other cities.

Impact of the results

A good reason to pursue large-scale bus electrification would be the lifecycle benefit of emissions and the low costs of operation. The investment in large-scale bus fleets is primarily influenced by four variables: fleet size, battery size, battery aging, and charging strategy. As reported in Paper III, fleet size is the most significant factor affecting emissions and costs.

With this in mind, stockholders and operators should fully consider the trade-offs between charging station configuration and battery size, between fleet size and charger size, and between charging methods and battery aging costs, when initially deploying a fleet. Paper III points out that even if the number of charging posts doubles, the benefits due to lighter batteries can reduce investments in general. In addition, there is a counter-intuitive conclusion that while the prevailing research suggests that depot charging is the most economical way to go (in terms of installation and charging costs), the maintenance costs associated with battery aging due to deep cycling will be several times greater than the charging expenses, as reported in Paper I. Therefore, opportunity charging may be more economical from a life cycle perspective.

While opportunity charging has been practically achieved as a costly infrastructure, Paper IV demonstrates that charger use is substantially below expectations, with an average utilization rate of 10.3% unavoidably leading to resource waste. However, this phenomenon cannot be fundamentally altered because the location of the charger is fixed, and the bus dwell time is relatively determined. But if the charging post is transformed into a mobile power supply device, dynamically transferring power to the EB in transit, the usage rate will vary qualitatively. As a result, in the future, when designing the bus network, the concept of laying out the charging infrastructure will be expanded. Operators will then be free to manage and distribute the dynamic charging facilities that are moving throughout the network rather than being limited to selecting a location and a capacity.

Finally, the use of public transit in logistics opens the door for efficiency improvements. Flexible transit systems, low-occupied transportation resources, and rising logistical demands are the most fertile ground for the growth of mixed transportation. Additionally, increased stakeholder networks and improved governmental support for demonstration programs can help mature the regulations and enhance cooperation among key players in efforts to make public transit more attractive and efficient.

Future works

Reviewing the roadmap planned for the EB system (Figure 1.2), there are still areas for further improvement.

For example, model selection in the planning stage can be included in the life-cycle cost analysis framework, and the resulting operating costs and charging demand will vary from different base energy consumption. In addition, different energy sources not considered in this thesis, such as hydrogen, hybrid energy, etc. will bring new advantages and challenges to the transit system. At this early stage of electrification, it is worth exploring whether a hybrid fleet system is technically feasible.

Besides, in addition to considering the peak-to-average power ratio, the ability to install high power chargers at each site depends on the capacity of the grid. The configuration of the power supply equipment and the safety of the installation are important influencing factors. The deployment problem thus has additional grid-related constraints. Furthermore, the cost of installing a charger may further include the investment of upgrading the grid and the expenses of maintaining the distribution network.

From an operational point of view, the speed at which the EB operates and the number of passengers boarding and alighting the bus both represent significant operational variables. The complexity of the charging problem is increased by additional stochasticity in addition to the energy consumption uncertainty taken into account in Paper II. The magnitude of the impact of these uncertainties and the modeling approach might be used as new research concepts. Additionally, crew scheduling is also a plan that has not yet been considered, mainly in terms of drivers' working hours, rest arrangements, and route allocation. The feasibility and economics at the operational level will be further optimized by combining crew scheduling with vehicle scheduling.

Finally, in order to promote investment and long-term commitment to mass electrification of public transportation, it is also important to continuously research new business models and specific policy measures to embrace emerging battery technology and charging methodologies.

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