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Limitations and suggestions of electric transit charge scheduling

Ziling Zeng[1], **David Daniels**[2] **and Xiaobo Qu**[1,3,*]

[1] Department of Architecture and Civil Engineering, Chalmers University of Technology, 41296 Gothenburg, Sweden
[2] Department of Space, Earth and Environment, Chalmers University of Technology, 41296 Gothenburg, Sweden
[3] State Key Laboratory of Automotive Safety and Energy, School of Vehicle and Mobility, Tsinghua University, Beijing 100084, People's Republic of China
[*] Author to whom any correspondence should be addressed.

E-mail: drxiaoboqu@gmail.com

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Abstract

A major factor hindering the popularization of electric buses (EBs) in the current automotive market is the high ownership cost of batteries and its significant upfront investment. For the daily maintenance of electric fleets, the amortized battery replacement cost is at least six times the charging cost. Thus, ensuring the healthy operation of the battery and prolonging the cycle life are some of the most concerned issues of the bus operators. In order to achieve the best operating mode, the operators are required to formulate an effective charging schedule with minimized battery wear. However, little quantitative formulation exists in prior literature to consider battery wear in bus charge scheduling. In this paper, a general formula is presented for battery wear cost consideration in charge scheduling based on the emerging literature. Then, the existing charge scheduling model is improved based on the proposed approach. A case study illustrates the significant difference in operating costs between charging plans developed with or without consideration of battery wear. The focus of this commentary is to present the crucial factors to improve the efficiency of EB operations and help make the charge scheduling models more realistic.

Nomenclature

ACC	Achievable cycle count
CC	Constant current
CV	Constant voltage
DOD	Depth of discharge
EB	Electric bus
EBCS	Electric bus charge scheduling
EOL	End of life
SOC	State of charge
TOU	Time of use

1. Introduction

1.1. Background

Although battery prices have dropped 85% in recent years from \$800 to \$150 kWh^{-1}, lithium-ion battery packs remain a high cost for EBs (He *et al* 2019). Since the lithium-ion battery pack of the EB can have a capacity of at least 100 kWh, a large portion of the bus ownership cost still be attributed to the battery. In terms of operating costs, the expenses of electricity to run an EB is a fraction of the cost of equivalent internal combustion engine fuel, reflecting greater energy efficiency. However, batteries will lose irreversible capacity as they age through cycles (Ramadesigan *et al* 2012) and calendars (Wang *et al* 2014). The degradation results in high replacement investments, which may offset the economic benefits of EBs. Once a battery loses 20%–30% of its original storage capacity, it is traditionally believed that the battery reaches the EOL. The

National Academy of Sciences (2010) projections for battery life range from 3 to 8 years in the near term to 9–15 years in 2030. The reason for this interval in the prediction is due to the difference in operating conditions and charging behavior.

The ZeEUS consortium reported that an 18 m bus with 350 kWh of battery capacity could cover a maximum range of 210 km, 65% less than diesel buses (Depré and Guida 2017). To ensure a stable transition from conventional to EBs, the shortfall in driving range should be offset by easy recharging. Thus, decision-makers need to properly schedule the charging events to efficiently recharge the battery while fulfilling the pre-defined timetable trips (Wang *et al* 2017, Zhang *et al* 2021c). Both the frequency of charging and the DOD in the developed charging schedule constitute important factors affecting battery degradation (Wood *et al* 2011). Without a well-planned charging activity, frequent replacement of batteries during the lifetime of an EB can sharply increase the cost at a later stage. Therefore, it is logical to incorporate certain battery degradation considerations into the bus charge scheduling from a cost perspective.

In previous studies of EBCS, the charging event is arranged with the lowest charging cost or the lowest demand charge (Yang *et al* 2018, He *et al* 2020). While these models can provide some degree of decision support for EB operators, we argue that they suffer from a vital shortcoming: their ignorance of battery losses and the significant post-production maintenance costs that result from battery aging. Since the battery cycle life is highly related to the DOD, a high-frequency charging strategy help to reduce the DOD while delaying battery replacement. However, the battery wear cost and charging cost are two conflicting optimization goals to some extent. Therefore, when only one of the two objects is taken into consideration, the result will turn out to be inaccurate. We argue that the inclusion of battery wear cost in the objective function of the EBCS model will help to improve the practicality of the existing methods. We will also introduce a general formula for calculating the wear cost that can be easily applied to the EBCS model.

1.2. Summary of take-away points

The global rate of adoption of EBs has accelerated rapidly, owing to four major factors: advances in battery technology, a diverse set of supportive policies to reduce emissions, government subsidies for EB purchases and operation, and regulations and standards that promote energy efficiency. Ambitious plans are in place worldwide for the development of EBs in 2035, including financial support, staff development, and infrastructure development.

However, current lithium battery technology has hit a snag and is unable to match the driving range of diesel vehicles, necessitating the purchase of more EBs to cover the transit network. In addition, the price of batteries remains at a high level. Over the life of an operating vehicle, different battery usage will lead to different battery replacement frequencies and potentially high maintenance expenses that are several times the cost of other operating expenses such as electricity. Thus, taking full account of battery charge and discharge during operation is key to extending battery life. At the same time, accurately characterizing battery aging through the charging and discharging process and incorporating it into the optimization process of the charging schedule will be an essential issue.

After summarizing existing studies, we introduce a discrete model based on empirical data that can describe battery aging in arbitrary SOC states and relies on a small number of input conditions. The applications in the EBCS model are presented accordingly. This detailed description paints a positive picture for the charge scheduling across different charging technologies.

The remainder of this perspective will briefly summarize the current state of EBCS (section 2), elaborate on the role of battery wear cost consideration, and provide concrete recommendations on how battery wear can be implemented in future models (section 3). Section 4 compares the operational performance under different scenarios to evoke the importance of battery wear consideration. This work ends with the conclusions and calls for further research to improve our understanding of the relation between battery aging and charge scheduling (section 5).

2. State-of-the-art review of EBCS problem

2.1. Problem description

This section aims to introduce what we refer to as the EBCS problem. For each bus, there is an arranged schedule consisting of a list of timetable trips that need to be served from morning to night. EBCS focuses on time and space scheduling of EB charging events depending on their access to various charging options: depot (Gao *et al* 2018) or en-route charging stations (Yang *et al* 2018) as shown in figure 1. Depot charging provides overnight charging opportunities with low-power chargers. As a result, during daytime operations, the buses rarely have the opportunity to recharge their batteries, and their operating range affects the

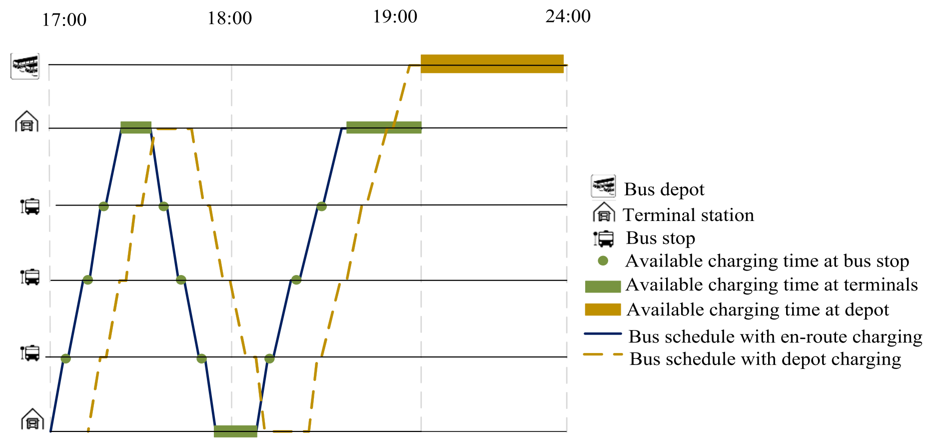

Figure 1. An illustrative example of depot and en-route charging.

number of timetable trips they can serve. In this case, the fleet is anticipated to employ a considerable battery to replace the conventional diesel buses.

Furthermore, because charging demand is highest at night, it is even more critical to coordinate charging activities to avoid additional load peaks created by a large number of EBs charging simultaneously, putting additional strain on the grid (Arif *et al* 2020). Different from depot charging, en-route charging provides easier accessibilities to the charging piles during bus operation. Chargers in the bus stop provide short-term power replenishment, and the terminal charging station guarantees sufficient energy for the next timetable trip service (Zhang *et al* 2021b). Note that bus schedule and charger configuration are pre-defined in the EBCS problem allowing planners to schedule when and where to charge vehicles based on their travel needs and the availability of charging stations (Ke *et al* 2016).

A CC–CV method is commonly used to charge the batteries in a non-linear process. The battery SOC increases linearly with time throughout the CC phase. Switching to the CV phase reduces the charging current and slows the charging speed to guarantee that the battery is fully charged. Due to the nonlinearity of the charging time, studies usually use a segmented functional form to describe the charging time at each stage (Pelletier *et al* 2018). However, there are also studies that directly assume a linearized charging process, i.e. a positive linear correlation with the charging power (Wang *et al* 2017). The fact is that it is not reasonable to charge the battery to full charge in linearized (CC) form. The entire process could be considered in the CC stage for short-time charging at the station, where only short-time partial charging is possible. For charging at the depot, on the other hand, the CV stage cannot be ignored. The current state of EBCS models and their main shortcoming.

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.

EBCS in the centralized depot is mainly designed for full charging at night. The focus of this problem is on planning the charging start time, not duration in general. Without considering the impact on the grid, the TOU energy price is one of the most critical factors in deciding the charging time. A genetic algorithm is a common solution strategy for problem-solving (Ke *et al* 2016, Gao *et al* 2018). To include the impact of EB charging on the grid, Arif *et al* (2020) proposed a mixed-integer linear programming model 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.

The emerging technology of en-route fast charging provides the promising potential to replenish the energy consumed during bus dwell time. Recent studies approached the en-route charge scheduling problem through mathematical models or simulation methods. In the context of mathematical optimization, mixed-integer programming models are widely used for problem formulation (Wang *et al* 2017, Abdelwahed *et al* 2020). The TOU charging costs, together with other operating costs such as trip running expenses, formed the primary objective function (Zhou *et al* 2020). The proposed models were solved by off-the-shelf solvers such as Cplex (Wang *et al* 2017, Abdelwahed *et al* 2020) or by customized greedy algorithm (Zhou *et al* 2020). Yang *et al* (2018) innovatively introduced a peak-to-average ratio to balance the charging demand distribution and mitigate the charging impact on the grid. It is worth noting that when considering charging at intermediate stations, there are often such assumptions that any arriving EB finds a free charging slot to avoid conflict (Abdelwahed *et al* 2020, Zhou *et al* 2020). This is unrealistic for dense, high-frequency urban transportation networks.

Regarding the simulation method, Markov decision process is introduced to describe the charging events (Wang *et al* 2020). The average reward reinforcement learning method is implemented for problem-solving (Chen and Liang 2020). According to the battery SOC threshold based on the full charging policy, Qin *et al* (2016) formulated an en-route charging strategy. 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 the SOC of 60%–64% is the most economical strategy and has the most negligible impact on the grid.

Some studies combine charge scheduling with other sub-problems of EB planning and operation. Sebastiani *et al* (2016) integrate charging station deployment and charge scheduling by a simulation optimization method. Their target is to minimize the number of charging stations and the extra charging time caused by energy replenishment. The Non-dominated Sorting Genetic Algorithm II(NSGA-II) algorithm is introduced to solve the bi-objective problem. Studies usually assume a fixed value for the charging time for joint consideration of charging station locating and battery sizing (Kunith *et al* 2017, Liu *et al* 2018). All these studies greatly simplify the charging behavior while ignoring the impact of the charging strategy on the battery. It is worth noting that, in the context of bus scheduling, Zhang *et al* (2021a) introduced a non-linear formula presented by (Lam and Bauer 2012) to calculate the battery loss caused by the utterly symmetrical charging and discharging behavior where the SOC variation and the average SOC level are captured. This method is not applicable to partial charging at the intermediate stations and is challenging to implement for most linear programming models.

Despite the exciting results and essential contributions of these models, here we argue that they have a key weakness. They largely—if not entirely—ignore battery wear, which leads to significant differences in battery cycle life. This ignorance overlooked the operational cost of battery replacement, which can be of the same order of magnitude as the charging cost.

3. Wear cost calculation to improve EBCS model

Battery applications can provide significant benefits to bus operators and the grid. However, the replacement cost brought by the aging of the battery cannot be underestimated. The prior mathematical models of charge scheduling are mostly linear programming, and the charging strategy prefers partial opportunity or full charging in the depot. Therefore, how to provide these models with practical strategies to capture the aging of the battery during the charging and discharging process is the main focus of this section.

Han *et al* (2014) introduced a function to formulate the unit wear cost for cycling a battery in the specific SOC range of EBs, based on a certain DOD, DOD = 1 − SOC. The model can indicate the wear cost of transferring 1 kWh when cycled from one SOC value to another. The current emerging research for electric vehicle (EV) charging schedule optimization uses a battery aging model that is only applicable to full charging (Zhang *et al* 2021a, 2022). However, the introduced model is suitable for capturing partial charging behavior with an arbitrary SOC range. These capabilities are necessary for opportunity charging, leading to the model being gradually used to optimize the partial charging of both light-duty and heavy-duty vehicles (Pelletier *et al* 2018).

The input of their model includes battery ownership cost and calibrated ACC versus DOD curve. A typical lithium-ion battery fits the function: $\mathrm{ACC}(\mathrm{DOD}) = a\mathrm{DOD}^{-b}$ where two battery-dependent parameters a and b can be acquired experimentally, the curve used in this work was proposed by (Zhou *et al* 2011), as shown in figure 2. After being discretized, the data can be further used to determine the wear cost. To differentiate the characteristics of different buses, a bus specific parameter is recommended $\mathrm{ACC}_{\mathrm{bus\_type}}(\mathrm{DOD})$ for each bus type.

Referring to Han *et al* (2014), the relationship between battery ownership cost $O_{\mathrm{bus\_type}}$ and unit wear cost $w_{\mathrm{bus\_type}}(\mathrm{SOC})$ for each bus can be formulated as:

$$O_{\mathrm{bus\_type}} = 2 \times \mathrm{ACC}_{\mathrm{bus\_type}}(\mathrm{DOD}) \times \sum_{\mathrm{SOC}=1-\mathrm{DOD}}^{1-\Delta\mathrm{SOC}} w_{\mathrm{bus\_type}}(\mathrm{SOC}) \times \Delta q_{\mathrm{bus\_type}} \tag{1}$$

where $\Delta q_{\mathrm{bus\_type}}$ is the energy consumption of bus n in each SOC interval $\Delta\mathrm{SOC}$, $\Delta q_{\mathrm{bus\_type}} = \Delta\mathrm{SOC}\times Q_{\mathrm{bus\_type}}$. Parameter $Q_{\mathrm{bus\_type}}$ indicates the battery capacity. The ACC is multiplied by two as one cycle consists of both charge and discharge phases.

By defining $\Delta\mathrm{SOC}$, constraint equation (2) yields $1/\Delta\mathrm{SOC}$ equations. By isolating the wear cost $w_{\mathrm{bus\_type}}(\mathrm{SOC})$ in each of these, the following $1/\Delta\mathrm{SOC}$ equations can be used to calibrate the wear cost function stated as constraint equation (1):

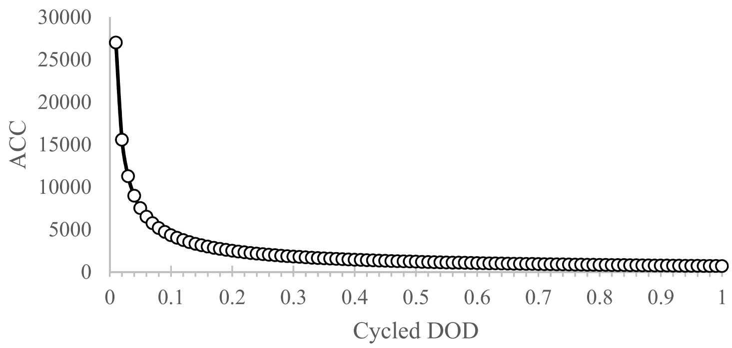

Figure 2. Illustration of ACC (DOD) function for a lithium-ion battery.

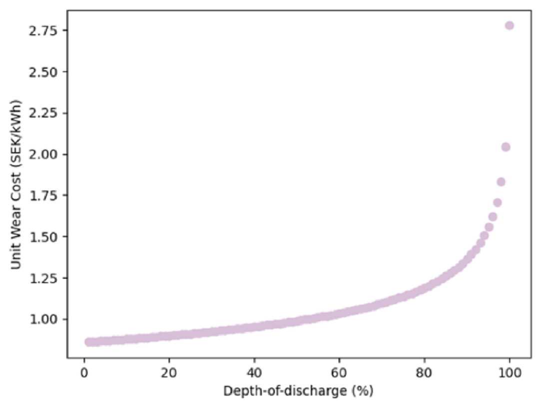

Figure 3. Wear cost obtained in a discrete manner.

$$w_{\text{bus\_type}}(1-\Delta\text{SOC}) = \frac{O_{\text{bus\_type}}}{\text{ACC}_{\text{bus\_type}}(\Delta\text{SOC})\times 2\times \Delta\text{SOC}\Delta Q_{\text{bus}_{\text{type}}}}$$

$$w_{\text{bus\_type}}(1-\Delta\text{SOC}) + w_{\text{bus\_type}}(1-2\times\Delta\text{SOC}) = \frac{O_{\text{bus\_type}}}{\text{ACC}_{\text{bus}_{\text{type}}}(2\times\Delta\text{SOC})\times 2\times(2\times\Delta\text{SOC})\times Q_{\text{bus\_type}}}$$

$$\vdots$$

$$\begin{aligned} & w_{\text{bus\_type}}(1-\Delta\text{SOC}) + w_{\text{bus\_type}}(1-2\times\Delta\text{SOC}) + \ldots + w_{\text{bus\_type}}(\Delta\text{SOC}) + w_{\text{bus\_type}}(0) \\ & \quad = \frac{O_{\text{bus\_type}}}{\text{ACC}_{\text{bus\_type}}(1.0)\times 2\times 1.0\rangle Q_{\text{bus\_type}}}. \end{aligned} \tag{2}$$

We subtract the two adjacent lines in constraint equation (2), and the wear cost corresponding to each SOC value can be obtained as a constraint equation (3):

$$w_{\text{bus\_type}}(\text{SOC}) = \frac{O_{\text{bus\_type}}}{\text{ACC}_{\text{bus\_type}}(\text{DOD})\times 2\times Q_{\text{bus\_type}}} - \frac{O_{\text{bus\_type}}}{\text{ACC}_{\text{bus\_type}}(\text{DOD}-\Delta\text{SOC})\times 2\times Q_{\text{bus\_type}}}. \tag{3}$$

Thus, the unit wear cost associated with each SOC value is determined with a pre-defined ACC function, battery size, and price. Using the ACC–DOD curve in figure 2, the discrete wear cost for a 100 kWh, 150 000 SEK battery is shown in figure 3.

To incorporate the unit wear cost in EBSP, the SOC interval can be customized, and each SOC value among the range corresponds to a different unit wear cost except for SOC = 100%. For those models that record SOC value with time, the total wear cost for each bus can be easily collected as constraint equation (4). If the battery SOC does not change at moment t, $\Delta q_{\text{bus\_type},t}$ should be 0. Therefore, the non-energy transforming time will not be multi-counted:

$$\text{wearcost} = \sum_{t=1}^{\text{operation\_end\_time}} w_{\text{bus\_type}}(\text{SOC}_t)\times\Delta q_{\text{bus\_type},t}. \tag{4}$$

But some models only focus on SOC value with the station, denoted by s. In this case, both the arrival (denoted by ASOC_s) and departure SOC (denoted by DSOC_s) at each charging station should be recorded since the SOC value is often the local minimum when arriving at the station, and when leaving the charging station, either maintain the same amount (i.e. not charging) or reach a peak (i.e. after charging). Thus, the battery wear for discharging and charging is recommended to be counted separately as in constraint equation (5):

$$\text{wearcost} = \sum_{s}\left(\sum_{\mathrm{SOC}=\mathrm{ASOC}_s}^{\mathrm{DSOC}_{s-1}-\Delta\mathrm{SOC}} w_{\text{bus\_type}}(\mathrm{SOC})\times\Delta q_{\text{bus\_type}}+\sum_{\mathrm{SOC}=\mathrm{ASOC}_s+\Delta\mathrm{SOC}}^{\mathrm{DSOC}_s} w_{\text{bus\_type}}(\mathrm{SOC})\times\Delta q_{\text{bus\_type}}\right). \tag{5}$$

4. Insights from comparative scenarios

In this section, we verify the importance of considering battery wear through different charging strategies: targeting charging cost (case 1), targeting wear cost (case 2), and targeting both costs (case 3). Note that calendar degradation is neglected in this study. The EBCS model implemented was proposed by Yang *et al* (2018), which focuses on en-route charging for a single bus line. Bus route 18 in the city of Gothenburg, Sweden, is selected as an example, where 212 trips are served by 51 buses with 100 kWh battery. In the simulation, this 16.7 km bus line is equipped with four 450 kWh high-power charging stations (ABB 2020), two at terminals and two at intermediate stations. The bus has four opportunities to recharge along the route. Each intermediate station is coupled with the nearest terminal to balance the demand profile. The energy price during 8:00–20:00 is set to 0.6 SEK kWh^{-1}, and the rate for the rest is set to 0.5 SEK kWh^{-1} according to the annual average electricity price reported by Nordpool (2021). Note that 1 SEK equals 0.10 USD. Firstly, the SOC trajectory of the vehicle and the power demand profile within 24 h for each charging group is shown in figures 4 and 5, respectively.

In case 1, almost every vehicle reaches the lowest SOC value at least once, i.e. 30% of capacity as set as default. Case 2 is the opposite, where the penalty for battery wear makes the vehicle charge frequently. Due to the limitation of the number of charging stations, only one bus with a SOC value is close to the lowest level. Case 3 balances the two costs. To a certain extent, it guarantees a larger charging frequency and improves the situation of the excessive DOD in case 1.

The total amount of charging is the same for the three cases, but there are major differences in the time distribution. The charging distribution in the second and third cases is relatively uniform compared with the first one, with the highest demand within 300 kWh h^{-1}. The first case places charging requests when the battery SOC reaches its lowest value or when the charging tariff is low and thus is prone to charging peaks, with the highest value being 133% of the first two cases.

In addition, the battery wear costs and charging costs are depicted in figure 6. It can be shown that battery wear costs account for a large portion of running expenditures, even six times that of charging costs, although this result is predicated on the assumption of low energy prices and high battery ownership costs in Europe, particularly in Sweden. Example 3 appears to provide the best solution when two components of the objective function are considered. However, it differs little from the result in case 2. This is due to the fact that the charging cost for opportunity charging is not highly adjustable. During peak hours, vehicles with low charges have to charge en-route in order to maintain regular functioning and connect to future services seamlessly. It can also be shown that focusing just on charging costs would result in the poorest solution, resulting in the highest wear costs and hastening battery replacement, which is clearly at odds with the planned goals. Because of the higher flexibility of overnight charging durations, the combined consideration of charging costs and battery deterioration may give superior outcomes in depot charging solutions.

The charging costs remain the same level in three cases due to the consideration of en-route charging. The available charging time is strictly limited to the bus dwell time. To ensure the driving range, buses may choose to charge in peak hours.

We also looked into the link between optimal charging behavior and battery cost and size, giving bus operators more options for reducing capital and operating expenses. The finding from figure 7 is consistent with equation (2), which shows that battery price is positively associated with the cost of battery wear. A linear increase in battery cost is caused by a greater battery unit price. The difference between battery wear and charging costs is predicted to be close to about two times at prices below SEK 750 kWh^{-1}. When battery ownership costs are not taken into account, the findings in the right columns reveal that using high-capacity batteries does not appear to minimize the operating strain, and one ideal option for Route 18 appears to exist. The overall cost reaches a minimum of 20 881 SEK d^{-1} when the battery capacity is 200 kWh, whereas

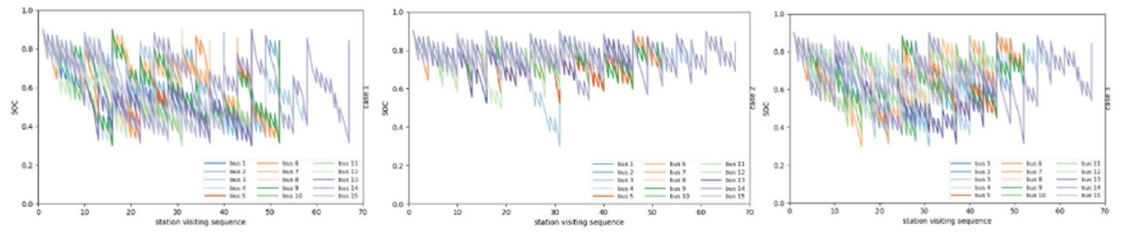

Figure 4. SOC curve for the bus fleet under three cases.

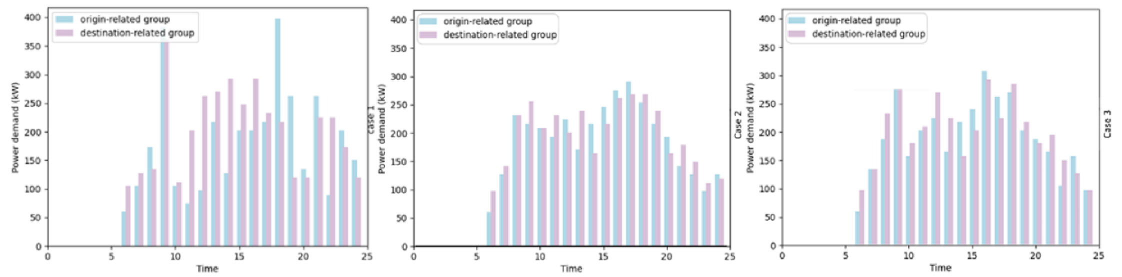

Figure 5. Charging demand distribution under three cases.

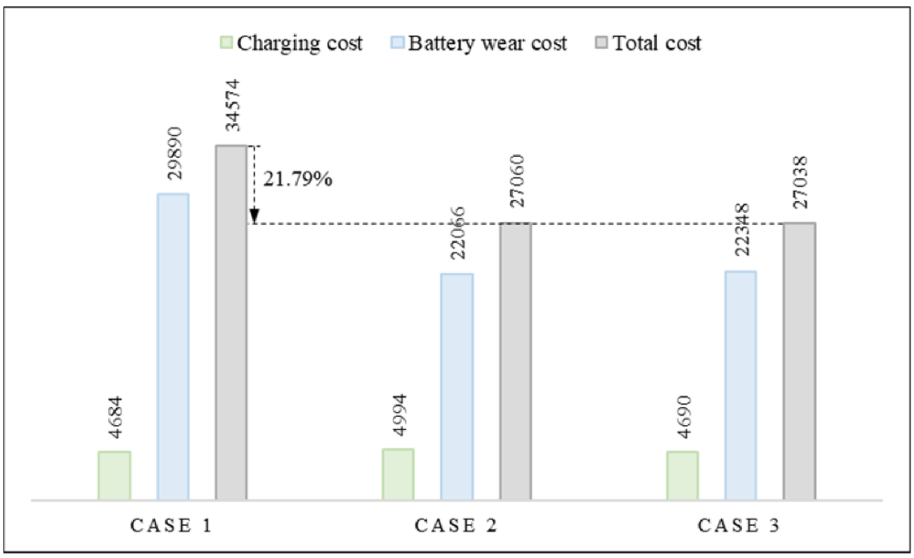

Figure 6. Operating costs of charging plans in three scenarios.

raising the battery capacity instead increases the total cost. This is because the increase in battery capacity also makes the cost per unit of battery wear increase. It is worth noting that different charging strategies and charging facilities also lead to different results, but since the model used is based on en-route static charging, other charging options are not considered for sensitivity analysis.

Two key modeling parameters are individually varied over realistic bounded ranges. Variation in the battery price has a more significant impact on the results. The total cost is mainly composed of the battery wear cost. The trend of battery price is almost linearly related to the total cost. It should be noted that the total cost is not linearly related to the change in battery capacity. The cost reaches a minimum at a battery capacity of 200 kWh and then slightly increases as the battery capacity increases.

In order to avoid incorrectly recommending bus operational strategies for charging, the EBCS model should take into account battery aging-related costs as part of operational expenses. In addition, the cost of the battery, its capacity, and the charging technique are all crucial factors to consider. The performance

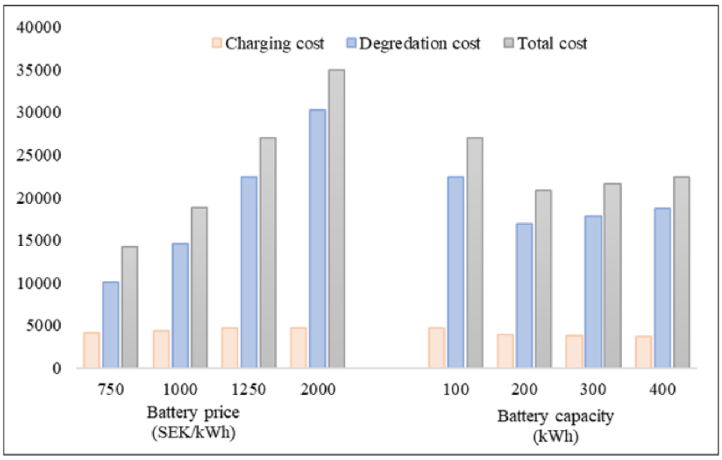

Figure 7. Sensitivity analysis for case 3.

comparison made in this section would support the method proposed in section 3 to be an efficient and expedient method.

5. Conclusion

Based on the above argumentation, we present a reliable method to strengthen the modeling of EBCS. To begin, modelers should be aware of the significant amount of battery replacement costs in bus operating, which are six times those of charging. Thus, battery management should be addressed with charging plan decision-making to assist limit the grid effect of large-scale EB charging. When a charging plan does not account for battery wear, the peak charging requirement for that schedule increases by 33%.

Second, a better approach is to consider the local price of electricity and the adjustability of charging time when selecting a target. For en-route charging, unless the price of electricity time varies significantly from time to time, the cost of charging will have little effect on the final choice of charging option. However, for terminal charging, the long optional time combined with the enormous cost variation would make charging costs a major determinant in the charging plan objective function.

Third, the proposal of the general implementation of wear cost calculation in different types of models can serve as a reference for modelers. Researchers may add battery wear into the target function with a few tweaks to the existing model. We noted that there are considerations of battery aging for electric vehicle charging, such as formulating a battery capacity rate fading function to calculate the battery degradation cost (Wei *et al* 2018) and other semi-empirical battery degradation models based on physicochemical methods (Zhu *et al* 2019) and weighted ampere-hour models (Millner 2010). Generalizing such approaches for most optimization models would also improve the realism and validity of the ESCS from the perspectives of battery electrochemical properties.

Fourth, one of the main reasons why battery wear must be considered is the high ownership cost of batteries. Although the unit price is assumed to be reduced to half of the current level (750 SEK kWh^{-1}), battery wear is still more than twice the charging cost. In this case, operators with tight resources are also suggested to consider the whole impact of battery capacity and charging techniques on bus operations. Because a larger battery is not always the best solution for daily usage, striking a balance between charging strategy and battery capacity can further optimize operating costs.

To conclude, models that take battery wear into account can yield more cost-effective operational solutions. Emerging EBCS models have started to become more complex, so the formulation of battery wear and other important factors should be easy to develop and address.

Data availability statement

The data that support the findings of this study are available upon reasonable request from the authors.

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ORCID iDs

Ziling Zeng https://orcid.org/0000-0002-5326-1525
Xiaobo Qu https://orcid.org/0000-0003-0973-3756

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