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Review Article

Vehicle and charging scheduling of electric bus fleets: A comprehensive review

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ABSTRACT: Transit electrification has emerged as an unstoppable force, driven by the considerable environmental benefits it offers. However, the adoption of battery electric buses is still impeded by their limited flexibility, a constraint that necessitates adjustments to current bus scheduling plans. Consequently, this study aspires to offer a thorough review of articles focused on battery electric bus scheduling. Moreover, we provide a comprehensive review of 42 papers on electric bus scheduling and related studies, with a focus on the most recent developments and trends in this research domain. Despite this extensive review, our findings reveal a paucity of research that takes into account the robustness of electric bus scheduling. Furthermore, we highlight the critical areas of considering diverse charging modes in electric bus scheduling and integrated planning of electric buses, which have not been adequately explored but hold the potential to greatly boost the effectiveness of electric bus systems. Through this synthesis, we hope that readers could acquire a thorough comprehension of the studies in this field and be motivated to address the identified research gaps, thus propelling the progress of transit electrification.

KEYWORDS: electric bus, vehicle scheduling, charging scheduling, literature review, pptimization

1 Introduction

Battery electric buses (BEBs), renowned for producing zero tailpipe emissions and minimal noise pollution, have been recognized as a significant component of future sustainable transit systems (Qu et al., 2022). In recent years, governments across the global have been promoting the transition of public transit from conventional bus fleets to BEBs to reduce reliance on oil. Over the past decade, the market share of BEBs has rapidly grown, with global sales surpassing $40.1 billion in 2021, and further growth with an expected annual rate of 13.5% from 2022 to 2030 (Grand View Research, 2022). China has been at the forefront of transit electrification, with a 71% market share for new energy buses in 2021 (Fig. 1), where BEBs play a leading role in that. However,

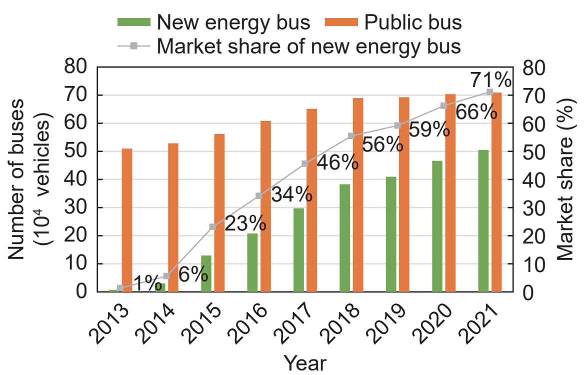

Fig. 1 Overview of public buses in China from 2013 to 2021①.

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despite their advantages, BEBs face certain drawbacks, such as the limited flexibility stemming from their shorter range and longer recharging times compared to traditional diesel buses. In Guangdong Province, China, BEBs have been experiencing frequent breakdowns during routes, further emphasizing the need for research and development in planning and scheduling electric bus fleets (Shu, 2023).

Introducing electric buses into a transit system requires decision-making across multiple levels, spanning strategic planning for the long-term, tactical planning for the short-term, and real-time operational control, as illustrated in Fig. 2 (Perumal et al., 2022)②. Effective planning across these levels is essential and indispensable to ensure the smooth and effective operations of BEBs. Strategic planning, which remains unchanged for years, involves designing the transit network and deploying the necessary charging infrastructure. Transit network design entails determining the

① The data of years 2013–2018 is from Li and Yao (2020); the data of years 2019, 2020, and 2021 is from Institute for Transportation & Development Policy (ITDP) (2020), Xinhua (2021), and Tonghuashun (2022), respectively.

② It is worth to note that our paper aims at providing a comprehensive review on electric bus scheduling. As we delve into this realm, we find that certain electric bus scheduling problems are intertwined with broader strategic planning problems (as expounded upon in Section 3.2.3) and intermingled with real-time control mechanisms (as discussed in Section 3.2.2). Consequently, Section 1 encompasses a broader scope, encompassing both long-term strategic planning and real-time operational control within the realm of electric transit decision-making.

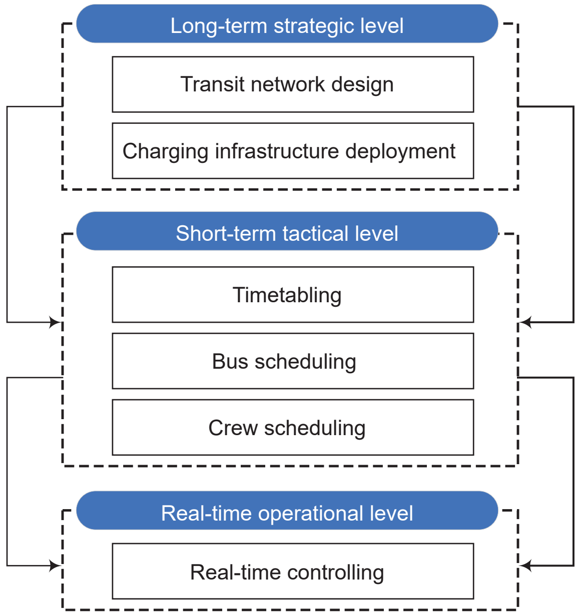

Fig. 2 Electric transit decision process.

arrangement of the transit system, such as bus line configurations, the mode of transit (e.g., local bus or express bus, bimodal or single-mode transit, ring-radial or grid transit network), and bus stop locations along each line (Tong et al., 2021b). The quintessential aim of the transit network design problem lies in the minimization of the generalized cost across the transit system, including the average agency cost per trip and average patron's travel cost. Another type of optimization problem at the long-term strategic level, denoted as the charging infrastructure deployment problem, strives to optimize the location, number, and mode of chargers at each charging station, which could include normal charging, fast charging, or battery swapping (Zeng et al., 2023; Zeng and Qu, 2023). Table 1 presents a succinct summary of the salient characteristics associated with each charging mode. In optimizing the deployment of charging infrastructure, the aim is to minimize the joint cost incurred by the construction of charging stations and the operation of BEBs, while considering the benefits and limitations of distinct charging modes.

At the tactical level, transit system decision-making involves timetabling, bus scheduling, and crew scheduling, as indicated in Fig. 2. Timetabling seeks to optimize bus service frequency and determine the most efficient departure times of buses based on anticipated passenger demand for each bus stop. The vehicle scheduling problem entails allocating buses to carry out a predetermined set of scheduled trips with the minimal possible operation cost for BEB fleets. Given the limited driving distance of BEBs, it is crucial to simultaneously consider charging needs while addressing the BEB scheduling problem (Zeng and Qu, 2023). Lastly, crew scheduling aims to establish the optimal duties of bus drivers to cover all scheduled bus trips with minimal total wages to be paid, subject to various labor union rules and regulations. These tactical-level decisions play a vital role in the effective implementation of electric bus service.

Real-life scenarios often involve uncertainty in traffic conditions and passenger demand, leading to deviations from BEB schedules. Any delay in a trip can have a cascading effect on the subsequent trips, even causing bus bunching in severe cases. Operators must therefore exert real-time control over BEBs to enhance punctuality, particularly in cases of unexpected delays. Furthermore, the original charging plan may become unfeasible due to the inaccurate estimation on energy consumption that is highly related to traffic conditions. Thus, real-time control of BEBs at the operational level can also help to prevent on-route breakdowns. The unpredictable nature of transit operations necessitates a responsive and adaptable approach to control buses, which includes real-time decision-making and agile response to changes in traffic and demand.

In this review, we aim to examine the current state of knowledge in the field of BEB scheduling on tactical level. To this end, we conduct a literature search using keywords such as "vehicle scheduling", "bus scheduling", and "electric bus", and analyze the selected articles with a focus on the modeling techniques and solution approaches used in these studies. As electric bus scheduling is often considered as part of the strategic planning problem, such as the line design and the deployment of charging infrastructure, we also review related studies in this area. Meanwhile, the electric bus scheduling problem is a special type of vehicle scheduling problem. Interestingly, many of the modelling techniques and solution approaches employed in tackling electric bus scheduling derive from their traditional diesel-powered counterparts. Recognizing this interconnectedness, we provide a concise overview of the diesel bus scheduling problem as well. Through our thorough analysis of 42 papers published in leading transportation journals, including 7 articles related to diesel bus scheduling and 35 articles on electric bus scheduling, we identify prevailing research orientations, advanced algorithms, and potential research directions. Except for a regular update of reference, our review differentiates itself from previous ones with a focus on the key setups and assumptions of reviewed studies. Specifically, we delve into crucial aspects such as the charging patterns, electricity pricing, and charging station capacities. Table 2 provides a summary of the studies that are taken into account in this paper. Our aim is to furnish readers with a comprehensive grasp of the most recent advancements and trends in this area through this study. We also hope that it will encourage researchers to address the identified research gaps, thereby hastening the development of transit electrification.

In the subsequent sections, this paper is structured as follows. The selected studies on the scheduling problem of diesel buses are reviewed in Section 2, addressing both the single-depot and multi-depot vehicle scheduling issue. Section 3 reviews the numerous

Table 1 Features of different charging modes (Xue et al., 2019)

Charging mode	Charging rate, C	Location	Advantage	Disadvantage
Normal charging	< 3C	Bus depot	Prolonging battery lifetime slight effect on electricity grid	Long recharging time requiring large battery packs
Fast charging	≥ 3C	Bus stops	Short recharging time requiring small battery packs	Accelerating battery capacity loss large effect on electricity grid
Battery swapping	< 3C	Specific spots	Short swapping time prolonging battery lifetime	Requiring a large area, high construction cost requiring a large number of batteries

Table 2 Number of papers reviewed for different types of bus scheduling

Category No.	Problem type	No. of reviewed papers	Time span (year)
1	Diesel bus scheduling problem	7	1987–2015
2	Electric bus scheduling problem	35	2013–2023

studies on the scheduling problem of BEBs with explicit consideration of BEBs' features. Lastly, Section 4 outlines forthcoming research avenues and summarizes the paper.

2 Diesel bus scheduling problem

Studies on vehicle scheduling problems began with the optimization of schedules for vehicles departing from a single depot (Freling et al., 2001; Paixão and Branco, 1987). The term used to describe this issue is the single-depot vehicle scheduling problem (SDVSP). In SDVSP, the buses start from the depot and consecutively cater to a series of trips throughout the operational period of the day. A sequence of trip services completed by a single bus is denoted as a trip chain, where the sequence of trips within a given trip chain is organized in an ascending order based on their departure time. If the ending station and starting station of two adjacent trips do not overlap, the bus may move without passengers, referred to as deadheads. The feasibility of a trip chain is determined by whether all included trips can be completed punctually. The cost of a trip chain usually comprises of a fixed cost term as well as a variable one that is correlated with the travel distance. Hence, the objective of SDVSP is to find the optimal bus-to-trip assignments with the least cost of all selected trip chains, satisfying that a set of predefined trips are served on time. Conventional SDVSP has been proven to be polynomially solvable with complexities of $O\left(n^3\right)$, where the number of trips to be covered is denoted as n. Since then, a variety of SDVSP models and specified polynomial-time algorithms have been created. These include the network flow model, transportation model, assignment model and the minimal decomposition model.

The transit operators often face the challenge of managing some vehicles departing from multiple depots, giving rise to the multi-depot vehicle scheduling problem, referred as MDVSP for short (Desaulniers et al., 1998). The MDVSP is inherently more complex than the SDVSP because it mandates that each vehicle initiates and terminates at the same depot. Notably, the complexity of MDVSP has been proven to be of the non-deterministic polynomial-time hard (NP-hard) classification (Bertossi et al., 1987). Researchers have suggested various solution methods to tackle the MDVSP, encompassing both heuristic and exact algorithms. Interested readers can find a comprehensive review of vehicle scheduling problem, including both SDVSP and MDVSP, in the works of Ibarra-Rojas et al. (2015) and Bunte and Kliewer (2009).

As demonstrated in previous studies, the multi-depot vehicle scheduling problem is often expressed as a set partitioning problem (Hadjar et al., 2006). In the subsequent sections, we will delve into the details of the set partitioning model, which would facilitate the introduction of some research on electric bus scheduling problem. We define V as the set of timetabled trips, R as the set of trip chains, and K as the set of bus depots. The formulation of the set partitioning model is presented as Eq. (1):

$$\min J = \sum\nolimits_{r\in R} c_r\lambda_r \tag{1a}$$

subject to

$$\sum\nolimits_{r\in R} A_i^r\lambda_r = 1, \forall i \in V \tag{1b}$$

$$\sum\nolimits_{r\in R} U_k^r\lambda_r \le v_k, \forall k \in K \tag{1c}$$

$$\lambda_r \in \{0,1\}, \forall r \in R \tag{1d}$$

The objective function of set partitioning model (1a) is to minimize the overall cost of the selected trip chains, where the binary variable λ_r is equal to one if trip chain $r \in R$ is chosen (i.e., served by a bus). Here, the parameter c_r indicates the cost of trip chain $r \in R$. Note that the cost components of c_r depend on the objective of studied MDVSP. It may include the operation and maintenance cost of buses. Meanwhile, the shift time between two adjacent trips can also be taken into account depending on the problem setting. Constraints (1b) ensure each scheduled trip $i \in V$ must be served once, and A_i^r is a binary parameter that equals one if and only if trip i is covered by trip chain $r \in R$. The number of vehicles departing from each depot is restrained by constraints (1c), where v_k denotes the upper bound on the number of vehicles at depot $k \in K$; U_k^r is a binary parameter that equals one if the bus serving trip chain $r \in R$ belongs to depot $k \in K$, and zero otherwise. The domain of the binary decision variables λ_r ($r \in R$) is defined in constraints (1d).

The formulation of the set partitioning model, is presented in the form of mixed-integer linear programming. However, it would become intractable for commercial solvers like CPLEX due to the vast number of feasible trip chains, even for small problems. To address this issue, column generation is commonly used. First, the models (1a)–(1d) is decomposed into a pricing subproblem as well as a restricted master problem (RMP) by relaxing the integrality constraints (1d). In RMP, only a subset of trip chains are considered, enabling commercial solvers to directly solve the RMP. The pricing subproblem generates new trip chains that can reduce the objective value of RMP and are not yet part of the RMP. The shortest path problem is formulated for the pricing subproblem of each depot. The termination of the column generation procedure occurs when there are no additional trip chains to be incorporated.

Meanwhile, in order to ensure the acquisition of viable integer solutions, it is commonplace to integrate the column generation technique into a branch-and-price methodology. To be specific, if the solution obtained by the column generation procedure is not integer, a branch-and-bound procedure is used to branch the fractional node into two child nodes in the branch-and-bound tree according to the predefined branching strategy. Then for the minimization problem, update the upper bound of the original problem and prune the node whose optimal value is no less than the newly updated upper bound. The branch-and-bound procedure terminates if there is no node can be further branched in the tree. For more details on the branch-and-price framework, readers can refer to Xu and Meng (2019) and Zhang et al. (2021a).

3 Battery electric bus scheduling problem

Our attention turns to the scheduling problem of BEBs, which represents an expansion of the conventional vehicle scheduling problem. The BEB scheduling problem is a special type of vehicle scheduling problem (VSP), where the BEBs' limited range and charging requirements are explicitly modeled. Research studies in this area may be categorized into two types, namely mixed-fleet bus scheduling problem and pure electric-fleet bus scheduling problem. The former and latter categories will be reviewed in Sections 3.1 and 3.2, respectively. Additionally, to enhance the readers' experience, we have presented a summary of the modeling features and solution approaches of selected BEB scheduling studies in Table 3.

3.1 Mixed-fleet bus scheduling problem

The gradual shift towards electrification in transit has prompted numerous studies on scheduling strategies for mixed fleets during this transitional phase. These studies typically predefine the composition of the bus fleet, comprising the quantity and categories of vehicles, thereby neglecting the optimization of fleet size. The goal is generally to minimize the overall expenses of operations as well as external emissions. Rinaldi et al. (2020) conducted a significant study on optimal scheduling problem for mixed bus fleet with a single terminal, where all trips that need to be serviced commence and end at the same terminal. To address this challenge, the researchers created a mixed-integer linear program combined with a customized decomposition scheme to decrease the model's intricacy. The efficiency of the proposed approach was then tested in two case studies from Luxembourg city. It was verified that the implementation of this solution could significantly contribute to the development of innovative decision-making systems aimed at supporting policymakers in addressing the ongoing transition from traditional bus fleets to more environmentally friendly ones. Another study by Zhou et al. (2020) extended this research by considering multiple terminals in the transit network and explicitly accounting for deadheading trips between different terminals in vehicle scheduling. A bi-level programming approach was utilized in this study, where the charging strategy and service scheduling were optimized on the lower and upper levels, respectively.

In contrast to the aforementioned problems, Li et al. (2018) jointly optimized fleet size and composition while considering budgetary constraints. To address this mixed fleet management problem, the researchers suggested a new method named the new life additional benefit-cost analysis. Similarly, Pelletier et al. (2019) presented a problem regarding the transition of diesel buses towards electric buses subject to budget constraint, with the objective of establishing replacement plans for transport companies that were cost-effective and helped meet their electrification goals. This review elucidated a progressive plan to substitute the existing bus fleet with a purely electric one, highlighting the crucial role of proper fleet management in the transition towards electrification.

3.2 Electric-fleet bus scheduling problem

The optimization of electric-fleet bus scheduling can be classified into three types, depending on the decisions made. The first type focuses solely on optimizing charging scheduling, while service scheduling for BEBs is predetermined or ignored (Ding et al., 2022; Liu et al., 2022; Zhang et al., 2021c; Zheng et al., 2023). Usually, the optimization of the charging strategy aims to minimize the overall charging cost and/or the cost brought by battery capacity fading, while fully considering charging station

Table 3 Selected studies on BEB scheduling optimization

Ref.	Problem type	Objective	Charging mode	Problem feature	Solution approach
Li (2014)	SDVSP	Minimize total operating cost	Battery swapping, Plug-in charging	Full charging, Limited chargers	Branch-and-price
Wang et al. (2017)	SDVSP	Minimize total operating cost	Plug-in charging	Fixed charging time, Limited chargers	CPLEX
Yang et al. (2018)	Single bus line	Minimize charging cost	Wireless charging	Partial charging, Time-of-use Electricity price	Two-step heuristic method
Tang et al. (2019)	SDVSP	Minimize total operating cost	Battery swapping, Plug-in charging	Full charging, Limited chargers	Branch-and-price
Rinaldi et al. (2020)	SDVSP	Minimize total operating cost	Plug-in charging	Full charging, Limited chargers	Time-based decomposition method
Liu and Ceder (2020)	MDVSP	Minimize fleet size and number of chargers	Plug-in charging	Partial charging, Limited charges	Heuristic method
He et al. (2020)	SDVSP	Minimize charging cost	Plug-in charging	Partial charging, Time-of-use, Electricity price	Solver CPLEX
Zhang et al. (2021a)	SDVSP	Minimize total operating cost	Plug-in charging	Full charging, Limited chargers, Battery management, Non-linear charging profile	Branch-and-price
Yıldırım and Yıldız (2021)	MDVSP	Minimize total operating cost	Plug-in charging, Wireless charging	Partial charging	Dynamic programming
Zeng et al. (2022)	SDVSP	Minimize total charging cost and wear cost	Plug-in charging	Partial charging, Battery management, Time-of-use electricity price	Solver GAMS
Zhou et al. (2022)	Single bus line	Minimize total operating cost	Plug-in charging	Partial charging, Battery management, Non-linear charging profile	Linearization and approximation techniques
Brinkel et al. (2023)	MDVSP	Minimize total charging cost	Plug-in charging	Partial charging, Time-of-use Electricity price	Simulation
Xie et al. (2023)	Single bus line	Minimize total operating cost and driver salary	Plug-in charging, Battery swapping	Partial charging Multiple charging modes	Two-stage solution algorithm

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capacity, time-varying electricity prices, and/or battery capacity fading mechanisms. The second type involves the joint optimization of charging and vehicle scheduling (Li, 2014; Zhang, et al., 2021a). In this problem, bus-to-trip assignments are optimized to achieve the minimal operating cost, with explicit consideration of the BEBs' charging requirements simultaneously. The third type is the integrated electric bus planning, which incorporates BEB scheduling into other high-level planning problems, such as the deployment of charging infrastructure and line planning (An, 2020; He et al., 2023; Liu et al., 2023a, 2023b). This type of planning takes a holistic approach to address electric bus scheduling problems and considers the interdependence of various planning factors. Subsequently, we shall delve into a detailed review of the three types of studies, one by one, as presented in Sections 3.2.1–3.2.3 respectively.

3.2.1 Solely optimizing charging schedule

Regarding studies that solely optimize charging scheduling, one remarkable paper by He et al. (2020) addressed the optimal schedules of BEBs' charging activities under fast charging mode, with the aim of minimizing the overall charging expenses. This research considered a partial charging policy and varying electricity prices over time to ensure the economic advantage of BEBs, given that on-route fast charging during on-peak periods may lead to an increase in electricity energy charges. The cost of charging a BEB depends greatly on the charging time since the unit price of electricity varies largely over the time. It is worth noting that the price charged during peak-demand periods can be 3–4 times that in off-peak periods. Meanwhile, the increasingly popular electric vehicles impose an ever-growing load pressure on the power grid. Without efficient coordination, the electric vehicles' charging activities may largely overlap with the peak periods of the daily load curve. To address this issue, the authors proposed a nonlinear nonconvex programming model that determined the optimal charging schedules and charging power. The model was then linearized using discretization techniques, making it easily solvable by commercial solvers. A real-world case study was used to demonstrate the proposed model. Results shown that by carefully modelling the charging decision process, the total charging cost could be reduced by up to 47.8%, from 767.0 to 400.6. It is important to note that, the model disregards charging station capacity and BEB-to-trip assignment for the sake of simplicity. Similarly, Liu et al. (2022) developed a model to optimize the charging schedules of BEBs with explicit consideration the variation of electricity tariffs over the time. Meanwhile, the stochasticity in travel time is also considered in their model, thereby enhancing the practicality and efficacy of their recommended charging plans. Later, studies in the area are further improved by He et al. (2023). They made a significant contribution by creating an estimation method that provides highly accurate energy consumption values, enabling a more realistic optimization of the charging strategy.

Besides the time-of-use electricity price, battery management is another nonnegligible factor in optimizing the charging plans of BEBs (Guillot et al., 2022; Tong et al., 2021a). Managing batteries is crucial in BEB scheduling and management. Usually, the initial investment required for BEBs is higher than that for conventional diesel buses due to the significant cost associated with the battery packs. Furthermore, the capacity of batteries in BEBs typically reduces over time as a result of charge and discharge cycling, leading to a decline in battery performance (Zhang et al., 2019). Reaching the end of life is a common occurrence when the battery' s capacity has fallen by 20%–30% of the initial value. Hence, the BEBs' batteries need be replaced periodically. A simple summarization of studies on battery capacity fading mechanism is presented in Table 4. To address the issue, Zhang et al. (2021b) proffered an innovative approach to electric fleet management, one that takes into account the real-world phenomenon of battery capacity loss stemming from the recurring charge and discharge cycling over the extended period. The researchers' empirical inquiry uncovered that adopting a battery state-of-charge regime that hovers within a low and tightly defined threshold can afford a lifespan extension of up to three years and a sizeable reduction in the overall cost of running an electric bus fleet, amounting to 24.7%.

3.2.2 Jointly optimizing charging and vehicle schedule

Joint optimization of vehicle and charging scheduling for electric transit systems constitutes a complex task with multiple dimensions, but it is ultimately more cost-effective and comprehensive than sole optimization of charging scheduling. Notwithstanding its concomitant complexities, most studies in the field of BEB scheduling focus on the combined optimization of charging and vehicle scheduling. One notable example is the work by Li (2014). This paper examined the optimal service and charging scheduling of BEBs from a single depot with a fixed charging time, which can be applied to fast charging and battery swapping. Its goal is to minimize the operational expense while adhering to a given set of trips. The approach started with the construction of a directed multigraph that represented each trip as a node in the graph, along with trip starting and ending times, as well as distance. Meanwhile, the charging station was also represented by a node in the graph, associated with station capacity. A discretization approach was used to convert the capacity constraint into a set of discrete nodes known as "the time-expanded nodes", and arcs were generated that satisfied the maximum travel range constraint. The problem was formulated using an arc-based approach, which can be solved using a

Table 4 Selected studies on battery capacity fading mechanism

Ref.	Influence factor	Aging type	Battery type	Model output
Hoke et al. (2011)	Depth of discharge, state of charge, temperature, time	Cycle aging, Calendar aging	$Li(NiCoAl)O_2$	Cots brought by battery capacity loss
Lam and Bauer (2013)	State of charge, current rate, temperature	Cycle aging	$LiFePO_4$	Remaining battery capacity
Omar et al. (2014)	Depth of discharge, current rate, temperature	Cycle aging	$LiFePO_4$	Remaining cycle number
Sarasketa et al. (2014)	State of charge, temperature, time	Calendar aging	$LiFePO_4$	Remaining battery capacity
Zhang et al. (2019)	Depth of discharge state of charge	Cycle aging	$Li(NiCoAl)O_2$	Remaining battery capacity

commercial solver. Additionally, the problem was reformulated as a set partitioning model (see that in Section 2), where the maximum travel range constraint was considered in the pricing subproblem when newly generating feasible trip chains. To be specific, the cost of trip chain c_r included fixed vehicle maintenance, travel and deadheading costs, and charging and waiting costs at the charging station. In addition to the existing constraints (1b)–(1d), a capacity constraint for the charging station was incorporated to guarantee the number of charging facilities being utilized is within the station's capacity at any given time. To solve the model, the authors also designed a customized column generation algorithm. In this algorithm, a multi-label correcting method was used to identify trip chains that had the least cost while meeting the maximum travel range constraint in the pricing subproblem. The study's numerical experiments confirmed that the column-generation-based approach outperformed the commercial solver by a significant margin.

In the realm of BEB scheduling, recent studies have broadened the scope of research by incorporating realistic operating features, such as battery degradation (Zhang et al., 2021b; Zeng et al., 2022; Zhou et al., 2022), the time-varying electricity tariffs (He et al., 2022; Yang et al., 2018; Zeng et al., 2022), nonlinear-charging profiles (Zhang et al., 2021a; Zhou et al., 2022), partial charging policies (Liu and (Avi) Ceder, 2020; Zhou et al., 2022), and limited charger availability (Wang et al., 2017). We now highlight some selected studies that embody the innovative approaches and noteworthy discoveries in this field. Regarding battery management, Zhang et al. (2021a) aimed at minimizing the overall operational cost of BEB fleet by determining the bus service and charging plans, while simultaneously incorporating the expense incurred by battery degradation. The problem was formulated as a set partitioning model (see that in Section 2), where the unique features of battery capacity loss were considered in the pricing subproblem. Within their model, the evaluation of the trip chain c_r was subject to the inclusion of a fixed cost term pertaining to the acquisition and maintenance of the vehicle, the expenditure associated with charging, and the expenses incurred as a result of battery capacity loss. The objective function also considered the vehicle acquisition cost term, enabling the optimization of the fleet size of the BEB fleet. The findings of this review indicated that integrating battery health factors into the BEB scheduling model can result in cost savings of 10.1%–27.3% and extend battery lifespan by an additional 47.2%–96.1%. In a subsequent scholarly contribution, Zhou et al. (2022) imbued the research with greater nuance by explicitly taking into account a partial charging policy. Employing a mixed-integer nonlinear programming model, the authors advanced a sophisticated framework for the studied problem and leveraged linearization and approximation techniques to arrive at a global solution. This work demonstrated the considerable influence of both battery size and initial state of charge of BEBs on the overall cost of the transit system.

Apart from battery capacity loss, the time-of-use electricity price is also a crucial factor in BEB scheduling as we previous explained in Section 3.2.1. To this end, Yang et al. (2018) modeled the time-varying electricity scheme carefully in the BEB scheduling optimization framework, ensuring that BEBs were directed to charge during off-peak periods to achieve a cost-effective and grid-friendly BEB schedule. Brinkel et al. (2023) conceived an innovative framework aimed at scrutinizing the pecuniary implications and power grid repercussions of various charging strategies. According to Brinkel et al. (2023), using only the charging-on-arrival strategy for BEBs would cause high demand peaks for charging, while the mitigation of these peaks can be achieved by adopting day-ahead charging strategies.

In the context of BEB scheduling, stochastic traffic condition is another factor that cannot be ignored. Bie et al. (2021) tackled this challenge by incorporating the stochastic volatilities in trip travel time and energy consumption in BEB scheduling. They included the expectation of delays in trip departure time in their objective function to enhance the on-time performance. In addition to the conventional static scheduling framework, researchers have also sought to investigate the dynamic scheduling of BEBs to address the model uncertainty. In particular, Tang et al. (2019), introduced a novel scheduling approach for BEBs under fast-charging mode that accounted for stochastic traffic conditions. The proposed strategy involved a combination of static and dynamic scheduling plans. To be specific, the static scheduling plan was optimized by incorporating a buffer distance into the vehicle scheduling model to handle the variability in trip time and energy consumption. The dynamic scheduling stage adjusted the plan obtained in the static stage periodically based on the current traffic conditions. Both the static and dynamic models were shown to be NP-hard. The authors reformulated the models into path-based forms and developed a specialized branch-and-price framework to address them. The proposed scheduling strategies were demonstrated through numerical cases based on a 15-day dataset extracted from the automatic vehicle location system in Beijing. The Results shown that as the buffer distance increase, the scheduled cost and fleet size increased as well. However, the realized total costs obtained through simulations did not necessarily rise as the breakdown rate significantly decreased. Therefore, the robust scheduling strategy proposed in this paper could reduce the on-route breakdown rate while maintaining the economic attractiveness of BEBs.

In spite of the extensive research on BEB scheduling, the studies on dynamic scheduling and the corresponding recovery strategies are very limited. Moreover, these studies usually rely on oversimplified assumptions. For example, Tang et al. (2019) neglected the time-varying electricity price. This would incur additional recharging costs and exert high load pressure on the power grid, given that the fast charging mode was considered in Tang et al. (2019). Consequently, the further advancement of dynamic scheduling and recovery policy of BEBs could be a promising area for future research.

3.2.3 Integrated electric bus planning

The optimization of BEB scheduling has been a topic of interest within the broader fleet management and charging infrastructure planning problems, as demonstrated by recent studies (An, 2020; Li et al., 2018; Wang et al., 2017; Xu et al., 2018, 2023; Zhang et al., 2022; Zhou et al., 2023). In particular, a mixed-integer linear programming technique was presented by Wang et al. (2017) to optimize the charging schedule of BEBs and to determine the ideal capacity and location of fast charging stations in a transit network with a single depot. Their aim was to minimize the overall operating cost of the transit system, which encompassed the BEBs' travel, charging, and waiting expenses, as well as the cost of constructing charging stations. The model assumed that the recharging duration was fixed and that the amount of energy recharged was a linear function of the recharging time. To simplify the optimization model, the BEB-to-trip assignment was predefined. The CPLEX solver was used to solve the model, and a case study was conducted in Davis, California, using the transit network to demonstrate the model's effectiveness. The Results shown that the replacement of diesel buses with BEBs could save about $500,000 in total social costs and $1,300,000 in travel costs. These findings offer further evidence that BEBs are a more cost-effective and environmentally friendly option compared to diesel buses. In a more recent study by An (2020), a more realistic formulation was adopted. A stochastic integer program was developed in this study to optimize the fleet size as well as the charging station locations, taking into account time-varying electricity tariffs and random bus recharging demand. Then, the model developed in this study was applied to the south–east region of Melbourne, Australia to demonstrate its practical use. The results showed that the adoption of fast charging could diminish the fleet size, as BEBs can be charged in a shorter time using chargers with high charging power. Zhang et al. (2022) formulated the integrated electric bus planning problem as a bi-level model, where the lower level model is to optimize the vehicle scheduling based upon given design of charging stations, see Eq. (2). The notations $\boldsymbol{\Phi}$ and $\boldsymbol{\Gamma}$ denote the set of decision variables on the tactical (i.e., lower) level and strategic (i.e., upper) level respectively. The upper level model aims at optimizing the design of charging station to minimize the total system cost, see Eq. (3). The system cost includes the construction cost of charging station, denoted as $f_{\text{upper}}(\boldsymbol{\Gamma})$, and the optimal operational cost optimized by model (2), denoted as $f^{*}_{\text{lower}}(\boldsymbol{\Phi}^{*}|\boldsymbol{\Gamma})$.

Lower-level problem: Optimal scheduling of BEB fleet

$$\min_{\boldsymbol{\Phi}} f_{\text{lower}}(\boldsymbol{\Phi}|\boldsymbol{\Gamma}) \tag{2}$$

subject to: constraints on tactical level.

Upper-level problem: Optimal design of charging station

$$\min_{\boldsymbol{\Gamma}} f(\boldsymbol{\Gamma}) = f_{\text{upper}}(\boldsymbol{\Gamma}) + f^{*}_{\text{lower}}(\boldsymbol{\Phi}^{*}|\boldsymbol{\Gamma}) \tag{3}$$

subject to: constraints on strategic level.

In the annals of prior research, BEB scheduling conundrum has also been inextricably intertwined with bus timetable problem. A pertinent case in point is offered by Xu et al. (2023), whose innovative study on the integrated electric bus timetabling and scheduling conundrums involved deploying a multi-commodity network flow mode that was seamlessly embedded into a time–space network-based framework. To navigate this complex model, a Lagrangian relaxation heuristic was deftly crafted. Impressively, the experimental results obtained from this study showed that the profit of electric transit system could be fortuitously augmented by anywhere from 5.29% to 20.28% via the proposed integrated method.

Currently, most studies on integrated electric bus scheduling only consider one type of strategic planning problem. Nevertheless, it is undeniable that integrating multiple planning problems in BEB scheduling could enhance the efficiency of BEB systems, given their interdependent nature. Of course, this may result in additional computational complexity, which could be the reason for the paucity of related studies. On the other hand, it is noteworthy that the integrated planning problem has been studied under over-simplified assumptions or heuristic solution approaches. For instance, Wang et al. (2017) and An (2020) predefine the BEB-to-trip assignment, while Xu et al. (2023) rely on a heuristic algorithm. To enhance the performance of the integrated planning problem that has been studied, it is crucial to alleviate the simplified assumptions or devise precise solution algorithms. However, achieving this goal demands more sophisticated modeling techniques and solution approaches.

4 Conclusions and discussions

In this paper, we offer an exhaustive review of the current state of electric bus scheduling, with a specific focus on cutting-edge advancements and emerging trends in this field. The literature on BEB scheduling reviewed here can be broadly classified into two categories: mixed-fleet bus scheduling and electric-fleet bus scheduling, the former of which deals with the gradual shift towards full electrification while the latter deals with complete electrification. We briefly discussed the development of the BEB scheduling literature and the unique features of their solution approach. We find that prior research on BEB scheduling tends to simplify the model by ignoring some crucial operational features, such as battery capacity loss, time-of-use electricity pricing, and partial charging policies. In subsequent studies, we see a growing trend toward considering more realistic operational features in BEB scheduling models, utilizing more advanced modeling techniques and solution methods.

However, despite the ever-growing body of research papers in this field, a research gap in BEB scheduling still exists. After reviewing existing studies, we have identified the following research gaps:

1) There is a significant lack of research that takes into account the robustness of BEB scheduling. The operation of BEBs can be affected by unexpected uncertainties that may cause deviations from the scheduled plan. Current studies tend to use simplified assumptions, which may not accurately reflect the real-world environment and could impact the effectiveness of proposed strategies. To address this, future research should focus on developing dynamic scheduling techniques and the corresponding recovery strategies to support the practical application of BEBs (Han et al., 2023) .

2) Existing research neglects the optimization of charging modes for BEBs. Each charging mode has its own unique advantages and disadvantages, and with the growth of charging infrastructure, there will be more options available. Integrating the selection of charging modes into BEB scheduling presents a promising area for future research.

3) In the realm of electric bus systems, integrated planning is a pivotal yet under-researched area. This involves tackling multiple planning challenges simultaneously, resulting in higher computational complexity. Nevertheless, it is imperative for researchers to address this challenge head-on to further boost the effectiveness and efficiency of BEB systems. Meanwhile, further extensions also involve the scheduling of BEBs considering some social and physical features (Chen et al., 2022; Gan et al., 2022).

Replication and data sharing

The related data can be found at https://doi.org/10.26599/ETSD.2023.9190017.

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Declaration of competing interest

The authors have no competing interests to declare that are relevant to the content of this article.

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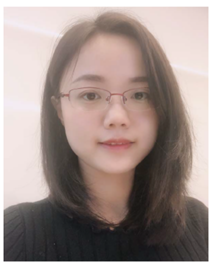

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