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Lifecycle Cost Optimization for Electric Bus Systems With Different Charging Methods: Collaborative Optimization of Infrastructure Procurement and Fleet Scheduling

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***Abstract*— Battery electric buses (BEBs) have been regarded as effective options for sustainable mobility while their promotion is highly affected by the total cost associated with their entire life cycle from the perspective of urban transit agencies. In this research, we develop a collaborative optimization model for the lifecycle cost of BEB system, considering both overnight and opportunity charging methods. This model aims to jointly optimize the initial capital cost and use-phase operating cost by synchronously planning the infrastructure procurement and fleet scheduling. In particular, several practical factors, such as charging pattern effect, battery downsizing benefits, and time-of-use dynamic electricity price, are considered to improve the applicability of the model. A hybrid heuristic based on the tabu search and immune genetic algorithm is customized to effectively solve the model that is reformulated as the bi-level optimization problem. A numerical case study is presented to demonstrate the model and solution method. The results indicate that the proposed optimization model can help to reduce the lifecycle cost by 7.77% and 6.64% for overnight and opportunity charging systems, respectively, compared to the conventional management strategy. Additionally, a series of simulations for sensitivity analysis are conducted to further evaluate the key parameters and compare their respective life cycle performance. The policy implications for BEB promotion are also discussed.**

***Index Terms*— Battery electric buses, public transit systems, lifecycle cost optimization, collaborative optimization, hybrid heuristic.**

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I. Introduction

ELECTRIFICATION of city bus systems is becoming a widespread policy choice to mitigate climate change and promote sustainable mobility in the field of urban transportation [1], [2], [3]. As one of the major types of electric buses, battery electric buses (BEBs) have attracted significant attention owing to their environmental benefits, such as, zero tailpipe emission [4]. In contrast to conventional diesel-powered buses, BEBs are powered solely by rechargeable batteries and are able to further reduce system-level emissions as renewable energy sources are introduced. Therefore, the promotion of BEB adoption has significance in the future of public transit systems. During the past decades, thanks to the ground-breaking technological improvements and rapid market-share growths for BEBs, there is an increasing trend to replace diesel buses with BEBs in many cities [5]. However, the promotion of BEBs in public transit systems is highly affected by the total cost associated with their entire life cycle from the perspective of urban transit agencies. For a BEB system, the lifecycle cost mainly comprises the initial capital cost and operating cost during the use phase. In addition, the charging methods also have significant impacts on the lifecycle cost of BEB systems. In general, two primary charging methods are implemented in BEB systems, including overnight charging and opportunity charging [6]. The overnight charging refers to charging during non-operational periods in the nighttime, and the BEBs are charged when parking at the terminal. By contrast, the opportunity charging refers to charging during the service operation, and the BEBs are usually charged on the bus stops with chargers [7]. These two different charging methods would contribute to considerable differences in terms of the lifecycle cost, for both initial capital and operating costs. For example, the opportunity charging often needs the charger with relatively higher charging power (i.e. fast charger) to charge BEBs during operation, which is much more expensive than that utilized for overnight charging (i.e. slow charger). Whereas, the on-board battery size with opportunity charging is relatively smaller in comparison to the ones with overnight charging, which would reduce the unit battery cost as well as the energy consumption rate owing to lightweighting benefits of battery downsizing [8]. Moreover, the transit system usually has several routes that need to be served. Different routes may exert different workloads on a bus fleet, and thus results in differences in the battery life spans [9]. As the battery reaches its end-of-life, it should be replaced with a new one and the operating cost is increased as consequence. Rationally scheduling the bus fleets to operate on certain routes has the potential ability to minimize the investment for battery replacements over the whole life of BEBs and thus reduce the lifecycle cost. In view of the characteristics of the lifecycle cost for BEB systems, a comprehensive optimization framework for the lifecycle cost is in dire need, which should consider both infrastructure procurement and fleet scheduling with different charging methods.

Over the years, efforts towards the lifecycle cost in terms of transportation electrification have attracted more attention from both the industrial and academic communities [10]. Several studies have discussed the lifecycle cost of electric vehicles (EVs) based on different analytical frameworks and EV models [11], [12], [13], [14], [15]. However, most of the existing literature is focusing on the lifecycle cost analysis for passenger EVs from the standpoint of individual drivers. There exist significant differences in the lifecycle cost between passenger EVs and BEBs. Compared to passenger EVs, for instance, BEBs generally have larger batteries, which further contributes to considerable additional weight and related energy consumption rate. Considering the features of BEBs, Cooney et al. [16] carried out the lifecycle assessment study to compare the environmental impacts of BEBs with diesel buses. Lajunen [17] further presented a lifecycle analysis of electric city buses based on extensive simulations in fleet operation, and the results showed that the energy efficiency of city buses can be improved by electrification. Nevertheless, solely focusing on the energy and environmental benefits has a limited attraction to public transit agencies, because the lifecycle cost for BEB system investment derives from more economic burdens, i.e. infrastructure procurement. Considering the purchase costs correspond to the initial cost of buses, Lajunen and Lipman [6] proposed the simulation models to assess the lifecycle cost for the transit systems with BEBs and other types of city buses. The results indicated that the bus purchase cost has significant impacts on the lifecycle cost for BEB systems. To investigate the effects of charger deployment on lifecycle cost, Bi et al. [18] provided an optimization framework to evaluate the system-level costs for BEB systems with opportunity charging, where the energy consumption reduction benefiting from battery downsizing was also discussed. Moreover, Bi et al. [19] developed an integrated lifecycle assessment and lifecycle cost model based on a bus system simulation. The objective considered both capital and energy costs, which also evaluated the lifecycle costs for BEB systems utilizing either overnight or opportunity charging. Lajunen [20] presented a lifecycle cost analysis for a fleet of BEBs based on a specific simulation tool. The results showed that high battery capacity is crucial for the overnight charging buses, whereas the opportunity charging buses can accept the batteries with relatively low capacity. The costs associated with infrastructure procurement, including purchase costs of buses and charging devices, have considerable impacts on the lifecycle cost of BEB systems. However, in the previous studies, the lifecycle cost analysis is mainly based on the basic consideration that the BEB fleets operate in the fixed routes, and thus the influences of fleet scheduling are usually ignored. As a matter of fact, when different BEB fleets operate on different routes, the daily workloads of the BEBs are different, which further leads to different battery degradation speed. Therefore, the scheduling of BEB fleets should be considered to extend the battery life span, and thus reduce the related operating costs for battery replacement over the whole life cycle.

For the scheduling of BEB fleets, several works have been done to establish the optimization methods to ensure cost-effective operations [21], [22], [23], [24], [25]. However, most of existing studies have been focused on the BEB fleet scheduling at the daily operational level, instead of the whole life cycle perspective. Since the battery degradation is a cumulative process, it is hard to effectively involve the influence of battery fading on the lifecycle costs into the daily operational frameworks. In order to explore the effects of battery degradation process on the lifecycle costs of BEB fleets, Zhang et al. [26] developed a long-term fleet management framework that considers the practical battery fading mechanism within predefined charging and discharge cycling. Furthermore, Wang et al. [9] proposed an optimization model for BEB fleet scheduling based on dynamic programming. The objective of the model was to minimize the battery replacement costs during the entire service life of the BEB fleets. The research results implied that the number of battery replacement over the entire life cycle can be reduced through the optimal scheduling for BEB fleets. Note that, whilst the aforementioned works have shown some achievements in the scheduling of BEB fleets for lifecycle optimization, there are still several challenges need to be overcame. Firstly, the previous studies only discuss the fleet scheduling with overnight charging while ignore the influences of opportunity charging on the lifecycle costs. BEB systems with different charging methods would result in different infrastructure procurement, energy consumption, and related fleet scheduling strategies. Secondly, the impacts of bus fleet size on the workload sustained by a single BEB and related battery fading behavior are not considered in the literature. That is, the number of round-trips that a BEB needs to operate would be affected by the number of vehicles in the bus fleet, which further exerts influences on the life span of the batteries equipped in BEBs. Finally, the existing studies neglected the effects of charging patterns on the battery fading rate, which also have significant impacts on the battery degradation and related costs during the fleet scheduling. The fast-charging pattern would accelerate the battery aging process, while the slow-charging pattern has a quite limited impact on the battery fading [27].

Overall, even though the aforementioned studies have made achievements in the lifecycle cost optimization of BEB systems, there are still some limitations that are summarized from two perspectives: from the perspective of optimization objective, the previous studies often focused on individual or partial cost components, whereas the comprehensive consideration for both initial capital cost and use-phase operating cost received little discussion; from the perspective of problem scenario, the existing studies mainly considered the case for overnight charging and often neglected the influences of several realistic factors on the lifecycle costs. In response to the research gaps, we attempt to advance the research frontier by developing a more comprehensive optimization framework considering the lifecycle cost of BEB systems. The major objective of this work is to optimize the total cost of BEB systems with different charging methods over a given planning horizon (i.e. the whole service life of the BEBs). We achieve this by investigating the collaborative optimization of infrastructure procurement and fleet scheduling with consideration of the realistic systems with overnight and opportunity charging methods, respectively. Collaborative optimization is a multidisciplinary design architecture that is well-suited to the collaborative problem with two interrelated objectives, and able to ensure that the corresponding schemes can match each other [28]. The factors from real-world scenarios are further considered in the problem, which has considerable effects on the lifecycle cost and can improve the applicability of the optimization results. Some managerial insights are discussed in detail based on the optimization results. To the best of our knowledge, this is the first time that the lifecycle costs of BEB systems with different charging methods are explored by the collaborative optimization of infrastructure procurement and fleet scheduling. Indeed, as regard to the lifecycle cost of BEB systems, it is necessary to deal with the infrastructure procurement and fleet scheduling at the same time, and the reasons primarily lie in the following two points. On the one hand, both the infrastructure procurement and fleet scheduling have significant effects on the lifecycle cost for BEB systems, which respectively contribute to the initial capital cost and use-phase operating cost over the entire life cycle. Ignoring any of them cannot obtain the accurate results for lifecycle cost optimization. On the other hand, there is a close interaction between the infrastructure procurement and fleet scheduling when determining the optimal lifecycle cost for BEB systems, where the strategy of infrastructure procurement directly affects the scheduling of BEB fleets, while the latter can provide guidance to the former. The proposed methods may be used by public transit agencies and related stakeholders to construct and manage the BEB-based urban transit systems in the decision-making process.

To be specific, the contributions of this study are summarized as follows. Firstly, a collaborative optimization framework is constructed for the lifecycle cost of BEB systems with overnight and opportunity charging methods, respectively. Both the infrastructure procurement and bus fleet scheduling are incorporated in the optimization framework, where the former has a significant impact on the latter and further affects the total costs over the whole service life, including both the initial capital cost and use-phase operating cost. Compared to the existing studies that only discuss the lifecycle costs under the situation that the BEB fleet operates in the fixed route, this work further considers the scheduling for BEB fleets to minimize charging cost and battery replacement cost over the whole service life of the BEBs. Meanwhile, the realistic factors from several aspects, such as battery aging mechanism, battery downsizing benefits, and time-of-use electricity price, are considered to improve the performance and applicability of the proposed model in real-world scenarios. Secondly, with full consideration of the model's complexity and unique characteristics, a hybrid heuristic-based algorithm is designed to search for the optimal solution, which consists of a tabu search (TS) framework and an immune genetic algorithm (IGA). Coordinating with the solution method, the original model is reformulated as a bi-level optimization problem, where the outer-level objective aims at the infrastructure procurement planning and the inner-level one responds to the BEB fleet scheduling. Finally, based on the proposed model and algorithm, a number of managerial insights that stemmed from the numerical case study are discussed. Further sensitivity analysis evaluates the individual contribution of key parameters to the optimal results and compares their respective life cycle performance between different charging systems. Moreover, compared to the existing formulations in previous literature, the proposed model simultaneously optimizes the BEB purchase cost, procurement cost of charging devices, charging cost and battery replacement cost over the whole planning horizon. The model is the combination of static and dynamic optimization problems, and several realistic factors are also considered in the constraints of the model.

The rest of this paper is organized as follows. Section II presents the problem description. The collaborative optimization model for the lifecycle cost of BEB system is built-in Section III. Section IV elaborates the hybrid TS-IGA method coupled with related model transformation for solving the problem. The numerical case study and simulations are furnished in Section V. Conclusions and policy implications are discussed in Section VI.

II. Problem Description

In this work, we consider a case in which a public transit agency intends to build an urban transit system with a certain number of BEB fleets to serve the same number of routes. The operator optimizes the infrastructure procurement and fleet scheduling to minimize the lifecycle cost of a BEB system while satisfying the predefined timetable for each route. Specifically, planning of infrastructure procurement refers to the purchase strategy of BEBs and matched charging devices, which contributes to the initial capital cost. Afterward, scheduling for the BEB fleets would be performed to determine the optimal matches between the BEB fleets and routes to minimize the operating cost during the use phase, including charging cost and battery replacement cost over the whole service life of the BEBs. It is noted that the fleet scheduling involved in this study is a dynamic programming and different from the fleet scheduling at the daily operational level, where the former aims to assign a certain number of bus fleets to serve the same number of routes while the latter usually determines the trip chains served by different buses [24]. Notably, we consider that the BEB fleets are fixed and do not involve the mixing of buses between fleets. Such a consideration ensures that the batteries equipped in a specific bus fleet will have the same utilization plan and thus result in

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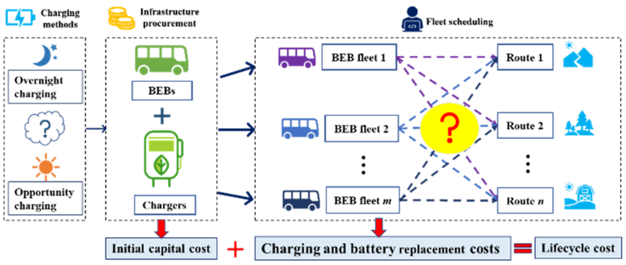

Fig. 1. Outline of the lifecycle cost optimization for a BEB system.

the similar aging condition over their service lives. This will not only improve the cost saving for BEB fleet management, but also help the operator efficiently manage the batteries in batches. Similar consideration has been discussed in a number of existing studies in fleet management at long-term operational level to achieve maximum cost saving [26], [29]. Moreover, two charging methods, i.e. overnight charging and opportunity charging, could be selected to charge the BEBs, and the system with different charging methods would result in significant differences in the lifecycle cost. Note that, in order to better compare the difference in lifecycle cost between overnight and opportunity charging systems, this study considers the case that an urban transit system can only select one kind of charging method, and the hybrid strategy where BEBs are charged partially by overnight charging and partially by opportunity charging is not discussed. The charging strategy with one kind of charging method, i.e. overnight or opportunity charging method, has been world-widely applied in several cities and discussed in related literature [20]. The outline of the lifecycle cost optimization for a BEB system is illustrated in Fig. 1.

To explicitly elaborate a BEB lifecycle optimization problem, several essential factors involved in BEB systems with different charging methods should be fully considered and will be covered in this section, including the energy consumption, minimum BEB fleet size, number of charging devices, and battery life span. For simplicity of problem description, we assume the existence of n routes that need to be satisfied in an urban transit system ($j = 1, \ldots, n$), and accordingly, the same number of BEB fleets, denoted as m, which should be formed to serve the routes ($i = 1, \ldots, m$; $m = n$). The notations used throughout this study are summarized in Table I.

A. Energy Consumption

Different charging methods considered in this study would lead to a capacity difference in the battery pack. Specifically, the battery capacity for the BEB operating in an opportunity charging system is often smaller than the ones in an overnight charging system. This is because the opportunity charging method provides frequent charging opportunities at major bus stops during operation hours, and thus a battery pack with a relatively small capacity can be used, compared with the

TABLE I
LIST OF NOTATIONS

Subscripts	
i	Index of the BEB fleet
j	Index of the routes
t	Index of the scheduled periods
Parameters	
T	Service life of BEBs
θ	Nominal capacity of battery without instruction of charging method
θ^{ON}	Nominal capacity of battery used for overnight charging method
θ^{OP}	Nominal capacity of battery used for opportunity charging method
τ_j^{in}	Operation interval for the timetable of route j
τ_j^{br}	Travel duration of a round-trip on route j
τ_j^{do}	Daily total duration for the timetable of route j
ECR	Adjusted energy consumption rate
ECR_{base}	Base energy consumption rate of the reference BEB
W_{base}^{bat}	Base battery weight of the reference BEB
W_{base}^{bus}	Base bus weight of the reference BEB
ρ	Battery specific energy
E_j	Energy consumption for a round-trip of route j
l_j	Driving distance of a round-trip of route j
λ_j	Probability of charging availability for route j
β	Usable state-of-charge range for the capacity of battery
σ	Adjustment coefficient for battery capacity considering the battery fading behavior
P	Charging power of the chargers in BEB system
μ	Overlapping coefficient for route network
D	Total days for the operation of BEB in a year
τ^{ch}	Charging time at bus stop
$NumB_j$	Minimum required number of BEBs for route j without instruction of charging method
$NumB_j^{ON}$	Minimum required number of BEBs for route j under overnight charging method
$NumB_j^{OP}$	Minimum required number of BEBs for route j under opportunity charging method
$NumC$	Required number of chargers without instruction of charging method (for opportunity charging)
$NumC^{OP}$	Required number of chargers for opportunity charging method
Q_{nom}	Total energy throughput over the whole life span of battery without instruction of charging method
Q_{nom}^{ON}	Total energy throughput over the whole life span of battery used in overnight charging method
Q_{nom}^{OP}	Total energy throughput over the whole life span of battery used in opportunity charging method
I_{ch}	Charging current rate
CL_{rate}	Rated battery cycle life without instruction of charging method
CL_{rate}^{ON}	Rated battery cycle life for overnight charging method
CL_{rate}^{OP}	Rated battery cycle life for opportunity charging method
CL^{OP}	Actual cycle life of the battery used in opportunity charging method
$\mathscr{C}_{bus}$	Purchase cost of a BEB
$\mathscr{C}_{chd}$	Purchase cost of a charger

TABLE I
(Continued.) LIST OF NOTATIONS

$Ꞓ_{bat}$	Unit battery cost
$Ꞓ_{ele}$	Unit charging cost
d_{rate}	Discount rate
ϕ_{bat}	Annual reduction rate of battery cost
Variables	
Y_i	Decision and integer variable, number of BEBs in the bus fleet i
X_{ijt}	Decision and binary variable, decision of whether to assign BEB fleet i to route j at scheduled period t
δ_{it}	Binary variable, representation of whether need to replace the batteries of BEB from fleet i during scheduled period t
ΔE_{ij}	Average energy consumption over the yearly operation on route j for a single BEB from bus fleet i
$NumC$	Required number of chargers without instruction of charging method (for overnight charging)
$NumC^{ON}$	Required number of chargers for overnight charging method
C_{lc}	Lifecycle cost for the BEB system
Q_{it}	Initial capability of energy throughput over the remaining useful life of the battery in the BEB from bus fleet i at the beginning of year t.
Function	
$CL(I_{ch})$	Number of charge-discharge cycles as the battery is fast charged at a constant charging current rate I_{ch} before reaching its end-of-life

overnight charging method that only charges the BEB during non-operational periods in the nighttime. In addition, the weight of the battery pack would be downsized as the capacity decreases. As well known, the battery weight accounts for about 20% of the total weight of BEB, considering the example of the long-range BEBs manufactured by BYD Auto Company [30]. It is noted that several existing studies have demonstrated that the vehicle mass has significant impacts on the energy consumption rate for a BEB, i.e., [18], [31]. For example, considering the unique characteristics of BEBs, such as the regenerative braking and higher powertrain efficiency, Bi et al. [31] have demonstrated that 10% vehicle mass reduction contributes to about 4.5% energy consumption reduction for a BEB. Based on such research results, we calculate the energy consumption rate of a BEB by considering the battery downsizing effects, as shown in (1). By this way, the difference in energy consumption rate between overnight and opportunity charging systems can be highlighted due to their significant difference in the battery capacity. The primary idea behind this equation is that the energy consumption rate (kWh/km) from baseline case is directly adjusted by the actual battery weight. The base energy consumption rate can be obtained by the vehicle performance test from BYD Auto company, where a reference BEB operates under conventional traffic conditions in an urban transportation system. This baseline case has also been adopted in related literature [18].

$$ECR = ECR_{base} \cdot \left(1 - \frac{W_{base}^{bat} - \theta/\rho}{W_{base}^{bus}} \times 4.5\%\right) \quad (1)$$

where ECR is the adjusted energy consumption rate; ECR_{base} is the base energy consumption rate of the reference BEB; W_{base}^{bat} and W_{base}^{bus} represent the base battery weight and base bus weight of the reference BEB, respectively; θ is the battery capacity (kWh); ρ is the battery specific energy, which associates the battery capacity with the battery weight, where the battery weight can be obtained by θ/ρ. Note that, the base bus weight W_{base}^{bus} is assumed to comprise the curb weight and constant average weight for the driver, passengers, and cargo. The fluctuation of ridership is not involved in this study.

Based on the adjusted energy consumption rate obtained by (1), the energy consumption for a round-trip (terminal to terminal) of a specific route can be calculated, as shown in (2).

$$E_j = ECR \cdot l_j \quad (2)$$

where E_j is the energy consumption for a round-trip of route j; l_j represents the driving distance of a round-trip for route j.

During the daily operation, the number of round-trips that a BEB needs to operate depends on the bus schedule and fleet size. Combined with the energy consumption for a round-trip, the average energy consumption over the yearly operation for a single BEB from a specific bus fleet is calculated as shown in (3).

$$\Delta E_{ij} = \frac{\tau_j^{do} E_j}{\tau_j^{in} Y_i} \cdot D \quad (3)$$

where ΔE_{ij} is the average energy consumption over the yearly operation on route j for a single BEB from bus fleet i; τ_j^{do} and τ_j^{in} are the daily total duration and operation interval for the timetable of route j, respectively; Y_i is the number of BEBs in bus fleet i; D is the total days for the operation of BEB in a year.

B. Minimum BEB Fleet Size Required for Each Route

When assigning a BEB fleet to a transit route, the bus fleet size needs to meet the minimum required number of BEBs for the route. Since different transit routes from a public transport system often have different timetables, they may have different requirements for minimum BEB fleet size to satisfy their specific bus schedules. Moreover, the overnight and opportunity charging methods also result in significant distinction in the minimum required number of BEBs in the bus fleet, which is discussed as follows.

For the overnight charging method, the minimum required BEB fleet size for a specific route depends on twofold aspects. On the one hand, the number of BEBs in a bus fleet should guarantee that all the operation intervals from the timetable are covered during the daily operation. On the other hand, the battery capacity and related driving range limitation also have impacts on the fleet size, because the BEBs from the overnight charging system can only be charged during non-operational periods in the nighttime. The calculation of the minimum required number of BEBs for a specific route under the overnight charging is presented in (4)

$$NumB_j^{ON} = \max(\left\lceil \frac{\tau_j^{br}}{\tau_j^{in}} \right\rceil, \left\lceil \frac{\tau_j^{do} E_j}{\tau_j^{in} \theta^{ON} \beta} \right\rceil) \quad (4)$$

where $NumB_j^{ON}$ is the minimum required number of BEBs for the route j under the overnight charging method; τ_j^{br} is the travel duration of a round-trip on the route j; θ^{ON} is the capacity of battery pack equipped in the BEB with overnight charging, and β is the related usable state-of-charge range which is widely used to alleviate the range anxiety [32]; $\lceil a \rceil$ represents the integer that is no less than the value of a.

Unlike overnight charging, the opportunity charging method can support the BEBs to be charged during the service operation using charging devices with high charging power and within a short charging time, i.e. 30s [20]. Therefore, the battery capacity has a quite limited influence on the BEB fleet size. The minimum required number of BEBs for a route under the opportunity charging is solely affected by the bus schedules, as given in (5). Note that, this equation is acceptable under the consideration of the short charging time and suitable to the conventional transit operation, where the dwelling time at bus stops is often less than 30s to pick up or drop off passengers. In some special scenarios, the operator intends to take a few minutes to charge the BEBs, in which the interaction between battery capacity, fleet size and schedules become more important [33], [34], [35]. For example, the travel duration for a trip increases as the charging time increases, which further result in the increase in the fleet size, under the specific bus schedule and battery capacity. This study focuses on the conventional scenario with short charging times. To consider the longer charging times, a straightforward way is to adjust the travel duration and charging time by considering the interaction between battery capacity, fleet size and schedules in the model.

$$NumB_j^{OP} = \left\lceil \frac{\tau_j^{br}}{\tau_j^{in}} \right\rceil \tag{5}$$

where $NumB_j^{OP}$ represents the minimum required number of BEBs for route j under the opportunity charging method.

C. Number of Charging Devices Required for a BEB System

In order to ensure the effective operation of a BEB system, an adequate number of charging devices should be constructed. The required number of chargers with different charging methods depends on different factors. For the overnight charging method, all the BEBs are charged at the terminal station during non-operational periods in the nighttime and the charging devices with relatively low charging power, i.e. slow chargers, are used to charge the vehicles. In view of this, we reasonably consider that the charging events are scheduled simultaneously and thus the number of chargers equals to the total number of BEBs, as shown in (6). The reasons for such a consideration mainly lie in the following two points. For one thing, it often takes more than six hours to charge a BEB due to large battery size and low charging power, and thus there is not enough time to complete more than one charging events by a charger during the non-operational periods in the nighttime [20]. For another, extra labors are needed to realize the sequential schedule of charging events, whereas it is difficult to find the labors who can undertake this work during nighttime in real-world scenarios.

$$NumC^{ON} = \sum_{i=1}^{m} Y_i \tag{6}$$

where $NumC^{ON}$ is the required number of chargers for the overnight charging system.

For the opportunity charging method, the BEBs can be charged when picking up or dropping off passengers at bus stops. The number of charging devices depends on the minimum number of chargers for a round-trip to guarantee the operability of the BEB. In view of this, the energy consumption, charging power levels, and charging time at bus stops have significant influences on the number of chargers. In addition, the route overlapping may occur in a network of routes, which is commonly seen in some compact cities. In this case, a bus stop may be covered by different routes, and thus the charger located in the bus stop may be utilized by BEB fleets for several different routes. To reflect the route overlapping, we define the overlapping coefficient in this study. Moreover, the availability of chargers may be affected by the route overlapping, because the charger located in a specific bus stop may be used by a BEB when another BEB from the different fleet reaching the bus stop at the same time. Let μ and λ_j respectively denote the overlapping coefficient for route network and the probability of charging availability for route j. The calculation of the number of chargers for the opportunity charging system is presented in (7). The calculation result ensures that the number of chargers can support the BEB finish each route without energy exhaustion during operation, and definitely avoids the situation that the BEB is unable to reach next charging station after charging at current charging station. Note that, the charging devices used in the opportunity charging system are chargers with relatively high charging power, i.e. fast charger. Furthermore, the optimal location of charging devices is not discussed because it is outside the scope of this work, and related well-studied methods are referenced in previous literature [18], [36], [37].

$$NumC^{OP} = \mu \cdot \sum_{j=1}^{n} \left\lceil \frac{E_j}{P \cdot \tau^{ch} \cdot \lambda_j} \right\rceil \tag{7}$$

where $NumC^{OP}$ represents the required number of chargers for the opportunity charging system; P is the charging power of the chargers; τ^{ch} is the charging time at bus stops.

D. Battery Life Span

The battery has a finite life span and the aging phenomenon occurs during the BEB operation. The battery embedded in BEBs should be replaced when reaching its end-of-life. The battery cycle life is one of the commonly-used indicators to characterize the battery life span, which is generally defined as the number of complete charge-discharge cycles that the battery is able to perform before that its capacity falls under 80% of its original rated capacity [38]. In this section, we use the battery cycle life to represent the battery life span due to its adaptation for BEB application. Without loss of generality, we assume that BEBs studied in this work are equipped with the Lithium iron phosphate-based battery that is world-widely used in BEBs [39]. As has been mentioned before, the BEBs with different charging methods are equipped with batteries with different capacities and charged using chargers with different charging power levels. These features contribute to significant differences in the battery cycle life between overnight and opportunity charging methods, as follows. On the one hand, the rated cycle life (CL_{rate}) of the battery used in the overnight charging system is shorter than that in the opportunity charging system. It is because the battery pack consists of a large number of battery cells and its cycle life is affected by the nominal capacity due to the influence of the inconsistencies caused by cell-to-cell parameter variations: the larger nominal capacity the battery pack has, the shorter rated battery cycle life is [40]. On the other hand, the actual battery cycle life of the battery used in the opportunity charging system is shorter than its rated battery cycle life. This is because the fast charging pattern has significant impacts on the battery aging behavior, and the battery fading rate is highly related to the charging power: the higher the charging power level is, the faster battery capacity fades [41]. In order to clearly reflect the difference in battery life span between overnight and opportunity charging systems, we calculate the total energy throughput over the entire lifetime of the battery by considering the differences in battery capacity, charging power and rated cycle life between the two charging systems. Let CL_{rate}^{ON} and CL_{rate}^{OP} denote the rated battery cycle life for overnight and opportunity charging methods, respectively. Based on the battery cycle life coupled with the capacity, the amount of total energy that can be stored in the battery over its whole life span for the overnight charging method is calculated, as shown in (8). In this way, the battery life span is converted into the total energy throughput over the entire lifetime.

$$Q_{nom}^{ON} = \theta^{ON} \cdot CL_{rate}^{ON} \cdot \sigma \tag{8}$$

where Q_{nom}^{ON} is the total energy throughput over the whole life span of the battery used in the overnight charging system; θ^{ON} is the nominal capacity of the battery used in the overnight charging system; σ is a coefficient designed to adjust the battery capacity due to the capacity loss caused by the battery fading behavior over the entire lifetime, which also has the ability to reflect the decision preference of the operator for the trade-off between the benefit from sufficient utilization and the risk caused by overuse. According to the general definition of the battery cycle life, we consider the value of coefficient σ ranging from 0.8 to 1. By this way, the normal level of the decision preference can be obtained if σ equals to 0.9, which shows that the operator gives an equal importance to the benefit from sufficient utilization and the risk caused by overuse of the battery.

For the opportunity charging method, we firstly borrow the empirical model developed by Omar et al. [42] to estimate the cycle life of the battery charged under a fast charging pattern. The model reveals the relationship between the number of cycles that could be achieved by the battery and the charging current rate used during fast charging processes, as shown in (9).

$$CL(I_{ch}) = 5963 \cdot \exp(-0.6531 \cdot I_{ch}) + 321.4 \cdot \exp(0.03168 \cdot I_{ch}) \tag{9}$$

where $CL(I_{ch})$ is the number of charge-discharge cycles as the battery is fast charged at a constant charging current rate before its reference capacity has decreased to 80% of its original nominal capacity; I_{ch} represents the charging current rate, which can be deduced by the charging power and battery capacity, as shown in (10).

$$I_{ch} = \frac{P}{\theta^{OP}} \tag{10}$$

where θ^{OP} is the nominal capacity of the battery used in the opportunity charging system. Afterward, the actual cycle life can be determined by comparing the rated cycle life and the result from (9), as given in (11).

$$CL^{OP} = \min\{CL_{rate}^{OP}, CL(I_{ch})\} \tag{11}$$

where CL^{OP} represents the actual cycle life of the battery used in the opportunity charging system. Therefore, the amount of total energy that can be stored in the battery over its whole life span for the opportunity charging method is obtained, as presented in (12).

$$Q_{nom}^{OP} = \theta^{OP} \cdot CL^{OP} \cdot \sigma \tag{12}$$

where Q_{nom}^{OP} is the total energy throughput over the whole life span of the battery used in the opportunity charging system. It is worth noting that, for the battery cycle life, only the cycling loss is considered and the calendar loss is neglected. This is reasonable, because the calendar loss in Lithium iron phosphate battery is very small, and thus has a negligible effect on the battery life span as compared to the cycling loss [26]. Moreover, the charging and discharging frequency would be increased as the battery is downsized, which is not considered into the estimation of battery cycle life. It is because the Lithium iron phosphate-based battery has low memory effect and thus the frequency of charging and discharging has a limited impact on the battery degradation as compared to the charging current rate [43]. Several existing studies have demonstrated that the charging current rate has adequate ability to estimate the battery cycle life [27], [42].

III. Collaborative Optimization Model for Lifecycle Cost of BEB System

Comprehensive optimization of lifecycle cost is necessary to explore the economic efficiency of the lifetime operation of a BEB system. Based on the joint consideration of the unique features of energy consumption, bus fleet size, charging device construction, and battery life span for BEB systems with different charging methods, a lifecycle cost optimization model is then developed. The two main components of the lifecycle cost are the initial capital cost and the use-phase operation cost, the latter of which can be divided into charging cost and battery replacement cost. In view of this, we establish a collaborative optimization framework to comprehensively optimize the infrastructure procurement and fleet scheduling, where the former has a significant impact on the latter and thereby affects the battery replacement cost over the whole planning horizon. For BEBs, their battery degradation is a time-dependent dynamic process, which is highly related to the matching strategy of BEB fleets and routes at each scheduling period. In this study, we consider the whole service life of the BEB as the planning horizon, and all the BEBs coupled with matched charging devices are purchased at same time. This is an expected scenario for a transit agency as a new BEB-based urban transit system is constructed [17].

For model formulation, we assume that the operator periodically determines the optimal matches of the BEB fleets and the routes at the beginning of each year, and accordingly the planning horizon is discretized into finite scheduled periods of one year. Let $\{1, \ldots, t, \ldots, T\}$ denote the set of scheduled periods with one-year intervals, where T is the whole service life of the BEB. Furthermore, the collaborative optimization framework has two decision variables, as follows. For one thing, the decision variable involved in the planning of the infrastructure procurement is the integer variable Y_i, which represents the number of BEBs in the bus fleet i, as has been described in Section II.A. For another, the decision variable involved in the bus fleet scheduling is denoted as the binary variable X_{ijt}, which is equal to 1 if the BEB fleet i is assigned to the route j during the year t; otherwise, this variable is 0. Based on the definition of X_{ijt}, the mathematical optimization model for the fleet scheduling can be designed as the dynamic programming, which aims to search the optimal values of X_{ijt} to optimize the use-phase operation cost. During the optimization process, the values assigned to X_{ijt} must satisfy the predefined timetable that does not change over the whole planning horizon. To unify the notations with different charging methods, the uniform notations without the instruction of charging methods are used for modeling, and the parameters for different charging methods can be taken into the corresponding portions. Based on these settings, the lifecycle cost optimization model for BEB system is constructed as

$$\begin{aligned}\min C_{lc} &= \sum_{i=1}^{m} \tilde{C}_{bus} Y_i + \tilde{C}_{chd} \cdot NumC \\ &+ \sum_{t=1}^{T}\sum_{i=1}^{m}\sum_{j=1}^{n} \Delta E_{ij} X_{ijt} Y_i \tilde{C}_{ele} (1+d_{rate})^{1-t} \\ &+ \sum_{t=1}^{T}\sum_{i=1}^{m} \theta \cdot \tilde{C}_{bat} (1-\phi_{bat})^{t-1} \delta_{it} Y_i (1+d_{rate})^{1-t} \end{aligned} \tag{13}$$

$$s.t. \ \sum_{i=1}^{m} X_{ijt} = 1, \quad (j = 1, \ldots, n; t = 1, \ldots, T) \tag{14}$$

$$\sum_{j=1}^{n} X_{ijt} = 1, \quad (i = 1, \ldots, m; t = 1, \ldots, T) \tag{15}$$

$$NumB_j \cdot X_{ijt} \leq Y_i, \quad (i = 1, \ldots, m; j = 1, \ldots, n; t = 1, \ldots, T) \tag{16}$$

$$Q_{it} + \delta_{it} Q_{nom} \geq \Delta E_{ij} X_{ijt}, \quad (i = 1, \ldots, m; j = 1, \ldots, n; t = 1, \ldots, T) \tag{17}$$

$$Q_{it} = \begin{cases} Q_{nom}, \\ \quad (i = 1, \ldots, m; t = 1) \\ Q_{it-1} + \delta_{it-1} Q_{nom} - \Delta E_{ij} X_{ijt-1}, \\ \quad (i=1, \ldots, m;\ j=1, \ldots, n;\ t = 2, \ldots, T) \end{cases} \tag{18}$$

$$X_{ijt} \in \{0, 1\}, Y_i \in Z^+, \quad (i = 1, \ldots, m; j = 1, \ldots, n; t = 1, \ldots, T) \tag{19}$$

Objective (13) minimize the lifecycle cost of the BEB system, which synchronously involves a static programming for infrastructure procurement and a dynamic programming for fleet scheduling, where C_{lc} is the lifecycle cost for the BEB system; $\tilde{C}_{bus}$ and $\tilde{C}_{chd}$ represent the purchase costs of a BEB (without battery) and a charging device, respectively; $\tilde{C}_{bat}$ and $\tilde{C}_{ele}$ are the unit battery cost and charging cost per kWh, respectively; d_{rate} is the discount rate; ϕ_{bat} is the annual reduction rate of battery cost, which is necessary to be considered due to the rapid development of the automotive battery industry in recent decades [44]; δ_{it} is defined as a binary variable with respect to the battery replacement, which is equal to 1 if the BEBs from fleet i replace their batteries during the year t when the old batteries reaching their end-of-life, and 0 otherwise. In this objective function, the first term determines the total cost for BEB purchase in the whole system, where the total number of BEBs is obtained by summing up the number of BEBs from all the fleets; the second term focuses on the total procurement cost of the charging devices, where the number of chargers purchased for a BEB system is influenced by the type of the charging methods, as has been discussed in Section II.C; the third term calculates the total charging cost over the whole planning horizon, and furthermore, the model considers that the unit charging cost differs for overnight and opportunity charging methods due to the influence of time-of-use electricity price, which presents the clear variations in unit charging cost from daytime to nighttime [45]; the final term gives the total cost for battery replacement over the whole service life of the BEBs, where the total number of batteries used for the lifetime operation of the BEB fleets is significantly affected by the matching strategy of BEB fleets and routes during the planning horizon. Note that, the salvage values are not considered in the objective function, because they are considered to be quite small after the expected service life, and thus have fairly limited impacts on the lifecycle costs [46]. Moreover, since we consider the service life of BEB as the planning horizon, the maintenance cost is also neglected. As a matter of fact, if necessary, it is straightforward to integrate the maintenance cost into the objective function, for instance, by adjusting the purchase cost.

Equations (14)-(19) present the constraints for the lifecycle cost optimization model. To be specific, constraints (14) and (15) indicate a consistent one-to-one match between each BEB fleet and each route, where one BEB fleet can only be assigned to one route, and meanwhile one route can only accept one BEB fleet for each scheduled period. Constraint (16) ensures that the number of BEBs from bus fleet i is no less than the minimum BEB fleet size required

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for route j, if the BEB fleet i is assigned to the route j during the year t. Constraint (17) guarantees that the maximum energy obtained by a single BEB from bus fleet i during the year t is no less than the energy required for its yearly operation on route j, if the BEB fleet i is assigned to the route j during the year t, where Q_{it} represents the initial capability of energy throughput over the remaining useful life of the battery equipped in the BEB from bus fleet i at the beginning of year t. Constraint (18) formulates the state transition equation for Q_{it}, which reveals the dynamic change trends of the battery's remaining useful life, represented as energy throughput, over the whole planning horizon. It is observed that, the fleet scheduling strategy in current year are highly related to the remaining useful life of the battery at the beginning of the subsequent year. Constraint (19) ensures that the decision variable X_{ijt} is the binary variable, and meanwhile the decision variable Y_i belongs to the integer.

The presented model is nonlinear due to the nonlinearity existed in both the objective function and constraints, even for its relaxations in case the decision variable Y_i is continuous. For the objective function, it can be observed that the final term is nonlinear, where the binary variable δ_{it} is highly related to the decision variable X_{ijt}. For the constraints, the constraints (17) and (18) are nonlinear, where the variable ΔE_{ij} is calculated based on the decision variable Y_i, as shown in (3). Note that, the third term of the objective function can be regarded as the linear term, because Y_i acts as the denominator in (3) and thus it can be cancelled out in the calculation process. The nonlinearity of the model results in significant complexity to solve the problem. This is because that, the conventional exact algorithms or commercial solvers have limited ability to solve the complex nonlinear models. Based on this, the customized solution method should be designed to obtain the solution of the problem.

IV. Model Transformation and Solution

A. Model Transformation Based on Bi-Level Programming

In the proposed model, the solution comprises two parts, including infrastructure procurement and fleet scheduling. For the infrastructure procurement part, the solution gives the number of BEBs purchased for each bus fleet and thus contains m variables upon the number of bus fleets in a public transit system. For each variable, the procurement decision is an integer value greater than zero. For the fleet scheduling part, the solution determines the BEB fleet scheduling during each scheduled period and accordingly contains $m \times n \times T$ variables upon the number of bus fleets and routes as well as the whole service life of the BEB. For each variable, the fleet scheduling is a binary value. Hence, it is difficult to synchronously search for all the possibilities with respect to both parts of the solution. Nevertheless, it is worth noting that there exists a hierarchical relationship between the two parts of the solution, where the infrastructure procurement is able to determine the key impacting factors for the BEB fleet scheduling. The main reasons for such a relationship are twofold: on the one hand, the number of BEBs in a bus fleet has a direct influence on the feasibility of the fleet to be assigned to different routes. In other words, the number of BEBs from a specific bus fleet should satisfy the minimum required fleet size for a route, if the BEB fleet could be matched with the route, as mentioned in Section II.B; on the other hand, the annual energy consumption for a single BEB operating on a specific route is affected by the number of BEBs from the corresponding bus fleet, as presented in (3). This characteristic further indicates that the BEB fleet size would influence the battery fading behavior during the scheduling process, as discussed in Section II.D. In view of the hierarchical relationship between the infrastructure procurement and fleet scheduling, combining the bi-level programming principle [47], the collaborative optimization model can be regarded as a bi-level optimization problem, where the outer-level objective aims to determine the optimal number of BEBs purchased for each fleet, and the inner-level objective searches the optimal matches between BEB fleets and routes during each scheduled period. In this way, the initial objective function, as shown in (13), can be decomposed into two interrelated functions to reduce the computational complexity, as given in (20) and (21). Basically, the outer-level objective function (20) has control over the decision variable Y_i, and the inner-level objective function (21) has control over the decision variable X_{ijt}.

$$\min C_{lc}^{outer} = \sum_{i=1}^{m} \tilde{C}_{bus} Y_i + \tilde{C}_{chd} \cdot NumC + C_{lc}^{inner} \tag{20}$$

$$\begin{aligned}\min C_{lc}^{inner} = & \sum_{t=1}^{T}\sum_{i=1}^{m}\sum_{j=1}^{n} \Delta E_{ij} X_{ijt} \hat{Y}_i \tilde{C}_{ele} (1+d_{rate})^{1-t} \\ & + \sum_{t=1}^{T}\sum_{i=1}^{m} \theta \cdot \tilde{C}_{bat} (1-\phi_{bat})^{t-1} \delta_{it} \hat{Y}_i (1+d_{rate})^{1-t}\end{aligned} \tag{21}$$

In the above functions, C_{lc}^{outer} and C_{lc}^{inner} are used to denote the associated costs obtained from outer-level and inner-level objective functions, respectively. Furthermore, to solve the bi-level optimization problem, once the outer-level objective function chooses the values of decision variable Y_i, the Y_i of the inner-level objective function become the constants. Thus, $\hat{Y}_i$ represents the decision variable Y_i with known values. It is observed that the final lifecycle cost is obtained as the outer-level objective is optimized.

B. Hybrid TS-IGA Solution Method

Through model transformation, the collaborative optimization model with two categories of decision variables is reformulated as the bi-level optimization problem that has two interrelated objectives with single category of decision variable. By this way, the model can be solved by separately handling the inner-level and outer-level subproblems. Note that, even though the computational complexity is reduced by the model transformation, it is still difficult to deal with the problem. The primary complexities for determining the solution of the bi-level optimization problem are summarized as follows. Firstly, there exists a transitive relation between the solutions of the two subproblems, where the outer-level subproblem sends its candidate solution to the inner-level subproblem, and then the inner-level subproblem provides its objective function value to the outer-level subproblem. Indeed, as regards the problems with the similar characteristic, there exist some exact algorithms that may have ability to deal with them. However, the exact algorithms are often available based on some strict conditions, and thus the heuristic algorithms are more widely used [48]. For instance, a most possible technique for solving the similar problems is the Benders decomposition method, whereas it is unable to solve the proposed model, because the model structure, e.g., the inner-level objective function (21), cannot satisfy the conditions of the Benders decomposition method [49]. Secondly, the scale of the candidate solution for the outer-level subproblem is large, which is the combination of a certain number of integers. Finally, the inner-level subproblem is a dynamic optimization problem, where the fleet scheduling in the immediately scheduled period has effects on that in the subsequent scheduled period. It is unrealistic to enumerate all the conditions to evaluate the use-phase operating cost for finding the optimal matches between BEB fleets and routes, which would increase exponentially with the increase in the number of scheduled periods.

Considering the abovementioned complexities in terms of the model, we attempt to introduce a hybrid heuristic to solve the bi-level optimization problem, which has been regarded as an effective combinatorial optimization technique in solving hard problems [50]. To this end, a hybrid heuristic solution method based on a TS and an IGA is customized to solve the model. Just like the characteristic of a bi-level problem, the framework of the solution method is constructed as a hierarchical structure, including inner-level and outer-level procedures. To be specific, the outer-level procedure is designed based on a TS framework to determine the number of BEBs in different fleet sizes, i.e., decision variable Y_i. In the outer-level procedure, the objective is to optimize the lifecycle cost, as shown in (20), where the initial capital cost can be calculated directly as the candidate solution of Y_i is chosen while the operating costs during use phase are obtained from the solution of the inner-level procedure. Given the above features of outer-level procedure, it is appropriate for TS. This is because TS has relatively high convergence rate and good adaptability for solving optimization models with complex solution spaces [51]. By using TS in the outer-level procedure, the integer variable Y_i can be efficiently optimized considering its interaction with the inner-level procedure. For the inner-level procedure, an IGA is designed to search the optimal matches between bus fleets and routes for each scheduled period, i.e. decision variable X_{ijt}, and determine the use-phase operating cost, i.e. C_{lc}^{inner}. The reason for choosing IGA lies in its strong ability to search global solution and good adaptability for dynamic programming with complicated solution spaces [52]. The inner-level procedure sends C_{lc}^{inner} to the outer-level procedure and thus the lifecycle cost, i.e. C_{lc}^{outer}, is obtained under the current candidate solution of Y_i. In this way, the TS and IGA are performed iteratively until the termination criteria is met. Fig. 2 presents the flowchart of the hybrid TS-IGA solution method. For the initial solution, the initial values of Y_i can be generated according to the

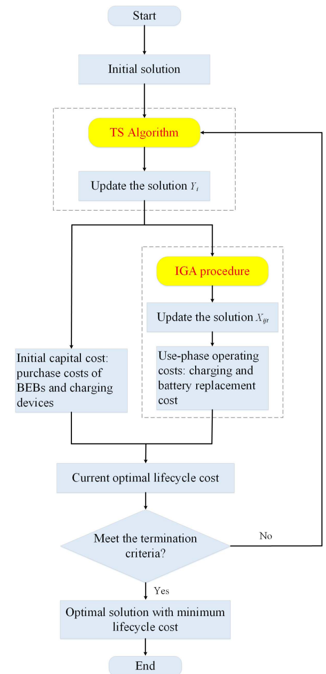

Fig. 2. Flowchart of the hybrid TS-IGA solution method.

minimum required BEB fleet size. For example, the initial Y_i should ensure that the number of BEBs in each bus fleet can meet the requirement of all the routes. On this basis, the corresponding initial value of X_{ijt} can be obtained using the IGA procedure, which need satisfy the constraints with respect to the fleet scheduling in the model. As a heuristic-based solution method, it should be noted that the computational solution obtained by the hybrid TS-IGA may be a satisfactory or near-optimal solution. For simplicity, the computational solution obtained by this hybrid heuristic is experientially called the optimal solution in this study. The implementations of IGA and TS for the inner-level and outer-level procedures are respectively detailed in following subsections.

1) IGA for the Inner-Level Procedure: In the hybrid TS-IGA framework, a specialized IGA is designed for the inner-level procedure to search the optimal matches between BEB fleets and routes. IGA is an improved algorithm based on the combination of the immune concepts and the genetic algorithm (GA), which has a better ability to refrain the degenerative phenomena during evolution, as compared to the typical GA [53]. To be exact, IGA utilizes the local information to intervene in the global search process and restrain or avoid repetitive and useless work to overcome the blindness in crossover and mutation operations. This advantage inspires several studies use IGA for solving dynamic scheduling problems, because it significantly increases the algorithmic performance to find the global optimal solution in a complicated solution space [52], [54]. Therefore, given the dynamic characteristic of the fleet scheduling problem, the IGA is well-suited for the inner-level procedure. In an IGA, a solution is encoded as an antibody that is often represented by a chromosome with a certain number of gene bits, similarly as the canonical GA [55]. In order to accommodate the

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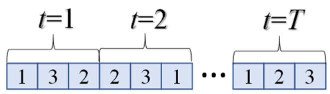


Fig. 3. Toy antibody with three BEB fleets.

problem characteristics of BEB fleet scheduling, we customize the antibody to represent the matches between BEB fleets and routes for each scheduled period. To be exact, an antibody is formed by a one-dimensional array with $m \times T$ elements, where the value of each gene bit is the serial number of the route that is matched to the corresponding BEB fleet. For example, Fig. 3 illustrates an antibody corresponding to the scenario with three BEB fleets. According to the set of scheduled periods, the antibody chromosome is partitioned into T groups, and each group has three gene bits representing the fleet scheduling for the corresponding t. Obviously, within the group of $t = 1$, the value of the first gene bit is equal to 1, which indicates that the BEB fleet 1 is assigned to the route 1 for $t = 1$; similarly, the value of the second gene bit within the group of $t = 2$, which is equal to 3, shows that the BEB fleet 2 is matched with the route 3 for $t = 2$.

In the IGA, the number of antibodies is defined as the population size. For each antibody, the fitness is calculated based on the inner-level objective function, as shown in (21). According to the fitness values, the antibodies from the population are sorted, and subsequently the best two antibodies are selected as the vaccines saved into a vaccine library. The vaccine is the representative of the elitist antibody, which plays a critical role in the efficiency of the algorithm [56]. In addition, an iterative operation is applied to update the antibodies through crossover, mutation and selection operations coupled with immune operator. The primary principle behind immune operator utilization is to intervene aptly in the variation of genes in individual antibody by using vaccines. It can improve the convergence rate and population diversity during the evolutionary process. To be specific, in the population of each generation, the two-point crossover is used in principle for the crossover operation using a specified crossover probability, and then the mutation operation is employed to exchange the values of randomly selected two gene bits according to a given mutation probability [53]. It is worth noting that, given the dynamic characteristics of fleet scheduling, both the crossover and mutation operations would perform T times for an specific antibody, because the gene bits in each group of t for the selected antibodies should be updated during the iterative process. The fitness values of the updated antibodies are also determined and sorted. Afterwards, the self-adaptive vaccine selection is introduced to ensure the validity of the vaccines, which refers to the adaptive capacity for updating the vaccine library during the evolutionary process. By this way, the vaccines can be replaced by the antibodies with better fitness values from the population of current generation.

For the selection operation, an immune operator is adopted to improve the convergence rate and population diversity, which composed of two operations: vaccination and immune balance. The vaccination operation aims to modify the anti-

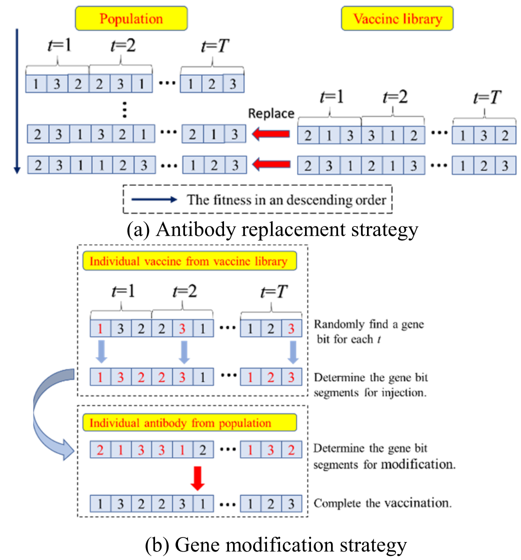


Fig. 4. Vaccination operation in the IGA.

bodies from the population in accordance with the vaccine library and thus raise the fitness with greater probability. In this study, we use both strategies of antibody replacement and gene modification to realize the vaccination operation, as illustrated in Fig. 4. As seen, case (a) presents the antibody replacement strategy, where the antibodies with worst two fitness values in the population are replaced by the vaccines from the vaccine library under the reverse order of fitness. By contrast, case (b) provides the gene modification strategy that modifies the genes on some bits for an individual antibody based on the vaccines, where the target antibodies and corresponding vaccines are randomly selected from the population and vaccine library, respectively; in particular, the gene bits marked by red color in the figure represent that they are selected to perform injection or modification between the vaccine and target antibody. A check operation is further implemented to test antibodies before and after the gene modification, and the antibody with better fitness value participate in the population. After the vaccination operation, the antibodies in the updated population are sorted again according to the fitness.

On the other hand, the immune balance operation can ensure the diversity of antibodies by simultaneously integrating the fitness and concentration into the selection probability of an individual antibody. The concentration is a specific concept in the immune balance operation, which is related to the similarity of antibodies. In this work, we use the fitness as the metric for the similarity of antibodies, and accordingly the concentration refers to the proportion of the antibodies that are similar to the target one in the population, including the target antibody itself. Meanwhile, the probability regarding the fitness is also determined based on the proportion of the fitness value for each antibody in the total fitness for all the antibodies from the population. Combining the probabilities of fitness and concentration, the selection probability for each antibody in the population is calculated based on the immune balance operation. A sketched derivation of the selection probability

Algorithm 1 IGA for the Inner-Level Procedure

Step 1: Randomly generate the antibodies with $m \times T$ gene bits to constitute the initial population.

Step 2: Determine the fitness value of each antibody-based on (21) and save the best antibody as the temporary solution.

Step 3: Establish the vaccine library and save the antibodies with the best two fitness values into the vaccine library.

Step 4: Perform the crossover operation to update the population using a specific crossover probability.

Step 5: Perform the mutation operation to update the population using a specific mutation probability.

Step 6: Determine the fitness value of each antibody from the updated population and sort the antibodies in descending order.

Step 7: Update the vaccine library based on the self-adaptive vaccine selection approach.

Step 8: Perform the vaccination operation on the population and then sort the antibodies in a descending order according to their fitness.

Step 9: Calculate the selection probability for each antibody based on the immune balance operation.

Step 10: Perform the selection operation using the roulette wheel selection method to update the population.

Step 11: Determine the fitness value of each antibody from the updated population and compare the best antibody with temporary solution. Save the best antibody as new temporary solution if its fitness value is better than the current temporary solution; otherwise, retain the current temporary solution.

Step 12: Output the optimal solution if the iteration reaches the maximum number; otherwise, return to Step 4 and continue the iterative repetitions.

with immune balance operation is detailed in Appendix in the interest of brevity. Afterward, the roulette wheel selection method is used to perform the selection operation according to the selection probability, which is an effective and commonly-used method in intelligent algorithms [57]. In this way, the population in the new generation is obtained until the termination criteria is satisfied. For IGA termination, we consider that the algorithm halts as the iterations reach the maximum number, which is often adopted as the termination criterion in intelligent algorithms [58]. The detailed steps of the IGA for the inner-level procedure are outlined in Algorithm 1.

2) TS Algorithm for the Outer-Level Procedure: For the outer-level procedure, a TS algorithm is customized to determine the optimal number of BEBs that are purchased for each bus fleet. TS is an effective heuristic procedure for guiding search in complex solution spaces, which is able to ensure the diversified search through the simulation of human intellectual activities, thereby realize the efficient global optimization [51]. To be exact, TS explores the solution space by constantly replacing recent solution with new one that escapes from the already visited solutions and their neighbors. In general, TS algorithm starts the search from an initial feasible solution. Considering the feature of the proposed model, we use the $1 \times m$ vector, i.e. $(Y_1, \ldots, Y_i, \ldots, Y_m)$, to represent the solution in the TS, where the value of Y_i is the number of BEBs in ith bus fleet. In this study, we consider that an effective initial solution for the TS need to ensure the feasibility of the matches between any bus fleets and routes, thereby the maximum-minimum required number of BEBs among all the routes could be regarded as the initial solution, which can be obtained using (4) or (5) for different charging methods. Afterwards, the solution would be iteratively improved through the movement of decision variable Y_i, where the candidate solutions corresponding to the current solution are searched based on the certain strategy. In the TS procedure, two types of movement strategies regarding the candidate solution generation are introduced, including the collective movement and individual movement. To be exact, the collective movement aims to adjust all the decision variables from the solution, while the individual movement solely alters one decision variable that is randomly selected from the solution, as shown in Fig. 5. As seen, cases (a) and (b) respectively illustrate the collective and individual movement strategies. For the sake of distinction, we use red color to highlight the decision variables that are selected from current solution to perform movement. The reason for such strategies lies in that the temporary solution is closer to the global optimal solution as the iterative generation increases, and accordingly the required movement intensity weakens. Therefore, the collective movement is mainly applied in the early iterative generations and the individual movement is used for the late iterative generations. For each type, a movement probability is introduced to guide the movement direction for the decision variable Y_i. The number of candidate solutions generated during each iterative generation is called candidate solution size.

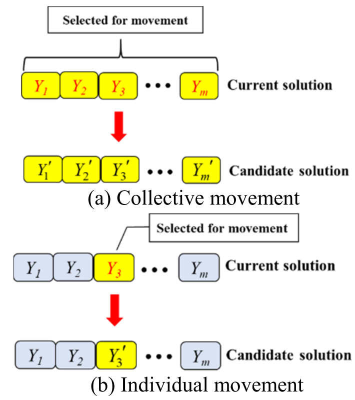


Fig. 5. Movement strategies regarding the candidate solution generation.

To circumvent the entrapment that the solution is trapped into local optimization, the TS procedure incorporates a memory structure to record the recent movements and whereby guide the search process. Such a memory structure is realized by establishing the tabu list in the TS. In the tabu list, each movement is formed by the $1 \times (m + 1)$ vector in accordance

TABLE II
ROUTE INFORMATION FROM THE CASE STUDY

Routes	Daily total duration (h)	Round-trip travel duration (min)	Operation interval (min)	Round-trip driving distance (km)
Route 1	12	80	20	22
Route 2	13	90	20	23
Route 3	13.5	105	20	25
Route 4	12.5	150	30	40
Route 5	13	120	30	32
Route 6	13	130	20	34

with the solution structure, and the maximum number of movements recorded in the tabu list is called the tabu length. For each movement, the last element records the optimal objective value obtained based on the corresponding solution which is recorded in the front m elements. Note that, the optimal objective value represents the optimal lifecycle cost under the solution, in which the use-phase operating cost is determined by the inner-level procedure, as shown in (20). In each iterative generation, the movement recorded in the tabu list is forbidden when generating the candidate solutions. By this way, the TS algorithm could be prevented from revisiting the solutions that has been accessed in the previous iterative generations. Moreover, to further improve the optimization efficiency, the TS procedure also adopts the aspiration criteria to overrule the tabu movements in certain situations. In this work, we consider the aspiration criteria in which the candidate solution from a specific iterative generation is directly regarded as the temporary solution, if its optimal lifecycle cost is less than that of the current solution, and meanwhile update the tabu list by adding the candidate solution coupled with optimal objective value. As the candidate solutions with given size are obtained, only the one with minimum lifecycle cost is considered in the aspiration criteria. On the other hand, if the aspiration criteria is not satisfied, a check procedure is implemented to determine whether the candidate solutions and corresponding optimal objective values exist in the tabu list. For the situation that all the candidate solutions belong to the tabu list, the candidate solution with minimum lifecycle cost is regarded as the temporary solution. On the contrary, if there exist the candidate solutions that are not prohibited by the tabu list, use the best one among them to act as the temporary solution. For both the situations, the tabu list is updated using the candidate solution with minimum lifecycle cost and corresponding objective value during each iteration. For TS termination, we consider that the algorithm halts as the iterations reach the maximum number. The detailed steps of the TS for outer-level procedure are outlined in Algorithm 2.

Algorithm 2 TS for Outer-Level Procedure

Step 1: Generate the initial feasible solution based on the maximum-minimum required number of BEBs for each route.

Step 2: Calculate the optimal lifecycle cost of the initial feasible solution based on (20) and save it as the temporary solution, where the use-phase operating cost is determined using Algorithm 1.

Step 3: Initialize the tabu list with a specific tabu length, where each movement is set as empty.

Step 4: Check the iterative generation and generate the candidate solutions under a specific size for the current temporary solution: if the current iterative generation is less than the half of the maximum number of iterations, perform the collective movement strategy to generate the candidate solutions; otherwise, perform the individual movement strategy to generate the candidate solutions.

Step 5: Calculate the optimal lifecycle cost of each candidate solution and sort the candidate solutions in an ascending order.

Step 6: Select the candidate solution with minimum optimal lifecycle cost and determine whether the aspiration criteria is satisfied: if it is satisfied, save the candidate solution as the new temporary solution and go to Step 8; otherwise, go to Step 7.

Step 7: Check whether all the candidate solutions and corresponding optimal lifecycle cost exist in the tabu list: if they all exist, save the candidate solution with minimum optimal lifecycle cost as the new temporary solution; otherwise, check the candidate solutions that do not exist in the tabu list and then select one with minimum optimal lifecycle cost among them as the new temporary solution.

Step 8: Update the tabu list by adding the candidate solution with minimum optimal lifecycle cost and corresponding objective value, and meanwhile deleting the earliest added movement from current tabu list.

Step 9: Output the optimal solution if the iteration reaches the maximum number; otherwise, return to Step 4 and continue the iterative repetitions.

V. NUMERICAL CASE STUDY AND SIMULATIONS

A. Example Scenario Description

In this section, a case study is presented to demonstrate the proposed model and solution method. Referring to the real-life scenario from a major city in China, we apply the lifecycle optimization model to a public transit system with six yet-to-be electrified bus lines, i.e. routes 1-6. TABLE II lists the information in terms of the studied routes in the case study, which exhibit considerably high heterogeneity for both length and the travel duration. Accordingly, six BEB fleets are considered in the case study, i.e. fleets 1-6.

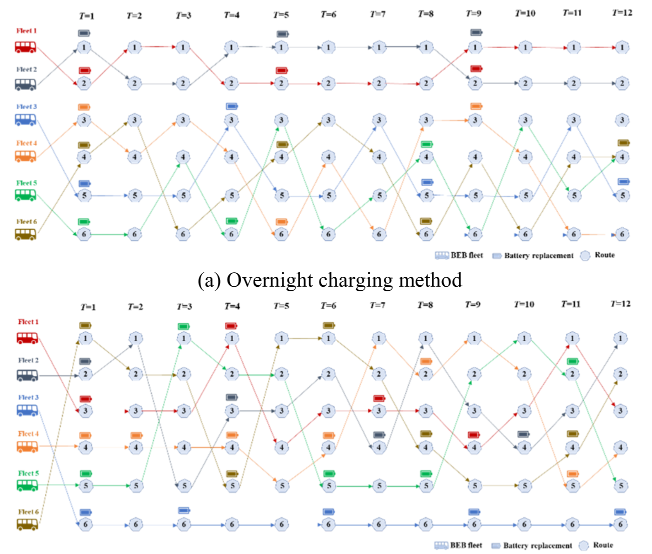
Besides the route information, the basic scenario parameters of the case study for overnight and opportunity charging methods are respectively presented in TABLE III, such as the parameters related to the purchase cost, energy consumption, and specific coefficients in the proposed model. Observably, most of the basic scenario parameters are assigned by reference to the related literature and the other ones are experientially

TABLE III
SCENARIO PARAMETERS OF THE CASE STUDY

Parameters	Symbols	Overnight charging	Opportunity charging	References
Service life of BEBs	T	12 (years)	12 (years)	[20]
Purchase cost of a BEB	$\mathcal{C}_{bus}$	350000 (€)	350000 (€)	[20]
Purchase cost of a charger	$\mathcal{C}_{chd}$	20000 (€)	250000 (€)	[20]
Unit battery cost	$\mathcal{C}_{bat}$	500 (€/kWh)	500 (€/kWh)	[20]
Battery nominal capacity	θ	300 (kWh)	150 (kWh)	[60]
Base consumption rate	ECR_{base}	1.24 (kWh/km)	1.24 (kWh/km)	[18]
Base battery weight	W_{base}^{bat}	2492 (kg)	2492 (kg)	[18]
Battery specific energy	ρ	0.13 (kWh/kg)	0.13 (kWh/kg)	[18]
Base bus weight	W_{base}^{bus}	15000 (kg)	15000 (kg)	[18]
Rated battery cycle life	CL_{rate}	1000 (#cycles)	1500 (#cycles)	[35],[60]
Charging power	P	50 (kW)	400 (kW)	[20]
Operating days in a year	D	365 (days)	365 (days)	/
Discount rate	d_{rate}	3%	3%	[20]
Annual reduction rate of battery cost	ϕ_{bat}	8%	8%	[38]
Unit charging cost	$\mathcal{C}_{ele}$	0.17 (€/kWh)	0.42 (€/kWh)	[39]
Adjustment coefficient of battery capacity	σ	0.9	0.9	/
Overlapping coefficient of road network	μ	/	0.9	/
Charging time at bus stops	τ^{ch}	/	30 (s)	[20]
Probability of charging availability for routes 1-6	λ_j	/	90%, 80%, 85%, 80%, 90%, 80%	/

given. Note that, TABLE III only presents the basic scenario parameters. Besides these basic scenario parameters, there are other parameters that can be deduced by the basic scenario parameters, as has been discussed in Section II. For instance, the battery weight can be obtained from battery nominal capacity θ and battery specific energy ρ, as shown in (1).

For the hybrid TS-IGA solution method, the primary parameters are given as follows: for the TS algorithm applied in the outer-level procedure, the candidate solution size, tabu length, and movement probability are respectively set as 20, 10, and 0.3; for the ICA applied in the inner-level procedure, the population size, crossover probability, and mutation probability are set as 50, 0.9, 0.1, respectively. The maximum number of iterations for both the procedures is set as 100. These parameters are obtained by referring to the typical parameter settings in the existing literatures that present similar logical structure behind the problem formulation [53], [59].



(a) Overnight charging method

(b) Opportunity charging method

Fig. 6. Optimal fleet scheduling and battery replacement for the case study.

B. Optimal Results and Analysis

For the BEB system with overnight charging method, the optimal numbers of BEBs that are purchased for the fleets 1-6 are 5,5,6,7,7,7, respectively; for the BEB system with opportunity charging method, the optimal number of purchased BEBs for the fleets 1-6 are 6,6,7,5,5,5, respectively. Accordingly, the optimal scheduling of the BEB fleets is illustrated in Fig. 6. The battery replacement during the planning horizon for each BEB fleet is also obtained based on the fleet scheduling results and presented in the figure. In addition, to clearly distinguish the different BEB fleets, we utilize different colors to mark the fleet scheduling coupled with battery replacement for the fleets 1-6 in the figure.

Based on the optimal solution of the case study, we can obtain the corresponding lifecycle cost of the BEB systems with overnight and opportunity charging methods, respectively. In total, the optimal lifecycle costs for overnight and opportunity charging systems are 30.20 M£€ and 47.96 M£€, respectively. This result indicates a significant difference in the lifecycle costs between overnight and opportunity charging systems. To further explore the underlying causes of the difference, Fig. 7 presents the components of the optimal lifecycle cost for the two charging systems, which include the charging cost, BEB purchase cost, charger phase cost, and battery replacement cost. On one hand, it is observed that the BEB purchase cost and battery replacement cost for the overnight charging are higher than the ones for the opportunity charging.

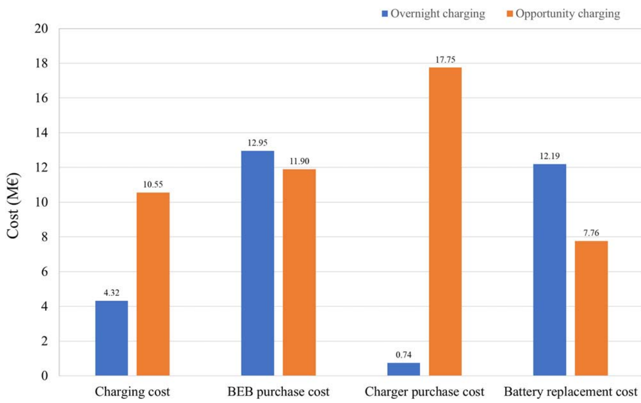
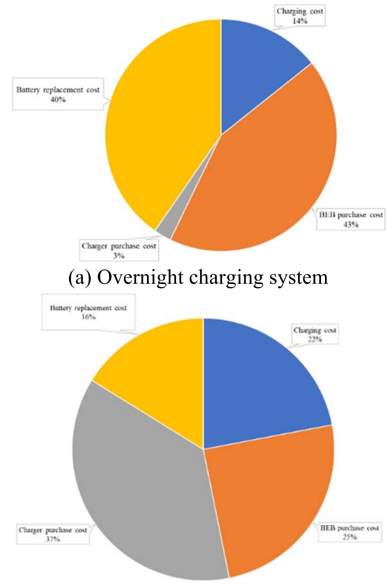


Fig. 7. Components of the optimal lifecycle costs.



(a) Overnight charging system

(b) Opportunity charging system

Fig. 8. Component proportion of the optimal lifecycle costs.

The result indicates that the overnight charging system requires a larger number of BEBs than the opportunity charging system. Meanwhile, the cost of batteries used in the overnight charging system is larger than that used in the opportunity charging system, because of higher battery capacity. Even though the number of battery replacements for overnight charging is less than that for opportunity charging during the whole service life of the BEBs, the higher cost of batteries still contributes to a higher total cost of battery replacement. On the other hand, the opportunity charging results in higher charging cost and charger purchase cost than the overnight charging. The difference in charging cost is mainly affected by the difference in unit charging cost between overnight and opportunity charging systems. This result also indicates that the time-of-use electricity price has a harsher influence on the charging cost as compared to the energy consumption reduction arising from battery downsizing effects. When it comes to the charger purchase cost, there exhibits a striking difference between the two charging systems, where the opportunity charging system costs 17.01 M£€more than the overnight charging system. Such a result mainly lies in that the purchase cost of the fast charger for opportunity charging is significantly higher than the slow charger for overnight charging. More importantly, it is worth noting that the difference in charger purchase cost is highly close to the difference in the total lifecycle cost between the two charging systems, i.e. 17.76 M£€. Therefore, it is concluded that the lifecycle cost difference stems primarily from the difference in the purchase cost of charging devices between overnight and opportunity charging systems.

Fig. 8 further provides the component proportion of the optimal lifecycle cost for overnight and opportunity charging systems, respectively. As can be seen, the BEB purchase cost and battery replacement cost dominate the lifecycle cost for the overnight charging system, where the sum of them accounts for 83% of the total cost. By contrast, for the opportunity charging system, the sum of BEB purchase and battery replacement costs only accounts for 41% of the lifecycle cost. On the contrary, the charger purchase cost occupies the largest proportion of the lifecycle cost for the opportunity charging system, whereas it has a negligible influence on the lifecycle cost for the overnight charging system.

As mentioned before, this study customizes the hybrid TS-IGA solution method to solve the model, thereinto IGA is the improved algorithm based on the combination of the immune concepts and GA. To evaluate the performance of the proposed algorithm, we further solve the model by using the hybrid heuristic algorithm based on the TS and canonical GA, i.e., hybrid TS-GA, and accordingly carry out the comparative assessment. The primary parameters of the hybrid TS-GA are consistent with the proposed hybrid TS-IGA to ensure the fair and valid comparison. The optimal solution derived from the hybrid TS-GA exhibits that the lifecycle costs for overnight and opportunity charging systems are 31.37 M£€and 49.43 M£€, respectively. By comparison, it is concluded that the proposed hybrid TS-IGA algorithm has the better performance to solve the model, which can reduce the lifecycle cost by 3.73% and 2.97% compared to the hybrid TS-GA algorithm for overnight and opportunity charging systems, respectively.

In a real-world scenario, public transit agencies often tend to adopt the conventional management strategy for BEB system, where all the fleets have a unified fleet size and keep driving on the fixed route pre-determined at the beginning of the planning horizon [9]. To evaluate the effectiveness of the proposed model, we compare the optimal lifecycle cost from the model with that from the conventional management strategy in which the fleet size meets the requirements for all the routes. To be specific, the conventional management strategy uniformly purchases seven BEBs for the fleets 1-6, and each fleet only serves one route without scheduling over the whole planning horizon. The results indicate that the proposed methods can reduce the lifecycle cost by 7.77% and 6.64% compared to the conventional management strategy for overnight and opportunity charging systems, respectively. Thereinto, for the overnight charging system, the proposed model can save 11.90% of BEB and charger purchase costs and 5.36% of battery replacement cost compared with the conventional management strategy; for the opportunity charging system, the proposed model can save 19.05% of BEB purchase cost and 7.29% of battery replacement cost as compared to the conventional management strategy. The above results show that the collaborative optimization of infrastructure procurement and fleet scheduling can help to reduce both the initial capital cost and use-phase operating cost.

C. Sensitivity Analysis

In the numerical case study, several key parameters of the example scenario are given by considering the real-life conditions referenced in existing studies, as shown in TABLE III. On this basis, we further carry out a series of simulations for sensitivity analysis to explore the relative importance of the key parameters for the optimal lifecycle cost. The parameters considered in the sensitivity analysis include the purchase cost of BEB, purchase cost of charger, unit battery cost, battery nominal capacity, charging power, and unit charging cost. The sensitivity analysis evaluates these parameters by changing their values individually. To be exact, the values of each parameter in sensitivity analysis are determined by respectively increasing and decreasing 20% from the base value that is presented in the aforementioned case study. The results of sensitivity analysis are summarized in Fig. 9, which presents the percentage difference of lifecycle costs obtained from the optimal results with variation of each parameter for both overnight and opportunity charging systems.

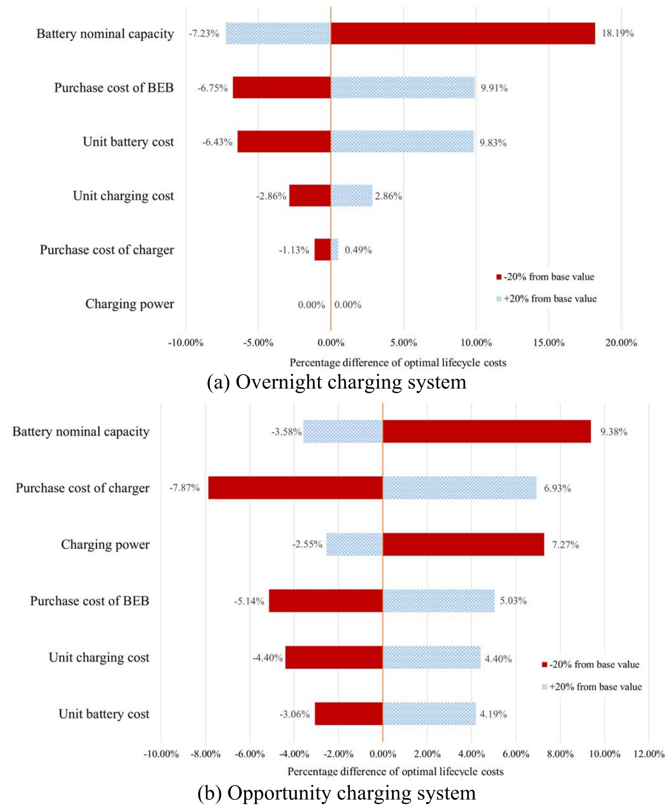
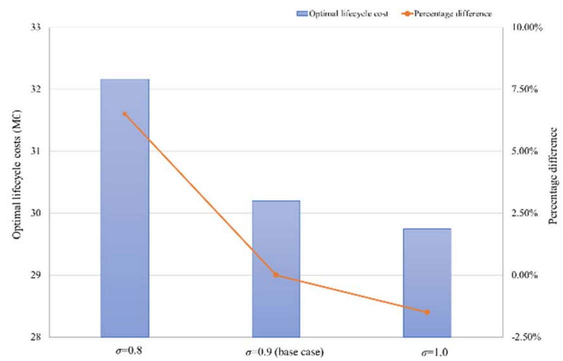


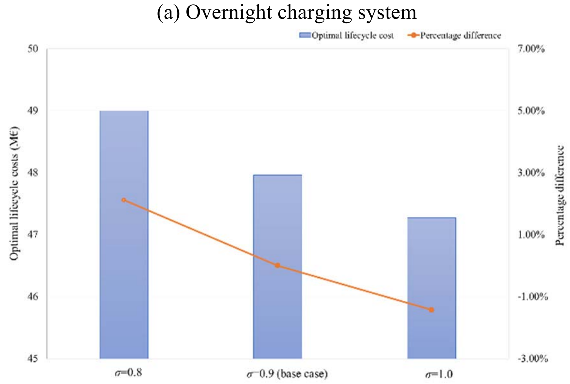
Fig. 9. Percentage difference of lifecycle costs with variation of each parameter.

In Fig. 9, cases (a) and (b) provide the results of sensitivity analysis for overnight and opportunity charging systems, respectively. For the overnight charging system, the optimal lifecycle cost is most sensitive to the battery nominal capacity, because the battery nominal capacity can not only affect the battery replacements but indirectly influence the required number of BEBs and energy consumption rate. The optimal results are also sensitive to the purchase cost of BEB and unit battery cost, which have primary effects on the BEB purchase cost and battery replacement cost, respectively. Since the unit charging cost and purchase cost of the charger is relatively low, the changes in them have comparatively limited impacts on the optimal results. In addition, the optimal lifecycle cost is least sensitive to the charging power, because the slow charging pattern used in overnight charging systems has an ignorable effect on battery fading rate as well as battery replacement costs. On the other hand, for the opportunity charging system, the optimal lifecycle cost is significantly sensitive to the battery nominal capacity, purchase cost of the charger, and charging power. Specifically, the battery nominal capacity has significant influences on the battery replacements and indirect influences on energy consumption rate. More importantly, unlike the overnight charging system, the changes in battery nominal capacity further affect the battery aging behavior, because the battery fading rate is highly related to the charging current rate under the fast charging pattern used in the opportunity charging system, which is associated with the battery nominal capacity and charging power. Thus, the charging power also has a considerable impact on the battery replacement cost. The purchase cost of charger has a significant impact on the optimal results owing to its relatively expensive price and large proportion in the lifecycle cost. Moreover, the optimal results are also sensitive to the purchase cost of BEB and unit charging cost, which directly affect the BEB purchase cost and charging cost from the lifecycle cost, respectively. The optimal lifecycle cost is least sensitive to the unit battery cost, because the battery used in opportunity charging system often has a relatively small nominal capacity. Moreover, the results also present that the battery performance improvement has greater benefits on the overnight charging system compared with the opportunity charging system. This is because the increase of driving range can reduce the fleet size for overnight charging system and thus save the BEB purchase cost. Therefore, it is better to charge using overnight charging method than opportunity charging method as the battery performance is improved.

Besides the aforementioned key parameters, we design an adjustment coefficient σ, ranging from 0.8 to 1, to adjust the battery capacity considering the battery fading behavior, and meanwhile reflect the decision preference of the operator for the trade-off between the benefit from sufficient utilization and the risk caused by overuse, as presented in (8) and (12) from Section II.D. If the adjustment coefficient σ is assigned a relatively large value, it indicates that the operator attaches greater importance to the benefit from sufficient utilization of the battery than that to the risk caused by its overuse. On the contrary, a relatively small value of the adjustment coefficient



(a) Overnight charging system



(b) Opportunity charging system

Fig. 10. Optimal lifecycle costs and related percentage differences under different adjustment coefficient σ.

σ indicates that the operator is more inclined to avoid the risk caused by overuse of battery than achieve additional benefit from its sufficient utilization. The normal level of the decision preference is obtained if the adjustment coefficient σ is equal to 0.9, which is applied in the numerical case study. Here, we further consider other two conditions with $\sigma = 0.8$ and $\sigma = 1.0$ to explore the impacts of the decision preference of the operator on the optimal results. Fig. 10 illustrates the optimal lifecycle costs and related percentage differences under different conditions with $\sigma = 0.8$, $\sigma = 0.9$ and $\sigma = 1.0$ for both overnight and opportunity charging systems, where the result under the condition with $\sigma = 0.9$ is obtained by the case study and thus regarded as the base case.

In Fig. 10, cases (a) and (b) present the optimal results and corresponding percentage differences for overnight and opportunity charging systems, respectively. It is observed that the optimal lifecycle costs for both the charging systems show a trend of change with the variation of adjustment coefficient σ. Specifically, a decrease of the adjustment coefficient σ would increase the lifecycle cost while an increase of that would reduce the lifecycle cost. This is because the adjustment coefficient σ significantly affects the battery replacements. Moreover, since the battery used in overnight charging system has a larger capacity and thus higher purchase cost than that used in opportunity charging system, the variation of adjustment coefficient σ has a slightly harsher impact on the optimal lifecycle cost of overnight charging system than that of opportunity charging system from the perspective of the percentage difference.

VI. Conclusion and Policy Implications

This study investigates the lifecycle cost optimization for BEB system by considering overnight and opportunity charging methods, respectively. A collaborative optimization model that simultaneously plans the infrastructure procurement and fleet scheduling are developed to comprehensively explore the economic efficiency of the lifetime operation of BEB system. Before modeling, we systematically analyze the essential factors involved in the BEB systems with the two different charging methods, including the energy consumption, BEB fleet size, number of chargers, and battery life span. In particular, the impacts of battery downsizing, charging patterns, and charging current rate on these factors are discussed and considered in the problem formulation. To effectively solve the proposed model, the collaborative optimization model is reformulated as the bi-level optimization problem and subsequently a hybrid heuristic solution method based on a TS and an IGA is customized by considering the hierarchical relationship between the infrastructure procurement and fleet scheduling. Moreover, a numerical case study is performed to demonstrate the proposed model and solution method, where most of the scenario parameters are assigned by reference to the real-life conditions and existing literature. The optimal BEB fleet sizes coupled with the optimal matches between fleets and routes are simultaneously obtained, and the optimal lifecycle cost can be reduced by 7.77% and 6.64% for overnight and opportunity charging systems, respectively, compared to the conventional management strategy. A series of simulations are further carried out to conduct sensitivity analysis and evaluate the key parameters on the optimal results. The results reveal the relative importance of the parameters for lifecycle cost and indicate the significant differences in their life cycle performance between overnight and opportunity charging methods, especially in that of the charger purchase cost and charging power, which is able to provide the managerial insights to public transit agencies and related stakeholders to construct and manage the BEB system. In addition, the research results can also contribute to the policy proposal for BEB promotion in the urban transit system under various regional features. Some of the policy implications are drawn as follows:

1) The construction of overnight charging systems often requires adequate land resources to provide long-term parking [61]. The results from the study indicate that the BEB purchase cost accounts for 93.48% of the initial capital cost for the overnight charging system. Therefore, for the regions that are suitable for the overnight charging method, introducing the purchasing subsidy policies of BEBs is an effective means to promote the electrification of the city bus system.

2) Frequent charging under fast charging patterns would bring challenges to the load capacity of the power grid, and the construction of an opportunity charging system has a high requirement to local power resources as consequence [61]. The results from the study imply that the charger purchase cost accounts for 59.68% of the initial capital cost for the opportunity charging system. Thus, the construction subsidy of charging devices can provide effective guidance to improve the attraction of BEBs in the regions that are suitable for the

opportunity charging method. Moreover, by introducing the appropriate construction subsidy of fast chargers, the transformation from overnight charging to opportunity charging can be guided to improve the energy and environmental performance of BEB system, because the bus weight reduction can induce the reduction of battery-to-wheel energy consumption and greenhouse gas emissions [31].

3) Even though the cost of Lithium iron phosphate batteries has been experiencing a gradually declining trend owing to its technological development, the battery replacement cost still accounts for a considerable proportion of the lifecycle cost for both charging methods. For some regions that are difficult to introduce subsidy policies, improving the battery efficiency is an effective method to enhance the competitiveness of BEBs in the urban transit system. Therefore, this is necessary to introduce targeted incentive policies to encourage operators to optimize the fleet scheduling over the whole life cycle and the battery replacement cost would be reduced as consequence.

Notably, the policy implications are inspired by the numerical results from the case study coupled with the sensitivity analysis considering a specific variation range of the parameters, whereas the realistic extent of potential changes in the values of the parameters are not comprehensively discussed. Our future work will further deal with the uncertainty of the parameters by using Monte Carlo analysis or other effective methods [62]. Moreover, this study considers the impacts of route overlapping on the required number of chargers with the opportunity charging method, which are reflected by defining the overlapping coefficient and probability of charging availability in the proposed model. Such definitions can reduce the model complexity yet leaves out the potential complexities of route network structure and traffic conditions. The structure of route network has potential effects on the location of chargers while the traffic conditions may fluctuate the travel duration between different bus stops. Therefore, built upon the collaborative optimization model, an in-depth investigation regarding the route overlapping effects will be carried out in future research based on real-world data. Meanwhile, the more realistic energy consumption models will also be applied in extending the lifecycle cost optimization of BEB system based on the real-world driving profile of different bus routes. In addition, this study evaluates the overnight and opportunity charging methods separately to better compare their impacts on lifecycle cost of BEB systems, while does not discuss the hybrid strategy with combination of different charging methods. The hybrid strategy may lead to lower lifecycle cost, which will be discussed in our future research.

Appendix
Derivation of Selection Probability With Immune Balance Operation in the IGA

Assume that f_{a_1} and f_{a_2} are the fitness values of any two antibodies a_1 and a_2 in the population. If the antibodies a_1 and a_2 are similar to each other, the following condition with a given similarity threshold ε should be satisfied:

$$-\varepsilon < f_{a_1} - f_{a_2} < \varepsilon \tag{A1}$$

Based on the similarity, the concentration of an antibody can be determined, which is the proportion of the antibodies that are similar to it in the population. Let con_{a_k} denote the concentration of antibody a_k, the probability in terms of the concentration is defined as shown in (B2).

$$pd_{a_k} = \begin{cases} \dfrac{1 - \frac{scon_a - 1}{num_a}}{num_a}, \\ \qquad \text{if } con_{a_k} \geq \dfrac{\max(con_{a_k}) + \min(con_{a_k})}{2} \\ \dfrac{(1 + \frac{scon_a - 1}{num_a}) \times \frac{scon_a - 1}{num_a - scon_a + 1}}{num_a}, \\ \qquad \text{if } con_{a_k} < \dfrac{\max(con_{a_k}) + \min(con_{a_k})}{2} \end{cases} \tag{A2}$$

where pf_{a_k} is the probability regarding the concentration of antibody a_k; $scon_a$ represents the number of antibodies whose concentration is less than the mean value of the maximum and minimum concentration values of the antibodies from the population; num_a is the population size.

Furthermore, the probability in terms of the fitness is denoted as pf_{a_k}, which is defined as the proportion of the fitness value for antibody a_k in the total fitness of all the antibodies from the population. Therefore, combining the probabilities of fitness and concentration, the selection probability for antibody a_k is calculated based on the immune balance operation, as shown in (B3).

$$ps_{a_k} = \varepsilon ps_{a_k} + (1 - \varepsilon) pf_{a_k} \tag{A3}$$

where ps_{a_k} is the selection probability for antibody a_k; ε is the trade-off coefficient between fitness and concentration.

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