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Optimization of Electric Bus Scheduling and Charger Location

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Abstract

In the pursuit of sustainable urban transportation, the transition from traditional fossil fuel-powered buses to battery electric buses (BEBs) presents a significant leap forward. However, this shift introduces a critical challenge in the form of the BEB scheduling and charger location (EBSCL) problem. The limited driving range of BEBs necessitates the strategic reassignment of buses for service trips, known as the electric vehicle scheduling problem. Simultaneously, the optimal placement of charging infrastructure adds complexity to the overall transit electrification process. Our study addresses this challenge by proposing an integrated model that optimizes both BEB scheduling and charger location. The source code is available at https://gitlab.com/AmirDavatgari/etcp.

Keywords:
bus scheduling; bus charger location; bus electrification; optimization

1. Introduction

Transit bus electrification holds significant importance in the broader context of sustainable urban transportation. The transition from traditional fossil fuel-powered buses to battery electric buses (BEBs) offers a range of benefits, encompassing environmental, economic, and social aspects [14]. Some of these are reduced greenhouse gas emissions, energy efficiency, lower operating costs, and noise reduction. Yet, electrification in the transit bus context revives essential infrastructural and operational problems as well. One such challenge is the need to reassign electric buses for revenue-generating service trips, referred to as the *electric bus scheduling problem*, due to the limited driving

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range of battery electric buses (BEBs). Additionally, there is the task of strategically placing charging locations to accommodate charging activities.

The electric bus scheduling problem refers to formation of *bus runs* based on a set of timetabled trips. These trips are characterized by essential spatio-temporal information, including their origin, destination, start time, and end time. The electric bus scheduling problem includes not only organizing trips into runs but also planning charging activities. While bus garages are primary locations for housing chargers, placing chargers at trip end locations could facilitate charging activities. Regular recharging at these locations could make BEBs function similarly to conventional diesel-powered buses. Resolving this necessitates solving a facility location problem (FLP) to identify optimal locations from a candidate set for housing these chargers. FLP decisions often have strategic implications, as altering or retracting them can be challenging and costly. Identifying the candidate facility set requires consideration of vehicle schedules as well. Perumal et al. [13] approached the VSP as a tactical planning problem, recognizing the need to address it whenever changes occur in the transit system, such as alterations in driving schedules, bus maintenance requirements, and spatial or temporal adjustments to bus routes. To address both concerns concurrently, we introduce the electric bus scheduling and charger location (EBSCL) problem.

In the existing literature, numerous studies have extensively explored the planning of charging facilities for BEBs. For instance, Liu et al. [11] presented a robust optimization model aimed at minimizing the total investment costs associated with deploying charging infrastructure for BEBs. Expanding on this work, Liu et al. [10] broadened the scope by incorporating seasonality and power matching into charger deployment. This extension highlighted the significant impact of BEB energy consumption characteristics on the optimal selection of charging station locations. A comprehensive approach was adopted in [2] by integrating charging facility planning and fleet scheduling, addressing uncertainties in charging demand through a stochastic integer optimization model. Meanwhile, Uslu and Kaya [15] proposed a model that focuses on determining optimal charging station locations and capacities, with an assumption of limited waiting time. Lin et al. [8] and Li et al. [7] approached BEB charger deployment as a multi-stage planning problem, optimizing station locations at various stages of the planning process.

In addition to determining optimal charger locations, the scheduling of the BEB fleet emerges as a critical concern. Niekerk et al. [12] made significant contributions by incorporating BEBs into the classical VSP, taking into account driving range limitations and linear charging. A more recent study by Cokyasar et al. [4] has further delved into BEB fleet scheduling, addressing the single depot VSP and proposing a heuristic solution approach. This innovative approach involves generating short tours that a BEB can serve, employing a mixed-integer non-linear program to combine tour tuples and ultimately generate bus runs. Various aspects of BEB fleet scheduling, such as charging event time, uncertainty in travel time, and energy consumption, have also been addressed by other studies [3, 17, 18, 19].

Existing optimization approaches often fall short by either assuming predetermined charging facility locations or neglecting the intricacies of the BEB scheduling. This gap in the literature underscores the need for more comprehensive models that consider both charger location and fleet scheduling in an integrated manner. Recognizing this critical interdependence, certain studies have introduced integrated models to address this synergy effectively [1, 9, 16]. Nonetheless, limited attention has been given to EBSCL problem. Our research seeks to bridge this gap by focusing on optimizing the scheduling of BEBs and strategically determining charging locations, taking into account the dynamic nature of routes. By acknowledging and addressing the EBSCL problem, our study aims to contribute novel insights and pave the way for more comprehensive and effective solutions, thereby advancing the current understanding of sustainable urban transit systems.

In the subsequent sections, Section 2 formally describes the EBSCL problem and presents the mixed-integer linear programming (MILP) model formulation. Next, we provide details about the data used for numerical experiments

in Section 3.1. Following that, we present a comprehensive case study design and discuss parametric choices to evaluate the performance of our proposed solution algorithm in Section 3.2. Finally, Section 4 concludes the study by summarizing the key findings and contributions of our work and discussing potential future research directions.

2. Problem definition

We now formally describe the EBSCL problem, which we model as an MILP. To ease reading, we use calligraphic letters to represent sets (e.g., $\mathcal{A}$), uppercase Roman letters for parameters (e.g., $\overline{B}$), lowercase Roman letters for variables and indices (e.g., y_{ij}), and Greek letters (e.g., α) as superscripts to modify parameters. Let $\mathcal{T}$ represent the set of timetabled bus trips, and let $\mathcal{E}$ denote the set of all feasible arcs connecting consecutive trips. The binary variable y_{ij} takes the value 1 if trip j is scheduled to follow trip i, forming valid sequences of bus trips. Chargers can be located at a set of candidate facilities, denoted by $\mathcal{F}$ that includes the garage denoted by d. This set is further partitioned into a subset $\mathcal{F}_{ij} \subseteq \mathcal{F}$ representing the candidate facilities which could be used in connection of trips i and j, and $\cup_{(i,j)\in\mathcal{A}}\mathcal{F}_{ij} = \mathcal{F}$. The binary variable e_{ijf} indicates whether recharging occurs between trips i and j at facility f. We symbolize the single garage with two indices s and t, that is every bus run starts from s and ends at t. Table 1 provides definition of sets, parameters, and variables used in the MILP model. The model to solve the EBSCL problem is formulated as follows.

$$\min \sum_{f\in\mathcal{F}} C^{\mu}_{f} x_f + \sum_{i\in\mathcal{T}} C^{\nu} y_{si} + \sum_{(i,j)\in\mathcal{E}} C^{\rho}\left(T^{\alpha}_{j} - T^{\beta}_{i}\right) y_{ij} \tag{1}$$

subject to,

$$\sum_{j:(i,j)\in\mathcal{A}} y_{ij} = 1 \qquad \forall i \in \mathcal{T} \tag{2}$$

$$\sum_{i:(i,j)\in\mathcal{A}} y_{ij} = 1 \qquad \forall j \in \mathcal{T} \tag{3}$$

$$\sum_{f\in\mathcal{F}_{ij}} e_{ijf} \le y_{ij} \qquad \forall (i,j) \in \mathcal{A} \tag{4}$$

$$u_{ijf} \le \overline{B} e_{ijf} \qquad \forall (i,j) \in \mathcal{A}, f \in \mathcal{F}_{ij} \tag{5}$$

$$\sum_{(i,j)\in\mathcal{A}} e_{ijf} \le \mathbb{M} x_f \qquad \forall f \in \mathcal{F} \tag{6}$$

$$v_{ij} \ge b_i - B_i - E_{ij} y_{ij} - \sum_{f\in\mathcal{F}_{ij}} \left(E_{if} + E_{fj} - E_{ij}\right) e_{ijf} + \sum_{f\in\mathcal{F}_{ij}} u_{ijf} - \mathbb{M}\left(1 - y_{ij}\right) \qquad \forall (i,j) \in \mathcal{A} \tag{7}$$

$$v_{ij} \le b_i - B_i - E_{ij} y_{ij} - \sum_{f\in\mathcal{F}_{ij}} \left(E_{if} + E_{fj} - E_{ij}\right) e_{ijf} + \sum_{f\in\mathcal{F}_{ij}} u_{ijf} - \mathbb{M}\left(1 - y_{ij} - z_{ij}\right) \qquad \forall (i,j) \in \mathcal{A} \tag{8}$$

$$v_{ij} \le \mathbb{M}\left(1 - z_{ij}\right) \qquad \forall (i,j) \in \mathcal{A} \tag{9}$$

$$b_j = \sum_{i:(i,j)\in\mathcal{A}} v_{ij} \qquad \forall j \in \mathcal{T} \tag{10}$$

$$b_i - B_i - \sum_{j:(i,j)\in\mathcal{A}} E_{ij} y_{ij} \ge -\mathbb{M} \sum_{j:(i,j)\in\mathcal{A}, f\in\mathcal{F}_{ij}} e_{ijf} \qquad \forall i \in \mathcal{T} \tag{11}$$

Table 1: Sets, parameters, and variables used in the MILP for the EBSCL.

Set	**Definition**
$\mathcal{A}$	set of all feasible arcs connecting two consecutive trips within the horizon, $\mathcal{A} = \mathcal{E} \bigcup (\{s\} \times \mathcal{T}) \bigcup (\mathcal{T} \times \{t\})$, where s and t indices denote the garage buses are dispatched from and return to, respectively
$\mathcal{E}$	set of arcs connecting consecutive trips $i \in \mathcal{T}$ (first) and $j \in \mathcal{T}$ (second), $\mathcal{E} = \left\{ (i,j) \,\middle|\, i,j \in \mathcal{T} \wedge i \neq j \wedge L \leq \left(T_j^{\alpha} - T_i^{\beta} - E_{ij}\right) \leq U \right\}$
$\mathcal{F}$	set of candidate charging facilities $f \in \mathcal{F}$, and $\mathcal{F}$ includes d, that represents the garage charging
$\mathcal{F}_{ij}$	subset of candidate charging facilities that provide reasonable deflection between trips $i \in \mathcal{T}$ and $j \in \mathcal{T}$, $\cup_{(i,j)\in\mathcal{A}} \mathcal{F}_{ij} = \mathcal{F}$
$\mathcal{T}$	set of timetabled bus trips
Parameter	**Definition**
$\overline{B}$	battery capacity in time units
B_i	energy consumption of trip $i \in \mathcal{T} \cup \{s\}$ measured in time units, and $B_s = 0$
C^{ν}	vehicle cost in time units
C^{ρ}	weight for time spent between service trips
C_f^{μ}	charging facility cost at candidate location $f \in \mathcal{F}$ in time units
D	maximum duration a BEB is allowed to spend in layover between two trips, anywhere other than garage, measured in time units
E_{ij}	energy consumption of traveling from last stop of trip $i \in \mathcal{T} \cup \mathcal{F} \cup \{s,t\}$ to first stop of trip $j \in \mathcal{T} \cup \mathcal{F} \cup \{s,t\}$ measured in time units, e.g., for every minute a bus drives, it consumes one minute of energy
L	minimum admitted recharging and/or layover time between two consecutive trips
$\mathbb{M}$	big number
R^{δ}	rate of recharge, i.e., energy (in time units) gained by recharging in one unit of time, e.g., R^{δ} minutes of driving range is gained by recharging a bus for one minute
T_i^{α}	start time of trip $i \in \mathcal{T}$
T_i^{β}	end time of trip $i \in \mathcal{T}$
U	maximum admitted recharging and/or layover time between two consecutive trips
Variable	**Definition**
b_i	state of charge (SOC) at the beginning of trip $i \in \mathcal{T} \cup \{s\}$ measured in time units, $b_i \in \mathbb{R}_{\geq 0}$
e_{ijf}	$\begin{cases} 1 & \text{if BEB recharges between trips } i \in \mathcal{T} \text{ and } j \in \mathcal{T} \text{ at facility } f \in \mathcal{F}_{ij},\ (i,j) \in \mathcal{A} \\ 0 & \text{otherwise} \end{cases}$
u_{ijf}	energy gained between trips i and j at facility $f \in \mathcal{F}_{ij}$ measured in time units, $u_{ijf} \in \mathbb{R}_{\geq 0},\ (i,j) \in \mathcal{A},\ f \in \mathcal{F}_{ij}$
v_{ij}	SOC at the beginning of trip j after serving trip i measured in time units, $v_{ij} \in \mathbb{R}_{\geq 0},\ (i,j) \in \mathcal{A}$
x_f	$\begin{cases} 1 & \text{if a charging facility is placed at candidate location } f \in \mathcal{F} \\ 0 & \text{otherwise} \end{cases}$
y_{ij}	$\begin{cases} 1 & \text{if trip } j \text{ is served after trip } i,\ (i,j) \in \mathcal{A} \\ 0 & \text{otherwise} \end{cases}$
z_{ij}	auxiliary binary variable used to linearize the max function, $(i,j) \in \mathcal{A}$

$$b_i - B_i - \sum_{j:(i,j)\in\mathcal{A}, f\in\mathcal{F}_{ij}} E_{if} e_{ijf} \geq 0 \qquad \forall i \in \mathcal{T} \tag{12}$$

$$b_i - B_i - \sum_{j:(i,j)\in\mathcal{A}, f\in\mathcal{F}_{ij}} E_{if} e_{ijf} + \sum_{j:(i,j)\in\mathcal{A}, f\in\mathcal{F}_{ij}} u_{ijf} \leq \overline{B} \qquad \forall i \in \mathcal{T} \tag{13}$$

$$b_s - B_s - \sum_{f\in\mathcal{F}_{sj}} E_{sf} e_{sjf} \geq 0 \qquad \forall j \in \mathcal{T} \tag{14}$$

$$b_s - B_s - \sum_{f\in\mathcal{F}_{sj}} E_{sf} e_{sjf} + \sum_{f\in\mathcal{F}_{sj}} u_{sjf} \leq \overline{B} \qquad \forall j \in \mathcal{T} \tag{15}$$

$$b_s \leq \overline{B} \tag{16}$$

$$0 \leq \left(T_j^{\alpha} - T_i^{\beta}\right) y_{ij} - \left(E_{ij} y_{ij} + \sum_{f\in\mathcal{F}_{ij}} \left(E_{if} + E_{fj} - E_{ij}\right) e_{ijf} + \frac{\sum_{f\in\mathcal{F}_{ij}} u_{ijf}}{R^{\delta}} \right) \leq D + \mathbb{M} e_{ijd} \qquad \forall (i,j) \in \mathcal{E} \tag{17}$$

$$e_{ijf},\ y_{ij},\ x_f,\ z_{ij} \in \{0,1\}, b_i,\ u_{ijf},\ v_{ij} \in \mathbb{R}_{\geq 0}$$

The objective function (1) minimizes the weighted total cost, including the cost of overall time between two consecutive trips, the vehicle costs associated with each scheduled run, and the charger facility costs. Constraints (2) and (3) ensure that each trip is both preceded and succeeded by exactly one other trip, forming a valid sequence. Constraints (4) guarantee that a BEB can recharge between trips $i \in \mathcal{T}$ and $j \in \mathcal{T}$ if they are connected. Constraints (5) ensure that the charging amount between consecutive trips does not exceed the battery capacity. Constraints (6) enforce that a charging facility must be located at $f \in \mathcal{F}$ if it is used by at least one BEB. Constraints (7) – (10) calculate the state of charge (SOC) before each trip, while constraints (11) – (13) maintain the SOC within feasible bounds. Constraints (14) – (16) regulate the SOC at the beginning of each run. Constraints (17) set bounds on the *layover time* between two consecutive trips. Here, layover time is defined as the time that a BEB is not serving a trip, not deadheading between two trips, and not charging.

3. Numerical experiments

3.1. Data

Our experiments use Chicago metropolitan region as a testbed. We randomly select a bus garage of the transit agency Pace Suburban Bus that serves 60 trips. The trip information, i.e. T_i^α and T_i^β are obtained from the General Transit Feed Specification (GTFS) data [5]. Figure 1 shows the location of the garage, the roadway links used in these trips, and five candidate charging facilities. The parameters used are summarized in Table 2. We assumed an average speed of 20 mph and used Manhattan distances as a basis for estimating deadheading energy consumption E_{ij} in time units. The energy consumption B_i is calculated as the time difference between T_i^β and T_i^α. We consider a bus with battery capacity $B^\kappa = [60, 90, 120]$ miles. To determine the BEB capacity in time units, we calculate $\overline{B} = \frac{B^\kappa}{V}$, which yields a battery capacity of three hours for $B^\kappa = 60$ miles.

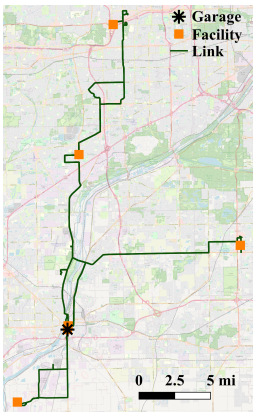

Fig. 1: Candidate facility, garage, and trip locations in the case study.

Regarding the charging infrastructure, we consider fast charging. The power for fast charging is $P = 450$ kW. To determine the rates of recharge, we calculate $R^\delta = \frac{P}{VR^\kappa}$, where R^κ is bus energy consumption rate in kWh/mile. These calculations yield recharge rates of $R^\delta = 3.068$, that is charging a bus for one unit of time increases the SOC by 3.068 time unit.

Table 2: Parametric values used.

C_f^{μ} (s)	C^{ρ}	V (mph)	R^{κ} (kWh/mile)	P (kW)	D (s)	$\mathbb{M}$	L (s)	U (s)
1,000	1	20	7.33	450	6,000	10^6	0	10,800

3.2. Case study

In the case study, we run 15 instances of the problem considering $B^{\kappa} = [60, 90, 120]$ miles and $C^{\nu} = [1, 1K, 10K, 50K, 100K]$, where K denotes a thousand. The instances are solved using the Python 3.6.9 interface to interface with the commercial solver Gurobi 10.0 [6]. Number of open facilities and the number of bus runs (i.e., nummber of busses) found by the optimization shown in Figure 2 are key performance indicators. In Figure 2a, we observe that the number of bus runs considerably decreases as vehicle cost C^{ν} increases. On the other hand, the bus range B^{κ} does not always impact the number of bus runs.

Figure 2b demonstrates the change in number of open facilities for different B^{κ} and C^{ν}. A strong correlation between C^{ν} and the number of open facilities is not found, however the number of facilities often increases as C^{ν} moves up. We observe that the number of facilities can decrease when the range increases. When B^{κ} changes from 60 to 90 and 120 miles at $C^{\nu} = 1$, we observe that the number of open facilities drops from two to one. In the case when it is one, the only open facility is the garage, while an additional candidate facility is chosen in the other case. We observe two open facilities in many cases because the combined travel time from garage to a trip's origin, servicing the trip, and from trip's destination to the garage is larger than $\overline{B}$. This finding shows that more facilities can be needed when trip times are close to the vehicle range.

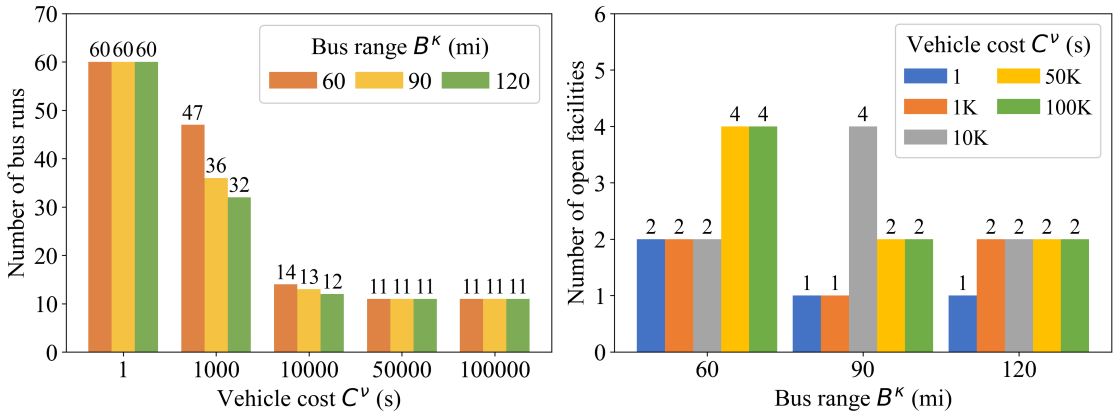

Fig. 2: Key performance indicators of the case study.

In these results, we also analyze the magnitude of times spent for service, deadhead, charging, and layover. Figure 3 shows the percent share of a day spent for these four activities in these 15 scenarios. As C^{ν} increases, we observe a larger service share indicating a higher vehicle utilization. This is because the number of bus runs decreases, resulting in each bus handling more trips and consequently increasing the service share. Moreover, as the bus range increases, the service share also increases. This is intuitive because a larger driving range enables the buses to serve more trips.

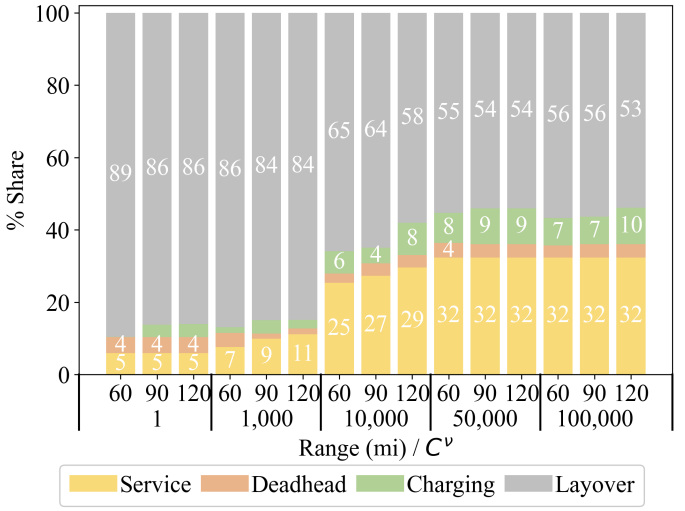

Fig. 3: Key performance indicators of the case study.

4. Conclusion

In this research, we tackle the EBSCL problem by formulating an MILP model. Our objective is to optimize BEB schedules and strategically identify charging facilities, especially at trip end locations. We illustrate the linearization process of the model, offer comprehensive insights into the utilized data, and present case studies to showcase the practicality of our proposed model.

The case study specifically examines a bus garage of Pace Suburban Bus in Chicago region, encompassing 60 trips and considering five potential charging locations that coincide with the terminal stops of the analyzed trips. While we can achieve optimality for this scenario, it is evident that the problem scale is not merely substantial but reaches a magnitude that exceeds the capabilities of off-the-shelf solvers. Addressing the scalability of the problem necessitates the incorporation of heuristic or metaheuristic solution methods.

This investigation concentrates exclusively on the location aspect, assuming that each identified site has the capacity to accommodate sufficient charging infrastructure. In essence, the study does not determine the charging capacity or schedule. Even with these simplifications, we highlight the inherent complexity of the problem, and introducing these factors would only amplify its intricacy. Moreover, the decision-making process for locations could be aggregated across different garages within a single transit service agency, allowing vehicles from various garages to recharge at locations overlapping with another garage's service area. In conclusion, our study marks an initial step in modeling and solving a substantial and intricate electrification problem, leaving numerous avenues for future research and exploration.

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