Investigating the Resource Allocation of Electric Buses with Uncertainty through Optimal Charging Strategy

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ABSTRACT

The development of urban battery electric buses (BEB) challenges bus operators due to the high expenses of BEB facilities. This paper aims to provide recommendations on the urban BEB resource allocation based on the optimal charging strategy. A network flow model was proposed to minimize the total operation cost with charging station capacity, vehicle battery capacity, and time compatibility constraints and was solved by the Adaptive Large Neighborhood Search algorithm with novel destroy/repair operators. A sensitivity analysis was implemented using random samples from clustered real-world data to simulate travel time and energy consumption uncertainty. The result shows that charging at night or shorter charging durations in the daytime can significantly increase the operation cost, mostly due to more buses with higher battery capacities in the fleet. Under the optimal strategy, a higher proportion of buses with small or medium battery capacity is required, thus decreasing the total cost. Sufficient charging resources can improve the robustness of the charging plan, while economic benefits no longer increase when the charging station capacity reaches a certain threshold. It indicates that bus operators can reduce the investment in chargers to ensure both economic benefits and operation stability. When the bus route is longer with higher energy consumption, buses with medium or high battery capacity become more demanding, while the requirement on the charging station capacity and the charging duration do not significantly change. This study provides references for proper charging planning, charging resource allocation, and fleet composition of urban electric bus systems.

Keywords: battery electric bus, charging scheduling, charging station capacity, fleet composition, energy consumption uncertainty
1. INTRODUCTION

Bus electrification is one of the main strategies to tackle climate and energy issues on the urban scale. In 2020, the proportion of new energy buses in urban public transport in China is 66.2%, and it is proposed to reach 72% in 2025 [1]. Compared with traditional diesel-powered buses, battery electric buses (BEB) have been proven to have better ecological benefits and more cost-competitive in the life cycle [2-4].

Despite the development of the technology, difficulties exist in the application and operation of BEBs. First, compared to diesel buses, the limited battery capacity of BEBs requires more vehicles to complete daily bus service, or more cost-effective charging planning to compensate for shorter ranges [5]. However, urban land shortage and difficulties in power grid expansion hinder the construction of charging infrastructure, restricting the charging accessibility, and reducing the service efficiency. An optimized scheduling and recharging plan with fleet composition and charging resources constraints are necessary to maximize resource utilization efficiency and reduce the total cost.

In current literature, BEB optimization mainly concerns three topics: electric vehicle scheduling problem (EVSP), fleet composition, and the deployment of charging infrastructure. The EVSP integrates traditional vehicle scheduling problem (VSP) (which assigns buses to cover a given set of trips [6]) with the route and recharging time constraints [7]. Adler (2014) proposed the Alternative-Fuel Multiple Depot Vehicle Scheduling Problem and its network flow model, which is widely adopted by other studies [8]. Li (2014) considered charging station capacity constraints in the optimization and solved it with a column-generation algorithm [9]. Wen et al. (2016) presented an EVSP model that allowed partial charging and solved the problem with a heuristic algorithm [10]. Focusing on large-scale multi-depot EVSP, Wang et al. (2021) proposed a genetic-algorithm-based column generation approach (GA-CG), which can be 40 times faster than the branch-and-price (BP) algorithm [11]. Researchers also combine EVSP with other factors, such as crew scheduling [12], power grid characteristics [13-15], and energy consumption uncertainty [16-18].

EVSP can be combined with fleet composition to investigate systematic optimization. For example, Olsen et al. (2020) extended the EVSP by considering a mixed fleet consisting of BEBs and diesel buses [19]. Similarly, Rinaldi et al. (2020) studied the mixed electric/hybrid fleet problem. The result demonstrated that introducing full-electric buses to the current fleet can reduce the operation cost while the marginal savings gradually decrease as more conventional buses are replaced [20]. Yao et al. (2020) established an optimization model considering multiple BEB types with different driving ranges, recharging duration, and energy consumption, and they conducted a case study with two BEB types [21]. Zhang et al. (2021) proposed a multi-vehicle-type EVSP model considering line change constraints and nonlinear charging, showing a reduced fleet size by allowing bus line change [22].
Chen et al., (2022)

Charging resource deployment affects vehicle scheduling, fleet size, and composition. For example, when charging stations are limited, vehicle utilization will be reduced due to inadequate recharging, and vehicles with larger batteries are required. To tackle this problem, Rogge et al. (2018) provided the cost-optimized planning of bus schedules, fleet composition, and the number of chargers. They proved that a mixed fleet could reduce the demand for chargers and the total vehicle purchasing cost [23]. Wang et al. (2022) developed an integrated optimization model for charger deployment and fleet scheduling for BEBs under the opportunity charging [24]. The sensitivity analysis indicated that BEB purchasing and energy consumption rates significantly impact the total cost. Lee et al. (2021) also discovered that a large fleet size and a high charging station capacity can reduce the minimum requirement of the battery capacity [25].

Despite the increasing number of studies on BEB optimization, most treat trip energy consumption as a static parameter, ignoring the impact of uncertain energy consumption. Some studies considered the uncertainty by integrating an energy consumption distribution [17, 25] or a robust optimization [18], while the influence of the time-varied energy consumption on the BEB deployment and the sensitivity of varied energy consumption levels are under investigation. On the other hand, few studies have discussed the robustness of charging strategies and charging resource allocation considering the randomness of the trip-wise energy consumption and travel time.

This paper investigates the most cost-effective charging resource allocation based on optimal bus scheduling considering the trip travel time and energy consumption uncertainty. The contribution of this study is twofold. First, to the best of our knowledge, this study is one of the first to access both the cost-effectiveness and the robustness of the urban BEB deployment, including the fleet composition, charging strategy, and charging resource allocation under energy consumption uncertainty. The proposed method uses an optimization program considering mixed fleet and charging station capacity constraints based on the random travel time and energy consumption samples generated from real-world data. Second, a case study and a group of sensitivity analyses conducted in Nanjing, China are presented to demonstrate the effectiveness of the proposed method and the relationship among charging strategy, fleet composition, and charging resource allocation. The impact of bus line distance and energy consumption level is further discussed.

2. METHODOLOGIES

The methodology of this study includes three main tasks, as outlined in Figure 1. First, the actual bus operation is analyzed, and the random samples are generated using the travel time and energy consumption distribution. Second, an electric vehicle
Chen et al., (2022) scheduling problem with charging station capacity (EVSP-CSC) is formulated, and an ALNS algorithm is proposed to solve the optimization. Finally, the optimal charging strategy with resource allocation recommendations is derived using the optimization algorithm.

Figure 1 Flow chart of this study

2.1 Data description and preprocessing

The global positioning system (GPS) and on-board diagnostics system (OBD) were used to collect the second-by-second operation data of five BEBs from one bus service line (bus line No.4) in Nanjing from April 22, 2021, to April 27, 2021 (six days). In total, 1,305,087 pieces of data, including second-by-second position, speed, battery voltage, and current, were collected. Daily bus service of the investigated line starts at 05:30 AM and ends at 11:30 PM with 64 round trips per day, 24.8 km per trip. Each round trip includes a dispatched trip from the terminus and a return trip to the terminus. All vehicles are recharged at the same station.

The data are first preprocessed with the following steps:

1. Delete the data outside the operation area according to GPS coordinates.
2. Delete the data with invalid values.
(3) Delete outlier data according to vehicle acceleration. Referring to Farzaneh (2015) [26], the threshold for detecting outlier data is identified as follows:

a) An upper limit of the 99-percentile value for instantaneous acceleration.

b) A lower limit of \(-4.4704 \text{ m/s}^2\) for instantaneous deceleration.

(4) Perform linear interpolation on data with a time interval of less than 10 seconds.

After data preprocessing, the data are divided into 108 round trips according to GPS coordinates of the terminus. Operation data of these trips, including average speed and energy consumption, were extracted. The total energy consumption over time \(T\) is illustrated in Equation (1), where \(U_t\) and \(I_t\) are the (second based) instantaneous voltage and current of the battery.

\[
E_{\text{cons}} = \int_0^T U(t)I(t)dt = \frac{1}{1000 \times 3600} \sum_{t=1}^{T} U_tI_t
\]  

(1)

2.2 Trips clustering and random sample generation

A multi-line bus service network based on real-world BEB data is generated in the study case. To further explore the variation of trip energy consumption and travel time, 100 random samples are generated based on the real-world operation data to simulate the uncertainty of travel time and energy consumption. To distinguish trips from different periods of a day, the K-Means method was used to cluster all the real-world trip records into three groups: peak, off-peak, and morning/evening period, according to the historical average travel time of Nanjing bus line No.4 captured by the AMAP API [27]. In each period, one pair of travel time and energy consumption from the corresponding group is randomly selected for each scheduled service trip. For trips that do not belong to bus line No.4, the travel time and energy consumption are scaled according to the route distance. Figure 2 illustrates the process of random sample generation. As a result, each trip set in the random samples is composed of all the service trips of the studied bus lines in one day. In every trip set, each trip includes a randomly selected travel time and energy consumption from the real-world operating dataset.
2.3 Modelling approach

2.3.1 Problem description

The EVSP-CSC proposed in this study considers the charging demand of BEBs and charging station capacity constraints with the following assumptions.

(1) The charging function of BEBs is assumed linear.

(2) Vehicles will be fully recharged at the charging station after finishing all tasks for the day to ensure that vehicles have enough power for the next day’s operation.

(3) Vehicles are recharged at the same charging station.

2.3.2 Network flow model

The model is defined on a directed multigraph $G = (N, A)$ where $N$ and $A$ represent all nodes and arcs in the graph. For bus type decision, we first defined bus type set $K = \{1, 2, ..., K\}$, in which each bus type $k \in K$ corresponds to battery capacity $E_k$ and charging rate $v_k$. $N = D \cup T \cup F$ represent all nodes in the graph. $D$ represents all depot nodes. For single depot operation mode, $D = \{o,d\}$ includes start and end nodes. For a trip node $i \in T$, the start time, travel time, and trip energy consumption are defined as $s_i$, $t_i$ and $e_i^k$ respectively, and corresponds to a recharging node $f_i \in F$.

In a network flow model, an arc $(i, j) \in A$ represents the connection, as well as the deadheading trip between nodes $i$ and $j$. There are four kinds of arcs in this paper:

(1) Deadhead trips from the depot, where $i \in \{o\}$, $j \in T$;

(2) Deadhead trips returning to the depot, where $i \in T$, $j \in \{d\}$;

(3) Deadhead trips between service trips, where $i, j \in T$ and $i \neq j$;

(4) Deadhead trips between service trips and charging events, where $i \in T$ and
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\[ j \in F, \text{ or } i \in F \text{ and } j \in T. \]  
Due to the correspondence between service trips and charging events, only arc \((i, f_i)\) is linked if \(i \in T.\)

For arc \((i, j) \in A\), travel time \(t_{ij}\) and energy consumption \(e_{ij}^k\) are defined. For simplification, we use the notation \(\delta^-(i)\) and \(\delta^+(i)\) to represent arcs that end and start at node \(i.\)

Similar to Li (2014) [9] and Tang et al. (2019) [28], time-expanded nodes are used for recharged vehicle amount calculation. We assume that each recharging event takes \(\beta \times U\) minutes, where \(\beta\) represents a fixed time interval, and \(U\) represents the number of unit intervals in one recharging event. Let \(R = \{r_1, r_2, \ldots, r_n\}\) denotes set of recharging time divisions. Each time division \(r_i \in R\) corresponds to a start time \(s_{r_i}.\) For \(r_i \in R\), let \(b^u(r_i)\) denotes the time division \(u\) intervals ahead of \(r_i.\) The amount of BEBs being recharged at the charging station can be calculated as the total number of vehicles selecting the recharging division \(r_i, b^1(r_i)\ldots b^{U-1}(r_i).\) Let \(I\) denotes set of time division indicators. Indicaor \((f, r_i) \in I\) represents the connection between recharging node \(f \in F\) and time division \(r_i \in R.\) A sample directed graph is presented in Figure 3. Infeasible arcs are deleted before running the optimization algorithm to reduce the number of variables as much as possible.

![Directed Graph Illustration](image)

**Figure 3 Illustration of the directed graph**

The binary variable \(x_{ij}^k\) represents the connections in the graph, where \((i, j) \in A \cup I\) is the arc or indicator of two nodes. When \((i, j) \in A, x_{ij}^k = 1\) if a bus of type \(k\) is assigned to operate on arc \((i, j).\) When \((i, j) \in I, x_{ij}^k = 1\) if time division \(j\) is selected for recharging event \(i\) for a bus of type \(k.\) Let \(y_i^k\) denotes the remaining battery power of a bus of type \(k\) at the beginning of node \(i \in N.\) For recharging event \(f \in F, let s_f\) denotes the start time of \(f, and y_f^k\) denotes the remaining battery power of a bus of type \(k\) when \(f\) is finished.
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1 The mathematical model is formulated as follows:

\[ \begin{align*}
\min & \sum_{k \in K} \sum_{(i,j) \in \delta^+(o)} c^k x^k_{ij} \\
+ & \sum_{r \in R} \sum_{k \in K} \sum_{f \in F} \left( y^r_k - y^f_k \right) c^r x^r_{fr} + \sum_{k \in K} \sum_{i \in T} \left( E^k - y^i_k \right) c^e x^e_{id} \\
+ & \sum_{k \in K} \sum_{(i,j) \in A} \left( t_i + t_{ij} \right) c^k x^k_{ij}
\end{align*} \] (2)

2 Subject to:

\[ \sum_{k \in K} \sum_{(i,j) \in \delta^+(i)} x^k_{ij} = 1 \quad \forall i \in T \] (3)

\[ \sum_{k \in K} \sum_{(f,j) \in \delta^+(f)} x^k_{fj} \leq 1 \quad \forall f \in F \] (4)

\[ \sum_{(i,j) \in \delta^+(i)} x^k_{ij} - \sum_{(j,i) \in \delta^-(i)} x^k_{ji} = 0 \quad \forall i \in T \cup F, \forall k \in K \] (5)

\[ \sum_{r \in R} x^k_{fr} - \sum_{(i,j) \in \delta^-(f)} x^k_{fj} = 0 \quad \forall f \in F, \forall k \in K \] (6)

\[ \sum_{(o,j) \in \delta^+(o)} x^k_{oj} - \sum_{(i,d) \in \delta^-(d)} x^k_{id} = 0 \quad \forall k \in K \] (7)

\[ s_i + t_i + t_{ij} - M \left( 1 - \sum_{k \in K} x^k_{ij} \right) \leq s_j \quad \forall i \in T, \forall (i,j) \in \delta^+(i) \] (8)

\[ s_f + U \cdot \delta + t_{fj} - M \left( 1 - \sum_{k \in K} x^k_{fj} \right) \leq s_j \quad \forall f \in F, \forall j \in T \] (9)

\[ s_f = \sum_{k \in K} \sum_{r \in R} s_r x^k_{fr} \quad \forall f \in F \] (10)
The objective is to minimize the total operating cost, including three components. The first component calculates the investment cost of all BEBs, where $c^k$ is the daily depreciation cost (or daily purchase cost) of a single bus of type $k$. The second component is the cost of electricity consumption from all recharging events, including partial recharging during operation and fully recharging after finishing all tasks. The third component is the time-dependent labor cost, where $c_t$ represents the labor cost per minute for service trips and deadhead trips.

Constraint (3) ensures that every service trip is fulfilled exactly once. Constraint (4) means that every possible recharging event can be performed at most once. Constraint (5) requires flow conservation. Constraint (6) ensures that all performed recharging events are assigned to a recharging time division. Constraint (7) enforces that the number of buses departed from and returned to the depot is the same. Constraints (8) and (9) specify the time compatibility of the connection between service trip and recharging event nodes and their subsequent nodes, respectively, where $M$ is a sufficiently large positive number. Constraint (10) enforces that the start time of the
recharging event node is consistent with the start time of the time division it links to.

Constraints (11) and (12) specify the energy consumption compatibility of the connection between nodes and their subsequent nodes, respectively, where $M$ is a sufficiently large positive number, too. Constraint (13) ensures that the remaining battery power of the vehicle at any time can not be lower than the safety level $\sigma$; Constraint (14) ensures that buses are fully charged when departing from the depot. In this paper, a linear charging function is used to approximate the charging process of BEBs, and because the charging duration is specified, the charging quantity of each recharging event equals $U \cdot \delta \cdot v^k$. Constraint (15) ensures that the remaining battery power does not exceed the battery capacity of the vehicle while calculating the charging quantity. Constraint (16) ensures that the total number of recharged vehicles at the charging station does not exceed the station capacity. Constraint (17) defines the domain of decision variables.

### 2.4 Optimization Algorithm

The Adaptive Large Neighborhood Search algorithm (ALNS) [29], which is widely used for varied kinds of vehicle routing problems (VRP), has been applied to solve EVSP and prove its efficiency [10, 22]. Therefore, ALNS is employed to solve the EVSP-CSC in this paper. The ALNS explores the neighborhood by destroying and repairing the current solution to increase the search range of the search space, and improve the probability of obtaining a better solution. Figure 4 illustrates the flow chart of the algorithm. We use a greedy insertion algorithm [30] to construct initial solutions. A roulette wheel selection and an adaptive weight adjustment method [29] are employed for operator selection, and the simulated annealing algorithm is used as the acceptance criteria. The algorithm terminates when $N$ iterations are executed, or $N'$ iterations occur without improvements. All hyperparameters of the ALNS are tuned before generating the solution.

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**Figure 4** Flow chart of the algorithm
2.4.1 Destroy operators

In each iteration, $\gamma$ trips and their recharging nodes are removed from the solution by a destroy operator with certain rules, where $\gamma$ is a random integer between $[\gamma_{min}, \gamma_{max}]$. Trip chains with fewer than two trips are removed to minimize the number of vehicles.

Three types of operators are used in this study, including a random removal, a time-related removal, and a neighbor-based removal. The random removal removes $\gamma$ trips from the solution randomly, expanding the range of search. The time-related removal aims to remove trips with similar start or end times, so that new feasible solutions are more likely to be constructed. The temporal relationship $R(i,j)$ between trip $i$ and $j$ is set to $\omega_1 \cdot |s_i - s_j| + w_2 \cdot |t_i - t_j|$, where $s_i$ and $s_j$ are the start time of trip $i$ and $j$, and $t_i$ and $t_j$ are the travel time of trip $i$ and $j$. $\omega_1$ and $\omega_2$ denote the weights of the two values, respectively. A smaller $R(i,j)$ indicates that the time correlation between two trips is greater. When performing the time-related removal, one trip is first removed randomly, then one of the removed trips is randomly selected, and the trip with the strongest temporal relationship is removed, and the process is repeated until $\gamma$ trips are removed. The neighbor-based removal removes one trip with the trips before and after in the current trip chain each time, expanding the range of single removals, and giving more insertion space for other trips.

2.4.2 Repair operators

Repair operators construct a new solution by inserting the removed nodes into the schedule with different strategies. For EVSP-CSC, the repair of the solution includes the insertion of the service trip nodes, the insertion of the recharging event nodes, and the selection of the vehicle type. In this paper, two repair operators, namely random insertion and greedy insertion, are used.

The random insertion aims to ensure the diversity of solutions and prevent local optimum. The available insertion positions in the corresponding trip chain for a removed trip should be compatible with the preceding and the following trip. In each iteration, one removed trip is randomly selected and inserted into a random position that is available. If no position is available, the trip would be inserted into a new trip chain with a randomly assigned vehicle type. After each inserted trip, the recharging node is inserted with a probability $p_{\text{charge}}$ and randomly assigned to a time-compatible recharging time division.

The greedy insertion operator is used to generate better feasible solutions as much as possible to ensure the convergence of the algorithm. The insertion cost equals the added deadhead trip distance after insertion[10, 22]. This calculation method has two disadvantages. On the one hand, in a single depot scenario, the distance of deadhead
trips among different trips is the same; therefore, this calculation method would increase the computation time with ignorable result improvement. On the other hand, inserting a recharging node only when the trip chain violates the energy compatibility constraint would prevent the BEBs with smaller ranges from being selected.

Therefore, the greedy insertion uses the same node insertion method as the random insertion, and selects the compatible and available recharging time division for each recharging node. When all nodes are inserted, the greedy insertion is applied again to replace BEBs with lower-cost alternatives while keeping the trip chain unchanged. The replacement is accepted if the total cost decreases and all constraints are met.

### 2.4.3 Penalty

This paper defines penalties for solutions that violate constraints. Specifically, the algorithm checks whether the generated solution violates the energy compatibility constraints and charging station capacity constraints, and adds the energy penalty $c_{\text{energy}}$ and the charging station capacity penalty $c_{\text{capacity}}$ to the total cost accordingly. At the same time, the algorithm determines whether to accept an infeasible solution by the acceptance criteria defined by the simulated annealing. Finally, the optimal solution is required to be feasible.

### 3. RESULTS AND DISCUSSIONS

#### 3.1 Energy consumption uncertainty of battery electric bus

Using the average trip time derived from the AMAP API, 108 trips from bus line No.4 are clustered into 3 periods, including 67 peak trips, 25 off-peak trips and 16 morning/evening trips, as shown in Figure 5.

![Figure 5 Trip clustering according to historical average travel time](image)

The travel time, energy consumption, average speed, energy consumption factor, braking ratio and acceleration standard deviation for each period are calculated, and the results are shown in Figure 6. The consumption factor is the energy consumption per unit distance travelled by the vehicle (kW/km). The braking ratio equals the
accumulated time that the driver presses the brake pedal divided by the total travel time in a single trip, and is used to describe the frequency of braking behavior. The acceleration \( \text{Std} \) is the standard deviation of the instantaneous acceleration in a single trip. The larger the value, the more frequent the acceleration and deceleration behavior of the vehicle and the more “aggressive” the driver.

Figure 6 (a) and (b) present the kernel density estimation (KDE) plots of travel time and energy consumption for three periods. The trip travel time in the peak period is the highest with an average travel time of 103 minutes, followed by the off-peak period, while the travel time is significantly shorter during the morning/evening period. The energy consumption during the peak period is generally higher than those in the off-peak period. The distribution of trip energy consumption during the morning/evening period is more dispersed, indicating more uncertain driving operations.

To further summarize the characteristics of each period, the boxplots of four trip features are plotted in Figure 6 (c) to (f). Trips in the peak period exhibit relatively low average speed and high energy consumption, probably due to the congested road conditions during peak hours. In contrast, higher average speeds of BEBs during the off-peak period lead to lower energy consumption factors than during the peak period. However, the average energy consumption factor for trips during the morning/evening period is high despite their high speed. This is due to more aggressive driving behavior, as evidenced by high average speed, low braking ratio and frequent acceleration behavior.
Figure 6 KDE plot and distribution of operation data in different periods

### 3.2 Case study

#### 3.2.1 Parameter values

A case study is conducted based on a real-world transit network with one depot and three bus lines in Nanjing, China. This network contains a total of 275 service trips per day, each containing two consecutive dispatch and return trips. The depot has 20 chargers with 60 kW power output, providing parking and recharging services for BEBs.

Using the method proposed in Section 2.2, service trips of each bus line are divided into three periods: peak, off-peak, and morning/evening period. Figure 8 shows the average travel time (a) and trip energy consumption (b) data of three lines. The data of bus line No.4 are obtained from the collected data, and bus lines No.52 and No.99 are scaled from No.4 according to the route distance. A hundred random trip sets consisting of three bus lines in one day are generated using the method in Section 2.2.
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Figure 7 The bus network with three bus lines

Figure 8 Average trip data of three bus lines (two-way, M/E refers to the morning/evening period)

To investigate the impact of different vehicle types, this study considers three BEB types varied by the capacity and the cost shown in Table 1. The daily depreciation cost is calculated assuming an average lifetime of 7.8 years per BEB and 360 days of operation annually[31]. Note this study does not consider the variation of vehicle types in energy consumption and charging rate. According to the survey result, the electricity price $c_e$ in Nanjing is 0.6416 CNY/kWh. The average salary of a driver is 5,500 CNY per month. Averaged by 22 working days per month and 8 hours per day, the labor cost $c_t$ is 0.5 CNY per minute for a BEB driver. The lowest battery electric level $\sigma$ to use the bus is 20%.
Table 1 BEB type information

<table>
<thead>
<tr>
<th>Vehicle Type</th>
<th>A</th>
<th>B</th>
<th>C</th>
</tr>
</thead>
<tbody>
<tr>
<td>Battery Capacity (kWh)</td>
<td>100</td>
<td>170</td>
<td>256</td>
</tr>
<tr>
<td>Daily Depreciation (CNY/day)</td>
<td>804.70</td>
<td>907.56</td>
<td>1039.14</td>
</tr>
</tbody>
</table>

3.3 Optimization result analysis

In order to investigate the impact of different charging strategies and charging resource allocation on bus scheduling and charging planning, this section conducts numerical analysis of optimization results on fixed charging duration and charging station capacity (number of chargers). The fixed charging duration is set in the range of [10,20,30,40,50,60] in minutes, and the number of chargers is set in the range of [6,8,10,12,14,16,18,20], generating 48 sets of parameter combinations. One hundred random samples are generated as the input of the optimization program using the method proposed in Section 2.2. Each set of parameter combinations is applied to these random samples to simulate the uncertain travel time and energy consumption. The best ten values from all the random runs are recorded for each scenario.

3.3.1 Cost-effectiveness and robustness

Figure 9 presents the mean and standard deviation of the operation cost obtained by optimizing 100 random samples with different parameter combinations. The average cost reflects the average performance of each parameter combination and the standard deviation represents the adaptability of each parameter combination to uncertain travel time and energy consumption.

When the fixed charging duration is 10 minutes, the average cost is significantly higher than the others, with an average of 51,970 CNY, and decreases by 2.60% when the fixed charging duration changes to 20 minutes. When the fixed charging duration exceeds 40 minutes, the total cost and the standard deviation tend to rise. The scenario comparison shows that a fixed charging duration of 30 or 40 minutes has a lower optimization cost and stronger robustness of the optimization results. Specific reasons will be discussed in Section 3.3.2.

In Figure 9, except for the row with a fixed charging duration of 10 minutes, both heat maps show a gradual decrease in cost and standard deviation from the top left to the bottom right. First, when the same fixed charging duration is employed, the average cost decreases with an increasing charging station capacity; then the average cost keeps stable when the number of chargers reaches a certain threshold. At the same time, the standard deviation tends to drop as the number of chargers increases, indicating that sufficient charging resources can improve resilience to uncertain environments. Secondly, average costs under different fixed charging durations exhibit different sensitivity to charging station capacity, manifesting as different thresholds. To be specific, the threshold is positively related to fixed charging duration. For example, the
threshold is about 8 when the fixed charging duration is 20 minutes and about 16 when
the fixed charging duration is 60 minutes. The thresholds imply that bus operators can
reduce the investment and allocation in charging infrastructure to maximize resource
utilization while ensuring high economic efficiency and robustness. Besides, when the
charging resources are limited, such as when only 6-8 chargers are available, adopting
a 20-30 minutes fixed charging duration will be more cost-effective and robust than a
longer time. Under current resource conditions (20 chargers at one station), it is most
economical to use a 30-minute fixed charging duration and allocate 16 chargers for this
bus network. The average cost of the optimal scenario is around 50,417 CNY.

3.3.2 Impact of the fixed charging duration

Figure 10 shows the average cost and the cost composition under different fixed
charging duration when the number of chargers is 16 (the optimal scenario based on
Section 3.3.1). As a comparison, this study uses the night charging strategy as the
control group, in which the vehicles are not allowed to be recharged during the daytime.
The average cost of night charging is the highest at 53,750 CNY, and it declines by 6.20%
to reach the lowest cost of 50,417 CNY when the fixed charging duration is 30 minutes.
When it exceeds 30 minutes, the average total cost increases steadily due to higher bus
purchasing costs. Nevertheless, the average cost of a 60-minute fixed charging duration
is still 5.37% lower than that of night charging.

The operation cost is mainly composed of vehicle purchasing costs and labor costs.
The electric cost accounts for a relatively small amount, with an average of 6.60%. A
negative correlation between the labor cost and the charging duration can be observed
since the increased charging duration leads to a decreasing number of recharging events,
thus reducing the distance of deadhead trips and working hours.
Figure 10 Impact of fixed charging duration on operation cost (number of chargers=16)

In terms of cost differences, vehicle purchasing cost dominates the total cost. Figure 11 shows the average number of vehicles of three types in the optimal solutions. The variation in the total vehicles required is minimal, while the difference between two adjacent charging durations is reflected in the proportion of different vehicle types. When night charging is performed, the fleet is mainly composed of type B (91.33%) and type C (7.84%) buses with higher battery capacity. When vehicles are allowed to be recharged during the operation time, the number of type A grows significantly, especially when the fixed charging duration is equal to 30 minutes, and its percentage reaches 75.35%.

The findings in Figure 11 indicate that in the case of insufficient recharging, increasing the vehicle’s driving range is necessary to maintain the service, leading to higher vehicle purchasing costs. Meanwhile, with the rising charging duration, vehicles with smaller capacities begin to manifest their strength in lower purchasing costs. When the charging duration is 30 minutes, type A buses reach the highest proportion, while the total number of buses remains unchanged, leading to the lowest vehicle purchasing cost.

Analyzing the relationship between the vehicle purchasing cost and the fleet composition, we found that a more flexible and sufficient charging duration can be more suitable for vehicles with lower battery capacity. When the duration is too short (such as 10 minutes), the state-of-charge (SOC) cannot be sufficient to support multiple consecutive trips. In this case, vehicles with higher capacity are required to keep the bus service, increasing the purchasing cost. On the other hand, if the duration is too long (such as 1 hour), to maintain the service, the network needs more vehicles or
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substitutes lower-capacity buses with their higher-capacity counterparts, leading to higher purchase costs as well. In contrast, when the charging duration is 30 to 40 minutes, the buses can retain sufficient SOC after each recharging event while meeting the service constraints; thus, buses with lower battery capacity can fit into the schedule.

Figure 11 Average number of buses required when different fixed charging durations are adopted (number of chargers=16).

3.4 Resource allocation for bus routes with longer distances

In order to test the sensitivity of the optimization results to the trip-wise energy consumption of the bus route, five artificial bus networks are constructed based on real-world data. In these five networks, we scale up the energy consumption and trip duration by 10%, 20%, 30%, 40%, and 50%, respectively, based on the aforementioned case, assuming the same trip starting schedule. The optimal results from 48 scenarios composed of six charging durations and eight charging station capacities are shown in Figure 12.

The optimal total cost and all cost components show a linear increase over the increasing level in Figure 12(a). Compared to the base case where no scaling up is performed, the total cost increases from 49,664 CNY to 74,065 CNY (49.13%) when the increasing level is 50%. 64.66% of the cost increase comes from the vehicle purchasing cost, corresponding to a rise of 3.4 vehicles for every 10% increment.

The proportion of bus types has a different trend from the total cost, as illustrated in Figure 12(b). When the energy consumption and travel time are increased by 20%, the optimal fleet is still composed of type A (57.8%) and B (42.2%), which is similar to the base case (0% increase). As the energy consumption and travel time grow, the proportion of type A drops, reaching the lowest point of 43.1% at an increasing level of 40%. At the same time, more vehicles of type B and type C are required.
It can be concluded that when the trip-wise energy consumption increases by 20% to 30%, which equals 23.93 kWh, 21.49 kWh, and 23.63 kWh, in peak, off-peak, and morning/evening periods, respectively, vehicles with small capacity can fulfill most of the service tasks with the optimal charging schedule. This energy consumption corresponds to a 31-km round trip, which can cover most urban bus routes in metropolitan areas [32]. Even when the increasing rate reaches 50% (38-km round trip), buses with small to medium battery sizes are still the most cost-efficient options.

In practice, however, most operators do not have confidence in small-capacity vehicle types, and are conservative in fleet composition, resulting in higher vehicle purchasing costs. On the other hand, when the energy consumption is much higher, the small-capacity vehicles cannot meet the greater energy demand, albeit with frequent recharging. In such circumstances, using small-capacity buses would increase the total number of vehicles. On the contrary, an appropriate increase in the larger-capacity vehicles is more cost-effective.

The increase in energy consumption and travel time also has implications for the selection of fixed charging durations and resource allocation. As shown in Figure 13,
when the increasing level equals 0%, the difference in cost among different fixed charging durations is insignificant, except for the 10-minute fixed charging duration. However, the range of the optimal charging duration becomes narrower with higher energy and travel distance levels. Eventually, it converges to 40 minutes at the 50% increasing level. Similarly, the cost-effective charging station capacity converges to the range of 14 to 20. The results illustrate the necessity to consider factors such as bus line distance and energy consumption level in the actual operation process. Generally, for single-depot bus services with 200-300 trips, the charging station capacity of 14 to 20 is recommended. The optimal recharging duration is varied from different energy consumption per trip. We recommend a 30-40 charging duration based on this study to ensure sufficient SOC and stable services.

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(Unit: 1000 CNY)
Figure 13 Heat maps of operation costs under each fixed charging duration and charging station capacity when the average travel time and energy consumption are increased by different levels (a to f indicates the increasing rate of 0% to 50% with the incremental of 10%)

4. CONCLUSION

In this study, an electric vehicle scheduling problem considering charging station capacity (EVSP-CSC) is proposed and formulated as a MILP model. An ALNS algorithm is developed with novel destroy/repair operators to solve the optimization problem. Trip-based energy consumption and its uncertainties of BEBs are captured using GPS trajectories and OBD data. In order to modify the uncertain condition of BEB operation, random energy consumption and travel time samples are generated from the average travel time-based trip clusters. Forty-eight scenarios are designed from six charging durations and eight charging station capacities.

The results show that recharging during the operating duration can reduce costs by up to 6.20% compared to the night charging scenario under uncertain conditions. This reduction arises from an increase in the proportion of small-capacity vehicles due to recharging events during the daytime. Meanwhile, the fleet composition is significantly affected by the fixed charging duration. The ratio of vehicle types with the smallest capacity reaches 75.35% when the charging duration equals 30 minutes, corresponding to the lowest average cost of 50,417 CNY. The results also indicate that the operation cost is more sensitive to charging station capacity when the charging duration is higher, while the optimal charging duration is relatively stable at 30-40 minutes. Besides, sufficient charging resources can improve the robustness of the vehicle schedules, while operators can reduce the investment in charging infrastructure based on the sensitivity of costs to the number of chargers.

To examine the impact of energy consumption level on the optimal charging plan, energy consumption and duration time of each trip are increased by 10% to 50% with an interval of 10%. The result shows that when the trip energy consumption increases by 20% to 30%, which represent most urban bus cases in metropolitan areas, vehicles
with small capacity can fulfill most of the tasks by getting recharged in the daytime, leading to much lower operating cost than the current operation practice. When the energy consumption increases by 50%, representing the extreme operation scenarios in most cases of the city scale, more vehicles with larger battery sizes are required, while buses with small or medium capacity are still the most welcomed types. At the same time, high energy consumption reduces the range of options for cost-effective charging duration and resource allocation. For bus networks with a similar trip size running in the single-depot mode, we recommend 30 to 40 minutes for each recharging event, and 14-20 chargers can be sufficient to serve the network optimally.

The result of this study can be a reference for proper charging planning, charging resource allocation, and fleet composition of urban electric bus systems. For further studies, multi-depot scenarios, mixed charging power outputs, and stations with solar rooftops can be considered for deep decarbonization. Furthermore, a dynamic scheduling or rescheduling approach can be implemented based on real-time bus operation information to tackle the energy consumption uncertainty.

AUTHOR CONTRIBUTION

Qiuzi Chen: conceptualization, data processing, algorithm development, result analysis, manuscript drafting and revision; Chenming Niu: data processing; Ran Tu: conceptualization, manuscript revision, supervision; Tiezhu Li: data curation; An Wang: manuscript revision; Dengbo He: manuscript revision

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