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Optimization of charging and discharging schedules for battery electric buses under the V2G environment

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Abstract

Due to the limited range of battery electric buses (BEBs), they might be used to replace diesel buses at a ratio of 2:1 in some bus lines, which makes the BEBs greatly underused in the early adoption stages. With the rapid development of vehicle to grid (V2G) technology, the spare BEBs can earn profits through discharging during load peak periods of the grid while improve the operational stability of the regional power grid. This study formulates a mixed integer model for the BEB charging and discharging scheduling problem with multi-depots. An adaptive large neighbourhood search fused with simulated annealing (ALNS-SA) is developed to solve the model. Numerical experiments on a real-world bus network in Jiading District, Shanghai, China show that the total costs of the proposed cross-line operation strategy under the V2G environment are 8.5% lower compared to the single-line operation mode.

Keywords: battery electric bus; vehicle to grid; bus scheduling; adaptive large neighbourhood search; simulated annealing

1. Introduction

In order to build an environment-friendly society, many countries and regions around the world are committed to achieving the carbon peaking and carbon neutrality goal. In recent years, bus operators in many countries have responded to these strategies by replacing traditional fuel buses with battery electric buses (BEBs). For example, Shanghai, China is dedicated to increase the proportion of BEBs to 96% until 2025 (Shanghai Municipal Road Transport Administration, 2021). Motivations include environmental concerns and economic benefits (Kapatsila et al., 2024; Guzman et al.,

2017). The United Nations also calls on developing countries to use BEBs to reduce greenhouse gas emissions (United Nations, 2022). Due to the limited range of battery electric buses (BEBs), operators may need to deploy two BEBs to replace one diesel bus on certain bus lines. This replacement ratio can lead to underutilization of BEBs during the early stages of adoption (Ministry of Transport, 2020). With the rapid development of vehicle to grid (V2G) technology, the spare BEBs can earn profits through discharging during load peak periods of the grid. This will not only improve the operational stability of the regional power grid, but also help the bus operator to relieve its financial pressure by better utilizing the existing BEB fleet. This study aims to investigate the joint optimization of BEB fleet size, trip assignment, and charging and discharging scheduling under the V2G environment.

The determination of the required fleet size is a crucial foundation in bus electrification (Yıldırım and Yıldız, 2021). Existing research indicates that the timetable of bus routes and battery capacity have dominant impacts on the BEB fleet size (Xu et al., 2023). When BEBs execute excessive task trips, suitable opportunity charging plans are needed to extend the driving range. As such, the resultant charging duration, especially under the slow charging mode, increases the complexity of BEB scheduling and charging problem (Pearre et al., 2011). However, in practice, many operators fail to optimize the number of BEBs to be purchased and their scheduling simultaneously. (Say et al., 2024). One reason for this is the different time horizon of timetable planning and investment decisions. Further, governments sometimes provide subsidies to incentivize the use of low-carbon BEBs to reach low-carbon goals (Giagnorio et al., 2024; Wang et al., 2024). Hence, at least in China, bus operating companies purchase more than the needed numbers of BEBs to replace gasoline vehicles for the current schedule (Zhou et

al., 2024). This raises the question as to how to better utilize the redundant BEBs and V2G concepts appear to be one answer.

Given the timetable, the BEB charging and scheduling problem aims to determine the bus and task trip assignment as well as the charging scheduling so that all the task trips will be carried out considering the BEB constraints (Gkiotsalitis et al., 2023; Hiermann et al., 2016; Schneider et al., 2014; An.,2020). An operation day is typically divided into a number of time windows and BEBs can occupy an integer number of time windows for (dis-)charging. The (dis-)charging costs/revenues can then be calculated based on the (predicted) time-of-day electricity prices.

Different assumptions regarding the permissible charging strategies have been made in the literature, such as, some allow partial charging whereas others do not. Zheng et al. (2023) demonstrated the revenue increase through the less restrictive partial charging strategy. Further factors that have an impact on charging cost include charging station power (Xie et al., 2023; Jia et al., 2024) and the capacity of the batteries (Bao et al., 2023; Li et al., 2019; Zhou et al., 2023). Wu et al. (2022) developed an algorithm combining heuristic and branch-and-price methods to compare the costs of a charging strategy between a first-in-first-out (FIFO) depot charging strategy and restricted charging periods strategy. It was found that the operational costs under the FIFO charging strategy were 6.8% higher than the restricted charging periods strategy for the four tested lines with a total of 376 trips. Technological advancements further reshape this landscape: high-power charging systems can reduce plug-in durations by 40-60%, while wireless charging innovations enable opportunistic energy replenishment for BEBs during scheduled stops, effectively decoupling charging operations from dedicated infrastructure requirements (Alwesabi et al., 2020; Jang, 2018).

Previous studies on BEB scheduling with charging considerations have primarily focused on single bus lines or single depots. However, adopting a multi-line or multi-depot operation mode could significantly improve the operational efficiency of regional BEB systems. In recent years, the scheduling problems of multi-depot or multi-line BEBs have gained much attention. Wang et al. (2017) considered a multi-depot scenario to optimize the operating costs of 15 bus routes in Davis, USA. For the cross-line operations in a multi-depot setting, Wang et al. (2021) proposed a heuristics column generation genetic algorithm to solve the bus scheduling problem for a problem with 290 trips. Further, Shang et al. (2023) and Wang et al. (2024) compared the costs of a multi-depot cross-line operation mode with a multi-depot single-line operation mode and showed a significant reductions for required vehicles and charging costs. Zhang et al. (2021) investigated the BEB scheduling problem considering non-linear charging profiles. For computational simplicity, the nonlinear charging rate were simplified as a multi-segment linear variation. To note is that further additional constraints such as parking capacity limitations at depots also constrain BEBs charging activities. The above studies on large-scale multi-depot cross-line operation modes have high complexity and exact algorithms often cannot obtain results within a few hours. Heuristic algorithms are necessary to solve the large-scale real-world problems within a reasonable calculation time.

Increasingly frequent extreme weather events as well as reliance on renewable energies have aggravated the grid volatility. Meanwhile, the rise of the electric vehicle era is increasing energy demand (Kumar et al., 2024). Vehicle to grid technology promises to mitigate the problem as the vehicles also become energy storage devices to supply electricity to the grid at times of need (Pilotti et al., 2023; Grasel et al., 2024; Yu et al., 2024). The revenue from discharging can also subsidize public transit operators. It is expected to achieve a win-win new public transportation operational model.

The integration of vehicle-to-grid technology into battery electric bus operations promises transformative opportunities for advancing sustainable urban mobility and flattening energy peaks. V2G-enabled BEB fleets can function as dynamic energy storage systems, enhancing grid stability through peak shaving and frequency regulation. Furthermore, BEBs can support the integration of renewable energy sources by storing surplus solar or wind power during off-peak periods and feeding it back to the grid during high-demand intervals, thereby addressing intermittency issues (Kempton et al., 2021). From an economic perspective, energy arbitrage strategies enable operators to leverage temporal variations in electricity prices—charging buses during low-cost periods (e.g., nighttime) and discharging during peak pricing windows to generate ancillary revenue (Amrovani et al., 2025).

Despite these advantages, integrating V2G into BEB scheduling introduces notable challenges. Frequent discharging impacts the state of charge of BEBs, potentially compromising the feasibility of trip chains (Lim et al., 2023). While progress has been made in single-depot scheduling research, critical gaps remain in addressing nonlinear charging dynamics, multi-depot coordination under real-world uncertainties, and the trade-offs between operational efficiency, battery longevity, and economic returns. These challenges underscore the need for advanced solution algorithms capable of balancing operational efficiency and economic benefits in V2G-enabled BEB systems (Perumal et al., 2022).

Infrastructure limitations further complicate V2G deployment, including insufficient bidirectional charging facilities and immature grid interconnection standards. Additionally, the marginal profitability of V2G discharging must be carefully evaluated, as it often fails to offset battery degradation and infrastructure investments without policy

interventions such as subsidies or tax incentives (Fei et al., 2023). The previous literature on the BEB scheduling problem is summarized in **Table 1**.

Table 1 Literature summary.

	Full BEB fleet	Charging type	Depot number	Discharging activities	Solution approach
Hiermann, Gerhard, et al. (2016)	✓	Full	One	No	BP-ALNS
Wang et al. (2017)	✓	Fixed period	One	No	Solver
Alwesabi, Yaseen, et al. (2020)	✓	Partial	One	No	Solver
Yıldırım and Yıldız (2021)	Mixed fleet	Partial	Multiple	No	Column Generation
Wang et al. (2021)	✓	Full	Multiple	No	Column Generation - Genetic Algorithm
Xie et al. (2023)	✓	Fixed period / Partial	One	No	Generation and Selection
Zheng et al. (2023)	✓	Full / Partial	One	No	Column Generation
This study	✓	Partial	Multiple	✓	ALNS-SA

As summarized in Table 1, the contributions of this study are as follows:

1. **Novelty:** To the best of our knowledge, this is the study to optimize charging and discharging schedules for multi-depot BEBs under V2G environment while incorporating partial charging strategies.
2. **Methodology:** To address the computational complexity of large-scale trip instances, we propose an adaptive large neighbourhood search (ALNS) fused with simulated annealing (SA), referred to as ALNS-SA.
3. **Performance:** Computational experiments demonstrate that ALNS-SA achieves optimal solutions for small-scale instances and delivers high-quality feasible solutions for larger instances.

4. **Insights:** A comprehensive sensitivity analysis identifies and discusses the impacts of fleet composition and charging/discharging costs on operational efficiency and economic viability.

The remaining part of the manuscript is organized as follows. Section 2 introduces a mixed-integer linear programming formulation. Section 3 presents the ALNS-SA fusion algorithm. Section 4 shows the results of different instances and Section 5 provides conclusions of our work.

2. Model formulation

2.1 Problem description

The following key assumptions are made:

- 1) BEBs are assumed to be homogeneous in terms of battery size, discharge and recharge rates. Linear charging and discharging are assumed such that the remaining energy linearly increases or decreases with the charging or discharging time (Sweda et al., 2017).
- 2) Each scheduled time tabled trip is assigned to one and only one BEB.
- 3) BEBs can operate across different bus lines.
- 4) BEBs charging and discharging are carried out at the nearest depot between two scheduled time tabled trips. In addition, BEBs need to return to the initial depot after completing its scheduled trips at the end of a day. The deadhead time of two scheduled trips includes the time for entering and leaving the depot.

We establish a connection network (N, A) to capture the BEB scheduling problem, where a node in N represents a scheduled trip or a depot and an arc in A represents the connection arcs (namely, deadhead arcs) between two nodes. Each node contains information on the service trip's start station, end station, the time of departure and arrival. Depots serve as the starting and ending source nodes to dispatch or receive the BEBs for its daily operation. Between any two trip nodes and/or depot nodes, there exist deadhead connections. The travel time for these connecting arcs is referred to as deadhead

time. The charging and discharging scheduling of BEBs is between two task trips i and j . The (dis-)charging start time must happen after the task trip i 's ending time plus the deadhead time between trip i 's end station and the charging depot. Similarly, the (dis-)charging end time must happen before task trip j 's starting time minus the deadhead time from the charging depot. **Fig.1** illustrates the connection network of BEBs. **Table 2** presents a list of notations for reference.

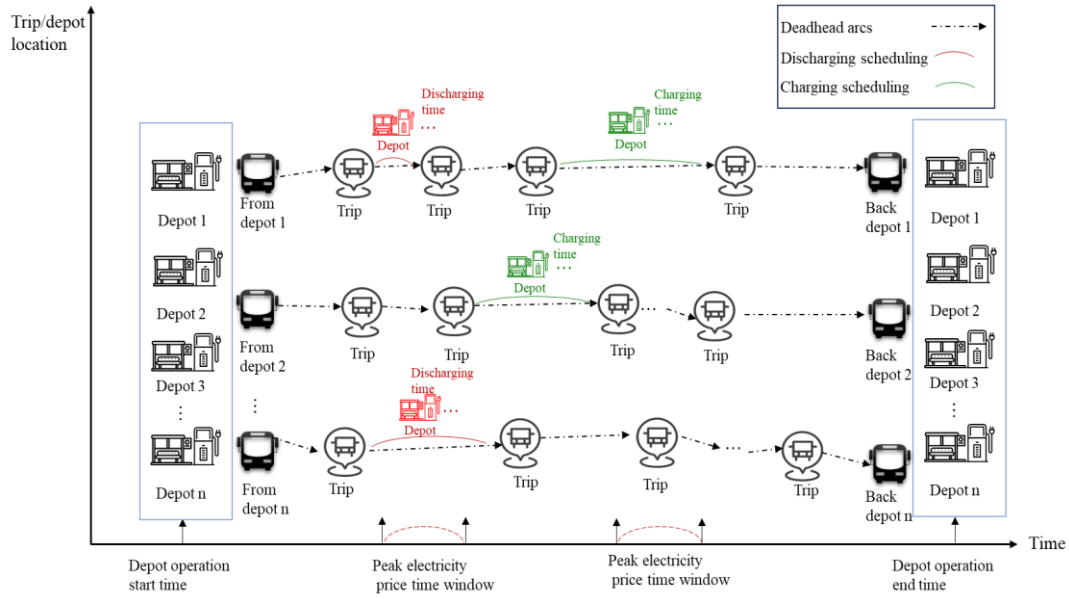


Fig. 1. Connection network illustration for BEB scheduling under the V2G environment

Table 2 Notation table.

Parameter	Definition
$K = \{k\}$	Set of BEBs
$Q = \{q\}$	Set of BEB task trips (nodes)
$O = \{o\}$	Set of depots
$N = \{i, j\}$	Set of nodes where i, j can be task trips or depots
$A^Q = \{(i, j)\}$	Set of feasible arcs connecting nodes i and j . Arc (i, j) is a “trip arc” if both i, j are task trip nodes; a “entering depot arc” if i is a task trip and j is a depot node; a “leaving depot arc” if i is a depot and j is a task trip node.
$A^O = \{(i, j)\}$	Set of feasible trip arcs related to depot o . Each trip arc has one depot if feasible for charging or discharging with the minimum accumulated deadhead time between the task trips and the depot. If the buffer time between trips i and j is too short for deadheading to any depot, charging between i and j would not be allowed.
$T = \{t\}$	Set of time steps
Cap_o	Number of parking spaces at depot o (capacity)
t_i^s, t_i^e	Start time and end time of task trip i
r_i	Running time of task trip i

$t_{i,j}^e$	Deadhead time from node i to j without charging or discharging activities.
$\hat{t}_{i,j}^e$	Deadhead time between node i and node j with (dis-)charging activities at the nearest depot which includes deadhead time from i to the nearest depot plus from the depot to j .
$t_{i,o}^e$	Deadhead time from node i to depot o .
$t_{o,j}^e$	Deadhead time from depot o to node j .
c^f	Fixed cost per electric bus(¥/day)
c^e	Unit deadhead cost (¥/min)
c_t^c	Unit charging cost (electricity cost) (¥/min) at time t . Electricity price fluctuates over time.
c_t^d	Unit discharging revenue (¥/min) at time t .
c_t^a	Unit discharging cost (¥/min) at time t due to battery degradation
r^c	BEB charging rate
r^d	BEB discharging rate
r^r	Power consumption rate when performing task trips
r^e	Power consumption rate when performing deadhead trips with no passengers on aboard
PW_{ot}	Available power (kW) in depot o at time t .
SOC_{min}	BEB's minimum SOC
SOC_{max}	BEB's maximum SOC
τ	Battery capacity(kWh)
M	A large positive number

Auxiliary variable

SOC_{ki}	BEB k 's SOC after completing trip i
t_{kij}^c	BEB k 's charging time between nodes i and j
t_{kij}^d	BEB k 's discharging time between nodes i and j

Binary decision variable

x_{kij}	Equals 1 if BEB k carries out trip j after serving trip i , 0 otherwise; Note that the first and last trips denote a depot, so that: $x_{koi}=1$ if BEB k departs from depot o to execute its first trip i , 0 otherwise $x_{kjo} = 1$ if BEB k returns to depot o after serving its last trip j , 0 otherwise
y_{kij}	Equals 1 if BEB k finishes trip i then performs task j immediately, 0 otherwise. It means that there is no charging or discharging activity between trips i and j
w_{kij}	Equals 1 if BEB k is charged between trips i and j , 0 otherwise
v_{kij}	Equals 1 if BEB k is discharged between trips i and j , 0 otherwise
z_k	Equals 1 if BEB k is utilized, 0 otherwise.

2.2. Model formulation

We utilize the connection network framework to formulate the problem. A^Q represents sets of feasible connecting trip arcs and feasible connecting trip-depot arcs. The variables y_{kij} , w_{kij} and v_{kij} can separately represent the connecting arcs for BEB performing two task trips i and j sequentially directly, execute a charging activity between carrying out the two task trips i and j , or execute a discharging activity between carrying out the two task trips i and j . When $x_{kij} = 1$, it indicates that one and only one variable among y_{kij} , w_{kij} and v_{kij} should be 1. If $x_{kij} = 0$, then the three variables y_{kij} , w_{kij} and v_{kij} should be 0 as well.

With this notation, the charging and discharging schedule problem (CP) for BEBs can be formulated as the following program:

$$\begin{aligned}
\min Z = & c^f \sum_{k \in K} z_k + c^e \sum_{k \in K} \sum_{i \in Q} \sum_{j \in Q} (t_{i,j}^e y_{kij} + \hat{t}_{i,j}^e w_{kij} + \hat{t}_{i,j}^e v_{kij}) \\
& + c^e \sum_{k \in K} \sum_{o \in O} \sum_{i \in Q} t_{o,i}^e x_{koi} + c^e \sum_{k \in K} \sum_{j \in Q} \sum_{o \in O} t_{j,o}^e x_{kjo} \\
& + \sum_{k \in K} \sum_{i \in Q} \sum_{j \in Q} \sum_{t \in T} c_t^c t_{kij}^c + \sum_{k \in K} \sum_{i \in Q} \sum_{j \in Q} \sum_{t \in T} c_t^a t_{kij}^d \\
& - \sum_{k \in K} \sum_{i \in Q} \sum_{j \in Q} \sum_{t \in T} c_t^d t_{kij}^d
\end{aligned} \tag{1}$$

s. t.

$$\sum_{k \in K} \sum_{i \in Q \cup O} x_{kij} = 1, \forall j \in Q, i \neq j \tag{2}$$

$$\sum_{k \in K} \sum_{j \in Q \cup O} x_{kij} = 1, \forall i \in Q, i \neq j \tag{3}$$

$$\sum_{i \in Q} \sum_{j \in O} x_{kij} \leq 1, \forall k \in K \quad (4)$$

$$\sum_{i \in O} \sum_{j \in Q} x_{kij} \leq 1, \forall k \in K \quad (5)$$

$$\sum_{i \in Q} x_{koi} = \sum_{j \in Q} x_{kjo}, \forall o \in O, k \in K \quad (6)$$

$$\sum_{i \in Q \cup O} x_{kij} = \sum_{i \in Q \cup O} x_{kji}, \forall j \in Q, k \in K \quad (7)$$

$$z_k \geq x_{kij}, \forall i \in O, j \in Q, k \in K \quad (8)$$

$$\sum_{j \in Q} \sum_{k \in K} x_{koj} \leq Cap_o, \forall o \in O \quad (9)$$

$$x_{kij} = y_{kij} + w_{kij} + v_{kij}, \forall k \in K, i, j \in Q \cup O, i \neq j \quad (10)$$

$$w_{kij}(t_j^s - t_i^e - \hat{t}_{i,j}^e) \geq t_{kij}^c, \forall k \in K, i \in Q, j \in Q \cup O, i \neq j \quad (11)$$

$$v_{kij}(t_j^s - t_i^e - \hat{t}_{i,j}^e) \geq t_{kij}^d, \forall k \in K, i, j \in Q \cup O, i \neq j \quad (12)$$

$$SOC_{k,i} = SOC_{max}, \forall k \in K, i \in O \quad (13)$$

$$SOC_{max} \geq SOC_{ki} \geq SOC_{min}, \forall k \in K, i \in Q \quad (14)$$

$$SOC_{kj} \leq M(1 - x_{kij}) + SOC_{ki} - \frac{r^r r_j}{\tau} - \frac{w_{kij} r^e \hat{t}_{i,j}^e}{\tau} - \frac{v_{kij} r^e \hat{t}_{i,j}^e}{\tau} \\ - \frac{y_{kij} r^e t_{i,j}^e}{\tau} + \frac{t_{kij}^c r^c}{\tau} - \frac{t_{kij}^d r^d}{\tau}, \quad (15)$$

$$\forall k \in K, i \in Q \cup O, j \in Q, (i, j) \in A^Q$$

$$SOC_{kj} \geq -M(1 - x_{kij}) + SOC_{ki} - \frac{r^r r_j}{\tau} - \frac{w_{kij} r^e \hat{t}_{i,j}^e}{\tau} - \frac{v_{kij} r^e \hat{t}_{i,j}^e}{\tau} \\ - \frac{y_{kij} r^e t_{i,j}^e}{\tau} + \frac{t_{kij}^c r^c}{\tau} - \frac{t_{kij}^d r^d}{\tau}, \quad (16)$$

$$\forall k \in K, i \in Q \cup O, j \in Q, (i, j) \in A^Q$$

$$\sum_{k \in K} \sum_{(i,j) \in A^o, t_i^e + t_{i,o}^e \leq t \leq t_j^s - t_{o,j}^e} (w_{kij} + v_{kij}) \leq Cap_o, \forall o \in O, t \in T \quad (17)$$

$$\sum_{k \in K} \sum_{(i,j) \in A^o, t_i^e + t_{i,o}^e \leq t \leq t_j^s - t_{o,j}^e} (t_{kij}^c r^c - t_{kij}^d r^d) \leq PW_{ot}, \forall o \in O, t \in T \quad (18)$$

$$x_{kij} = 0, \forall k \in K, (i,j) \notin A^Q \quad (19)$$

$$x_{kij} \in \{0,1\}, \forall k \in K, i,j \in Q \cup O, i \neq j \quad (20)$$

$$y_{kij} \in \{0,1\}, \forall k \in K, i,j \in Q \cup O, i \neq j \quad (21)$$

$$w_{kij} \in \{0,1\}, \forall k \in K, i,j \in Q \cup O, i \neq j \quad (22)$$

$$v_{kij} \in \{0,1\}, \forall k \in K, i,j \in Q \cup O, i \neq j \quad (23)$$

The objective function minimizes the total costs for the BEB system which includes BEB capital costs, charging costs, deadhead costs, the battery degradation costs and revenues due to discharging to the grid. Constraints (2) - (3) express that BEBs depart from one depot and each task trip can be executed by only one BEB. Constraints (4) - (5) require each BEB to depart from or return to at most one depot at the beginning/end of the day. Constraints (6) require that each BEB returns to the same home depot where it departs from. Constraints (7) are flow balancing constraints at a trip node which require that after a BEB completes a trip, it will either proceed to execute another trip or return to the home depot. Constraints (8) calculate the actual number of BEBs in use. Constraints (9) represent the BEB storage capacity of each depot. Constraints (10) represent that if task trip i and task trip j are connected, i.e. trip j is the immediate task trip after trip i , three possible cases could happen, i.e. the BEB deadhead to the start station of trip j directly after performing trip i with $y_{kij} = 1$; the BEB goes to the nearest depot to get charged between the task trips i and j with $w_{kij} = 1$; the BEB goes to the nearest depot to get discharged between the task trips i and j with $v_{kij} = 1$. Constraints (11) and (12) limit the upper bounds of charging and discharging durations for trip nodes. For example,

in (11), the BEB travels to the nearest depot to get charged between the task trips i and j when $w_{kij} = 1$. The maximum charging duration t_{kij}^c should be the start time of task trips j minus the end time of task trips i and deadhead time to the nearest depot. At the same time, v_{kij} and discharging duration t_{kij}^d will be all 0 in Constraints (12). The same principle applies when $v_{kij} = 1$. The maximum discharging duration t_{kij}^d is the start time of task trips j minus the end time of task trips i and deadhead time to the nearest depot, while w_{kij} and charging duration t_{kij}^c are all 0 in Constraints (11). Constraints (13) require that any BEB initially departing from the home depot should be fully charged. Note that we do not require that a BEB will be fully charged when it goes back to a depot for charging between two task trips in the middle of the day. Constraints (14) ensure that any BEB must operate within a safe battery status. Constraints (15) and (16) ensure that the remaining SOC of the battery after the BEB completes a trip are within the permissible SOC range. When trip j is executed after trip i , the SOC is obtained from the SOC after the previous trip i minus the electricity needed for trip j , deadhead energy consumption, discharging energy consumption plus the charging energy between trips i and j if it happens. Constraints (17) require that the number of buses charging or discharging at depot o in any time step t should be less than the maximum charger number available. Note that that because a trip sequence (i, j) corresponds to a single depot o , we only need to count the number of BEBs that are (dis-)charging at a depot in time step t . Constraints (18) indicate that the total power of BEBs charging or discharging at depot o in any time step t should be less than the maximum available power at that time. Constraints (19) expresses that all trip sequences must be within the feasible set A^Q .

3. Solution algorithm

The formulated CP is challenging to solve for large scale problems. We utilized two heuristic algorithms, i.e. elitist genetic algorithm (EGA) and improved adaptive large neighbourhood search fused with simulated annealing (ALNS-SA) to handle the problem. Please note that the feasible connection arcs set A^Q has elements in the form of (i, j) . If i and j are both trip nodes, the trip arc $(i, j) \in A^Q$ is also referred to as trip pair which indicates the two trips are connectable. The multi-line trip nodes in set Q should be arranged in ascending order based on their start times. Then, we number these trip nodes. We further sort the trip pair in A^Q by the interval time between the two trips i and j in ascending order to facilitate the construction of the initial solution.

3.1 Initial solution construction

Before introducing the two solution algorithms, we first introduce the procedure to construct an initial solution.

Step 1: Select a BEB $k \in K$ that has not yet been assigned with any trips. The first trip assigned to BEB k is trip i with the earliest start time in task trip set Q . The nearest depot to the departure station of trip i is assigned as the BEB home depot. Delete trip i from set Q .

Step 2. If set Q is empty, we have constructed an initial solution for BEBs' trip chains that contains all the timetabled task trips. Terminate the procedure.

Step 3. Check if there exists a trip pair (i, j) for task trip i in the feasible arc set A^Q . If yes, proceed to Step 4. Otherwise, go back Step 1.

Step 4. Check if the SOC of BEB k is sufficient to execute trip j following trip i . If yes, go to Step 5. Otherwise go to Step 6.

Step 5. Calculate the BEB arrival time to the nearest depot with the least deadhead distance between trip pair (i, j) , which may not be the home depot of BEB k .

Step 5.1: Check if the arrival time of BEB k at the nearest depot is during the peak electricity price hours. If yes, discharging activity is considered. If no, Proceed to Step 5.2 directly. The discharging duration is $discharge_{duration} = \min \{(SOC_{kj} - SOC_{min}) / r^d, (t_j^s - t_i^e - \hat{t}_{i,j}^e), T_{peak}\}$, representing the redundant SOC after performing j , maximum stay duration at the depot, and the peak electricity duration. Go to Step 5.2.

Step 5.2: Add trip pair (i, j) into the trip chain of BEB k . The executed trip j is deleted from set Q . Trip pair (i, j) is deleted from set A^Q . Trip j is updated as the current last trip of BEB k i.e. set $i \leftarrow j$ and go back to Step 3.

Step 6. When the SOC of k is not enough to perform task j directly, charging activity should be added between these two trips: Calculate the maximum charging duration $charge_{duration} = \min \{(SOC_{max} - SOC_{ki}) / r^c, (t_j^s - t_i^e - \hat{t}_{i,j}^e)\}$, with the two terms representing the time for the BEB to be fully charged and BEB stay time at the depot, respectively. Check if the updated SOC can sustain to carry out trip j after charging. If yes, proceed to Step 6.1. Otherwise, proceed to Step 6.2.

Step 6.1. Set the charging duration to the maximum possible charging duration and add trip pair (i, j) into the trip chain of BEB k . Delete trip pair (i, j) from set A^Q . Delete the executed trip j from set Q . Trip j is updated as the current last trip of BEB k i.e. make $i \leftarrow j$ and go back to Step 3.

Step 6.2. In this case, additional charging is still not enough for the next trip j . Go back to Step 3 to test another feasible trip pair (i, j_1) from the set A^Q . When set Q is empty, the obtained BEBs' trip chains is set as the initial solution.

3.2 Elitist genetic algorithm

EGA is an optimization method based on genetic algorithm (GA). It differs from the GA by incorporating an elitism strategy, where the fittest individuals from each

generation are preserved and passed directly to the next generation without undergoing crossover or mutation. In this paper, an individual refers to the trip chain that each BEB executes. The EGA's procedure is designed as follows.

Step 1: Initialization

Each BEB's trip chain is taken as an individual chromosome and the initial total cost Z is considered. The iteration index is $gn = 1$ and maximum iteration number is gn_{max} .

Step 2: Fitness function of a trip chain solution

The total deadhead distance of a trip chain is taken as its fitness value. In the elite strategy, 20% trip chains with largest values (worst trip chains) are selected as parents' trip chains, which shall be destroyed later. The remaining trip chains are reserved to protect the good trip chains from being destroyed.

Step 3: Crossover

Step 3.1: For each selected parent trip chain, search for its trip pair with the longest deadhead distance, and then divide the trip chain into two parts.

Step 3.2: Randomly select two BEB trip chains, reconnect their divided trip chain segments with each other. If the four trip segments can be reconnected into new feasible trip chains, it constitutes a new offspring solution. Repeat Step 3.2 until all the 20% worst trip chains have been tested. Otherwise, the solution remains unchanged and proceed to Step 6.

Step 4: Calculate the fitness of the offspring solutions.

Step 5: Compare the fitness of the parent and offspring trip chains. If the fitness of the offspring solutions is lower than that of the parents, the total cost Z is reduced and the offspring solutions are retained. Otherwise, we keep the parents' solution.

Step 6: The initial solutions, BEBs' charging or discharging time solution and Z is updated. Let $gn = gn + 1$. If $gn = gn_{max}$, the loop is terminated. Otherwise, go back to Step 2.

While in the crossover operation in EGA Step 3, a BEB needs to execute a portion of other BEB's trips which may lead to infeasibility of the new trip chain due to battery capacity constraints. Thereby this method may reduce the quality of the optimal solution. The following, alternative, ALNS-SA fusion algorithm aims to mitigate the issue of excessive variation in the new trip chain during each iteration.

3.3 ALNS-SA fusion algorithm

The main idea of the ALNS algorithm is to destroy some BEB trip chains and then repair them by dynamically searching for its neighbour solutions with minor changes in the executed trips. Starting from the initial solution, the program randomly selects two trip chains to destroy in each iteration via a destroy operator. Destroying two trip chains at a time intends to improve the algorithm efficiency. A trip chain is destroyed in the way that one trip of it is deleted from the trip chain and is temporally stored as an isolate trip (referred to as destroyed trip). The remaining trip chain will have a longer interval at the place of the destroyed trip. The destroyed trips will be inserted into another trip chain via a repair operator. During the repair process, it is necessary to dynamically adjust the duration of charging and discharging to ensure that new feasible trip chains can be obtained. If the destroyed trip cannot be repaired because there are no other feasible trip chains to be inserted to, we restore the initial solution without destroy. If the destroyed trip can be repaired, we recalculate the total cost for the amended trip chains. In order to accelerate the optimization process, we utilize different destroy and repair operators and update their probability of being selected dynamically based on the quality of the obtained solutions.

In addition, the SA fusion algorithm was utilized to allow for acceptance of bad solutions to increase the diversity of the ALNS. It could help prevent the ALNS being trapped in a local optimal solution and accelerate the convergence speed. **Fig. 2** is the flowchart of the ALNS-SA fusion algorithm.

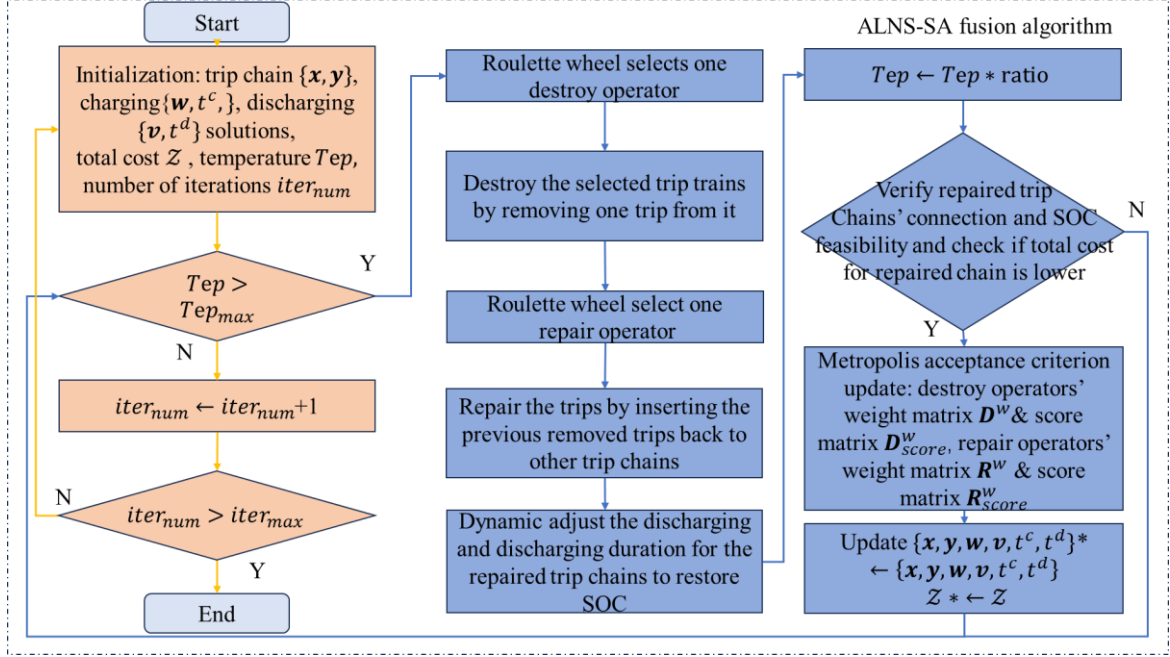


Fig. 2. The flow chart of ALNS-SA fusion algorithm

The fusion algorithm contains two loops. The inner loop utilizes SA with initial temperature, termination temperature and cooling coefficient to control the iteration process. The inner loop is controlled by reducing the initial temperature to the final temperature using the cooling factor. Then the outer loop sets the number of iterations. The fusion algorithm can achieve globally searching for the optimal solution. In the inner loop, a selection roulette function is constructed to randomly choose destroy or repair operators based on the weight matrices. The initial weight matrix of each operator is set to 1. The weights of the destroy and repair operators are updated based on the costs of the newly generated solution and the previous solution. When the cost of the new solution is less than or equal to that of the original solution, the selected operator's weight is increased. Otherwise, the generated solution needs to update the weight according to the

metropolis acceptance criterion. The transition probability *Prob* must be greater than the random number in the range [0, 1] generated by the system to satisfy the acceptance rule. The designed transition probability formula is:

$$Prob = e^{-(cost_{total}^{new} - cost_{total}^{old})/\varphi} \quad (23)$$

where $cost_{total}^{new}$ and $cost_{total}^{old}$ represent the total costs of the new solution and the old solution, respectively and φ is the current temperature. The functions for selecting destroy and repair operators are designed separately by *doDestroy* and *doRepair*. The term *updateWeight* and *updateScore* represent the function of updating the weight matrix and score matrix.

4. Case study

The models and solution algorithms were tested on a real-world bus network consisting of 5 bi-directional bus routes in the Jiading District of Shanghai, China. The two bus depots are Anting Depot and Huangdu Depot. The selected bus routes are shown in **Fig. 3**. There are 7 bus terminals for the 5 bus routes with the detailed information shown in the Appendix table. All numerical experiments were run on a Dell computer with 16 GB of RAM and 2.40 GHz of Intel i9-10920X CPU.

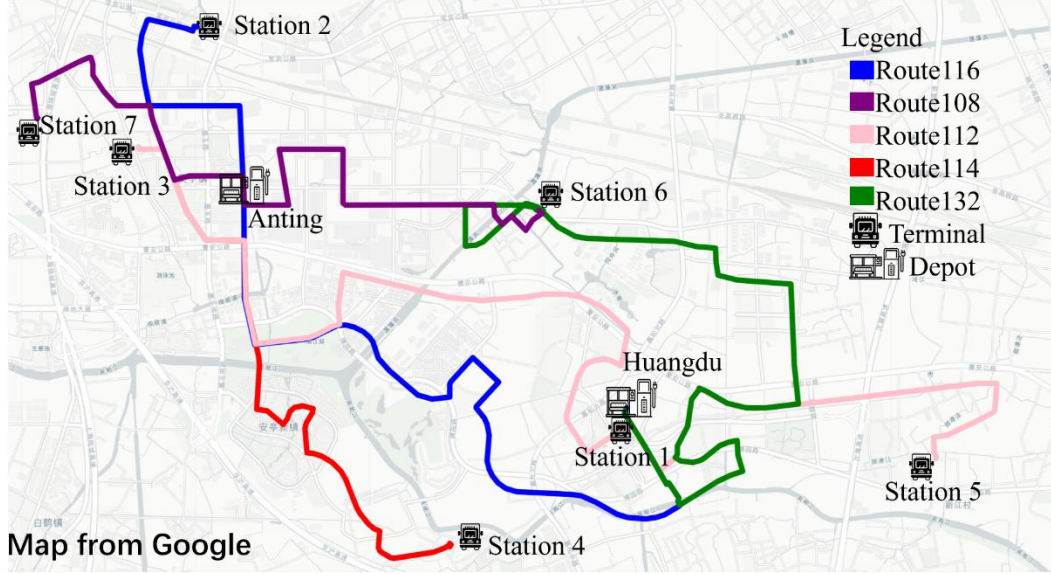


Fig. 3. The investigated BEB routes

The detailed timetable for each line can be found in **Appendix B**, where each line's task trip departure time is based on a fixed timetable. There are a total of 418 timetabled trips. Each depot's daily operating hours are from 5:00 to 23:59. The experiment uses a common fast-charging power of 60 kW. The maximum loads power of Huangdu and Anting depot are 1200 kW and 1800 kW, respectively. The unit cost of battery degradation is set as 0.1¥/kWh. This is based on following data: The lifetime of a BEB is assumed to be 8 years and the purchase cost to be 500,000 ¥, which is equal to an average daily cost of 171.2 ¥. These parameter settings are based on data from the operator in the Jiading district and the selected vehicle model, which is the "Sunwin SWB6109EV16G". The initial temperature, termination temperature and cooling factor in the ALNS-SA's inner loop are 100°C, 10°C, and 0.97, respectively. The algorithm's outer loop iteration is set to 100. Operator's weight is set to 1.5. **Table 3** represents the parameter values utilized in the tests. **Table 4** shows the commercial time-of-use electricity prices in Shanghai in 2023. The discharging recovery price is assumed to be consistent with the charging time-of-use electricity prices.

Table 3 Parameter setting

Parameter	Value
r^r	0.15 kWh/min
r^c	1 kWh/min
r^d	1kWh/min
r^e	0.1 kWh/min
c^f	171.2 ¥/day
c^e	0.5 ¥/min
τ	100 kWh
SOC_{min}	20%
SOC_{max}	100%

Table 4 Commercial time-of-use electricity prices in Shanghai in 2023

Period	Time	Price(¥/kWh)
Peak	10:00 - 15:00	1.2893
	18:00 - 21:00	
Normal	7:00 - 10:00	0.8731
	15:00 - 16:00	
	21:00 - 23:00	
Off-peak	23:00 - 24:00	0.4570
	0:00 - 7:00	

4.1 Performance of the solution algorithms

We utilize the commercial solver Gurobi 10, EGA and ALNS-SA to solve our model. All three methods were solved within a time limit of 6 hours. **Table 5** shows the operation time and total cost of the three approaches in various scale testing cases.

Table 5 Objective value and computation time by the three approaches for different problem scales

Method\problem scale		20 trips	50 trips	200 trips	418 trips
Gurobi	Total cost (¥)	3109.1	4599.4	--	--
	Computation time (s)	1.78	617.6	--	--
EGA	Total cost (¥)	3433.5	5000.1	7691.5	9036.2
	Computation time (s)	0.1	0.5	3.0	61.5
ALNS-SA	Total cost (¥)	3146.6	4630.9	7000.6	8758.3
	Computation time (s)	4.1	14.7	65.2	202.3

In **Table 5**, the ALNS-SA fusion approach gains significantly higher solution quality compared to EGA. Gurobi was unable to find feasible solutions for the 200 trips and 418 trips tests within 6 hours. In the 50 trips' test, although the total cost obtained by the ALNS was 0.7% higher than Gurobi, its solution time was 42 times shorter. Overall,

the ALNS-SA fusion approach demonstrates the best performance among these three methods.

Fig. 4 indicates the cost breakdowns obtained by the ALNS-SA under different test cases. The capital costs of the BEB fleet constituted the largest proportion in the operation costs. The deadhead cost and daytime charging cost increased with the number of trips, which is expected. The discharging revenue constituted around 7%-25% of the total cost, which indicates the great advantages of V2G in better utilizing the BEB fleet, especially when the number of executed trips is relatively low.

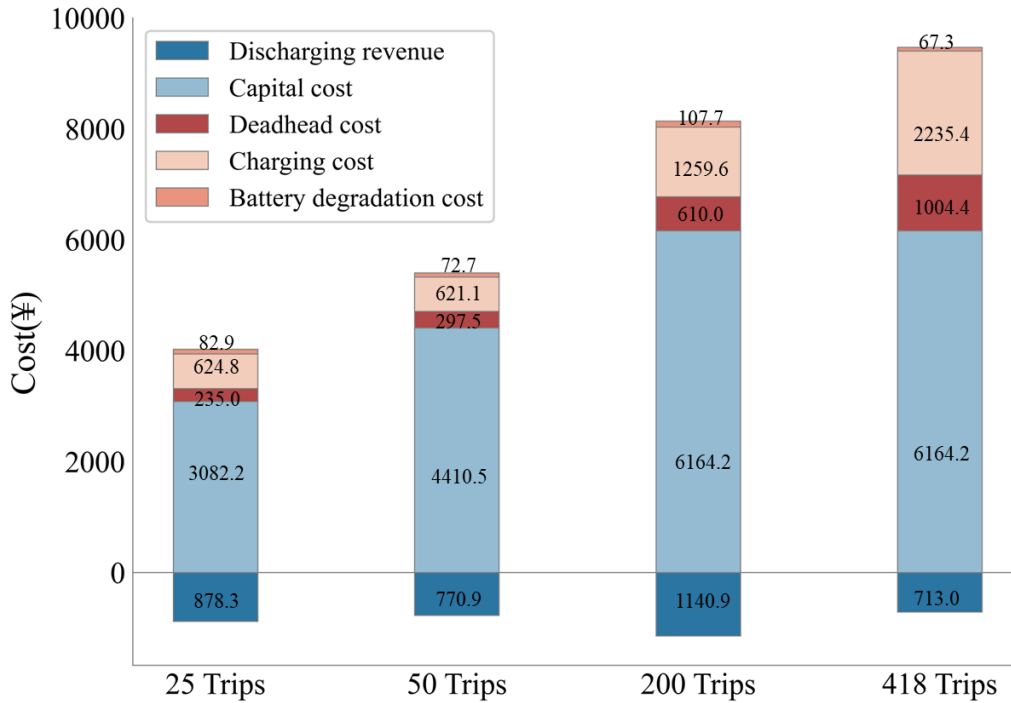


Fig. 4. Cost breakdowns obtained by the ALNS-SA

We assume BEBs can be fully charged overnight at depots in the non-bus operation hours from 23:30-5:30, which also falls within the low electricity price range. The unified start time for BEBs' overnight charging is midnight. **Fig.5** shows the charging and discharging start time and duration for each BEB for the case with 418 trips. The discharging time of BEBs are more concentrated during peak electricity price periods.

BEBs tend to get charged during the afternoon or night time after carrying out some trips in the morning time.

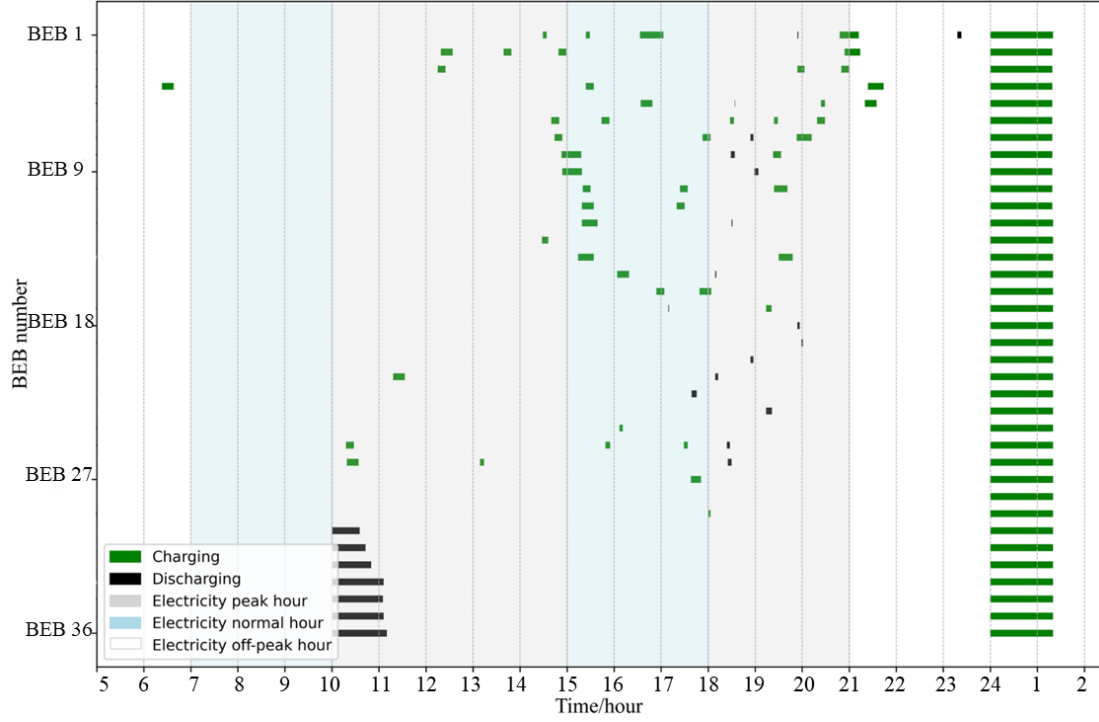


Fig. 5. Each BEB's charging and discharging times

Fig. 6 displays the scheduling of trips for the five bus routes in both inbound and outbound directions. Not all BEBs have discharging activities, which depends on the total amount of executed trips by the vehicles and the time intervals between two trips. BEBs with fewer executed trips may have a remaining SOC that allows them to discharge in electricity peak hours to get some revenue. For route 116 and route 132, they have a common terminal station as Huangdu depot. The BEBs entered the depot to charge or discharge without incurring any deadhead distance. Since the travel distance of one trip on each route varies, the energy consumptions are also different for performing these route trips. This also leads to variations in the duration of discharging activities at the same time period, as seen in BEB30-BEB36. Additionally, the BEB needs to return to the home depot after completing its last trip for a day. Therefore, if the BEB's SOC is insufficient to return to the home depot after completing the last trip, it needs to charge

before returning. If the SOC is still above the minimum threshold upon returning to the depot, the BEB can also discharge at the nearest depot before returning.

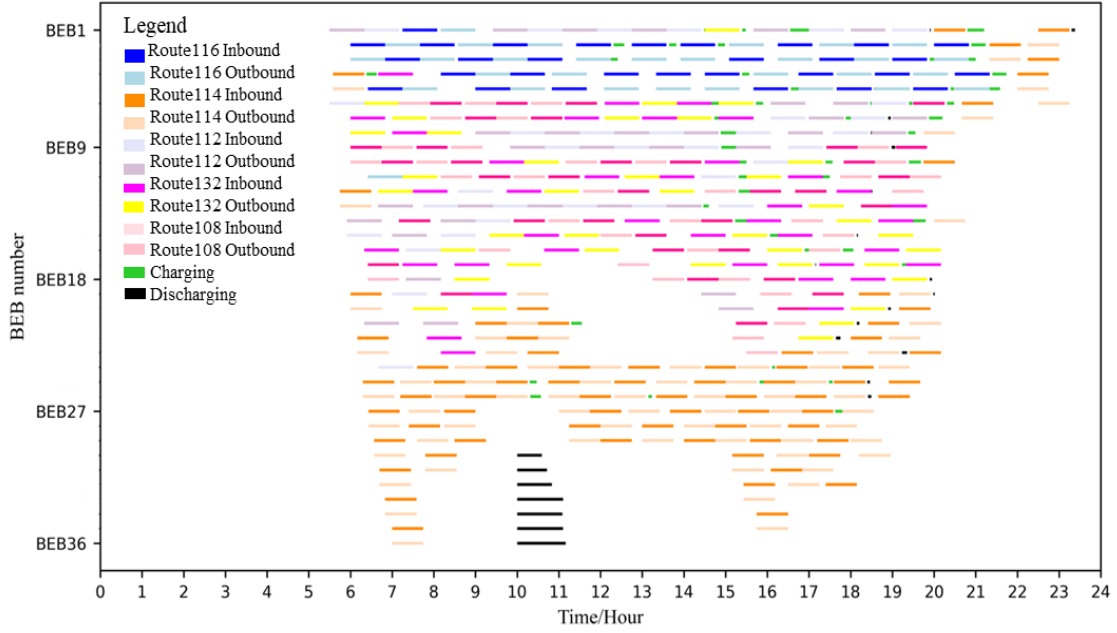


Fig. 6. BEB daytime scheduling under the V2G environment

4.2 Effects of cross-line operation

In many cities, a bus only operates on and belongs to a single bus route, which is also the case in Jiading District, Shanghai. In this study, we allow BEBs to operate cross-lines which incurs deadhead costs but is able to reduce the total costs. **Table 6** shows the cost breakdowns for the five bus routes with single-line and cross-line operation modes.

Table 6 Cost analysis in the single-line and cross-line operation modes

	Route 116	Route 114	Route 112	Route 132	Route 108	Single-line	Cross-line
Total BEB number	6	12	6	8	7	39	36
Capital cost (¥)	1027.2	2054.4	1027.2	1369.6	1198.4	6676.8	6164.2
Deadhead cost (¥)	140.0	242.5	160.0	140.0	215.0	897.5	1004.4
Charging cost (¥)	508.3	1000.3	358.6	444.2	386.5	2697.6	2235.4
Discharging revenue (¥)	65.5	92.5	4.3	45.6	85.8	293.7	713.0
Battery degradation cost (¥)	6.2	8.7	0.4	4.3	8.1	27.7	67.3
Total cost (¥)	1734.8	3381.0	1549.7	1995.1	1877.6	10538.2	8758.3

Under the single-line operation, Route 114 required the highest number of BEBs among the five operating routes because it carried out the largest number of timetabled

trips. The cross-line operation requires 36 BEBs, which is 3 less than the 39 utilized in the single-line operation mode. Since cross-line operation can utilize vehicles from different routes to handle the trips with different starting times, it saves on the number of BEBs required. Even with a smaller BEB fleet size, the cross operation gained higher discharging revenue. A reason is that the cross-line operation creates larger intervals of spare time in peak electricity hours through deadheading, hence providing more opportunities for BEBs to engage in discharging activities. Further, the charging cost in cross-line operation is lower. Due to varying energy consumption across different routes, some BEBs in the single-line operation mode may need to charge during peak electricity periods to complete the next trip on the same route. This leads to slightly lower charging costs for cross-line operation compared to single-line operation.

In order to have an arguably fair comparison, we increase the fleet size in the cross-line operation mode to 39 as well, with 36 BEBs carrying out task trips, and the remaining 3 BEBs responding to the electricity grid to gain revenues only (and possibly being used as a back-up vehicle in practice). Considering the charging and discharging power, the remaining BEBs can be scheduled to discharge during the two peak electricity price periods. The discharged amount for each BEB per discharging activity is 80% battery SOC. Thus, the total daily discharging revenue for each vehicle is calculated by multiplying the electricity price at the time of discharging by the discharged amount. It's about 206.3 ¥ whereas each BEB's charging cost is 69.8 ¥. **Table 7** compares the costs under different fleet sizes between the cross-line operation mode and the traditional single-line operation mode under the V2G environment.

Table 7 Cost comparison for different BEB fleet sizes

	Single-line operation	Fixed fleet size line operation	cross-Optimized cross-line operation
Total BEB number	39	39	36
BEB fixed cost (¥)	6676.8	6676.8	6164.2
Deadhead cost (¥)	897.5	1004.4	1004.4
Charging cost (¥)	2697.6	2444.8	2235.4
Discharging revenue (¥)	293.7	1366.2	713.0
Battery degradation cost (¥)	27.7	101.6	67.3
Total cost (¥)	10537.9	8861.4	8758.3

In the optimized cross-line mode operation with the optimal fleet size of 36, the total cost is the lowest among the three modes, although the discharging revenue was lower. It indicates that utilizing dedicated BEBs for grid responding services alone is not economical. However, if the bus company has already purchased abundant BEBs, getting the idling BEBs to participate in the V2G market is financially beneficial. In response to the above situation, public transportation companies can optimize costs under the V2G environment based on various operational scenarios. The scenarios can help in scheduling decisions and with fleet size decisions as the results show the potential benefits of an additional bus.

In addition to variations in operational models, some papers also used the less flexible “full charging type” and the “fixed period charging type”. We show the increase in cost when these types are employed. For the fixed period type we employ off-peak electricity price periods as in Xie et al. (2023). **Table 8** provides a comparison of the costs with three charging types. It is evident from the table that the adopted partial charging type has the lowest total cost. While the fixed period charging type during low electricity prices requires a larger number of vehicles. Overall, partial charging is more suitable for BEB operations under V2G environment.

Table 8 Cost comparison for different charging type

	Partial charging	Full charging	Fixed period
Total BEB number	36	40	49
BEB fixed cost (¥)	6164.2	6848.8	8388.8
Deadhead cost (¥)	1004.4	1285.0	1187.5
Charging cost (¥)	2235.4	1460.5	1335.7
Discharging revenue (¥)	713.0	563.7	881.7
Battery degradation cost (¥)	67.3	53.2	83.2
Total cost (¥)	8758.3	9083.8	10113.5

4.3 Sensitivity analysis

Parameters such as discharging unit price, charging rate, and discharge rate all affect the daily operating costs. **Table 9** expresses the three parameter values in different scenarios assuming increases and decreases of 0.5 from the base value. **Fig.7** illustrates the variation in various costs under different scenario assuming the optimal fleet is used.

Table 9 Parameter values in different scenarios

Parameter \ Scenario	1	2	3	4	5	6	7	8	9	10	11	12
Unit discharging price (¥/Kwh)	1.29	0.79	1.29	1.29	0.79	1.79	1.29	1.29	1.79	1.29	1.29	1.29
Unit battery degradation price (¥/Kwh)	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.6	0.6	0.6
Charging power (kWh/min)	1	1	0.5	1	0.5	1	1.5	1	1.5	1	1	1.5
Discharging power (kWh/min)	1	1	1	0.5	0.5	1	1	1.5	1.5	1	1.5	1

In **Fig.7**, it can be found that the unit price of discharging has a significant impact on the daily operating costs in Scenarios 6 and 9. In Scenarios 1, 3, and 7, we increased the charging power from 0.5 to 1.5. Scenario 3 with the slowest charging power had the highest capital cost and total cost among the three scenarios. Increasing the charging power of BEBs increased the energy gained per unit of time. As a result, it can provide

more opportunities for discharging activities without being constrained by BEBs' SOC. To reduce the total cost, the operating company can also increase the charging power to enable more BEBs to participate in discharging activities. Scenarios 1, 4, and 8 show the impacts of discharging power on various costs. The discharging rate has a marginal impact on the total cost and revenue. Scenarios 1 and 10 reveal that higher unit battery degradation price leads to increases in total costs. Among Scenarios 10, 11, and 12, Scenario 12—despite having the highest charging power—achieved the largest discharge revenue while simultaneously reducing the total costs. Furthermore, sensitivity analysis across varying parameters scenarios shows that the computation time of ALNS-SA ranges from 102.1 to 104.9 seconds, demonstrating its robustness under different parameters scenarios.

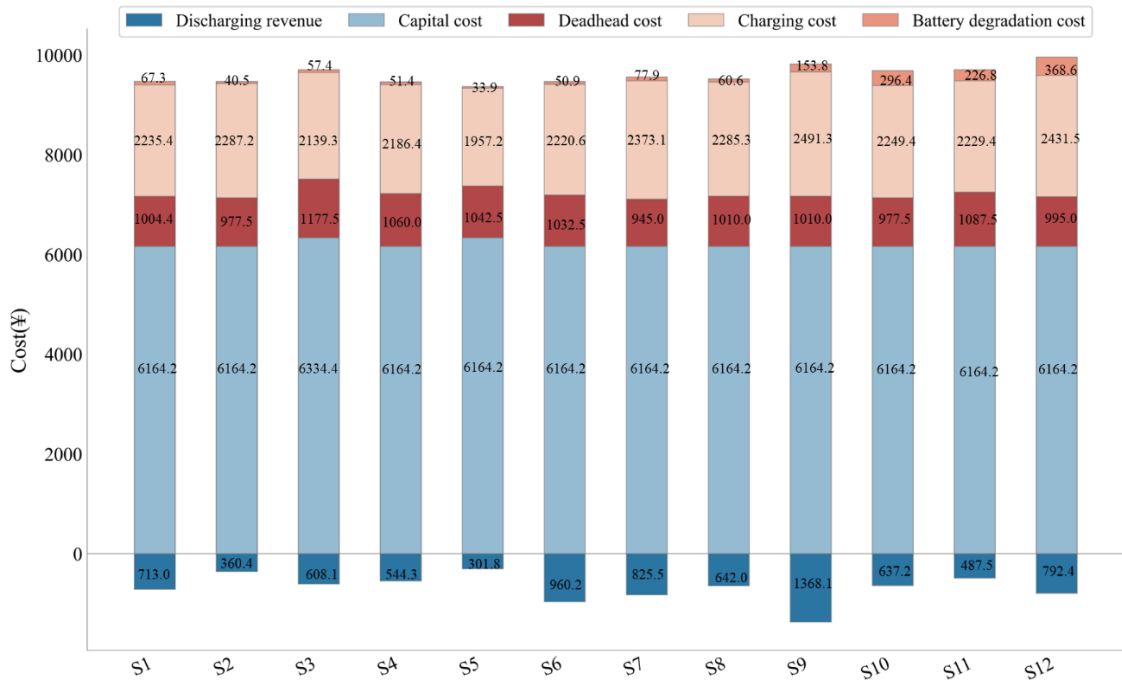


Fig.7. Results for the parameter sensitivity test

5. Conclusion

In this study, we developed a joint optimization model for trip scheduling and (dis-)charging scheduling of battery electric buses in a vehicle-to-grid environment. To

solve the model, we proposed an adaptive large neighborhood search with simulated annealing fusion algorithm, which dynamically adjusts (dis-)charging activities. In terms of computational efficiency, the ALNS-SA algorithm achieved near-optimal solutions (within 0.7% of Gurobi's exact results) for small-scale instances with 50 trips, while reducing computation time by a factor of 42. For large-scale problems, ALNS-SA outperformed the evolutionary genetic algorithm (EGA) in solution quality, demonstrating its ability to balance computational efficiency and accuracy.

Experimental results indicate that the cross-line operation mode with an optimized fleet size yields the lowest operational costs in a V2G environment. If a bus company has already invested in a surplus of BEBs, it can leverage idle vehicles to participate in the V2G market, generating additional revenue. Furthermore, sensitivity analysis highlights electricity price and charging rate as critical cost drivers. To minimize charging duration and associated expenses, bus operators should prioritize the adoption of fast-charging infrastructure.

While V2G discharging revenues are modest but non-trivial (Fei et al., 2023), their economic viability depends on government incentives to offset unmodeled challenges. These include accelerated battery degradation due to high-frequency cycling, infrastructure investment costs, and increased driver workload resulting from the complexity of cross-line scheduling. Additionally, this study does not account for dynamic factors such as weather-dependent energy consumption and passenger load fluctuations. Future research should incorporate these variables to provide a more comprehensive analysis.

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Appendix A

Detailed steps of the adaptive large neighbourhood search and simulated annealing fusion algorithm:

We need to first design the destroy and repair operators of the ALNS. Set $Q_{destroy}$ is utilized to store the destroyed trips after applying the destroy operator. Set $A_{destroy}$ stores the affected trip pair due to the destroy operation. The key for feasible trip chain reconstruction lies in dynamically adjusting the charging and discharging durations between trip pairs, which is also the innovation of this algorithm.

(1) Destroy operator

We designed two destroy operators, maximum deadhead distance destroy operator and maximum trip pair interval destroy operator. To widen the range of destroyed solutions, we perform the destroy operator on two random BEB trip chains simultaneously.

I) Maximum deadhead distance destroy operator

For a selected BEB trip chain, (i, j') represents the trip pair with the maximum deadhead distance among its executed trip pairs. Only trip j' is removed from the original trip chain. The destroyed trip j' and trip pair (i, j') are placed into sets Q' and A' , respectively.

II) Maximum trip pair interval destroy operator

The trip pair (i, j') to be selected is the one with the longest interval time. The other operations are the same with the maximum deadhead distance destroy operator.

(2) Repair operator

The repair operators are also designed in two types: minimum deadhead distance repair operator and minimum trip pair interval repair operator.

I) Minimum deadhead distance repair operator

Select a trip j' from the set of destroyed trips Q' . If the trip originates from BEB k before it was removed, we will not consider inserting it back into BEB k during the repair operator. The trip j' is inserted to the trip chain with the smallest deadhead distance from $i1 \rightarrow j' \rightarrow i2$. In addition, the trip pairs $i1 \rightarrow j'$ and $j' \rightarrow i2$ must be feasible, which is guaranteed if they are in set A^Q . The repaired trip chain might also need to adjust the charging or discharging duration to ensure its feasibility. We perform the repair operator repeatedly until the set Q' is empty or when the maximum number of repair iterations is reached. If j' cannot be inserted to any other trip chains, we retain the original solution.

II) minimum trip pair interval repair operator

The operations are the same with the minimum deadhead distance repair operator, except that the destroyed trip j' is inserted to another trip chain where the trip pair interval from $i1 \rightarrow j' \rightarrow i2$ is no greater than that of the previous destroyed trip pair.

(3) SOC feasibility repair

After performing the trip insertion repair operator, we need to recalculate the SOC value throughout the updated trip chain and possibly adjust charging and discharging durations to ensure trip chain feasibility. We consider three cases based on the insertion position of the trip j' , which are at the front, end, and the middle position of the trip chain.

I) Trip j' is inserted to the front of the trip chain

When trip j' is inserted to be the first trip of the trip chain, the home depot of the BEB trip chain o_{old} can be replaced with a new depot o_{new} with the minimum deadhead distance to j' . The additional energy needed SOC' is calculated by the following formula:

$$SOC' = SOC'_{low} - SOC_{min} - run_{j',r^r} - t_{o_{new},j'}^e - t_{j',i}^e + t_{o_{old},i}^e \quad (26)$$

where SOC'_{low} is the minimum SOC throughout the old trip chain before insertion, and trip i is the first trip of the old trip chain before insertion.

When SOC' is negative, this BEB requires additional charging to complete those trips. We extend the charging duration when BEB enters the depot during periods of low electricity prices first and continue to the high price hours gradually until the SOC feasibility of the new trip chain is fulfilled. If the added energy is still not enough, we gradually decrease the discharging time to gain more energy.

When SOC' is positive and the SOC values satisfy Constraints (14) after running each trip, it indicates that the new trip chain is feasible already, and there might be some surplus energy throughout the trip chain. We first try to extend the discharging duration during peak electricity price intervals to consume this surplus. Then we reduce the charging duration in the peak price hours and off-peak hours sequentially until the surplus is reduced to the minimum level.

II) Trip j' is inserted to the end of the trip chain

When trip j' is inserted to the end of the trip chain, the additional energy needed, SOC' , is calculated by the following formula:

$$SOC' = SOC'_{last} - SOC_{min} - run_{j,r^r} - t_{i,j,r^e}^e \quad (27)$$

Where SOC'_{last} is the BEB's remaining SOC after performing the last trip of the old trip chain before insertion, and trip i is the last trip of the old trip chain before insertion. The dynamic adjustment procedure for the charging and discharging duration is the same as the method described above.

III) Trip j' is inserted to the middle of the trip chain

Inserting trip j' to an intermediate position $(i1, i2)$ requires checking whether there were charging or discharging activities between $(i1, i2)$ before the insertion. The additional energy needed is calculated by the following formula:

$$SOC' = SOC'_{low} - SOC_{min} - run_{j,r^r} - t_{i1,j}^e r^e - t_{j,i2}^e r^e + \hat{t}_{i1,i2}^e r^e - \widetilde{SOC}_{\Delta} \quad (28)$$

The value of $\widetilde{SOC}_{\Delta}$ varies depending on whether there is a charging or discharging activity between $(i1, i2)$. When there is a charging or discharging activity between $(i1, i2)$, the $\widetilde{SOC}_{\Delta}$ formula are as follows respectively:

$$\widetilde{SOC}_{\Delta} = duration_{i1,i2}^c r^c \quad (29)$$

$$\widetilde{SOC}_{\Delta} = -duration_{i1,i2}^d r^d \quad (30)$$

where $duartion_{i1,i2}^c$ represents the BEB's charging duration between trip pair $(i1, i2)$ before insertion and $duration_{i1,i2}^d$ expresses the BEB's discharging duration between trip pair $(i1, i2)$ before insertion. The dynamic adjustment of charging and discharging duration follows the same approach as described above.

(4) Adjustment of discharging start time

To maximize BEBs' discharging revenues during peak electricity price periods, we further revise the initial start time for discharging activities in the solution fining. This step is effective mainly for cases where there is a prominent interval between two trips and includes a peak electricity price period for discharging. Initially, the BEB discharging start time is set to the time of arrival at the nearest depot. We expect the BEB's discharging activities to occur during peak electricity period. If some BEBs' initial discharging start times do not fall within this peak-price period, we can increase discharging revenues by delaying the discharging to increase the revenue.

Appendix B. Detailed trip timetables and deadhead time matrix

Table B1 Timetables of selected buses in Jiading District Five

Line	Inbound trip start time				Outbound trip start time				
Route116	06:00	06:25	06:50	07:15	06:00	06:25	06:50	07:15	07:40
	07:40	08:10	08:35	09:00	08:10	08:35	09:00	09:25	09:50
	09:25	09:50	10:15	10:50	10:15	10:50	11:25	12:05	12:45
	11:25	12:05	12:45	13:20	13:20	13:55	14:30	15:05	15:40
	13:55	14:30	15:05	15:40	16:15	16:45	17:15	17:40	18:05
	16:15	16:45	17:15	17:40	18:30	19:00	19:30	20:00	20:30
	18:05	18:30	19:00	19:30					
	20:00	20:30							
	5:35	5:45	6:00	6:10	6:18	6:26	6:00	6:15	6:30
	6:34	6:42	6:50	7:00			7:00	7:10	7:20
Route 114	7:12	7:24	7:36	7:48	8:00		7:55	8:10	8:22
	8:15	8:30	8:45	9:00	9:15		8:55	9:05	9:20
	9:30	9:45	10:00	10:15			10:05	10:15	10:30
	10:30	10:45	11:00	11:15			11:15	11:30	11:45
	11:30	11:45	12:00	12:20			12:30	12:50	13:10
	12:40	13:00	13:20	13:40			14:10	14:30	14:45
	14:00	14:15	14:30	14:45			15:30	15:40	15:50
	15:00	15:10	15:18	15:26			16:10	16:20	16:30
	15:35	15:45	15:55	16:05			17:00	17:10	17:20
	16:13	16:21	16:30	16:40			17:52	18:04	18:16
Route 112	16:50	17:00	17:12	17:24			18:52		
	17:36	17:48	18:00	18:12			19:05	19:20	19:30
	18:25	18:40	18:55	19:10			20:10	20:30	20:50
	19:25	19:40	20:00	20:20			21:50	22:10	22:25
	20:40	21:00	21:20	21:40			22:40	23:00	
	22:00	22:15	22:30						
	05:30	05:55	06:20	06:40			05:30	05:55	06:20
	07:00	07:20	07:45	08:10			07:20	07:45	08:10
	08:35	09:00	09:25	09:50			09:25	09:50	10:15
	10:15	10:40	11:05	11:30			11:30	11:55	12:20
Route 132	11:55	12:20	12:45	13:10			13:35	14:00	14:25
	13:35	14:00	14:25	14:50			15:40	16:05	16:35
	15:15	15:40	16:05	16:35			18:00	18:30	19:00
	17:05	17:35	18:00	18:30					
	19:00								
	06:00	06:20	06:40	07:00			06:00	06:20	06:40
	07:15	07:30	07:50	08:10			07:30	07:50	08:10
	08:30	08:55	09:20	09:45			09:20	09:45	10:10
	10:10	10:39	11:08	11:37			11:37	12:06	12:35
	12:06	12:35	13:00	13:25			13:50	14:10	14:30
Route 108	13:50	14:10	14:30	14:50			15:30	15:50	16:05
	15:10	15:30	15:50	16:05			16:50	17:15	17:40
	16:20	16:35	16:50	17:15			18:40	19:00	19:20
	17:40	18:00	18:20	18:40					
	19:00	19:20							
	06:00	06:25	06:45	07:10			06:00	06:25	06:45
	07:35	07:55	08:10	08:25			07:55	08:10	08:25
	08:45	09:05	09:30	09:55			09:30	09:55	10:20
	10:20	10:45	11:10	11:35			11:35	12:00	12:25
	12:00	12:25	12:50	13:15			13:40	14:00	14:25
	13:40	14:00	14:25	14:50			15:35	15:55	16:15

15:15	15:35	15:55	16:15	17:25	17:50	18:15	18:40	19:05
16:40	17:05	17:25	17:50	19:30				
18:15	18:40	19:05	19:30					

Table B2 Depots and different lines' station deadheading time matrix

	Huangdu depot	Anting depot	Station1	Station2	Station 3	Station 4	Station 5	Station 6	Station 7
Huangdu depot	0	20	0	20	20	10	10	15	20
Anting depot	20	0	20	10	0	10	25	15	15
Station 1	0	20	0	20	20	10	10	15	15
Station 2	20	10	20	0	10	10	25	15	10
Station 3	20	0	20	10	0	20	25	15	5
Station 4	10	10	10	10	20	0	15	15	25
Station 5	10	25	10	25	25	15	0	20	25
Station 6	15	15	15	15	15	15	20	0	20
Station 7	20	15	15	10	5	25	25	20	0

Table B3 Terminal station ID

Terminal station ID	1	2	3	4	5	6	7
	Huangdu bus station	Anting North Railway station	Antinglao street station	Dengjiajiao station	Lianxi road station	Changji east road station	Xiangyang village station

Table B4 Terminals and trip duration for the tested bus lines

	Route 116	Route114	Route112	Route132	Route108
Start/Terminal station	Station 1 Station 2	Station 3 Station 4	Station 3 Station 5	Station 6 Station 1	Station 7 Station 6
Trip duration (min)	50	45	50	50	45

Table B5 shows the BEB scheduling solution by the ALNS-SA fusion approach for the case with 418 trips. Node number starts from 0 to 419. Nodes 0 and 1 represent Huangdu depot and Anting depot, respectively. The remaining nodes represent task trips. Characters C and D represent BEB's charging and discharging activities, respectively. After optimization, the total number of BEBs is 36.

Table B5 BEB scheduling obtained by the ALNS-SA fusion approach.

BEB number	Trip chain	BEB number	Trip chain
1	1-6-27-32-53-106-127-146-167-186-207-C-229-C-256-C-287-304-321-D-408-C-418-D-1	19	1-24-47-70-98-225-226-271-300-394-403-D-1
2	0-2-23-42-63-82-103-122-C-142-C-162-C-183-202-223-242-263-282-C-412-417-0	20	0-25-59-99-224-236-280-306-329-D-402-0
3	1-3-22-43-62-83-102-123-C-143-163-182-203-222-243-262-C-283-C-413-416-1	21	1-26-66-184-215-244-C-250-281-315-D-396-405-1
4	1-4-C-28-52-73-92-113-132-152-172-C-193-212-233-252-273-292-C-414-1	22	1-34-68-185-214-245-251-299-D-392-401-1
5	0-5-12-33-72-93-112-133-153-173-192-C-213-232-D-253-272-C-293-C-415-0	23	0-35-78-195-234-261-374-385-397-D-404-0
6	0-7-19-41-60-91-110-131-150-168-189-208-C-239-C-266-296-C-313-C-342-C-410-419-0	24	0-37-124-165-194-235-264-295-318-339-352-361-C-372-383-390-399-0
7	1-8-39-61-90-111-130-148-169-188-209-C-238-267-286-C-305-D-320-C-411-1	25	1-44-105-144-175-204-C-254-285-310-333-348-357-C-368-379-C-388-D-400-1
8	0-9-38-69-96-117-136-157-176-197-216-C-247-276-297-D-312-C-407-0	26	0-45-104-145-174-205-C-255-284-311-C-332-349-356-369-378-389-D-398-0
9	1-10-31-50-81-116-137-156-177-196-217-C-246-277-308-325-D-336-1	27	1-54-115-154-265-294-319-338-353-360-371-380-C-391-1
10	1-11-30-51-80-108-129-151-170-191-210-228-C-257-289-C-316-331-C-406-1	28	0-55-114-155-274-303-326-345-354-365-376-387-0
11	1-13-49-71-100-121-140-158-179-198-227-C-259-288-C-317-330-343-1	29	1-64-125-164-275-302-327-344-355-364-375-384-C-393-1
12	1-14-29-58-87-118-139-161-180-199-231-C-260-290-322-D-337-1	30	0-65-134-D-358-373-382-395-0
13	0-15-36-67-86-107-126-147-166-187-206-C-237-268-307-324-346-0	31	1-74-135-D-359-370-381-1
14	1-16-40-76-97-120-141-160-178-211-230-C-258-291-323-340-C-409-1	32	0-75-D-362-377-386-0
15	0-17-46-77-109-128-149-171-190-218-249-C-278-309-D-341-0	33	1-84-D-363-1
16	1-18-57-79-101-138-159-200-221-240-269-C-301-C-334-351-1	34	0-85-D-366-0
17	1-20-48-88-119-181-219-248-279-D-314-335-C-350-1	35	1-94-D-367-1
18	1-21-56-89-201-220-241-270-298-328-347-D-1	36	0-95-D-0