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Optimization of electric vehicle scheduling with multiple vehicle types in public transport

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ABSTRACT

The effective scheduling of electric buses (EBs) for multiple vehicle types is essential for the sustainable practice of public transport. This paper proposes a new methodology for the electric vehicle scheduling problem with multiple vehicle types (*MVT-E-VSP*) in public transport based on a given multi-vehicle-type timetable. First, with explicit consideration of differences in driving range, recharging duration and energy consumption of EBs for multiple vehicle types, an optimization model is established to minimize annual total scheduling costs, including the purchase costs of EBs and chargers, the operating costs of deadheading and timetabled trips, etc. Then, a heuristic procedure is developed to find the optimal solution considering recharging trips and the substitution between electric vehicle (EV) types. Finally, the proposed methodology is validated using a real-world transit network in Daxing District, Beijing. The optimization result provides transit agencies with guidance on the purchase and schedule of EBs for multiple vehicle types, as well as the deployment of chargers. Comparative analysis indicates the proposed method considering the substitution between EV types reduces annual total scheduling costs by 15.93% compared with the conventional method. Sensitivity analysis reveals that the current recharging power (240 kW) and discharging depth (80%) are approximately economical.

1. Introduction

In recent years, many cities have experienced serious traffic congestion with the fast-paced urban growth. To deal with this problem, promoting the public transport has become the consensus of the whole society (Sui, Shao, Yu, Sun, & Li, 2019). Meanwhile, global warming, largely caused by the heavy use of fuel vehicles in road transport, is becoming a major environmental issue in many countries (Ong, Mahlia, & Masjuki, 2011; Rahimi & Davoudi, 2018). It is urgent to adopt suitable energy policy to reduce emissions in transportation sector (Ong, Mahlia, & Masjuki, 2012), and electric vehicles (EVs) play an effective role in the low-carbon transition (Daramy-Williams, Anable, & Grant-Muller, 2019). Therefore, under dual pressure of congestion and pollution, zero-emission EVs used in public transport (i.e., electric buses (EBs)) are drawing more attention. However, the further promotion of EBs is hindered by existing limitations, such as limited driving ranges, insufficient chargers, long recharging duration and upfront purchasing cost (Amirhosseini & Hosseini, 2018; Bakker, 2011; Langbroek et al., 2019). In addition, a high-level planning is strongly needed in commercial transport, and vehicle scheduling is a crucial step in the planning process. Vehicle scheduling is the process of assigning vehicles to the trips of a given timetable, which is closely related to scheduling costs for operators (Ceder, 2007). For EBs, their limitations must be taken into account in the vehicle scheduling process.

Moreover, with the renewal of the fleet and the promotion of EBs, many bus routes are operated with multiple vehicle types, in that capacity waste or in-vehicle overcrowding are more likely to occur under single-vehicle-type organization mode (Hassold & Ceder, 2012). The application of multiple vehicle types can improve the reliability of operation for fluctuating demand and save scheduling costs for operators (Ceder, 2011). Therefore, the effective schedule of EBs for multiple vehicle types can not only cut scheduling costs from the operator's perspective, but also alleviate traffic congestion and air pollution from the social point of view. In this way, the sustainable development of public transport is further promoted. This is the motivation for studying the electric vehicle scheduling problem with multiple vehicle types (*MVT-E-VSP*) in public transport. However, as far as we know, the research on this field is still insufficient.

Distinct from the previous study, this paper incorporates EBs for multiple vehicle types into the *MVT-E-VSP*. The methodological advance is the consideration of differences in the driving range, recharging duration and energy consumption of multiple EV types. This is significant because it provides the theoretical foundation for the modeling work and is closely related to scheduling costs for transit agencies.

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The other merit lies in the heuristic algorithm considering the insertion of recharging trips and the substitution between different EV types. This substitution can significantly reduce the number of EBs needed and thus save scheduling costs. This paper is organized as follows. Section 2 covers a literature review. Section 3 looks at the methodology. The optimization result of a real-world transit network in Beijing is presented in Section 4 accompanied with comparative analysis and sensitivity analysis. At last, conclusions and future research are elaborated in Section 5.

2. Literature review

EBs have energy, environmental, and economic benefits for the society compared with conventional fuel buses (He, Song, & Liu, 2019; Lajunen, 2014; Ou, Zhang, & Chang, 2010), while multiple vehicle types can improve the operation reliability for fluctuating demand and cut scheduling costs for operators. Although the usage of EBs for multiple vehicle types increases the difficulty of scheduling, it is worthwhile to be studied due to its high value for the sustainable development of public transport.

During the past decades, numerous problems associated with the scheduling of vehicles in public transport have been studied. Among them, the most classical is the standard vehicle scheduling problem (*VSP*). The *VSP* refers to the problem of determining the optimal assignment of vehicles to cover all timetabled trips. A chain of trips is assigned to each vehicle although some of them may be deadheading trips in order to reach optimality (Bunte & Kliewer, 2010). The *VSP* can be divided into the single-depot *VSP* (*SD-VSP*) and the multi-depot *VSP* (*MD-VSP*). In the *SD-VSP*, vehicles can only be housed in a single depot. The *SD-VSP* can be described as a minimum cost flow problem (Desrosiers, Dumas, & Solomon, 1995) or an approximate assignment problem (Dadana & Pinto Paixao, 1995). The *MD-VSP* refers to the case in which vehicles can be housed in multiple depots. The number of feasible solutions to this problem is extremely large, so there is also a problem of computational efficiency. The *MD-VSP* can be described as connection network models including the multi-commodity network flow model (Lóbel, 1998, 1999; Mesquita & Paixao, 1992) and the set partitioning model (Bianco, Mingozzi, & Ricciardelli, 1994; Oukil, Amor, Desrosiers, & Gueddari, 2007; Soumls, 1994). However, the connection network has the drawback of the consideration of all possible connections between compatible trips. To avoid this drawback, time-space network models are proposed to describe the *MD-VSP* (Kliewer, Mellouli, & Suhl, 2002; Laurent & Hao, 2009; Naumann, Suhl, & Kramkowski, 2011; Pepin, Desaulniers, & Hertz, 2009). A lot of algorithms are developed to solve the models, including Deficit Function Method and Greedy Algorithm in early days, as well as Tabu Search, Genetic Algorithm, Large Neighborhood Search Heuristic and other intelligent optimization algorithms in recent years.

Based on the above research, the *VSP* is extended to different variants, one of which is the electric vehicle scheduling problem *(E-VSP)* considering recharging demand caused by limited driving ranges. Li (2014) proposed a vehicle scheduling model for EBs with either battery swapping or fast charging, and developed the column-generation-based algorithm to solve the problem. Panhathai, Sununtha, and Rathakarn (2015) presented a method to schedule EBs using energy demand related to total driving distance and energy consumption rate, which could be used as an effective tool for the scheduling of EBs for multiple depots. Wen, Linde, Ropke, Mirchandani, and Larsen (2016) presented a mixed integer programming formulation and a large neighborhood search heuristic for the *E-VSP* to minimize the number of needed vehicles and the total deadheading distance. Wang, Huang, Xu, and Barclay (2017) developed a framework to optimize EB recharging scheduling, which provided planning and operational decisions to minimize annual total costs. Sensitivity analysis was conducted to provide transit agencies with suggestions on the development of a fast charging system. van Kooten Niekerk, van den Akker, and Hoogeveen (2017) explored the *E-VSP* by presenting two models that differed in the level of detail resembling the actual processes. The models were solved by an integer linear programming and a column generation under different instances. Rigas, Ramchurn, and Bassiliades (2018) solved the *E-VSP* by algorithms including an incremental mixed integer programming algorithm, a greedy algorithm and a tabu search-based local search algorithm. The application of each algorithm was discussed in detail. The research mentioned above focuses on the *E-VSP* with a single vehicle type. The substitution between different EV types have not been taken into account.

To improve the reliability of operation for fluctuating demand and save scheduling costs, multiple vehicle types are often used in practice. When purchasing vehicles or establishing a fleet, transit agencies have to face the challenge to choose the vehicle type, which leads to another variant of *VSP*, that is, the vehicle scheduling problem with multiple vehicle types *(MVT-VSP)*. Kliewer, Mellouli, and Suhl (2006) modeled the *MVT-VSP* and solved a real-world problem with thousands of scheduled trips. They established one time-space network layer for each depot-vehicle-type-combination and solved them separately. Ceder (2011) proposed the deficit function method to solve the *MVT-VSP* based on given vehicle types, where the categories were sorted by the vehicle cost in descending order. Each trip could be performed by its original vehicle type or other types listed in the prior order. Hassold and Ceder (2014) developed a method for the *MVT-VSP* based on the minimum cost network flow model, which considered the substitution between vehicle types. These works are conducted based on conventional fuel buses, rather than EBs. Reuer, Kliewer, and Wolbeck (2015) defined the multi-vehicle-type vehicle scheduling problem with EVs (*MVT-(E)VSP*) considering a mixed fleet composed of conventional buses and EBs. They solved this problem based on the solution of the *VSP* and gave bounds on the percentage of EBs. Li, Lo, and Xiao (2019) developed a formulation for the *MVT-VSP* including EBs and conventional fuel buses. They formulated an integer linear program to find the global optimal solution. This problem can also be seen as the *MVT-(E) VSP* considering a heterogeneous fleet of vehicles using alternative energies.

As mentioned above, there is a comprehensive body of literature on the *VSP* and its variants. However, little study has incorporated EBs for multiple vehicle types into the framework of the *MVT-E-VSP*. This paper proposes a new methodology for the *MVT-E-VSP*. The novelty of this work can be presented as follows:

1 The scheduling problem of EBs for multiple vehicle types is proposed and defined as the *MVT-E-VSP*.
2 An optimization model is established to minimize annual total scheduling costs, including the purchase costs of needed EBs and chargers, the operating costs of deadheading and timetabled trips, etc. Differences in driving range, recharging duration and energy consumption of various vehicle types are considered in the modeling work.
3 A heuristic procedure is developed to find the optimal solution, with additional consideration of recharging trips and the substitution between EV types based on their technical characteristics.

3. Methodology

To use EBs for multiple vehicle types more effectively, this section develops a cost-effective decision-making methodology that can assign each trip of a given timetable to an EB for a suitable type while considering the recharging demand and the substitution between vehicle types.

3.1. Problem description

The input to the *MVT-E-VSP* includes a set of timetabled trips for multiple vehicle types, a set of vehicle types, and a set of depots where

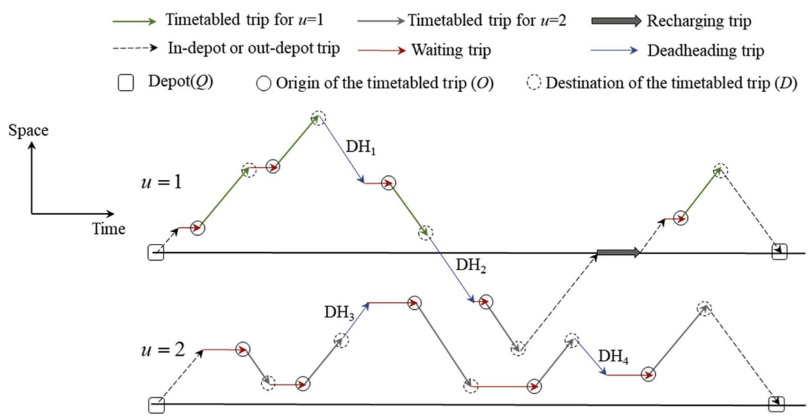


Fig. 1. Time-space network based on two EV types.

EBs are recharged or housed overnight. The *MVT-E-VSP* can be described as follows: Given a set of timetabled trips for multiple vehicle types, each of them corresponds to a specific start time, end time, start terminal and end terminal. The goal is to find the schedule of each EB so that: (1) all timetabled trips can be performed successfully; (2) each trip can only be in one schedule of an EB for a suitable type; (3) the scheduling costs are the lowest.

Compared with the conventional fuel bus, the EB has to perform not only timetabled trips, but also recharging trips. EBs can be recharged at the nearest depot or return to its base depot whenever a timetabled trip is performed. In addition, the solution for multiple vehicle types is as follows: Define U as the set of vehicle types ($u \in U$). U is sorted in descending order by the vehicle capacity. If type u_1 lists before u_2, it means that the vehicle capacity for type u_1 is higher than that for type u_2. Each timetabled trip can be performed by its original vehicle type or other types listed in the prior order (i.e., the substitution between EV types). To illustrate the *MVT-E-VSP*, a time-space network based on two EV types is shown in Fig. 1.

As is illustrated in Fig. 1, the time-space network $G = (V, A)$ is established. V is the set of nodes, and $V = Q \cup O \cup D$. Q represents the set of depots; O and D represent the origin and destination of timetabled trips, respectively; Each node in $O \cup D$ is related to a time and a terminal. A is the set of trips (arcs) including six categories: the timetabled trip for $u = 1$, the timetabled trip for $u = 2$, the recharging trip, the in-depot or out-depot trip, the waiting trip and the deadheading trip. A chain of trips is formed by orderly connecting the six trip categories, that is, the schedule of an EB within a day. Besides, $u = 1$ lists before $u = 2$ in descending order of vehicle types, so EBs for $u = 1$ can perform timetabled trips for $u = 2$ besides its own timetabled trips by inserting a deadheading trip, e.g., DH_2 in Fig. 1.

In addition, to simplify this problem, several major assumptions are made:

(1) Unexpected events such as traffic accidents, extreme weather, etc., are not considered so that all trips can be performed as planned.
(2) The energy consumption rate (i.e., the amount of energy consumed per unit distance) is fixed for a certain vehicle type under a certain load situation, but different EV types with different passenger loads have different energy consumption rates.
(3) All types of EBs are fully charged at the end of each recharging trip.
(4) All chargers are homogeneous fast chargers, and each charger is equipped with one outlet.

Note: For assumption (1), unexpected events rarely occur in practice, so their influence on the *MVT-E-VSP* can be ignored. For assumption (2), Yu and Lu (2013) conduct an electric scooter field-test and clarify that the energy consumed is almost proportional to the driving distance. So, the energy consumption rate is assumed to be fixed for a certain type under a certain load situation. Besides, different vehicle types with different passenger loads have different energy consumption rates, since the vehicle type and load situation have great influence on the energy consumption rate. For assumption (3), due to the shorter recharging duration with fast chargers, it is realistic and convenient to operate chargers if EBs are fully charged at the end of each recharging trip. In addition, assumption (4) ensures that all chargers have the same recharging power and each charger can only charge for one EB simultaneously. Although there are now two or more outlet chargers available, most tend to be slower and cost higher (Wang et al., 2017). Therefore, assumption (4) hardly affects the real-time application.

3.2. Model formulation

For modeling convenience, the timetabled trip is defined as i or j in the model. Let U be the set of vehicle types ($u \in U$). Let S be the set of timetabled trips for all vehicle types. Let S_u be the set of timetabled trips for type u ($i, j \in S_u$), such that $S = \sum_{u \in U} S_u$. Let K be the set of EBs for all vehicle types. Let K_u be the set of EBs for type u ($k_u \in K_u$), such that $K = \sum_{u \in U} K_u$. In addition, let P be the set of chargers ($p \in P$) and Q be the set of depots ($q \in Q$).

Other parameters and variables are listed as follows:

Parameters:

D_u	the maximum driving range of the EB for vehicle type u, in km;
C_q^u	the capacity of depot q for vehicle type u;
α	the discharging depth of EBs for all vehicle types;
θ_u	the recharging rate (i.e., the extended driving distance with the energy recharged per minute) of the EB for vehicle type u, in km/min;
t_p^u	the recharging duration of the EB for vehicle type u, in min;
e_i	end time of timetabled trip i, in min;
s_j	start time of timetabled trip j, in min;
t_{ij}	the deadheading duration from the destination of i to the origin of j, in min;
l_{iq}	deadheading distance between the destination of i and depot q, in km;
l_{qj}	deadheading distance between depot q and the origin of j, in km;
c_u	purchase cost of an EB for vehicle type u, in CNY;
c_0	purchase and installation costs of a charger, in CNY;
c_1	fixed cost of a recharging trip, in CNY;
c_u^2	operating cost per unit deadheading distance of the EB for vehicle type u, in CNY/km;
c_u^3	operating cost per unit passenger-carrying distance of the EB for vehicle type u, in CNY/km;
l_{ij}	deadheading distance between the destination of i and the origin of j, in km;
l_i/l_j	driving distance of timetabled trip i/j, in km;
δ	annualized factor;
N	the number of operating days per year.

Variables:

Y_{k_u}	0-1 variable indicating if EB k_u has been used within a day;
R_p	0-1 variable indicating if charger p has been used within a day;

Z_i^p	0-1 variable indicating if the EB is recharged by charger p after performing timetabled trip i;
$X_{k_u}^{ij}$	0-1 variable indicating if timetabled trips i and j are connected, and both performed by EB k_u;
$X_{k_u}^{qj}$	0-1 variable indicating if EB k_u performs timetabled trip j after going out of depot q;
$X_{k_u}^{iq}$	0-1 variable indicating if EB k_u goes into depot q after performing timetabled trip i;
E_i/E_j	extended driving distance with the residual energy at the end of i/j, in km;
$S_{k_u}^q$	0-1 variable indicating if EB k_u departs from depot q at the beginning;
$E_{k_u}^q$	0-1 variable indicating if EB k_u returns to depot q at the end of its schedule.

An optimization model for the proposed *MVT-E-VSP* can be formulated as follows:

$$\min Z = Z_1 + Z_2 + Z_3 + Z_4 + Z_5 \tag{1}$$

$$Z_1 = \sum_{u \in U} \sum_{k_u \in K_u} \delta c_u Y_{k_u} \tag{2}$$

$$Z_2 = \sum_{p \in P} \delta c_0 R_p \tag{3}$$

$$Z_3 = \sum_{p \in P} \sum_{u \in U} \sum_{i \in S_u} N c_1 Z_i^p \tag{4}$$

$$Z_4 = \sum_{u \in U} \sum_{k_u \in K_u} \sum_{i \in S_u} \sum_{j \in S_u} N c_u^2 l_{ij} X_{k_u}^{ij} \tag{5}$$

$$Z_5 = \sum_{u \in U} \sum_{i \in S_u} N c_u^3 l_i \tag{6}$$

Subject to:

$$\sum_{p \in P} Z_i^p \le 1, \quad \forall\, i \in S_u \tag{7}$$

$$\sum_{u \in U} \sum_{k_u \in K_u} \Big(\sum_{i \in S_u} X_{k_u}^{ij} + \sum_{q \in Q} X_{k_u}^{qj} \Big) = 1, \quad \forall\, j \in S_u \text{ and} i \ne j \tag{8}$$

$$\sum_{u \in U} \sum_{k_u \in K_u} \Big(\sum_{j \in S_u} X_{k_u}^{ij} + \sum_{q \in Q} X_{k_u}^{iq} \Big) = 1, \quad \forall\, i \in S_u \text{ and } i \ne j \tag{9}$$

$$e_i + t_{ij} X_{k_u}^{ij} \le s_j, \quad \forall\, i, j \in S_u,\ \forall\, k_u \in K_u \tag{10}$$

$$E_i - l_{iq} \ge (1 - \alpha) D_u, \quad \forall\, i \in S_u,\ \forall\, u \in U \tag{11}$$

$$E_j = \begin{cases} E_i - l_{iq} + \theta_u t_p^u - l_{qj} - l_j, & \text{if } Z_i^p = 1 \\ E_i - l_{ij} - l_j, & \text{if } Z_i^p = 0 \end{cases} \quad \forall\, i, j \in S_u,\ \forall\, u \in U \text{ and } X_{k_u}^{ij} = 1 \tag{12}$$

$$S_{k_u}^q = E_{k_u}^q, \quad \forall\, k_u \in K_u,\ \forall\, q \in Q \tag{13}$$

$$\sum_{k_u \in K_u} S_{k_u}^q = \sum_{k_u \in K_u} E_{k_u}^q \le C_q^u, \quad \forall\, q \in Q,\ \forall\, u \in U \tag{14}$$

Objective (1) is to minimize annual total scheduling costs (i.e., Z), including Z_1, Z_2, Z_3, Z_4 and Z_5. Z_1 represents the purchase cost of EBs for all vehicle types which is determined by the number of EBs needed to cover all timetabled trips. Z_2 represents the purchase and installation costs of chargers which are determined by the number of chargers needed to cover all recharging trips. Z_3 represents the fixed recharging cost determined by the number of recharging trips. Z_4 is the operating cost of deadheading trips which is related to deadheading distance. Z_5 is the operating cost of timetabled trips determined by passenger-carrying distance. Note that Z_3 refers to the fixed cost resulting from the startup and operation of each recharging trip. The variable cost of the recharging trip comes from the electricity consumption, which is essentially calculated in Z_4 and Z_5.

As for the constraints, (7) means that the EB cannot be recharged on more than one charger at the same time. Constraints (8) and (9) specify that each timetabled trip i or j can only be performed by one EB for a certain type. Besides, constraint (8) enforces that j is connected to one predecessor trip which can be either another timetabled trip i or an out-depot trip. Constraint (9) ensures that i is connected to one successor trip which can be either another timetabled trip j or an in-depot trip. Constraint (10) provides the condition to ensure that i and j are connected. Constraint (11) ensures that the residual energy in an EB should never be less than the lower limit. Constraint (12) refers to the residual energy at the end of each timetabled trip. Furthermore, to facilitate the recharging and maintenance of EBs for multiple vehicle types, constraint (13) enforces that each EB eventually returns to the depot from which it departs after performing its schedule. In addition, considering the practical application, constraint (14) indicates that the number of EBs for a certain type housed in a depot overnight cannot exceed the depot capacity for this type.

3.3. Algorithm for the MVT-E-VSP

As the proposed *MVT-E-VSP* is an NP hard problem, we develop a heuristic procedure to solve the *MVT-E-VSP* in large instances. Genetic Algorithm (GA) is used as the main flow of the procedure, and an algorithm to obtain feasible schedules of EBs is actually developed for the fitness computation.

3.3.1. The algorithm to obtain feasible schedules of EBs

The *VSP* can be seen as a "bin-packing problem". A set of sorted timetabled trips are "loaded" in several vehicles ensuring constraints (8)–(10). Compared with the *VSP*, the recharging trip should be considered in the *E-VSP*. For each EB, the extended driving distance with residual energy at the end of i (i.e., E_i) should be examined. If E_i doesn't satisfy constraint (11), a recharging trip should be inserted into the EB after the predecessor timetabled trip of i. Then, timetabled trip(s) affected by the recharging trip should be "unloaded" from this EB and returned to S_u for reassignment.

In addition, due to the introduction of EBs for multiple vehicle types, the algorithm needs to be further improved. Taking the schedule of EB k_u ($u = 1$) as an example, timetabled trips $i \in S_u$ ($u = 1$) can firstly be "loaded" orderly in k_u ($u = 1$) ensuring relevant constraints until no other $i \in S_u$ ($u = 1$) can be "loaded" in it. Then timetabled trips for types listed inferior to u ($u = 1$) are "inserted" to the remaining space of k_u ($u = 1$) until it is "filled up". Other EBs for different types are "filled" in this way until all timetabled trips are performed. It should be noted that each i can only be performed by its original vehicle type u or other types listed prior to u in the descending order of U. Finally, to reduce the penalty cost of empty seats caused by the substitution, a transfer procedure of timetabled trips should be conducted ensuring no change of current EBs. The right part of Fig. 3 summarizes the above procedure.

3.3.2. GA to find the optimal sorting of timetabled trips

The algorithm in 3.3.1 can only find a feasible solution under a given sorting of timetabled trips. So, GA is introduced to optimize the sorting and find the optimal solution of the *MVT-E-VSP*.

Real number encoding is adopted in this section. Each chromosome

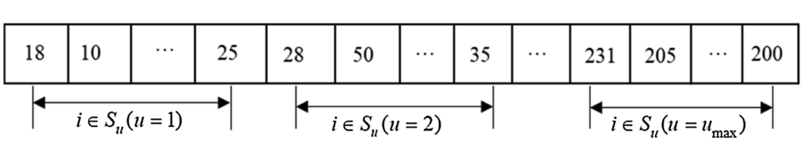


Fig. 2. The diagram of chromosome encoding.

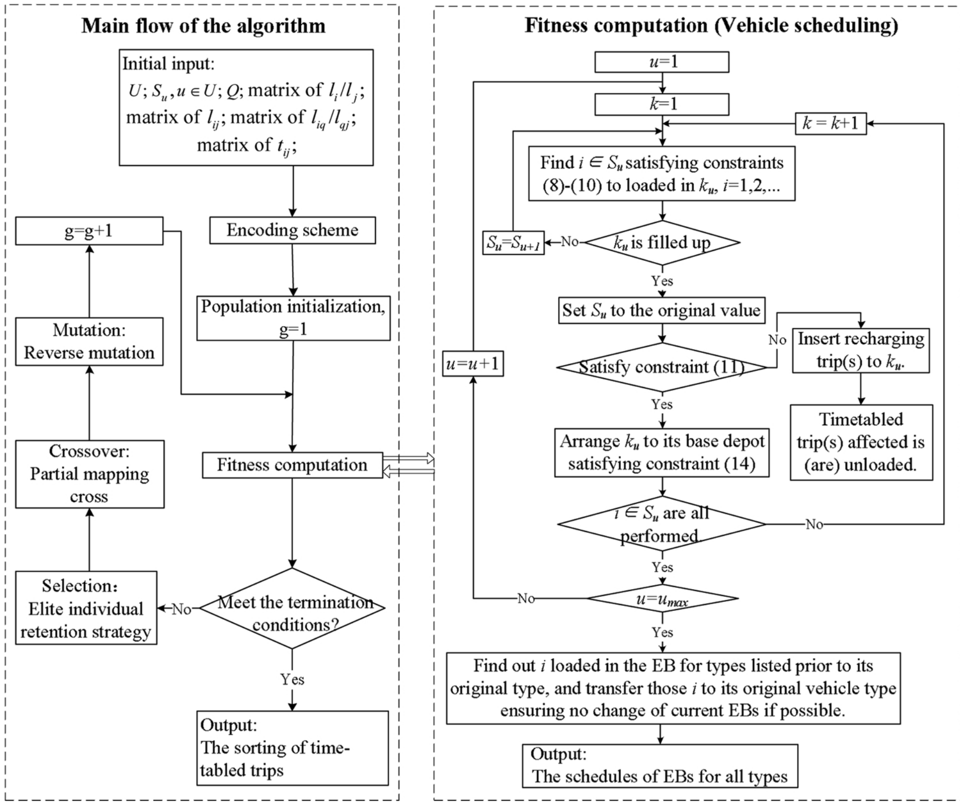


Fig. 3. A heuristic procedure for the *MVT-E-VSP*.

represents a random sorting of timetabled trips. Note that timetabled trips are only randomly sorted within its vehicle type. The diagram of chromosome encoding is shown in Fig. 2. The number on each gene indicates the # of the timetabled trip for a certain type. The whole sequence indicates the sorting of timetabled trips; i.e., for $i \in S_u$ ($u = 1$), timetabled trip 18 is firstly "loaded" to an EB, followed by timetabled trip 10 and other timetabled trips for type $u = 1$. The same is true for $i \in S_u$ ($u = 2, 3, \ldots, u_{\max}$).

In order to improve the global convergence ability of GA, the elite individual retention strategy is additionally considered. Moreover, to ensure that the evolved individual is feasible, the partial mapping cross and reverse mutation are adopted in the process of evolution. GA is essentially used as the main flow of the heuristic procedure, which is shown in the left part of Fig. 3.

In summary, the heuristic procedure for the *MVT-E-VSP* is given in Fig. 3.

4. Case study

To verify the applicability of the proposed methodology, the optimization model and heuristic algorithm in Section "3 Methodology" are applied to a real-world transit network in Daxing District, Beijing.

4.1. Network description and data preparation

The transit network contains two depots including Huangcun Railway Station depot (Depot 1) and Fuyuan Community depot (Depot 2) as well as four bus routes including Xing 11, Xing 12, Xing 36 and Xing 47, as shown in Fig. 4.

Two EV types are studied, namely Jinlong XMQ6850G EB (Type 1) with 25 seats as well as Hager KLQ6650GEV (Type 2) EB with 15 seats. These two EV types are shown in Fig. 5. The optimal multi-vehicle-type timetable, used as an input, has been obtained aiming at minimizing the travel cost for passengers and operating cost for operators. There are 931 timetabled trips of the obtained timetable, including 231 timetabled trips for Type 1 and 700 timetabled trips for Type 2. For these timetabled trips, the earliest start time is set at 0 min, and the time step is set at one minute. Table 1 lists partial timetabled trips for both types, as well as their start times and end times.

According to the market research, the electricity price for the general industry in Daxing District is 0.7 CNY/kWh. The recharging power of the charger is 240 kW. The battery capacity of the EB for Type 1 and Type 2 is 204 kW h and 120 kW h, respectively. The purchase cost per EB for Type 1 and Type 2 is 2,300,000 CNY and 1,500,000 CNY, respectively. In addition, the average energy consumption rate of EBs for Type 1 is 1.2 kW h/km for carrying passengers and 1.1 kW h/km for deadheading, while that of EBs for Type 2 is 1.0 kW h/km for carrying passengers and 0.9 kW h/km for deadheading. (Gao & Zou, 2016). So, parameters of both types of EBs can be obtained, as illustrated in Table 2. Furthermore, the purchase and installation costs per charger are 100,000 CNY. The capacity of Depot 1 is 60 for Type 1 and 50 for Type 2, while that of Depot 2 is 30 for Type 1 and 40 for Type 2.

To extend the battery life, the discharging depth of EBs for both types is set as 80%, i.e., $\alpha = 80\%$ (Paul & Yamada, 2014). The fixed cost of a recharging trip c_1 is 13.4 CNY (Li, 2014). There are 360 operating days per year, i.e., $N = 360$. As EBs have an average life of 7.8 years, the fixed capital costs are annualized with an assumed 8-year useful life and a 10% interest rate. So, the annualized factor δ is calculated using the economic engineering formula (A/P, 10%, 8) = 0.1874 (Wang et al., 2017).

In addition, through the experimental analysis, parameters of GA are set as follows: the population size is 1000; the number of iterations is 1000; the crossover probability is 0.7; the mutation probability is 0.1; the rate of elite individual retention is 0.2.

4.2. Optimization result

The proposed framework is programmed using python-3.6.5. All

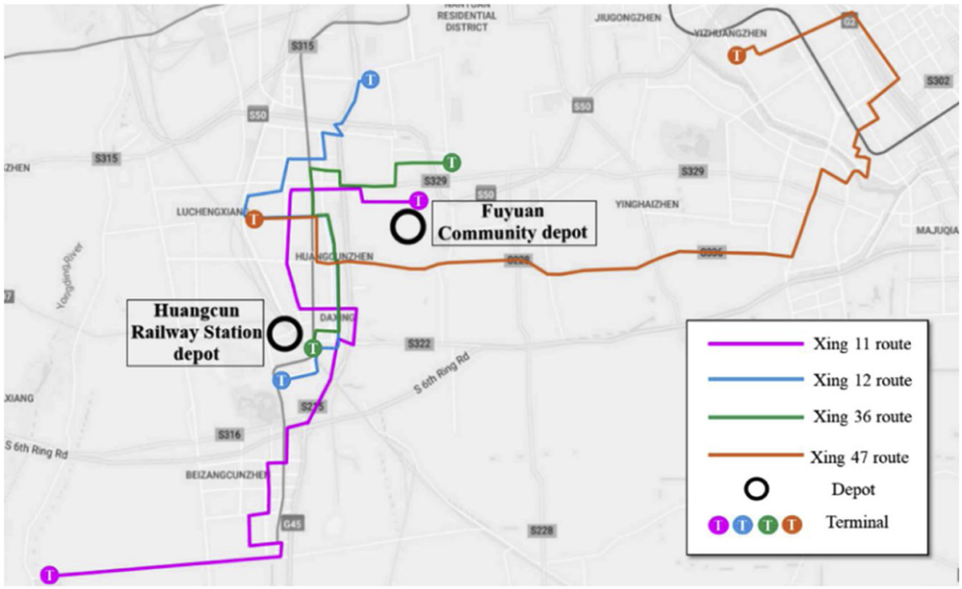


Fig. 4. A transit network in Daxing District.

computational experiments are run on a Dell laptop with 4G RAM and 2.40 GHz CPU under Windows 10 environment.

The optimal annual total scheduling costs (Z) are 61,822,268 CNY, containing the annualized purchase cost of EBs for both vehicle types (Z_1) at 53,558,920 CNY, the purchase and installation costs of chargers (Z_2) at 655,900 CNY, the fixed recharging cost (Z_3) at 651,240 CNY, the operating cost of deadheading trips (Z_4) at 1,967,818 CNY and the operating cost of timetabled trips (Z_5) at 4,988,390 CNY. 76 EBs for Type 1 and 74 EBs for Type 2 are needed to cover all timetabled trips. 59 EBs for Type 1 and 41 EBs for Type 2 are housed in Depot 1, while 17 EBs for Type 1 and 33 EBs for Type 2 are housed in Depot 2 overnight. Besides, Depot 1 needs to deploy 21 chargers to complete 76 recharging trips, while Depot 2 needs to deploy 14 chargers to complete 59 recharging trips.

Moreover, Table 3 lists the schedules of partial EBs for both types. The second column of Table 3 lists the # of the EB for each type. The

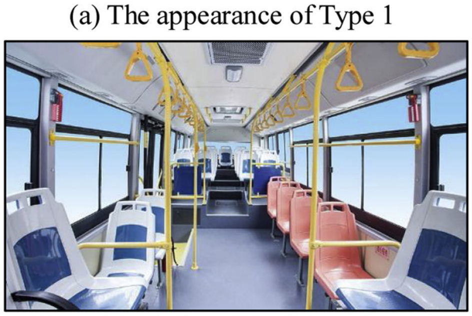
Table 1
Information of timetabled trips.

S_1			S_2		
i	s_i(min)	e_i(min)	i	s_i(min)	e_i(min)
1	0	85	232	240	325
2	5	90	233	246	331
3	10	95	234	252	337
4	15	100	235	258	343
5	20	105	236	264	349
…	…	…	…	…	…
230	160	264	930	690	794
231	170	274	931	705	809

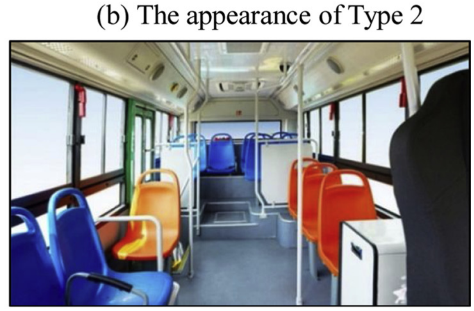
Note: S_1 denotes timetabled trips for Type 1; S_2 denotes timetabled trips for Type 2; i is the # of timetabled trips; s_i and e_i are the start time and end time of i, respectively.

(a) The appearance of Type 1

(b) The appearance of Type 2



(c) The interior of Type 1



(d) The interior of Type 2

Fig. 5. The appearance and interior of two EV types.

Table 2
Parameters of EBs for both vehicle types.

Vehicle type	D_u(km)	t_p^u(min)	θ_u(km/min)	c_u^2 (CNY/km)	c_u^3 (CNY/km)
Type 1	170	51	3.3	0.77	0.84
Type 2	120	30	4.0	0.63	0.70

third column lists the # of the depot used to house EBs, where 1 and 2 refer to Depot 1 and Depot 2, respectively. The fourth column shows the number of trips performed by the corresponding EB. The fifth column provides the schedule of this EB (i.e., the chain of trips), in which the positive number represents the # of timetabled trips, and -1 represents the recharging trip.

It can be seen from Table 3 that EBs for both Type 1 and Type 2 are housed more in Depot 1 than in Depot 2 owing to the larger capacity of Depot 1 for both types. It can also be seen that the schedules of EBs for Type 1 are generally longer than those for Type 2, which is not only due to the larger driving range for Type 1, but also due to the consideration of the substitution between vehicle types (i.e., EBs for Type 1 can perform timetabled trips for Type 2, but the opposite is not true). In addition, most EBs need to be recharged at least once within a day, especially for those performing more trips. However, EB 74 for Type 2 is not recharged as it only performs two trips within a day, and its driving range can easily cover the total driving distance, including the deadheading distance and passenger-carrying distance.

4.3. Comparative analysis

To verify the performance of the proposed method, a conventional method for the *MVT-E-VSP* is introduced, in which the *MVT-E-VSP* is divided into two *E-VSPs*. Each vehicle type is solved separately, and the substitution between EV types is not considered. In comparison, the proposed method solves the problem on the global level, considering the substitution of an EB with higher capacity for one with lower capacity. Differences in the driving range, recharging duration and energy consumption of EBs for different vehicle types are fully considered in the proposed method. Table 4 shows the optimization results of the two methods. Table 5 provides a detailed comparison between each cost component of these two methods.

The results in Tables 4 and 5 show that the proposed method reduces annual total scheduling costs by 11,714,480 CNY and improves the total costs by 15.93% compared with the conventional one. In terms of five cost components, Z_1 in the proposed method is 18.55% lower than that in the conventional one. This is because that the proposed method considers the substitution between vehicle types and thus significantly reduces the number of EBs for Type 2 with few growths in the number of EBs for Type 1. Besides, the proposed method requires more chargers and more recharging trips, since the average driving distance of each EB is longer, especially for EBs for Type 1 which can perform timetabled trips for both types. Therefore, the proposed method results in an obvious worsening in Z_2 by -29.63% as well as a worsening in Z_3 by -3.85% compared with the conventional method. Additionally, these two methods have the same passenger-carrying distance, but the proposed method results in a slight worsening in Z_5 by -6.93%, which owes to the higher energy consumption rate of EBs for Type 1. In other words, EBs for Type 1 may perform timetabled trips for Type 2 in the proposed method, inducing the penalty cost of empty seats which is essentially reflected in Z_5. Moreover, there is no obvious change law of Z_4 in these two methods, although Z_4 in the proposed method is slightly lower than that in the conventional one in Table 5, which might be due to the characteristics of the heuristic algorithm itself.

It can be seen that Z_1 is the most important component of annual total scheduling costs, accounting for more than 86.00%. The proposed method cuts this component significantly and thus improves the total costs by 15.93%, although it results in no much improvements in other four cost components.

Table 4
Optimization results of two methods.

Related indicators	Conventional method	Proposed method
The number of EBs for Type 1	73	76
The number of EBs for Type 2	122	74
The number of chargers	27	35
The number of recharging trips	130	135
Deadheading distance of EBs for Type 1 (km)	2207	4403
Deadheading distance of EBs for Type 2 (km)	6033	3295
Passenger-carrying distance of EBs for Type 1 (km)	4838	11,256
Passenger-carrying distance of EBs for Type 2 (km)	12,706	6288
Annual total scheduling costs (Z) (CNY)	73,536,748	61,822,268

Table 3
Schedules of partial EBs for both types.

Vehicle type	# of the EB	# of the depot	The number of trips	The chain of trips
Type 1	1	2	10	73, 21, 570, 155, 597, −1, 191, 97, 63, 425
	2	1	10	160, 91, 44, 526, −1, 189, 748, 106, 58, 692
	3	1	9	15, 144, 576, 154, 600, −1, 745, 99, 70
	4	1	11	171, 218, 800, 156, 598, −1,183,744,98,52,423
	5	1	10	74, 20, 569, 148,809, −1,188,290,116,65
	6	1	10	2, 137, 571, 149, 814, −1, 493, 102, 50, 688
	7	1	9	159, 123, 42, 354, −1, 743, 826, 114, 66
	8	2	10	172, 93, 40, 806, 730, −1, 503, 115, 61, 693
	…	…	…	…
	76	1	8	12, 711, 875, −1, 824, 504, 659, 410
Type 2	1	1	9	431, 704, 340, −1, 612, 479, 396, 763, 679
	2	1	10	780, 496, 795, 722, −1, 368, 271, 645, −1, 768
	3	1	8	857, −1, 803, 908, 627, 749, −1, 405
	4	1	9	694, 558, 442, −1, 616, 484, 640, 514, 849
	5	2	7	432, 554, 336, −1, 272, 829, 306
	6	2	8	429, 551, 712, −1, 879, 917, 889, 848
	…	…	…	…
	74	1	2	736, 384

Table 5
Detailed comparison between cost components of two methods.

Cost component	Cost result (CNY)		Cost reduction of proposed method (CNY)	Relative improvements of proposed method (%)
	Conventional method	Proposed method		
Purchase cost of EBs (Z_1)	65,758,660	53,558,920	12,199,740	18.55
Purchase and installation costs of chargers (Z_2)	505,980	655,900	−149,920	−29.63
Fixed recharging cost (Z_3)	627,120	651,240	−24,120	−3.85
Operating cost of deadheading trips (Z_4)	1,980,065	1,967,818	12,247	0.62
Operating cost of timetabled trips (Z_5)	4,664,923	4,988,390	−323,467	−6.93
Annual total scheduling costs (Z)	73,536,748	61,822,268	11,714,480	15.93

4.4. Sensitivity analysis

In the *E-VSP*, driving range and recharging duration are two important parameters, so are them in the proposed *MVT-E-VSP*. Driving range and recharging duration are determined by the discharging depth of EBs and the recharging power of chargers, respectively. Sensitivity analysis is conducted to understand the impact of these two parameters on the vehicle scheduling strategies and annual total scheduling costs.

Table 6 lists the optimal annual total scheduling costs obtained by the proposed method under different combinations of the recharging power and discharging depth. It can be seen that the total costs decrease as the discharging depth upgrades, which is in that more timetabled trips can be performed by an EB with the increase in the driving range. Thus, the number of EBs needed to cover all timetabled trips is reduced. Similarly, under a constant discharging depth, the total costs are reduced as the recharging power increases, due to the shorter recharging duration at the higher recharging power. EBs have more time to perform timetabled trips, and thus the number of EBs needed also obviously decreases.

Fig. 6 shows the optimal total costs under different combinations of these two parameters more intuitively. The X-axis denotes the discharging depth of 60%–90%. The Y-axis denotes the recharging power of 60 kW–360 kW. The Z-axis represents the optimal total costs under different combinations of two parameters.

To evaluate the application of the current discharging depth and recharging power, sensitivity analysis on these two parameters is conducted separately. Annual total scheduling costs changing with the recharging power at 80% discharging depth is plotted in Fig. 7(a), and that changing with the discharging depth at 240 kW recharging power is shown in Fig. 7(b).

From Fig. 7(a), it can be obtained that annual total scheduling costs decrease by 21.7% as the recharging power increases from 60 kW to 240 kW. When the recharging power is larger than 240 kW, the total costs drop very slowly, only 2.15% from 240 kW to 360 kW. Similarly, from Fig. 7(b), we can calculate that the total costs decrease by 7.13% as the discharging depth increases from 60% to 80%, and there is almost no reduction in the total costs when the discharging depth exceeds 80%. Therefore, the current recharging power (240 kW) and discharging depth (80%) are both approximately economical.

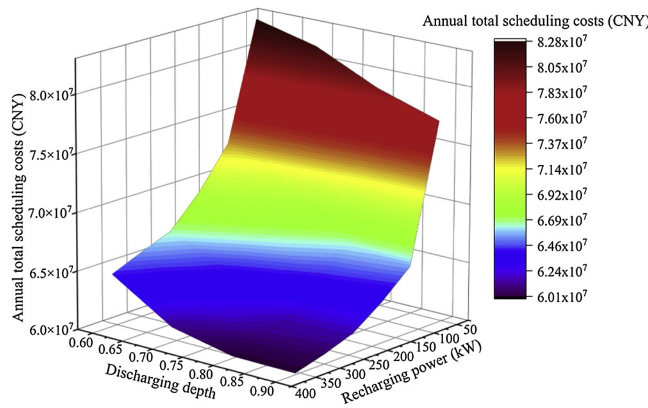


Fig. 6. Annual total scheduling costs under different parameter combinations.

5. Conclusions

In this work, we present a new methodology for the *MVT-E-VSP* considering EBs for multiple vehicle types. The proposed methodology makes an effort on the following two aspects. First, an optimization model is established aiming at minimizing annual total scheduling costs, which gives (1) the purchase cost of EBs for all vehicle types; (2) the purchase and installation costs of chargers; (3) the fixed recharging cost; (4) the operating cost of deadheading trips; and (5) the operating cost of timetabled trips. Differences in the recharging duration, driving range and energy consumption of EBs for multiple vehicle types are explicitly considered in the modeling work. Second, a heuristic procedure is developed to solve the proposed *MVT-E-VSP*, combining the algorithm to obtain feasible schedules of EBs (fitness computation) and GA to find the optimal solution (main flow of the procedure). This procedure considers the insertion of recharging trips and the substitution between EV types.

We successfully apply the proposed methodology to a real-world transit network in Daxing District, Beijing. The optimization result provides the optimal number of EBs needed for both types and their corresponding schedules, as well as the number of chargers needed. Comparative analysis shows that the proposed method can reduce annual total scheduling costs by 15.93% compared with the conventional method in which each EV type is solved separately. Bedsides, sensitivity analysis shows the impact of recharging power and discharging depth

Table 6
Annual total scheduling costs under different combinations of two parameters (CNY).

		Recharging power (kW)					
		60	120	180	240	300	360
Discharging depth	60%	82,723,377	72,617,253	69,197,991	66,566,510	65,578,160	64,500,990
	70%	81,431,381	69,643,701	66,517,735	64,082,631	62,621,615	61,284,675
	80%	78,963,154	66,324,422	64,605,170	61,822,268	61,177,161	60,164,217
	90%	77,272,361	65,648,146	63,478,755	61,715,795	60,820,811	60,128,744

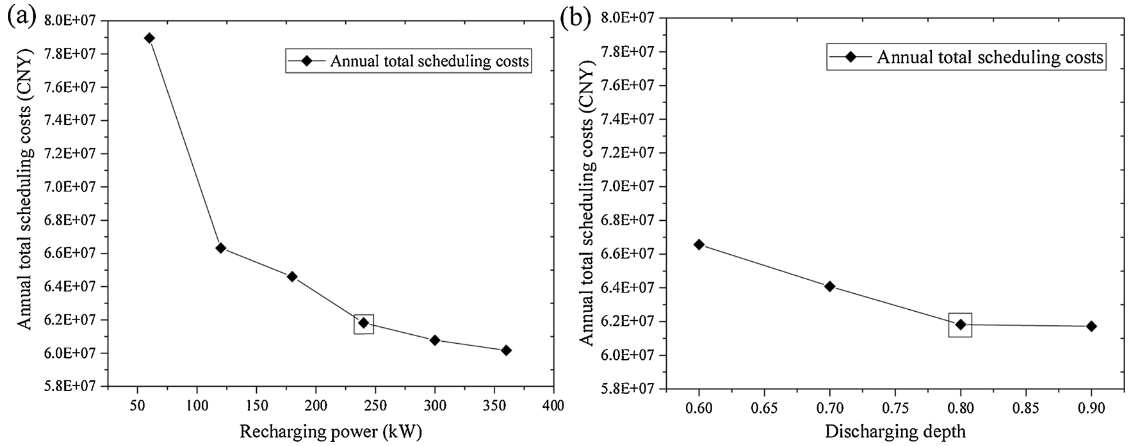


Fig. 7. a) The impact of recharging power on annual total scheduling costs. b) The impact of discharging depth on annual total scheduling costs.

on the total costs, and reveals that the current recharging power (240 kW) and discharging depth (80%) are approximately economical. The findings can provide transit agencies with comprehensive guidance on the effective scheduling of EBs for multiple vehicle types and the reasonable deployment of chargers, which contribute to the promotion of EBs and further achieve the sustainable development of urban public transport.

This work can be extended in a few directions. First, crew scheduling will become more complicated due to the introduction of EBs for multiple vehicle types, so it is necessary to study the implications of multiple EV types for the crew scheduling. Second, unexpected events might happen even if the probability is small. The *MVT-E-VSP* will be enormously influenced when unexpected events occur. So future research on the *MVT-E-VSP* can consider unexpected events. Third, the energy consumption of EBs is subject to a fair number of uncertain factors such as the weather, road conditions and so on (Pelletier, Jabali, & Laporte, 2019). But due to the lack of real-time traffic information, we only estimate the average energy consumption rates after considering the uncertainties comprehensively. Future study may consider uncertain energy consumption rates instead of average energy consumption rates. Finally, the recharging duration is affected by many factors such as remaining energy, the length of next trips, etc., and it is not necessary to have EBs fully charged after any recharging trip. Therefore, future research can consider the determination of the optimal recharging duration.

Declaration of Competing Interest

None.

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