IEEE Access
Multidisciplinary | Rapid Review | Open Access Journal

Received December 25, 2019, accepted January 3, 2020, date of publication January 7, 2020, date of current version January 15, 2020.

Digital Object Identifier 10.1109/ACCESS.2020.2964391

Collaborative Optimization of Vehicle and Charging Scheduling for a Bus Fleet Mixed With Electric and Traditional Buses

GUANG-JING ZHOU[1], DONG-FAN XIE[1,2], XIAO-MEI ZHAO[1], AND CHAORU LU[3]
[1]School of Traffic and Transportation, Beijing Jiaotong University, Beijing 100044, China
[2]Key Laboratory of Transport Industry of Big Data Application Technologies for Comprehensive Transport, Beijing Jiaotong University, Beijing 100044, China
[3]Department of Civil and Environmental Engineering, Norwegian University of Science and Technology (NTNU), 7033 Trondheim, Norway

Corresponding author: Dong-Fan Xie (dfxie@bjtu.edu.cn)

This work was supported in part by the National Natural Science Foundation of China under Grant 71961137008, Grant 71621001, Grant 71671014, Grant 71771012, and Grant 71631007, and in part by the Sustainable mixed urban transit system with electric and conventional buses (SMUrTS) under Grant 299078.

ABSTRACT To address sustainable development issues of urban traffic, electric buses will join traditional bus system, and the scheduling of bus fleet should be adjusted due to the distinct features of electric buses. To this end, this paper develops a Multi-objective Bi-level programming model to collaboratively optimize the vehicle scheduling and charging scheduling of the mixed bus fleet under the operating conditions of a single depot. The upper level determines the vehicle scheduling to minimize the operating cost and carbon emissions under the constraints of connecting time between trips and the limited driving range of electric buses. The lower level is a charging scheduling problem that considers the charging time and the limited driving distance constraint to minimize the charging cost. The proposed model is solved with an integrated heuristic algorithm. The vehicle scheduling problem is addressed with the iterative neighborhood search algorithm based on simulated annealing, while the charging scheduling problem is solved with a greedy dynamic selection strategy based on the approach of multi-stage decision. Finally, case study is carried out based on a mixed bus fleet in Beijing, and the results validate the availability of the proposed model and solution algorithm.

INDEX TERMS Vehicle scheduling, charging scheduling, mixed bus system, multi-objective bi-level programming, collaborative optimization.

I. INTRODUCTION

Because of the high energy conversion efficiency and low carbon emissions, electric bus (eBus) has been continuously introduced to many public transit systems all over the world. However, due to the driving range limitation, long charging time, and high purchase costs, it may not be realistic to replace all the traditional buses in the public transit system by eBus. Therefore, the bus system mixed with both traditional and eBus will exist in many cities for a long period [1].

Vehicle scheduling is an important decision problem in the planning process of transit system operation. In addition, vehicle scheduling is the process of assigning vehicles to the trips of a given timetable, which is closely related to scheduling costs for operators [2].

The associate editor coordinating the review of this manuscript and approving it for publication was Shaohua Wan.

Regarding to the vehicle scheduling problem, most studies were conducted for two typical scenarios: single-depot vehicle scheduling problem (SDVSP) and multiple depot vehicle scheduling problem (MDVSP). Since SDVSP is the basis of vehicle scheduling, this study focuses on SDVSP. Surely, the proposed approach can be easily extended to address MDVSP.

A. TRADITIONAL BUS SCHEDULING

Since the scheduling of buses would significantly influence the service quality and efficiency of the public transit system, numbers of researchers are trying to solve the problems by considering different objectives. For instance, the cost in the optimization objective of reference [2] included the purchase cost of buses, the purchase and installation costs of chargers, the operating cost of deadheading trips, the operating cost of timetabled trips and energy consumption cost. In the optimization objective of vehicle scheduling, besides the cost of operation, carbon emission has also been paid attention by scholars. Reference [3] took operation cost and carbon emission as the optimization objective of vehicle scheduling, and applied the model to the public transport network in the Sao Paulo region. Finally, a set of trade-offs between operating costs and emissions were discovered. Reference [4] provided a carbon emission model of diesel buses, and the carbon emission (mainly including CO_2, THC and CO) was calculated according to the operation mode of the diesel buses under the actual road conditions of Beijing. Consequently, operational cost and emission should be considered into the vehicle scheduling problem of mixed bus system.

In addition, vehicle scheduling optimization algorithm, generally divided into mathematical algorithm and heuristic algorithm. For small-sized and medium-sized examples, exact approaches have been proposed. Reference [5] provided a branch and bound algorithm to deal with the case with up to 3 depots and 70 trips. References [6] considered vehicle scheduling as a network flow problem and designed branch-and-bound-based algorithms to solve the problem with up to 3 depots and 600 trips. Reference [7] presented a column generation-based solution approach to solve the problem with up to 8,563 trips. In addition, near optimal solutions were obtained by applying the algorithm to a case with more than 10,000 trips. Reference [8] presented a column generation-based branch-and-cut algorithm to solve cases with up to 6 depots and 750 trips.

Heuristics have been extensively used for large-sized problems. Reference [9] presented two heuristics to solve cases with 400 trips. Reference [10] presented a variable fixing heuristic to obtain near optimal solutions of cases with up to 8 depots and 11,062 trips. Reference [11] presented a column generation-based heuristic to obtain near optimal solutions of five examples involving 8, 12 or 16 deports and 1,500, 2,000, 2,500, or 3,000 trips. Reference [12] provided five different heuristics, i.e., a Lagrangian heuristics, a truncated branch-and-cut approach, a truncated column generation heuristics, a large neighborhood search, and a Tabu search heuristics. There are also studies to integrate vehicle scheduling with other transit system operation planning process. For example, reference [13] presented a new model for integrated timetabling (TT) and vehicle scheduling (VS) problem, and proposed a diving-type heuristic approach to solve this problem. Reference [14] presented a new model for integrated vehicle scheduling (VS) and crew scheduling (CS) problem, and proposed local search and simulated annealing algorithm to solve the problem. Compared with the heuristic algorithm, the mathematical algorithm can get more accurate solutions. However, the heuristic algorithm has its advantages for solving the vehicle scheduling problems with large-scale trips in a limited time.

B. eBUS SCHEDULING

Under the pressure of congestion and pollution, zero-emission eBus used in public transport are drawing more attention. However, there are some unsolved problems with eBus, such as limited driving ranges, long recharging duration and upfront purchasing cost [15], [16]. The study of pure eBus fleet focuses on the modeling by considering limited driving ranges and long recharging duration of eBus. Reference [17] proposed a vehicle scheduling model for eBus with either battery replacement or fast charging, and developed the column-generation-based algorithm to solve the problem. Reference [18] 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. Reference [19] presented an integer linear programming, and developed a column generation for the E-VSP. Reference [20] solved the E-VSP by integrating an incremental mixed integer programming algorithm, a greedy algorithm and a Tabu search-based local search algorithm.

Simultaneously, the centralized charging of eBus has a great impact on the load of the National grid, and the National grid company has implemented the "Time-of-use Price" policy. Therefore, it is an urgent problem to reduce the charging cost of bus company while reducing the load of power grid. The problem of adjusting the charging time of eBus to achieve the above goals can be called the eBus charging scheduling problem (EBCSP). Several studies have been conducted on charging scheduling. Reference [21] pointed out that the optimal charging strategy can reduce carbon dioxide emission by 31%. Reference [22] compared three charging strategies: "Uncontrolled charging (UNC)", "Demand Side Management (DSM)" and "Vehicle-to-Grid (V2G)". The case study indicated that compared to the UNC, DSM and V2G reduced 11.60% and 12.83% average annual charging cost, respectively. To maximize the profit of the charging station and reduce peak electrical load, reference [23] proposed a framework to offer dynamic price considering different charging deadlines and scheduling of charging processes. Reference [24] regarded the charging scheduling problem of known electricity price as a single-stage decision problem, and took the charging start time as the decision variable. In addition, it regarded the charging scheduling problem of unknown electricity price as a multi-stage decision problem, and the online adaptive algorithm was used to solve the problem. The EBCSP can be solved by using multi-stage decision making and charging time as decision variable. However, optimization time is closely related to the number of variables and stages. How to optimize the number of variables or the number of stages is a problem that needs to be studied.

In addition, the energy consumption of eBus is affected by many factors, such as vehicle speed, mass and gradient of the terrain. Reference [25] considered the influence of vehicle mass, speed and gradient of the terrain on vehicle energy consumption. In particular, this paper pointed out that the energy consumption of electric commercial vehicle may increase when it goes uphill, while the battery would be recharged during the downhill process because of regenerative brake system. Reference [26] found that eBus can achieve energy saving benefits under the condition of stop-and-go and idling, comparing to conventional diesel buses. Although the aforementioned references have studied the energy consumption model of eBus, the energy consumption per unit is usually fixed in the static vehicle scheduling [2], [14] since the models can be easily extended by considering the energy consumption model. In addition, the models and algorithms may not be affected by the different characteristics of routes, although the results would be distinct. Therefore, this study ignores the impact of route characteristics on energy consumption of eBus.

In general, the emissions of eBus include direct and indirect carbon emissions. Reference [26] proposed a carbon emission model which considering the effects of regional power sources (i.e. coal-fired power, renewable power, etc.), transportation loss and battery charging/discharging loss on vehicle carbon emission. The actual operation data of Beijing and Macao are compared and analyzed. The results indicated that the carbon emission was relatively serious in Beijing where the proportion of coal-fired power was large. However, pure electric bus fleets are generally considered to be zero emission fleets [27], [28], particularly for the studies on bus scheduling problems. Therefore, the carbon dioxide and nitrogen oxides emissions of eBus are not taken into account in this paper.

C. MIXED BUS SCHEDULING

Due to the introduction of eBus, many bus routes are operated with multiple vehicle types in some cities. For the mixed bus system, capacity waste or in-vehicle overcrowding are more likely to occur by still using single-vehicle-type organization mode [29]. Since by considering multiple vehicle types into scheduling can reduce costs for operators [30], several studies have been conducted on this topic. Reference [25] proposed a time-space network layer for each depot-vehicle-type-combination and solved vehicle scheduling problem with multiple vehicle types (MVT-VSP) separately. Reference [31] developed a method for the MVT-VSP based on the minimum cost network flow model, which considered the substitution between different vehicle types.

Mixed bus fleets, include the mix of different capacity bus types, as well as the mix of different energy consumption bus types. Reference [32] developed a formulation for the MVT-VSP including eBus and traditional fuel buses. It formulated an integer linear program to find the global optimal solution. Reference [2] proposed 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. Although the difference between eBus and traditional bus is considered in the above literature, the charging strategy of eBus is to use ‘‘Charge immediately upon arrival’’ strategy directly, while the charging cost under ‘‘Time-of-use Price’’ policy is not considered. The mixed bus fleet includes both traditional bus scheduling problems and charging scheduling problems for eBus. Therefore, this paper focuses on the modeling and algorithm of vehicle scheduling and charging scheduling coordination optimization for mixed bus fleets.

D. MOTIVATION AND CONTRIBUTION

Although a number of studies have been conducted on vehicle scheduling and charging scheduling, the following questions regarding to the collaborative optimization of mixed bus fleets are still open: (1) the modeling of mixed bus system since it is different from traditional bus system in operation; (2) how to take into account the characteristics of eBus (such as driving range limitation, long charging time) in the scheduling? (3) the collaborative optimization of vehicle scheduling and charging scheduling; and (4) the design of efficient algorithm for the mixed bus system.

To address the aforementioned issues, this study develops a Bi-level programming model to address the MDVSP with a bus fleet mixed with traditional buses and eBus. The motivations and contributions are as follows:

(1) Considering single depot and mixed bus fleet, a Multi-objective Bi-level programming model is proposed to provide optimal bus scheduling and charging scheduling.

(2) To solve the proposed Bi-level programming model (NP-hard), an integrated heuristic algorithm is developed by integrating the greedy dynamic selection strategy into iterative neighborhood search algorithm.

(3) The performance of different local search strategies (such as, shift, 2opt* and block) are investigated for the mixed bus system. Moreover, eight initial solution generation strategies are proposed and evaluated by considering the characteristic of mixed bus fleet.

(4) Considering the ‘‘Time-of-use Price’’ policy, the greedy dynamic selection strategy is designed to solve the charging scheduling problem of eBus. The algorithm can reduce the number of decision variables and the search range by pre-calculate the quantity of electricity that can charged in different price periods between trips. Moreover, the optimality of the greedy algorithm is verified.

The rest of the paper is organized as follows: In Section 2, the scenarios as well as the related concepts are briefly introduced. In Section 3, a Multi-objective Bi-level programming model is developed to optimize bus scheduling and charging scheduling. In Section 4, integrated heuristic algorithm is designed for the proposed model. In Section 5, a case study is conducted to compile the bus scheduling and charging scheduling of mixed bus fleet in a certain depot in Beijing. Finally, conclusions are made in Section 6.

II. PROBLEMDESCRIPTIO

Bus scheduling and dispatching is crucial for the service quality and profit of the public transit service companies. For traditional public transit system, refueling time of traditional buses would not significantly affect the service quality. However, by introducing electric buses into the public transit system, additional issues related eBus, such as driving range limitation and charging time, should be considered. Consequently, the operation of the public transit system mixed with

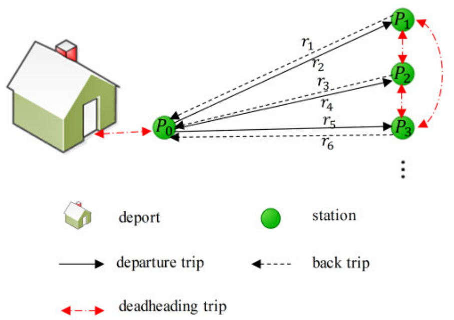


FIGURE 1. Operation diagram of a single bus depot.

$$p_s(r) \xrightarrow{r} \boxed{p_e(r) \quad p_s(r')} \xrightarrow{r'} p_e(r')$$

FIGURE 2. Trip connections without charging.

eBus and traditional buses will be more complicated than traditional public transit system.

A. SYMBOLIC MEANING

To clearly describe the problem and the scheduling model, the notations used in this study are listed In Table 1.

B. TRANSIT SERVICES

Transit services are a series of bus trips served by public transport companies and executed by public transport vehicles [14]. In order to guarantee the service quality, each trip has a scheduled departure time and arrival time. In this paper, the bus scheduling and charging scheduling strategy is proposed for a group of buses which are serving several routes with a single depot, as shown in Figure1. Let $P = \{P_0, P_1, \ldots, P_n\}$ represent the begin/end station set of the bus line, and suppose each station has a charging pile. And let $R = \{r_1, r_2, \ldots, r_k\}$ represent the trip set of the operation. A station may have different meanings in different trips, such as P_0 is a starting point in departing trips and a point of arrival in returning trips. And there are two types of bus on the depot, i.e., a set of eBus $V_e = \{v_k^e\}$ and a set of traditional bus $V_o = \{v_{k'}^o\}$.

C. TRIP CHAIN

The purpose of designing a vehicle scheduling scheme is to properly assign buses to serve different routes. During a day, the trips served by a bus forms the trip chain of the bus.

Connection refers to the activities between the terminal $p_e(r)$ of trip r and the starting station $p_s(r')$ of trip r'. The connection for conventional buses is shown in Figure 2. For eBus, due to the constraint of the driving range, it is necessary to check the state of charge (SOC) before assign the eBus to the next trip. If the SOC is not sufficient for the next trip, the eBus should go to the charging station P_s, as shown in Figure 3.

TABLE 1. Symbolic meaning.

Symbol	Meaning
$r_i, i = 1,2,\ldots,n$	Passenger trip, n is the maximum number of passenger trips
d	Depot
$R = \{r_1, r_2, \ldots, r_n\}$	The set of all passenger trips
$r_{ij}, i, j \in R$ and $i \neq j$	Deadheading trip/connecting trip
$R' = \{r_{ij}\}$	A set of all deadheading trips, including pull-in and pull-out trips and transfer trips
r_{ce}, r'_{ce}	The trip of the eBus to the charging station, c is the number of charging
$R_e = \{r_{ie}, r'_{ie}\}$	The set of charge trip
$p_s(r_i)$	The starting station of trip r_i
$p_e(r_i)$	The ending station of trip r_i
$t_s(r_i)$	The departure time of trip r_i
$t_e(r_i)$	The arrival time of trip r_i
l_i	The length of trip r_i
τ_i	The type of bus v_i
$V(r_i) = \{\tau_0, \tau_e\}$	The set of all vehicle types available for trip r_i (τ_o denotes fuel bus and τ_e denotes electric bus)
$p_s(r_{ij})$	The departure station of connecting trip r_{ij} ; If r_{ij} is the trip that leaving the depot, then $p_s(r_{ij}) = d$
$p_e(r_{ij})$	The end station of connecting trip r_{ij} ; If r_{ij} is the trip that returning the ends to the depot, then $p_e(r_{ij}) = d$
$t_s(r_{ij})$	The departure time of connecting trip r_{ij}
$t_e(r_{ij})$	The arrival time of connecting trip r_{ij}
l_{ij}	The kilometer of connecting trip r_{ij}
$v_k^e, k = 1,2,\ldots,m_1$	The eBus available for a trip.k is the index of eBus. m_1 is the total number of the eBus
$V_e = \{v_k^e\}$	The set of all eBus available for a trip
$v_{k'}^o, k' = 1,2,\ldots,m_2$	The traditional bus available for a trip.k' is the index of traditional bus. m_2 is the total number of traditional bus
$V_o = \{v_{k'}^o\}$	The set of traditional buses available for a trip
k_{v_i}	The maximum mileage of v_i :for electric bus it represents the kilometer under full charged state (without charging during the trip);for traditional bus, it refers to the mileage under full fuel state (without refueling during the trip)
S_d	The set of depot. Only a single depot d is considered in this study
x_{ij}^k	If electric bus k serves trip i and trip j, $x_{ij}^k = 1$; otherwise $x_{ij}^k = 0$
y_{ij}^k	If traditional bus k connects trip i and trip j, $y_{ij}^k = 1$; otherwise $y_{ij}^k = 0$
w_1	The cost of passenger trips
w_2	The cost of deadheading trips
w_3	The cost of energy consumption that includes fuel and charging costs
w_4	The cost of charging
c_1	Unit mileage cost of electric bus (passenger trip)
c'_1	Unit mileage cost of traditional bus (passenger trip)
c_2	Unit mileage cost of electric bus (deadheading trip)

TABLE 1. ***(Continued.)*** **Symbolic meaning.**

c'_2	Unit mileage cost of traditional bus (deadheading trip)
g	Fuel consumption of unit mileage for traditional bus
ε	Charging capacity per unit time
$p(t)$	Time varying electricity price
q	Electricity consumption per unit kilometer
M	Carbon emissions per unit mileage for electric buses
M'	Carbon emissions per unit mileage for traditional buses
t_j^k	The time for electric bus k starts charging before trip j
Δt_{ij}^k	Charging time of electric bus k connecting trip i and trip j during the connecting time
$t_{se}(i,j)$	The minimum length of the required connection time between trip i and trip j, if trip i and j are operated by traditional buses, $t_{se}(i,j)$ is the preparation time before departure; otherwise, $t_{se}(i,j)$ is the preparation time before departure and recharging time required
t_f	The preparation time before a trip
s_i^k	Battery remainder after trip i
s_t^k	Electric capacity of battery in time t

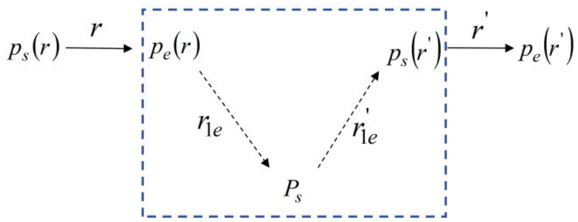


FIGURE 3. **Trip connection under charging condition.**

The trip chain of traditional bus consists of two sub trip sets, i.e., actual operation trip set R and deadheading trip set R', as shown in Figure 4. Where the deadheading trip includes departing trip r'_1, return trip r'_3 and the transfer trip r'_2 (transfer between stations). The number of dispatched buses is equal to the number of buses returned return to the depot. The connecting deadheading trip refers to the non-passenger trip added in order to increase the usage of buses. It is important to note that inter-station transfers (such as r'_2) require travel time, and the connection of the trip shall ensure that it arrives at the departure station before the start of the next operation trip.

Different from the traditional bus trip chain, the charging cycle set R_e is applied to the pure eBus trips chain, as shown in Figure 5. It should also be noted that the charging behavior of eBus, i.e., a eBus needs to be recharged when the remaining battery power is not enough to cover the next trips.

D. CHARGING SCHEDULING

Generally, eBus will need to be charged several times during the day to provide proper service quality. In addition, considering the ''Time-of-use Price'' policy, proper charging

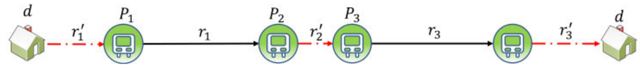


FIGURE 4. **Trip chain of traditional bus.**

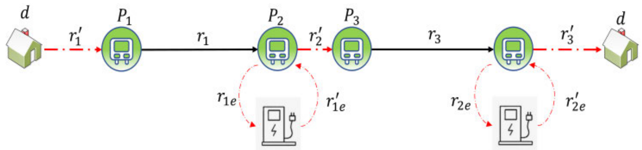


FIGURE 5. **Trip chain of electric bus.**

scheduling should be able to minimize the cost of electricity and maximize the usage of eBus. Therefore, system level energy consumption cost (include the electricity and gasoline costs) and emission will be reduced.

Because of the needed charging time, driving range limitation, and battery capacity drop at low temperature, pure eBus system may need more vehicle than traditional bus system to achieve the same service. As a transition mode from pure conventional bus system to pure eBus system, mixed bus fleet takes the advantages of both traditional buses and eBus.

In addition, for most vehicle scheduling in practice, the eBus are charged immediately when they arrive at the charging station. That is, charging scheduling is not optimized which may result in additional charges.

The ''Time-of-use Price'' policy provides an opportunity for charging scheduling. Charging the same amount of electricity for eBus during different time may cause different charging costs. Taking Beijing as an example, electricity prices are divided into three price points, i.e., low, medium and high prices, which are detailed in the case study section. In addition, in order to ensure the service life of eBus, the discharging depth threshold should be set. Reference [33] proved that 30% SOC is a reasonable discharging depth.

III. VEHICLE SCHEDULING AND CHARGING SCHEDULING OF MIXED BUS FLEET

Considering the vehicle scheduling and charging scheduling of the mixed bus system, a Bi-level planning model is designed. The upper layer is the vehicle scheduling model that considering the operating cost and carbon emissions and the lower layer is the charging scheduling model that considering the charging cost. In the upper layer, the eBus is charged immediately when it arrive the terminal station of the trip. Based on the trip chains from upper layer, lower layer calculates the charging scheduling by considering connection time, arrival time and departure time of the trip of trip chains as constraints. Results from lower layer are feed backs to the upper layer. Therefore, the collaborative optimization results are obtained.

A. MIXED VEHICLE SCHEDULING

Vehicle scheduling is applied to properly assign trips to the vehicles in the system. Traditional vehicle scheduling problem has certain goals, such as minimizing operating costs or carbon emissions. However, there is some contradiction between the low cost nature of traditional bus and the low carbon nature of electric bus. Therefore, the vehicle scheduling problem of the mixed bus system is formulated as a multi-objective optimization problem which is going to minimizing operating costs and minimizing carbon emissions.

1) OBJECTIVE FUNCTIONS

$$min\ Obj = \min(\alpha_1 Obj_1 + \alpha_2 Obj_2) \tag{1}$$

The objective of vehicle scheduling optimization is divided into two parts: Obj_1 is operating costs and Obj_2 is carbon emissions. α_1 and α_2 are the weights of the two goals, respectively.

a: OBJECTIVE FUNCTION 1: OPERATING COSTS

Operating cost includes the costs of passenger trips, deadheading trips and the cost of energy consumption. Among them, the passenger cost is calculated by the multiplication of the passenger trip mileage of traditional buses and eBus and the corresponding mileage cost per unit, as shown in Equation (3). The cost of deadheading operation includes the cost of deadheading trips and connecting cost of passenger trips, as expressed by Equation (4). The energy consumption cost includes the cost of electricity and fuel, as expressed by Equation (5). The charging cost of the electric bus is divided into the day time charging cost and the nighttime charging cost. Equation (6) represents the power loss for the entire working day.

$$\min Obj_1 = \min\{w_1 + w_2 + w_3\} \tag{2}$$

Among them:

$$w_1 = c_1 \sum_{k=1}^{m_1} \sum_{j=1}^{n} \sum_{i=0}^{n} x_{ij}^k l_j + c_1' \sum_{k'=1}^{m_2} \sum_{j=1}^{n} \sum_{i=0}^{n} y_{ij}^k l_j \tag{3}$$

$$\begin{aligned} w_2 = {} & c_2 \sum_{k=1}^{m_1} \left(\sum_{i=1}^{n} \sum_{j=1}^{n} x_{ij}^k l_{ij} + \sum_{j=1}^{n} x_{oj}^k l_{0j} + \sum_{i=1}^{n} x_{i0}^k l_{i0} \right) \\ & + c_2' \sum_{k'=1}^{m_2} \left(\sum_{i=1}^{n} \sum_{j=1}^{n} y_{ij}^{k'} l_{ij} + \sum_{j=1}^{n} y_{oj}^{k'} l_{0j} + \sum_{i=1}^{n} y_{i0}^{k'} l_{i0} \right) \end{aligned} \tag{4}$$

$$\begin{aligned} w_3 = {} & \left(\sum_{k=1}^{m_1} \sum_{\rho=1}^{n_k} \int_{t_k^\rho}^{t_k^\rho + \Delta t_k^\rho} \varepsilon(t) P(t) dt + P(t_0) \right. \\ & \left. \cdot \left(\sum_{k=1}^{m_1} Q_k - \varepsilon \sum_{k=1}^{m_1} \sum_{\rho=1}^{n_k} \Delta t_k^\rho \right) \right) \\ & + \left(\sum_{k'=1}^{m_2} \left(\sum_{i=1}^{n} \sum_{j=1}^{n} y_{ij}^{k'} l_{ij} + \sum_{j=1}^{n} y_{0j}^{k'} l_{0j} + \sum_{i=1}^{n} y_{i0}^{k'} l_{i0} \right) g \right) \end{aligned} \tag{5}$$

$$Q_k = q \cdot \sum_{i=1}^{n} \sum_{j=0}^{n} \left(l_{0i} + l_i + l_{ij} + l_j \right) x_{ij}^k \tag{6}$$

b: OBJECTIVE FUNCTION 2: CARBON EMISSIONS

In general, carbon emission can be used as the indicator of environmental performance. Then, the objective function can be expressed as Equation (7).

In this paper, without concerning the source of electricity, the direct carbon emission of eBus is set to be 0, that is $M = 0$; while for traditional buses, the carbon emission per mile can be calculated according to empirical operating data.

$$\begin{aligned} \min Obj_2 = {} & M \sum_{k=1}^{m_1} \left(\begin{aligned} & \sum_{i=1}^{n} \sum_{j=1}^{n} x_{ij}^k l_{ij} + \sum_{j=1}^{n} x_{0j}^k l_{0j} \\ & + \sum_{i=1}^{n} x_{i0}^k l_{i0} + \sum_{j=1}^{n} \sum_{i=0}^{n} x_{ij}^k l_j \end{aligned} \right) \\ & + M' \sum_{k'=1}^{m_2} \left(\begin{aligned} & \sum_{i=1}^{n} \sum_{j=1}^{n} y_{ij}^{k'} l_{ij} + \sum_{j=1}^{n} y_{0j}^{k'} l_{0j} \\ & + \sum_{i=1}^{n} y_{i0}^{k'} l_{i0} + \sum_{j=1}^{n} \sum_{i=0}^{n} y_{ij}^{k'} l_j \end{aligned} \right) \end{aligned} \tag{7}$$

2) CONSTRAINTS

Regarding to empirical operation of mixed bus fleet, the vehicle scheduling should satisfy the following constraints:

– Each trip $r \in R$ can only served by one vehicle;

– Each trip connection $r_{ij} \in R'$ can only be assigned to one vehicle, and the connecting time of the trip is less than the time gap between the start of the next trip and the end of the existing trip;

– Each vehicle should return to the depot after completing the activities of one day;

– The number of assigned vehicles should be no larger than the total number of vehicles at the depot;

– If two trips are operated by the same vehicle, there should be sufficient preparation time before the next trip.

Specifically, the constraints are listed as follows:

$$\sum_{k=1}^{m_1} \sum_{j=0}^{n} x_{ij}^k \left(1 - \sum_{k=1}^{m_1} \sum_{j=0}^{n} x_{ij}^k \right) = 1 \quad \forall i \in R \tag{8}$$

$$\sum_{k=1}^{m_1} \sum_{i=0}^{n} x_{ij}^k \left(1 - \sum_{k=1}^{m_1} \sum_{i=0}^{n} x_{ij}^k \right) = 1 \quad \forall j \in R \tag{9}$$

$$\sum_{k=1}^{m_1} \sum_{j=1}^{n} x_{0j}^k = \sum_{k=1}^{m_1} \sum_{i=1}^{n} x_{i0}^k \tag{10}$$

$$x_k = 1 - \max\left\{ 1 - \max\left\{ \sum_{i=0}^{n} \sum_{j=1}^{n} x_{ij}^k, 0 \right\}, 0 \right\} \quad \forall i, j \in R,\ k \in V_e \tag{11}$$

$$\sum_{k=1}^{m_1} x_k = m_1 \tag{12}$$

$$\sum_{i=1}^{n} \sum_{j=1}^{n} x_{ij}^k l_{ij} + \sum_{j=1}^{n} x_{0j}^k l_{0j} + \sum_{i=1}^{n} x_{i0}^k l_{i0} \le L \quad \forall k \in V_e \tag{13}$$

$$t_{se}(i, j) \cdot x_{ij}^k \le t_e(j) - t_s(i) \quad \forall i, j \in R,\ k \in V_e \tag{14}$$

$$x_{ij}^k \left(1 - x_{ij}^k \right) = 1 \quad \forall i, j \in R,\ k \in V_e \tag{15}$$

$$\sum_{k'=1}^{m_2}\sum_{j=0}^{n} y_{ij}^{k'}\left(1-\sum_{k'=1}^{m_2}\sum_{j=0}^{n} y_{ij}^{k'}\right)=1 \quad \forall i \in R \tag{16}$$

$$\sum_{k'=1}^{m_2}\sum_{i=0}^{n} y_{ij}^{k'}\left(1-\sum_{k'=1}^{m_2}\sum_{i=0}^{n} y_{ij}^{k'}\right)=1 \quad \forall j \in R \tag{17}$$

$$\sum_{k'=1}^{m_2}\sum_{j=1}^{n} y_{0j}^{k'}=\sum_{k'=1}^{m_2}\sum_{i=1}^{n} y_{i0}^{k'} \tag{18}$$

$$y_{k'}=1-\max\left\{1-\max\left\{\sum_{i=0}^{n}\sum_{j=1}^{n} y_{ij}^{k'},0\right\},0\right\} \quad \forall i,j\in R,\ k'\in V_o \tag{19}$$

$$\sum_{k'=1}^{m_2} y_k = m_2 \tag{20}$$

$$t_{se}(i,j)\cdot y_{ij}^{k'} \le t_e(j)-t_s(i) \quad \forall i,j\in R,\ k'\in V_o \tag{21}$$

$$y_{ij}^{k'}\left(1-y_{ij}^{k'}\right)=1 \quad \forall i,j\in R,\ k'\in V_e \tag{22}$$

$$\sum_{i=1}^{n}\sum_{j=1}^{n} y_{ij}^{k'} l_{ij}+\sum_{j=1}^{n} y_{0j}^{k'} l_{0j}+\sum_{i=1}^{n} y_{i0}^{k'} l_{i0}\le L \quad \forall k'\in V_o \tag{23}$$

$$\sum_{k=1}^{m_1}\sum_{i=0}^{n} x_{ij}^{k}+\sum_{k'=1}^{m_2}\sum_{i=0}^{n} y_{ij}^{k'}=1 \quad \forall j\in R \tag{24}$$

$$\sum_{k=1}^{m_1}\sum_{j=0}^{n} x_{ij}^{k}+\sum_{k'=1}^{m_2}\sum_{j=0}^{n} y_{ij}^{k'}=1 \quad \forall i\in R \tag{25}$$

Constraints (8) and (16) ensure that the trip i and its adjacent following trip j can only be executed by one vehicle. Constraints (9) and (17) ensure that the trip j and its forward trip ii can only be performed by one vehicle; Constraints (8), (9), (16), (17), (24) and (25) jointly ensure that each trip is executed only once. Constraints (10) and (18) guarantee that the vehicle departed from the depot will eventually return to the depot. Constraints (11) and (19) indicate the numbers of eBus and fuel buses that perform tasks during the day, respectively. Constraints (12) and (20) indicate that the number of vehicles that performing the trips is equal to the number of vehicles that housed in the depot. To ensure the overall life balance of buses, the daily mileage of each bus is restricted, as expressed by constraints (13) and (23). Constraints (14) and (21) indicate that there should enough preparation time between the end of trip i and the start of trip j, if both trips i and j are served by vehicle k. Constraints (15) and (22) are 0-1 variable constraints.

B. CHARGING SCHEDULING MODEL

1) OBJECTIVE FUNCTION

Considering "Time-of-use Price" policy, the bus companies attempt to properly charge the buses and minimize the charging cost. Therefore, the objective function is formulated as follows:

$$w=\min w_4 \tag{26}$$

$$w_4=\left(\sum_{k=1}^{m_1}\sum_{\rho=1}^{n_k}\int_{t_k^\rho}^{t_k^\rho+\Delta t_k^\rho}\varepsilon(t)P(t)dt+P(t_0)\cdot\left(\sum_{k=1}^{m_1}Q_k-\varepsilon\sum_{k=1}^{m_1}\sum_{\rho=1}^{n_k}\Delta t_k^\rho\right)\right) \tag{27}$$

2) CONSTRAINTS

Regarding to the charging scheduling of eBus, the following assumptions are made:

– The remaining energy of the battery before the next trip should be enough for executing the next trip. As well, the remaining energy can't beyond the capacity of the battery.

– The charging time of an eBus should be after the arrival at the charging station, and it should ensure that the required charging time can't exceed the connecting period between the adjacent trips.

In detail, the constraints regarding to the charging scheduling are expressed as follows:

$$t_{se}(i,j)=\begin{cases} t_f \\ \Delta t_{ij}^k+t_f \end{cases} \quad \forall i,j\in R \tag{28}$$

$$t_{\min(i,j)}^k \le \Delta t_{ij}^k \le t_{\max(i,j)}^k \quad \forall i,j\in R,\ k\in V_e \tag{29}$$

$$t_{\min(i,j)}^k = g\left(s_i^k+30\%-s_t^k\right) \quad \forall i,j\in R,\ k\in V_e \tag{30}$$

$$t_{\max(i,j)}^k = g\left(1-s_t^k\right) \quad \forall i,j\in R,\ k\in V_e \tag{31}$$

$$t_e(i)\le t_j^k \le t_s(j)-\Delta t_{ij}^k \quad \forall i,j\in R,\ k\in V_e \tag{32}$$

Constraint (28) represents $t_{se}(i,j)$ is the minimum length of the required connection time between trip i and trip j, it can be divided into two categories by whether it needs to be charged or not. t_f is the preparation time that doesn't include charging behavior before serving the next trip. According to whether the arrival depot of trip i and the departure depot of trip j are the same site, t_f can be divided into two cases. If the sites are the same, t_f consists of the time of vehicle turns and the time of driver shift, otherwise, it needs to add inter-station transfer time. Constraint (29) represents requirement for charging time for eBus. Constraints (30) and (31) ensure that the SOC of a vehicle is not less than 30% [33] when returning to the depot, and gives the upper and lower boundaries of the charging time. Constraint (32) represents the time range for starting the charging. Accordingly, vehicle k can be recharged from $t_e(i)$ of entering the charging station. To satisfy the requirement of charging time, the charging should be started before $t_s(j)-\Delta t_{ij}^k$.

IV. SOLUTION ALGORITHM

In section 3, we present a Bi-level programming model for vehicle scheduling and charging scheduling. Bi-level programming problem has been proved to be NP-hard. Therefore, a heuristic algorithm is designed to solve it. When upper-level programming decision variables are constrained by lower-level programming, lower-level programming is

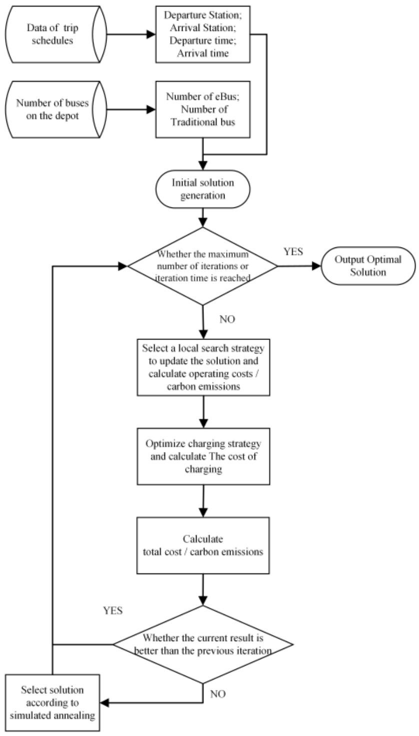


FIGURE 6. **The framework of algorithm.**

TABLE 2. **Algorithm1.**

Algorithm 1: iterative neighborhood search algorithm based on simulated annealing
Step1: Get information of trips and vehicles, such as, departure and arrival station of trips, departure time, arrival time, the available vehicles. Arrange the trips in ascending order in terms of departure time;
Step2:Generate the initial solution and calculate the cost $f(s)$ .Let $s^*=s$, $f^*=f(s)$, $s_{current}=s$;
Step3: Let number of iteration $iter=0$, current time $t_{start}=time_{now}$, and set the maximum iteration number to be $iter_{\max}$ and the longest running time to be $t_{\max}$. Define the solution after each optimization as s_t ;
Step4:A search method is applied to optimize the charging process, and calculate $f(s_t)$;
Step5:If $f(s_t)<f^*$, $s^*=s_t$ go to Step7;otherwise go to Step6;
Step6: The random number $p'=N(0,1)$ is generated, and the probability $p=\exp((f(s_t)-f^*)/T)$ is calculated by simulated annealing algorithm. If $p'<p$, $s_{current}=s_t$;
Step7: Let current time $t_{end}=time_{now}$;
Step8: If the termination condition, i.e., $t_{end}-t_{start}>t_{\max}$, is satisfied, output vehicle scheduling and charging scheduling; otherwise, proceed to Step3.

regarded as an independent decision-making problem. Therefore, the solution process can be depicted as follows:

– First, solve the optimal value of lower-level programming under the given feasible scheme of upper-level programming;

– Then, with the optimal solution of the lower-level programming, solve the upper-level programming to find the overall optimal solution.

So far, many heuristic algorithms have been proposed to solve the vehicle scheduling problem, such as genetic algorithm, iterative neighborhood search algorithm, and so on. In this study, an improved iterative neighborhood search algorithm is designed to consider different characteristics of electric and traditional buses in the local search strategies.

To solve the lower-level charging scheduling problem, a greedy search strategy is designed based on multi-stage decision-making.

The framework of the proposed algorithm is shown in Figure 6. First, relevant data is extracted according to the trip information and vehicle Information. Second, the initial solution is generated according to the strategy of initial solution generation. Third, setting the number of iterations and the iteration time, Iterative neighborhood search strategy and greedy dynamic search strategy are input to the proposed optimization model. Therefore, the optimal solution is obtained when the termination condition is satisfied.

In addition, the bus fleet consists of both traditional bus and eBus in this paper, to promote the readability of the paper, it is clarified that if not specified, ''bus/vehicle'' can be any bus/vehicle of the fleet, which can be traditional bus or eBus.

A. ITERATIVE NEIGHBORHOOD SEARCH

For the scheduling problem of a large-scale bus system, it is crucial to find a satisfactory solution within limited time. Since the iterative search algorithm has been proved to get a good solution within a reasonable computing time, it is applied to solve the upper-level vehicle scheduling problem [14].

The core idea of Iterative Neighborhood Search is to iteratively generate alternative scheduling schemes by exchanging the vehicles to serve the same trips, and accept the new scheme with better objective value, until the iteration stopping condition is satisfied. In detail, the algorithm is presented in Algorithm 1.

As in Algorithm 1, Iterative Neighborhood Search algorithm for mixed bus operation system contains several essential components, including initial solution generation, search sub-algorithms for different bus exchange modes, simulated annealing, which will be detailed introduced.

1) INITIAL SOLUTION GENERATION

For the mixed bus system, the generation of initial solution is to assign the buses to serve all the trips under the model constraints. To clearly depict the method of generating initial solution, the following definitions are listed as:

– $V^N = \{V_o^N, V_e^N\}$ denotes the set of vehicles that are unused, where $V_o^N \in V_0$ is the set of traditional bus, and $V_e^N \in V_e$ is the set of eBus. Initially, $V_o^N, V_e^N = \varnothing$.

– $V^O = \{V_o^O, V_e^O\}$ denotes the set of vehicles that are unused, where $V_o^O \in V_0$ is the set of traditional bus, and $V_e^O \in V_e$ is the set of eBus. Initially, $V_o^O, V_e^O = \varnothing$.

TABLE 3. Initial solution generation scheme.

	I	II
Types of vehicles Prioritized (New/Used)	Unused buses	Used vehicles
Types of Unused vehicles Prioritized (Oil/Electricity)	eBus	Traditional Buses
Types of Used vehicles Prioritized (Oil/Electricity)	eBus	Traditional Buses

TABLE 4. Initial solution generation strategy.

Strategy	Scheme
①	II、I、I
②	I、I、I
③	I、I、II
④	I、II、I
⑤	I、II、II
⑥	II、I、II
⑦	II、II、II
⑧	II、II、I

– $\hat{V}_r \in V$ is the set of vehicle that can assigned to trip r. Initially, let $\overline{V_r} = \emptyset$.

– $E^v_{residue}$ is the residual power of vehicle v. Initially, let $E^v_{residue} = 1$.

– $\overline{r_s}$ is the trip of vehicles leaving the depot, and $\overline{r_e}$ is the trip of vehicles returning to the depot.

During the process of initial solution generation, only one trip is checked for each iteration. If a vehicle $v \in \hat{V}_r$ can satisfy the following conditions (33), it is assigned to trip r.

$$v \in \hat{V}_r \rightarrow \begin{cases} \tau_v \in V(r) \\ t_s(r) - t_e(r) - t^v_{\overline{r}r} \geq 0 \\ E^v_{residue} \geq l^v_{\overline{r}r} + l_r \end{cases} \tag{33}$$

Equation (33) illustrates that of the assigned vehicle belongs to the available vehicle set $\hat{V}_r$, and the connection time and power constraints should be satisfied as well.

Different initial solution generation scheme can be designed, as shown in Table 3. Take Strategy ① as a example. First, if $V^O \neq \emptyset$, we give priority to the vehicles that used,that is, select the vehicle in V^O, second, if $V^O_e \neq \emptyset$, we give priority to the eBus, that is, select the vehicle in V^O_e, otherwise, select the vehicle in V^O_o; in addition, if $V^O = \emptyset$, we select the vehicle in V^N, second, if $V^N_e \neq \emptyset$, we give priority to the eBus, that is, select the vehicle in V^N_e, otherwise, select the vehicle in V^N_o. Thus, by randomly combining the schemes in Table3, we can define the different strategies in Table 4.

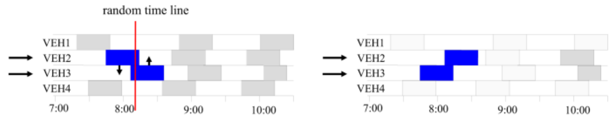


FIGURE 7. Shift (1) process.

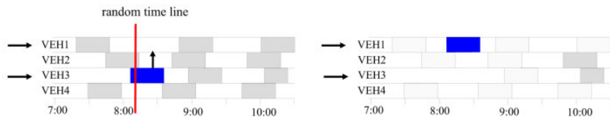


FIGURE 8. Shift (2) process.

2) LOCAL SEARCH STRATEGIES

Usually, the initial solution may not be optimal due to the large amount of feasible solutions. To improve the initial solution, three different local search strategies are developed, namely Shift, 2opt*, and Block, respectively.

a: SHIFT

In terms of the initial solution, the trip chains of all buses are obtained, and the neighborhood of the trip chains for each bus can also be obtained. Regarding to Shift strategy, it is expected that a better solution can be obtained by exchanging the bus to serve a trip. If the operation time of two trips is similar, the possibility of the services of the involved vehicles remain feasible after shift is great. In addition, a time point can be selected at random during the day's operating time, and we draw a line based on this time point, we call it "random timeline ". For the mixed bus system, the Shift strategy contains two cases:

– Two different vehicles can be randomly selected in different vehicles that are crossed by timeline. Then, exchange their trips that are crossed by the timeline and check whether the services of the involved vehicles remain feasible after shift. If a better local solution is obtained, then update the solution (Figure 7).

– In addition, we can't guarantee that the time line goes through the trip in every vehicle, it's also possible to cross the no-trip interval. If exchange trips, one vehicle can provide the trip, the other vehicle can receive the trip (no-trip interval), it means that the trip can also be moved, and determine whether the trip connection requirements are met after the move (Figure 8).

It should be noted that because the timeline and vehicles are selected randomly, there may be a situation that the timeline doesn't go through the trips or the services of the involved vehicles don't remain feasible after trip exchanging. Therefore, the maximum iteration number $iter^v_{max}$ is given when select vehicle after timeline selected. The vehicle selection process will be terminated if a predetermined stopping condition is satisfied, that is, either the solution meets the connection requirements, or the maximum iteration number is reached.

The terminated condition of the whole shift process is the specified iteration time.

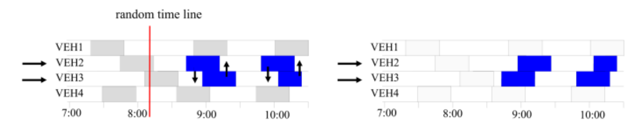


FIGURE 9. **2opt* process.**

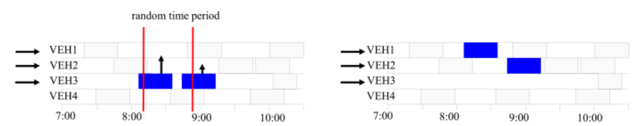


FIGURE 10. **Block process.**

*b: 2opt**

Based on the Shift strategy, the shift can only be carried out between a couple of trips for each time, resulting in the lower efficiency. To promote the efficiency of the algorithm, the 2opt* strategy allows the exchanging between multiple couples of trips at a time, the trip chain is divided into two parts. The part behind the time line of the two vehicles is exchanged, as illustrated in Figure 9. Likewise, the maximum iteration number $iter_{max}^{v}$ is set to ensure the termination of the vehicle selection.

c: BLOCK

Block is an alternative strategy which adopts Multi-vehicle shift strategy to improve the efficiency of the algorithm. In detail, the Block strategy is depicted as follows:

To successfully shift multiple trips simultaneously, time lines are set. Note that, only one of the time lines is random selection, and the other is determined by time intervals.

– To choose at least two trips for exchange, the time interval can be set as the total operating time of the two trips. Other schemes (such as more than two trips are selected for each exchange) can be determined by relaxing the time interval;

– Next, the trip is exchanged separately, as shown in Figure 10. During each exchange, determine whether the services of the involved vehicles remain feasible.

3) SIMULATED ANNEALING

One of the most serious drawbacks of heuristic algorithms is that they may converge to a local optimal solution. To address this problem, several advanced algorithms have been developed, such as Tabu search, simulated annealing, and so on.

In this study, simulated annealing is employed to jump out of local optimum. Simulated annealing is a probabilistic meta-heuristic used to find a good approximation of the global optimum of a given function [34]. References [14] proved simulated annealing has better optimization effect, and the simulated annealing formula and parameters are derived in the literature. Briefly, if the current solution is superior to the optimal solution obtained from the previous iteration for each iteration, the current solution is set to be the new optimal solution. Otherwise, check the following conditions:

$$p < p' \tag{34}$$

$$p = \exp((f - f^*)/T) \tag{35}$$

where p' is a random parameter rang within [0, 1]; p is the random variable calculated by simulated annealing. If the condition (34) is satisfied, the iteration search is continuously performed with the current solution, although it is not the optimal solution. The cost calculated for the current iteration is the current optimal cost. T is the current temperature, which is generally within [0.6, 0.9]. Here, T is set 0.8.

$$\mu_{\Delta f} = \sum_{k=1}^{k_{\max}} (f_k - f)/k_{\max} \tag{36}$$

$$T_0 = \mu_{\Delta f}/\log 0.8 \tag{37}$$

$$T_{\text{time}} = T_0 - T_0\left(t_{current}/t_{\max}\right) \tag{38}$$

where $\mu_{\Delta f}$ is the optimal mean value obtained by the iterations in advance. Equation (37) is used to calculate the initial temperature T_0. Equations (38) are used to determine the temperature T after each iteration.

4) STOP CONDITIONS OF ITERATION

Since it is expected to get a satisfactory solution within limited time, The maximum search time is set for the algorithm.

B. ALGORITHMS FOR CHARGE SCHEDULING

Based on the decision-making process of charging scheduling, one can find that it has obvious staged characteristics. The charging process obeys the non-aftereffect rule. Therefore, dynamic programming can be applied for charging scheduling.

The time complexity of dynamic programming algorithm is mainly determined by three factors: the total number of states in the problem, the number of states involved in each state transition, and the required time of each state transition. In charge scheduling, the total number of states is the sum of the number of chargeable states in each rechargeable gap; the number of states involved in state transition is the amount of charge in each rechargeable gap; and require time for state transition is the time for subsequent charging decision-making. Obviously, the charging state is a continuous variable. And the number of trips is very large for a bus system. Therefore, an appropriate approach is needed to solve this charging scheduling problem which is a computational problem.

First of all, the unit of calculation for eBus charging scheduling is the percentage of SOC rather than charging time, because it can reduce the number of decision variables and the number of states. Taking Figure 11 as an example, it is assumed that 30% SOC is required before the execution of trip 7. Without considering the different charging and discharging rates of different power, the charging efficiency of eBus is about 3% SOC per minute. That is, it takes 10 minutes to charge between trip 5 and trip 7. If the charging time is

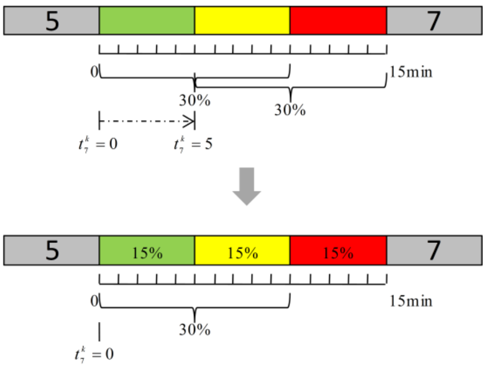


FIGURE 11. Schematic diagram of charge scheduling with priority to electricity price.

taken as the unit of calculation, the charging start time can be taken from 1 to 5. Thus, there are 5 decision variables and 5 states. Since the trip chains is known, if the percentage of SOC is taken as the unit of calculation, the percentage of SOC in each electricity price period can be directly calculated in the interval between the trips. Therefore, it can be charged 15% SOC directly during the low price period. However, the period of low electricity price is insufficient, the remaining 15% SOC can be recharged during the medium price period. Therefore, the charging start time can be directly determined, the number of decision variables is 1 and the number of states is 1.

In addition, because the charge of the previous phase will affect the operation of the next trip and the state of the next phase of the charge, the percentage of SOC required before the next tip is not determined. Due to the no-aftereffect of dynamic programming, the decision process can be divided into several sub-stages. In terms of the "Time-of-use Price", the "greedy" strategy is employed to generate the initial solution. That is, attempting to arrange the charging during the low price period. Furthermore, based on the initial solution, the optimal solution of the problem is obtained by adjusting the charging time.

Before the introduction of the algorithm, the following assumptions are made in terms of empirical bus fleet operations.

– Before the bus serves the first trip, the remaining battery capacity of the electric bus is 100% SOC.

– In the operation process, the remaining electricity can't be less than 30% SOC.

– The discharging speed difference between high and low power periods can be ignored for the time being.

1) INITIAL SOLUTION GENERATION

The initial solution generation of charging scheduling is mainly affected by both "Time-of-use Price" policy and the charging constraints.

In this study, the greedy strategy is adopted to generate the initial solution. Intuitively, we try to assign the eBus to

TABLE 5. Algorithm 2.

Algorithm 2：Charge Scheduling (Greedy Strategy + Multi-stage Decision)
Step1: Obtain the time interval period and time interval set Period between trip chains and "Dynamic Price" Standard;
Step2: Let $period=[t_s,t_e,low,medium,high]$, where t_s is the start time of charging in the period; t_e is the end time of charging in the period; *low* , *medium* , *high* represent chargeable quantities with the low, middle and high price, respectively;
Step3: Priority should be given to charging at low and medium price in each period until the time when the battery is full or low and medium price is fully used for charging. If the charging amount during the period of low and medium price cannot satisfy the next trip, the charging is needed during the period of high price so that the minimum demand can be satisfied;
Step4: Judge whether the charging quantity in the current stage can be replaced by charging in the following low-price period, until all the connecting periods are searched.

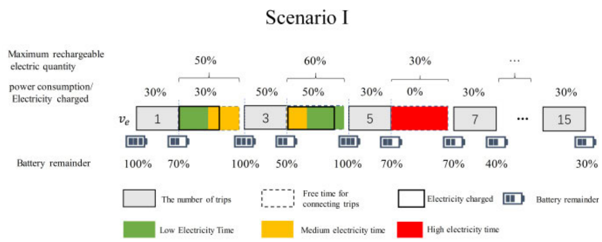


FIGURE 12. Initial solution of charge scheduling (1).

grid during the low and medium price periods rather than the high price periods. In general, the available charging time is constrained by two aspects as shown in section 3.

Considering trip-level power consumption of the eBus and the maximum chargeable capacity of each charging period, the objective of charging scheduling is to properly assign eBus to the charge station to satisfy its charging demand and minimize the cost. Refer to Algorithm 2 for charging scheduling algorithm. The charging schedule execution steps is shown in Table 5.

In Figure12, an example is taken to intuitively illustrate Algorithm 2. The connection section between trip 1 and trip 3 belongs to the middle and low price period, and the charging capacity is 50% SOC. We choose to charge 30% SOC to fill up the battery capacity. The connection section between trip 3 and trip 5 still belongs to the low and middle price period, charging 50% SOC to fill up the battery capacity; the connection section between trip 5 and trip 7 belongs to the high price period. The minimum charge is 0% SOC and the remaining power is still 30% SOC after the completion of the trip 7.

In Figure13, another example is shown. If the connecting period between trips 3 and 5 is the high price period, we should not charge the vehicle at this time. However, the remaining energy is 20% SOC after executing the trip 5, which is not satisfied the constraint that discharging depth can't be less than 70% SOC. Therefore, it is necessary to

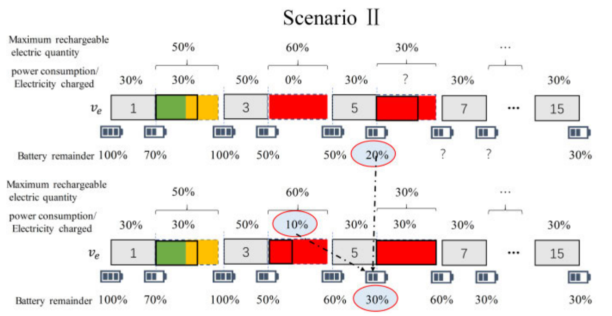


FIGURE 13. Initial solution of charge scheduling (2).

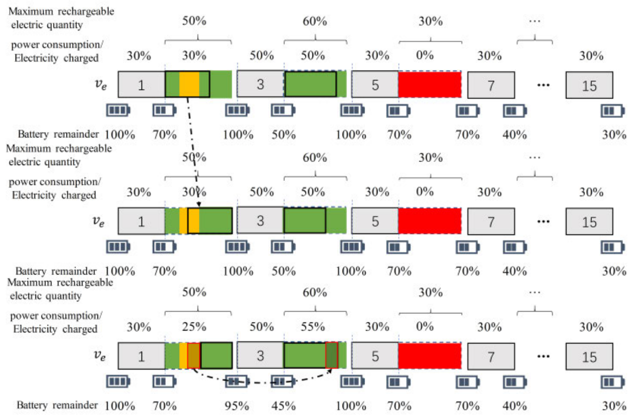


FIGURE 14. Charge scheduling optimization.

charge at least 10% SOC before executing the trip 5. Because this time period is a high electricity price period, charging should be as little as possible. Consequently, charging 10% SOC is sufficient.

2) SOLUTION SPACE OPTIMIZATION

According to the process of generating initial solution, one can see that the minimum charge is chosen during the high price period, which can't be further optimized. Nevertheless, during the middle and low price period, we choose the maximum charge, which may lead to the subsequent low price period can't be fully utilized. To obtain the optimal solution, a simple approach is proposed with two steps:

– Optimize the charging time in the same charging period;

– Find a replacement scheme in the subsequent charging period.

It should be noted that if less charging in the period of middle price in the preceding paragraph leads to insufficient power consumption in the period of high price, more charging in the period of high price will lead to worsening solution of the problem. Therefore, this case should be identified when the scheme is optimized.

As shown in Figure14, case 1 and case 2 doesn't fully used the charging duration that has low electric price. Case 3 is suggested by the proposed method to minimize the charging cost.

3) STOP CONDITIONS OF ITERATION

The aforementioned algorithm is performed from the first rechargeable period to the last one in a day. That is, from the first rechargeable period to the last rechargeable period, the charging demand in the middle price period is optimized, and the charging scheme converges and the optimal solution is obtained.

The proof the algorithm is given in Appendix.

V. CASE STUDY

All experiments are conducted on a desktop computer with an Intel(R) Core i5-6500CPU @ 3.20GHz, 8 gigabytes of RAM, running Windows 7 Enterprise. Our algorithm is implemented as single-thread code in Python.

In this section, case studies are carried out based on the real state of a depot and bus routes in Beijing to evaluate the performance of the proposed model and algorithm. First, the convergence of the vehicle scheduling algorithm is analyzed. Moreover, the application scenarios of different initial solution generation strategies are described. Finally, the optimization results of the vehicle scheduling and charging scheduling model are compared and analyzed. And the feasibility of the model and algorithm is illustrated.

A. SCENARIO DESCRIPTION

In terms of empirical conditions, we assume:

– The maximum daily mileage for each bus is 500 km [14];

– Average speed of the vehicle for trips without passenger: 40km/h [14];

– The number of charging stations is sufficient so that the eBus can be charged once arriving at the station;

– eBus can be charged at the ends of the bus route;

– The preparation time is 3 minutes for changing of drivers;

– The number of electric and traditional buses in the system are predetermined.

The bus parameters in this paper are obtained from references [32], [35] and [36]. Under conditions that allow the replacement of vehicle accessories and batteries, the mileage of the bus is 400,000 km. In addition, after removing the subsidy and adding the cost of replacing the battery, the purchase cost of electric bus is 0.29 million dollars, and it is 0.1 million dollars for the traditional bus. Other parameters are shown in Table 6.

Accordingly, the cost of traditional buses is 0.2518 $ per kilometer, and fuel cost is 0.3065 $ per kilometer. The cost of eBus is 0.7143 $ per kilometer, and electricity cost is shown in Table 7. (The above values can be adjusted according to specific areas and models).

The DaWaYao station is employed in the case studies, which contains3 bus lines, i.e., 959, 961 and 973. The detailed bus line information is presented in Table 8.

In practice, the headway between trips of one bus line is 10 minutes. Therefore, 575 bus trips per day are available, and 79 fuel buses can be used at the depot. According to the current eBus replacement scheme in Beijing, it needs

TABLE 6. Parameters set for different bus types.

	eBus	traditional bus
Mileage within the life cycle	400000km[a]	400000km[a]
Energy consumption rate	1.3 kWh/km[a]	0.35L/km[a]
Purchase cost($\times 10^4$\$)	21.43[a]	8.64[a]
Maintenance costs within the life cycle($\times 10^4$\$)	7.14[a]	1.43[a]
Unit cost of energy consumption(\$)	[b]	0.88
Exhaust emissions($CO + NX_O$)	0	1.12g/km[c]
Energy capacity	230 kWh[c]	350L[c]
Charging efficiency	9.1 kWh/min[d]	—

[a] from reference[35].
[b] is given in table 7.
[c] from reference[32].
[d] from reference[36].

TABLE 7. Time-of-use price.

Time interval	Low price periods	Medium price periods			High price periods	
	23:00-7:00	7:00-10:00	15:00-18:00	21:00-23:00	10:00-15:00	18:00-21:00
Electricity price ($\$ / kw \cdot h$)	0.0563	0.0992			0.1435	

TABLE 8. Detail information of bus lines 959, 961 and 973.

line number	Line information	Mileage/km
959	MenTouGouShiChangCun→ The depot of DaWaYao 5:00 (First Bus) - 21:00 (Last Bus) The depot of DaWaYao→MenTouGouShiChangCun 6:00 (First Bus) - 22:00 (Last Bus)	47
961	XiLaoDianCun→ The depot of DaWaYao 5:20 (First Bus) - 20:40 (Last Bus) The depot of DaWaYao→XiLaoDianCun 6:30 (First Bus) - 22:00 (Last Bus)	27
973	HeiQiaoNan→ The depot of DaWaYao 5:00 (First Bus) - 21:00 (Last Bus) The depot of DaWaYao→HeiQiaoNan 5:00 (First Bus) - 21:00 (Last Bus)	47

TABLE 9. The ID of the station.

ID	1	2	3	4
Name	DaWaYao Depot	MenTouGou ShiChangCun	XiLao DianCun	HeiQiao Nan

1.3 electric vehicles on average to replace 1 traditional bus. In the following case studies, 50% of the traditional buses are replaced by 52 eBus. Therefore, the mixed bus system contains 92 buses totally.

The ID of the end station of bus lines is shown in Table 9. The distance of the deadheading trip that connected the end station of bus lines is given in Table 10. Deadheading time of the trip can obtained by the distance divided by the speed.

TABLE 10. The distance between two stations/(km).

ID	1	2	3	4
1	0	12.1	14.8	28.7
2	12.1	0	7.4	38.5
3	14.8	7.4	0	36.1
4	28.7	38.5	36.1	0

B. RESULTS

1) CONVERGENCE OF THE PROPOSED ALGORITHM

To select a reasonable iteration time and algorithm parameters, we compared the convergence process of various local search methods, as shown in Figure 15.

In terms of local search methods, we can find that 2opt* is better than the other two methods. This is reasonable because shift and block only move and exchange one or two trips at a time, and the eBus scheduling has the constraint of charging time. It will take more time to judge whether the services of the involved vehicles remain feasible after each search. Differently, 2opt* selects more than one trips at a time, as well determine whether the services of the involved vehicles remain feasible. Thus, the required time can significantly reduced. Consequently, it is possible to obtain a satisfactory solution more quickly in a finite time range for 2opt*.

In terms of the maximum number of iterations $iter^v_{max}$ for vehicle selection, the termination condition of vehicle selection iterative search is to get the optimal solution or to achieve the maximum number of iterations. Therefore, if the $iter^v_{max}$ is too small, the opportunity for vehicle exchange may be too limited; if the $iter^v_{max}$ is too large, it will undoubtedly increase the search time. To get an appropriate $iter^v_{max}$, $iter^v_{max} = 5, 10$ *and* 15 are selected and tested. Figure14 (a) shows that $iter^v_{max} = 15$ is better than $iter^v_{max} = 5$ *or* 10; Figure14 (b) shows that $iter^v_{max} = 10$ is better than $iter^v_{max} = 5$ *or* 15 in terms of optimization. Because the iteration parameters are assumed randomly, the parameter is further judged when evaluating the effect of the initial solution.

In terms of iteration time, optimization targets for cost and carbon emissions reveal different results:

(1) For the cost, when optimization time is 6 minutes, with $iter^v_{max} = 5, 10$ *and* 15, the results can reach to 91%, 85%, and 100% of the results for optimization time of 15 minutes;

(2) For the carbon emissions, when optimization time is 10 minutes, with $iter^v_{max} = 5, 10$ *and* 15, the results can reach 93%, 95%, and 84% of the results when the optimization time is 15 minutes;

As a consequence, when the objective is cost, the iteration time is set as 6 minutes; while it is set as 10 minutes when the objective is carbon emissions.

2) IMPACTS OF INITIAL SOLUTION GENERATION STRATEGY

In section 4, eight initial solution generation strategies are proposed. We tested the application scenario and the results are shown in Figure16. For the operation cost, strategies 5 and 7 achieved better optimization results, since they give

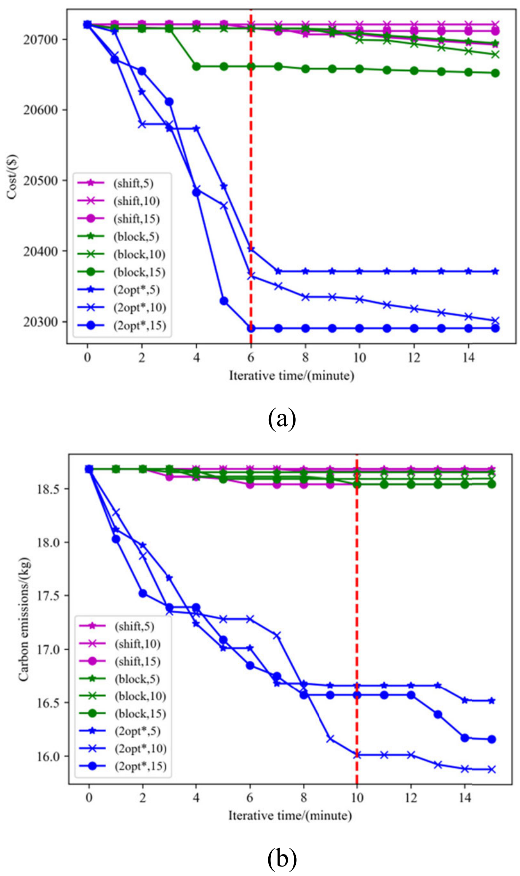


FIGURE 15. **Convergence of the local search method of shift, block, 2opt* and the maximum number of iterations $iter^v_{max}$ for vehicle selection. (a) Performance of three neighborhood Search methods under Cost Optimization; (b) Performance of three neighborhood Search methods under carbon emission optimization.**

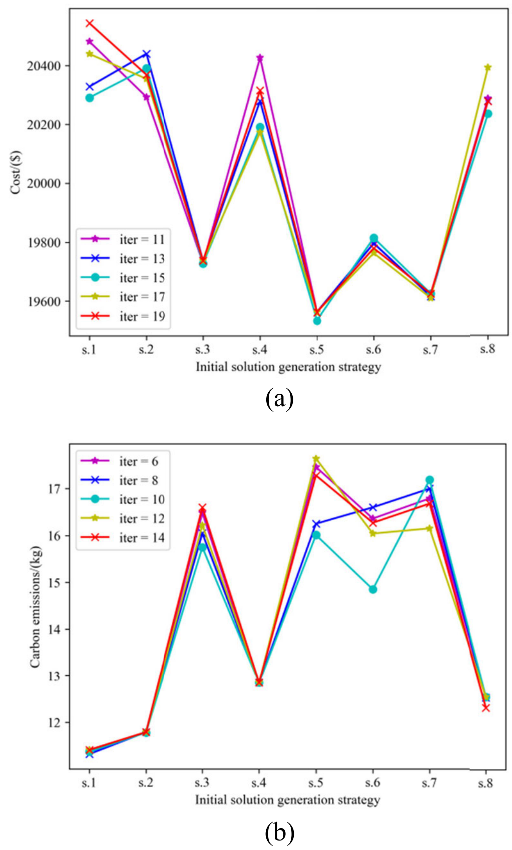


FIGURE 16. **Comparison of optimization results under different initial solution generation strategies and iterations $iter^v_{max}$ for vehicle selection. (a) Performance of eight initial solution generation strategies under Cost Optimization; (b) Performance of eight initial solution generation strategies under carbon emission optimization.**

priority to traditional buses to serve the bus trips. Since unit mileage cost of traditional buses is lower, the operation cost is lower when traditional buses serves more trips; For the carbon emissions. Strategy 1 and strategy 2 can get better optimization results. The major reason is that eBus are zero emission. If eBus served more trips, less carbon emissions is expected in the system comparing to traditional buses.

In terms of the maximum number of iterations $iter^v_{max}$ for vehicle selection, the optimal $iter^v_{max}$ obtained in the previous section are centered and obtained 5 parameters respectively. In some initial solution strategies, different parameters behave differently. However, comparing the 8 strategies, the better the initial solution strategy is, the less influence the $iter^v_{max}$ has on the solutions, as shown in Figure 16.

For the mixed buses scheduling in this paper, different initial solution generation strategies have great impacts on the final optimization results. The major reason is that there are many constraints in the scheduling of mixed buses system, and the degree of local search optimization is limited. If a good initial solution is obtained, a satisfactory solution can be obtained.

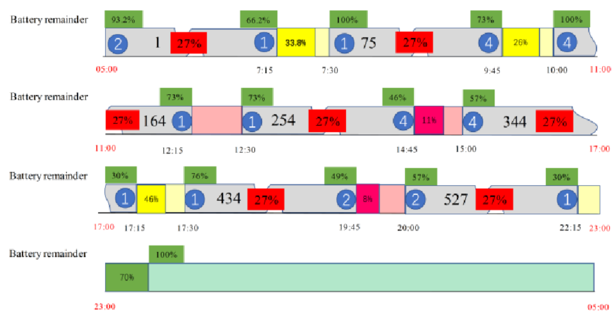


FIGURE 17. **Vehicle and Charging Scheduling of an eBus. The station is marked on both ends of each trip. The number (27%) on the surface of the trip is energy consumption. The number (such as, 33.8%) between the trips is quantity of electricity that charged. The meaning of different colors between trips: Green means low price periods, Yellow means medium price periods, Red means high price periods.**

3) CHARGING SCHEDULING

Considering the "Time-of-use Price" in Beijing, bus companies hope to reduce the costs by optimizing the charging scheduling. In practice, eBus are charged immediately when they arrive at the charging station, without considering the different price of electricity during different time.

Based on the proposed greedy search dynamic selection strategy, Figure17 shows the operation and charging of an eBus in one day after optimization of charging scheduling. One can see that the eBus takes 7 trips, i.e., trips 1, 75, 164, 254, 344, 434, and 527. For detail, the charging scheduling is explained as follows:

(1) The periods between trips 1 and 75 and trips 75 and 164 are middle price periods. Thus, charge the battery to 100% SOC.

(2) The periods between trips 164 and 254 and trips 254 and 344 are high price periods. Therefore, there is no charging between trips 164 and 254. However, if the battery is not charged between trips254 and 344, the remaining energy can't meet the requirement that the battery should not be less than 30% SOC at any time. Therefore, a minimum charge of 11% SOC is selected between trips 254 and 344.

(3) The period between trips 344 and 434 is the medium price period, which is preferred for charging. However, due to the 3 minutes preparing time, the remaining charging time can't charge battery to 100% SOC.

(4) The period between trips 434 and 527 is the high price period, charging 11% SOC is to meet the constraint that the battery should not be less than 30% SOC at any time. After carrying out trip 527, the battery is charged at low price period to 100% SOC.

From the above periodic analysis, it can be seen that no other plan can reduce costs, so the plan is optimal. When charging using the "Charge immediately upon arrival" scheme, the cost of electric charging for the vehicle is 55.4249 \$, and after optimization, the cost of electric charging is 39.5074 \$.

4) SOLUTION RESULTS

For public transport operators, the vehicle number and the corresponding types are determined. In the operations, they pay more attention to reduce operating costs. Therefore, we set $\alpha_1 = 1$ and $\alpha_2 = 0$ for the case study. In addition, from a social point of view, with the consideration of eBus, carbon emissions should be lower. Therefore, case studies are carried out with $\alpha_1 = 0$ and $\alpha_2 = 1$ as well.

The above analysis verifies the applicability of different parameters under different targets. Therefore, this section selects the optimal parameters and compares the performance of different vehicle types. The results are shown in Table11, where the parameters are the initial solution generation strategy, the local search method, the iteration time and the maximum number of iterations $iter^{v}_{max}$ for vehicle selection. P-trips is Passenger-trip; and DH-trip is Deadheading-trip.

From Table 11, one can see when the optimal target is cost, the traditional buses have longer mileage than the eBus; while when the optimal target is carbon emissions, the eBus have longer mileage than the traditional buses.

In addition, we can find that the overall kilometers of DH-trips is larger, this is because we assume that there is only one depot, and vehicles can only depart from one depot. When the first trip does not depart from the depot, the bus must carry out additional DH-trip. Therefore, some buses can be parked at terminals of the bus line to reduce DH-trips during actual operations.

TABLE 11. Optimized solution/(km).

Optimization objective	Parameter	eBus P-trip km	eBus DH-trip km	Traditional bus P-trip km	Traditional bus DH-trip km
Cost	(s.5, 2opt*,6,15)	10479	3616	12846	3833
	(s.7, 2opt*,6,17)	10683	3726.3	12642	3715.2
Carbon emission	(s.1, 2opt*,10,8)	15816	4856.4	7509	2639.4
	(s.2, 2opt*,10,10)	14895	4797	8430	2908.2

TABLE 12. Optimized solution/(\$).

Optimization objective	Parameter	Strategy1	Strategy2	Δf
Cost	(s.5,2opt*,6,15)	1822.12	1588.05	12.85%
	(s.7, 2opt*,6,17)	1837.95	1598.24	13.04%
Carbon emission	(s.1, 2opt*,10,8)	2617.11	2372.69	9.34%
	(s.2, 2opt*,10,10)	2609.88	2382.31	8.72%

The results of the comparison between the optimal charging strategy (Strategy2) presented in this paper and the "Charge immediately upon arrival" strategy (Strategy1) are shown in Table 12. We found that the proposed strategy can reduce the charging cost by 8%-13%. Compared with the result of optimization objective "carbon emission", the result of optimization objective "cost" has a more significant reduction of charging cost, more than 10%. The reason for this result may be that when the optimization objective is cost, the distance of eBus operation is relatively short (as shown in Table 11), the gap between eBus trip chains is relatively large, and the optimization algorithm has a greater chance of charging at the low price stage, so the result of optimization is better; however, when the optimization objective is "carbon emission", the gap of eBus trip chains is small, the optimization opportunity is small, and the optimization effect is limited.

VI. CONCLUSION

In this paper, a Multi-Objective Bi-level programming model is developed to collaboratively optimize the vehicle scheduling and charging scheduling of the mixed bus fleet. Furthermore, a high-efficiency algorithm is designed to solve the proposed model. Case studies are carried out for the scenario with one depot and three bus lines (575 bus trips per day). The results indicate that compared with shift and blocks, 2opt* has good performance in mixed bus operation, and the initial solution generation strategy has great influence on the final optimization results. In addition, comparing with the traditional "charging at arrival" strategy, the charging strategy proposed in this paper can reduce 8%-13% charging costs.

The proposed method provides a proper scheduling and charging strategy of a bus fleet mixed with eBus and traditional buses. Various conditions may be changed due to the introductions of eBus. Consequently, further studies should be conducted about this topic. First, this paper doesn't consider the impact of terrain, passenger capacity and frequent bus start and stop on bus energy consumption and carbon emissions, and this paper assumes constant energy consumption per kilometer and carbon emission per kilometer. Therefore, it is necessary to developed vehicle scheduling models considering proper energy consumption and carbon emission models of buses. Second, this paper does not consider the impact of bus charging strategy on the service life of electric buses, which needs further study. Third, public transport system with multiple depots should be considered in the future studies.

APPENDIX

OPTIMAL PROOF OF CHARGING ALGORITHM

In the charging scheduling part, we adopt a dynamic search algorithm based on greedy strategy. Firstly, according to its periodic characteristics, the optimization of dynamic programming has been guaranteed, and then we prove the optimality of its greedy strategy.

The charging time interval is numbered according to the increasing order of time $k = 1, \ldots, n$; Select the middle and low electricity prices to be named strategy 1, select the high electricity prices to be named strategy 2, strategy set $S = \{strategy1, strategy2\}$.

(1) When $k = 1$, the algorithm chooses strategy 1. We only need to prove that there is an optimal solution that contains strategy 1. Let $A \left\{i_1, i_2, \ldots, i_j\right\}$ be a optimal solution. If $i_1 \neq strategy1$, then replace with strategy 1 to get A',that is:

$$A' = (A - \{i_1\}) \cup \{strategy1\}$$

And strategy 1 is less expensive than i_1, so A' is also a optimal solution to the problem.

(2) let $i_1 = 1, i_2, \ldots, i_k$ be the strategy combination selected by the first k-step order of the algorithm, then there is an optimal solution:

$$A = \{i_1 = 1, i_2, \ldots, i_k\} \cup B$$

If S' is a follow-up strategy combination of $i_1, i_2, \ldots, i_k$:

$$S' = \left\{j|s_j > i_k, j \in S\right\}$$

Then B is a optimal solution of S'. If not, if S' has a solution B' and $\left|B'\right| > |B|$, Then the current optimal solution $\{i_1 = 1, i_2, \ldots, i_k\} \cup B'$ will make the cost of A more, which is in conflict with the optimal solution A.

(3) According to the proof of the inductive basis, the first step of the algorithm to select the least costly strategy can always obtain a optimal solution. Therefore, there is an

optimal solution $B^* = \{i_{k+1}, \ldots\}$ to the sub-problem S'. Since B^* and B are both the optimal solutions of S'. So $|B^*| = |B|$, then:

$$\begin{aligned} A' &= \{i_1 = strategy1, i_2, \ldots, i_k\} \cup B^* \\ &= \{i_1 = strategy1, i_2, \ldots, i_k, i_{k+1}\} \cup \left(B^* - \{i_{k+1}\}\right) \end{aligned}$$

As much as A's cost, it is also an optimal solution. And it exactly includes the strategy of $k+1$ step selection before the algorithm, according to the inductive proposition.

REFERENCES

[1] M. Glotz-Richter and H. Koch, "Electrification of public transport in cities (Horizon 2020 ELIPTIC project)," *Transp. Res. Procedia*, vol. 14, pp. 2614–2619, Jan. 2016.

[2] E. Yao, T. Liu, T. Lu, and Y. Yang, "Optimization of electric vehicle scheduling with multiple vehicle types in public transport," *Sustain. Cities Soc.*, vol. 52, Jan. 2020, Art. no. 101862.

[3] B. Sun, "Optimal bus scheduling considering operating costs and emissions: A multiple objective, mixed integer programming framework," M.S. thesis, Univ. Minnesota, Minneapolis, MN, USA, Dec. 2015.

[4] S. Zhang, Y. Wu, J. Hu, R. Huang, Y. Zhou, X. Bao, L. Fu, and J. Hao, "Can euro V heavy-duty diesel engines, diesel hybrid and alternative fuel technologies mitigate NOX emissions? New evidence from on-road tests of buses in China," *Appl. Energy*, vol. 132, pp. 118–126, Nov. 2014.

[5] G. Carpaneto, M. Dell'Amico, M. Fischetti, and P. Toth, "A branch and bound algorithm for the multiple depot vehicle scheduling problem," *Networks*, vol. 19, no. 5, pp. 531–548, Aug. 1989.

[6] M. Forbes, J. Holt, and A. Watts, "An exact algorithm for multiple depot bus scheduling," *Eur. J. Oper. Res.*, vol. 72, no. 1, pp. 115–124, Jan. 1994.

[7] A. Löbel, "Vehicle scheduling in public transit and Lagrangean pricing," *Manage. Sci.*, vol. 44, nos. 12, pp. 1637–1649, Dec. 1998.

[8] A. Hadjar, O. Marcotte, and F. Soumis, "A branch-and-cut algorithm for the multiple depot vehicle scheduling problem," *Oper. Res.*, vol. 54, no. 1, pp. 130–149, Feb. 2006.

[9] A. Haghani and M. Banihashemi, "Heuristic approaches for solving large-scale bus transit vehicle scheduling problem with route time constraints," *Transp. Res. A, Policy Pract.*, vol. 36, no. 4, pp. 309–333, May 2002.

[10] V. Gintner, N. Kliewer, and L. Suhl, "Solving large multiple-depot multiple-vehicle-type bus scheduling problems in practice," *OR Spectr.*, vol. 27, no. 4, pp. 507–523, Aug. 2005.

[11] S. Kulkarni, M. Krishnamoorthy, A. Ranade, A. T. Ernst, and R. Patil, "A new formulation and a column generation-based heuristic for the multiple depot vehicle scheduling problem," *Transp. Res. B, Methodol.*, vol. 118, pp. 457–487, Dec. 2018.

[12] A.-S. Pepin, G. Desaulniers, A. Hertz, and D. Huisman, "A comparison of five heuristics for the multiple depot vehicle scheduling problem," *J. Scheduling*, vol. 12, no. 1, pp. 17–30, Feb. 2009.

[13] J. P. Fonseca, E. Van Der Hurk, R. Roberti, and A. Larsen, "A matheuristic for transfer synchronization through integrated timetabling and vehicle scheduling," *Transp. Res. B, Methodol.*, vol. 109, pp. 128–149, Mar. 2018.

[14] C. Ciancio, D. Laganà, R. Musmanno, and F. Santoro, "An integrated algorithm for shift scheduling problems for local public transport companies," *Omega*, vol. 75, pp. 139–153, Mar. 2018.

[15] B. Amirhosseini and S. H. Hosseini, "Scheduling charging of hybrid-electric vehicles according to supply and demand based on particle swarm optimization, imperialist competitive and teaching-learning algorithms," *Sustain. Cities Soc.*, vol. 43, pp. 339–349, Nov. 2018.

[16] J. H. Langbroek, M. Cebecauer, J. Malmsten, J. P. Franklin, Y. O. Susilo, and P. Georén, "Electric vehicle rental and electric vehicle adoption," *Res. Transp. Econ.*, vol. 73, pp. 72–82, Mar. 2019.

[17] J.-Q. Li, "Transit bus scheduling with limited energy," *Transp. Sci.*, vol. 48, no. 4, pp. 521–539, Nov. 2014.

[18] M. Wen, E. Linde, S. Ropke, P. Mirchandani, and A. Larsen, "An adaptive large neighborhood search heuristic for the electric vehicle scheduling problem," *Comput. Oper. Res.*, vol. 76, pp. 73–83, Dec. 2016.

[19] M. E. van Kooten Niekerk, J. M. van den Akker, and J. A. Hoogeveen, "Scheduling electric vehicles," *Public Transp.*, vol. 9, nos. 1–2, pp. 155–176, 2017.

[20] E. S. Rigas, S. D. Ramchurn, and N. Bassiliades, "Algorithms for electric vehicle scheduling in large-scale mobility-on-demand schemes," *Artif. Intell.*, vol. 262, pp. 248–278, Sep. 2018.

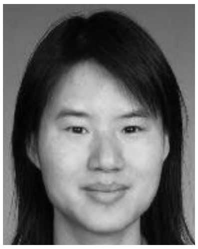
[21] C. G. Hoehne and M. V. Chester, "Optimizing plug-in electric vehicle and vehicle-to-grid charge scheduling to minimize carbon emissions," *Energy*, vol. 115, pp. 646–657, Nov. 2016.

[22] A. González-Garrido, A. Thingvad, H. Gaztañaga, and M. Marinelli, "Full-scale electric vehicles penetration in the Danish Island of Bornholm—Optimal scheduling and battery degradation under driving constraints," *J. Energy Storage*, vol. 23, pp. 381–391, Jun. 2019.

[23] S. Limmer and T. Rodemann, "Peak load reduction through dynamic pricing for electric vehicle charging," *Int. J. Elect. Power Energy Syst.*, vol. 113, pp. 117–128, Dec. 2019.
[24] A. Arif, M. Babar, T. I. Ahamed, E. Al-Ammar, P. Nguyen, I. R. Kamphuis, and N. Malik, "Online scheduling of plug-in vehicles in dynamic pricing schemes," *Sustain. Energy, Grids Netw.*, vol. 7, pp. 25–36, Sep. 2016.
[25] D. Goeke and M. Schneider, "Routing a mixed fleet of electric and conventional vehicles," *Eur. J. Oper. Res.*, vol. 245, no. 1, pp. 81–99, Aug. 2015.
[26] X. He, S. Zhang, W. Ke, Y. Zheng, B. Zhou, X. Liang, and Y. Wu, "Energy consumption and well-to-wheels air pollutant emissions of battery electric buses under complex operating conditions and implications on fleet electrification," *J. Cleaner Prod.*, vol. 171, pp. 714–722, Jan. 2018.
[27] S. Pelletier, O. Jabali, J. E. Mendoza, and G. Laporte, "The electric bus fleet transition problem," *Transp. Res. C, Emerg. Technol.*, vol. 109, pp. 174–193, Dec. 2019.
[28] A. Islam and N. Lownes, "When to go electric? A parallel bus fleet replacement study," *Transp. Res. D, Transp. Environ.*, vol. 72, pp. 299–311, Jul. 2019.
[29] S. Hassold and A. Ceder, "Multiobjective approach to creating bus timetables with multiple vehicle types," *Transp. Res. Rec.*, vol. 2276, pp. 56–62, Jan. 2012.
[30] A. A. Ceder, "Public-transport vehicle scheduling with multi vehicle type," *Transp. Res. C, Emerg. Technol.*, vol. 19, no. 3, pp. 485–497, Jun. 2011.
[31] S. Hassold and A. A. Ceder, "Public transport vehicle scheduling featuring multiple vehicle types," *Transp. Res. B, Methodol.*, vol. 67, pp. 129–143, Sep. 2014.
[32] L. Li, H. K. Lo, and F. Xiao, "Mixed bus fleet scheduling under range and refueling constraints," *Transp. Res. C, Emerg. Technol.*, vol. 104, pp. 443–462, Jul. 2019.
[33] J. Gao, "Research on the pure electric vehicle scheduling problem considering time-of-use price," M.S. thesis, Dept. School Traffic Transp., Beijing Jiaotong Univ., Beijing, China, 2018.
[34] C. Koulamas, S. Antony, and R. Jaen, "A survey of simulated annealing applications to operations research problems," *Omega*, vol. 22, no. 1, pp. 41–56, Jan. 1994.
[35] Y. Deng *et al.*, "Guang Zhou Chun Dian Dong Gong Jiao Che Yu Ran You Gong Jiao Che Jing Ji Xiao Yi Dui Bi(Comparison of economic benefits between electric bus and fuel bus in Guangzhou)," (in Chinese), *J. Chin. Foreign Entrepreneurs*, vol. 2017, no. 24, pp. 154–162, Aug. 2017.
[36] Y. Wang, Y. Huang, J. Xu, and N. Barclay, "Optimal recharging scheduling for urban electric buses: A case study in Davis," *Transp. Res. E, Logistics Transp. Rev.*, vol. 100, pp. 115–132, Apr. 2017.

GUANG-JING ZHOU received the B.S. degree in traffic engineering from the Shandong University of Science and Technology, China, in 2018. He is currently pursuing the master's degree with the School of Traffic and Transportation, Beijing Jiaotong University. His current research interests include transit timetabling and vehicle scheduling.

DONG-FAN XIE received the B.S. degree in traffic engineering and the Ph.D. degree in traffic and transportation planning and management from Beijing Jiaotong University, Beijing, China, in 2005 and 2011, respectively. From May 2011 to May 2015, he was a Research Fellow with the School of Civil and Environmental Engineering, Nanyang Technological University. From May 2012 to December 2016, he was a Lecturer with the School of Traffic and Transportation, Beijing Jiaotong University, where he is currently an Associate Professor. His current research interests include traffic flow modeling, pedestrian modeling, and network traffic dynamics.



XIAO-MEI ZHAO received the B.S. and M.S. degrees in control engineering from the Shaanxi University of Science and Technology, China, in 1997 and 2000, respectively, and the Ph.D. degree in control science from Zhejiang University, China, in 2003. From April 2003 to November 2014, she was a Lecturer and an Associate Professor with the School of Traffic and Transportation, Beijing Jiaotong University, where she has been a Professor with the School of Traffic and Transportation Engineering, since 2014. Her research interests include traffic flow modeling, traffic control, and traffic dynamics.

CHAORU LU received the B.S. degree in civil engineering from the Hunan University of Science and Technology, in 2011, the M.S. degree in civil engineering from Texas A&M University-Kingsville, in 2014, and the Ph.D. degree in civil engineering from Iowa State University, in 2017. He is currently a Postdoctoral Fellow with the Norwegian University of Science and Technology. His research interests include connected and automated vehicles, traffic flow theory, and intelligent transportation systems.