Integrating Transit Route Network Design and Fast Charging Station Planning for Battery Electric Buses

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ABSTRACT There are currently rising applications of battery electric buses in public transportation system, given their energy efficiency and societal benefits. However, limited range and time-consuming charging processes significantly reduce the operational efficiency of battery electric buses system. Thanks to fast charging technology, battery electric buses can run continuously through rational planning of fast charging system. Therefore, to achieve an effective and economic electric transit route network, electric transit route network and fast charging stations should be simultaneously and systematically deployed. This study develops a bi-level programming framework to formulate the electric transit route network design problem. Where, the upper-level model is to determine the route structure and charging station location to optimize the total costs of both user and operator, the lower-level passenger assignment model is to calculate user cost for upper-level model. Then, the proposed model is solved by a modified genetic algorithm (GA), which can search all possible route structures through specifically designed genetic operators. A numerical example from Swiss road network is employed to demonstrate the applicability of bi-level model and performance of modified GA.

INDEX TERMS Battery electric bus, transit route network design, frequency setting, fast charging.

I. INTRODUCTION

In recent years, battery electric buses (BEBs) have been regarded as the most promising alternatives for conventional buses equipped with internal combustion engines towards reducing exhaust emission in public transportation systems, given the advantages they have in zeros emission and high energy efficiency [1], [11]. Beijing, a city with approximately eight million bus trips on a weekday, will replace all its diesel buses with new energy vehicles by the end of 2020, and over 90% of these new energy vehicles are electric buses. Shenzhen is progressing even faster, buses in the major city have all been electrified at the end of 2017 [24].

Restricted by the limited driving range and the longer charging duration, early models of BEBs cannot compare with conventional diesel buses. However, recent advances in fast charging technologies have helped facilitate the penetration of BEBs. A fast charging station offers more than 150 kW charging power, which can fully charge a BEB with battery capacity of 45 kWh in 18 minutes [35]. With fast charging technologies, BEBs can utilize dwelling time at bus stop or terminal to recharge batteries and thus can continuously carry out operations [22], [31].

For the transit route network design problem of BEBs system, in addition to determine transit lines and stop nodes to meet demand patterns, extra elements like the battery size, charging time and charging station requirements of BEBs should also be considered explicitly during the design process. Due to the limited battery size, BEBs often need daytime charging and thus incur a long charging delay, the need to recharge BEBs while offering a good level of passenger service brings significant challenges for planning the transit network operated by BEBs. Although the fast charging technologies have the potential to reduce the delays involved in stopping for bus charging, it will lead to a considerable large increase in operation cost, thus the implementation cost...
of fast charging stations should be considered at the planning stage.

The trade-off between passenger satisfaction and operator cost is well recognized in transit network design problem, another trade-off between battery capacity requirement of BEBs and deployment of charging stations is also important in electric transit route network design problem. For a single electric transit line with fast charging system, increasing the density of fast charging stations could lead to reducing the on-board battery sizes of BEBs, hence jointly optimizing on-board battery sizes and allocation of fast charging stations can further reduce the upfront costs of the BEBs system. With regards to the proposed electric transit route network design problem, we focus on reasonable implementation of fast charging stations to improve operation efficiency and minimize the charging delay for BEBs system.

For successful integrating BEBs into the public transportation system, we need to simultaneously tackle the route design, fast charging stations locating, frequency and battery size setting problems. The research is proposed to develop decision-support tools for the planning of electric transit networks, or at least accommodate the gap between high passenger demand and inefficient operation of city BEBs. However, developing comprehensive design model and efficient algorithm for electric transit route network design problem brings more challenge. For one thing, designing electric transit routes needs to consider limitations and infrastructure requirement of BEBs. For another thing, a realistic description of the electric transit route network design problem requires more complicated optimization model, which may lead to a significant computation burden in performing thorough search of solution space, even though the general network design problem is already NP-hard [17].

To address the above problem, this study proposes a bi-level framework to design electric transit routes, determine deployment of fast charging stations and on-board battery size of BEBs on each route. The bi-level framework is solved through a modified genetic algorithm (GA), which relies on GA to design potential route structures and a neighborhood search algorithm to optimize the route frequency. With a feasible route structure and corresponding frequencies, the total passengers’ travel time and total operator cost are separate calculated by solving the transit assignment model and a fast charging station planning model. We then examine the effects of parameters such as fleet size, dwell time and battery price on the objective value.

### A. LITERATURE REVIEW

Due to its practical meaning, transit network design problem has received considerable interests in the literature for five decades [12]. Transit network design defining the route structures and associated operational characteristics such as frequencies and vehicle allocation is the strategic planning process for urban public transportation system [14], [17]. Guihaire and Hao [10], Kepaptsoglou and Karlaftis [17] and Ibarra-Rojas et al. [14] provide comprehensive review of previous work. Some of the studies are summarized in Table 1.

However, only a few research achievements have incorporated environment impact as design objectives in the transit network design problem. Delle Site and Filippi [5], [6] seek to minimize fuel consumption when planning a public bus system from the operator perspective, where bus mileages are used as an index to the character of fuel consumption. Gallo et al. [9] incorporate external cost minimization in designing a transit network to evaluate the benefits due to car use reduction. Some studies consider the mixed fleets of new energy buses and fossil fuel buses in modeling the transit network design problem. Beltran et al. [1] investigate the new energy vehicle allocation problem in bus fleet, they address the problem in the network design procedure with green fleet size constraint. Fusco et al. [7] conduct a cost effectiveness evaluation for operating electric bus fleet on some transit routes, numerical results show that introducing the electric vehicle can lead to higher investment cost but lower environment and energy cost. Jovanovic et al. [15] address a neuro-fuzzy approach for planning green vehicle lines and distributing green vehicles, taking adverse gases and
buses noise as externalities of environment. Pternea et al. [29] develop a nonlinear programming model for the transit network design problem which incorporates environmental impacts and deployment of electric buses, an iterative approach coupled with GA is introduced to solve a real problem in network of Heraklion.

As for the case of fully electric vehicle fleet, studies mainly concentrate on deployment of charging infrastructures and sizing of battery capacity for ensuring the normal operation of BEBs system. Chen et al. [3] develop a mixed integer linear model to system planning of feeding stations in an electrical transit bus system, including battery capacity, locations and types of feeding stations and so on. Ke et al. [16] focus on planning a fully electric bus system in Penghu, a comprehensive model is introduced to reduce the total construction cost including electric buses, batteries, chargers and electricity. Kunith et al. [18] recently develop a mixed integer programming model to jointly optimize charging infrastructure and on-board battery sizes for a multi-line BEBs system. In the same line, Liu et al. [23] aim to build a fast charging system on existing transit network, they first formulate a mixed integer linear model to determine deployment of fast charging stations and battery sizes, then a corresponding robust model is developed to handle the electricity consumption uncertainty of BEBs. So far, only two studies have addressed the transit network design problem with fully electric vehicle fleet and optimizing charging infrastructure. Iliopoulou et al. [12] present a bi-level programming model to jointly allocate fast charging facilities and design transit routes for a BEBs system. However, they take battery sizes of BEBs as exogenous and do not consider the route choice of passengers. Iliopoulou and Kepaptsoglou [13] extend their previous bi-level model to handle the combined route network layout and charging facilities location problem for on-line electric buses system.

Solution algorithm designing is also a challenge for the transit network design problem. As reported by Kepaptsoglou and Karlaftis [17], The traditional transit network design problem belongs to NP-hard problem which cannot be solved using accurate algorithm. Some studies focus on the use of metaheuristic approaches in the traditional transit network design problem. Among these algorithms, GA is one of the most popular methods. Chakroborty and Wivedi [2] use a GA based search procedure for obtaining optimal route layout, the results of numerical analysis show that the GA is preferable to the optimization tools. Ngamchai and Lovel [28] explore seven genetic operators to facilitate the solution search in different transit network design problem. Peterli [30] test a heuristic bus network design model on a real medium network example, the result reports that GA is efficient and can produce rational bus network. Szeto and Wu [33] employ a GA approach hybridized with neighborhood search heuristic to tackle the transit network design and frequency setting problem simultaneously, they develop specific genetic operators and diversity control mechanism to improve the searching capability of GA.

In recent years, shortage of refueling infrastructure becomes the most cited bottleneck which restricts the adoption of alternative-fuel vehicles. To alleviate these problems, there have been increasing research interests focused on the methods of charging infrastructure planning. Lim et al. [21] adopt a flow-refueling location model to locate refueling stations for alternative-fuel vehicles. They develop three heuristic algorithms for solving the considered problem. Kim and Kuby [19] extend the flow-refueling location model to examine the effects of path deviations for vehicles refueling on the optimal locations of fueling stations. Sathaye and Kelley [37] investigate a large-scale charging stations planning problem with demand uncertainty, and they introduce a continuous charging station location model to guide publicly funded charging station locations to supplement private charging infrastructure. Wu and Sioshansi [38] characterize the uncertainty of electric vehicle flow by randomly sampling the tour-record data, a stochastic flow capturing location model is formulated to optimize fast charging station locations by capturing maximum expected volume of electric vehicles. Miralinaghi et al. [27] formulate a robust optimization model to study the refueling station location problem with demand uncertainty and multi time periods. Moreover, they propose a link-based bi-level model to describe the route choice behavior of drivers regarding the construction of refueling stations. Miralinaghi et al. [26] identify the approaches including construction of charging station or transformation of existing gas stations to promote electric vehicle adoption, they propose a bi-level model for the multi-period planning of charging station under budget restrictions.

B. FOCUS OF THIS STUDY

As mentioned before, only a few articles have tried to address the electric transit network design problem while considering the deployment of charging station location. None of study addresses the integration of the route design, fast charging station planning, battery capacity and frequency setting for public transportation system with a fully BEBs fleet. In the present study, we consider the electric transit network design problem in a fast charging BEBs system, and purpose to minimize the total passengers and operator cost in the system by simultaneously determining the transit routes, location of fast charging stations and battery sizes. Under some common assumptions, we formulate the proposed problem into a bi-level programming problem, the upper-level problem is a nonlinear mixed integer programming problem to minimize weighted sum of unsatisfied demand, total user and operator cost, and the lower-level problem represents a transit passenger assignment problem to capture the total passengers’ travel time. A modified genetic algorithm (GA) is designed to solve the bi-level problem.

The main contributions of this study are listed as follows:

(1) Multiple fast charging stations locating problem is addressed during the electric transit network design process.

(2) In the methodological aspects, a bi-level programming mode is proposed to tackle the electric transit network
design problem. The model is able to minimize the total investment cost while providing high quality transport service.

(3) We develop a modified GA for the bi-level mode, the modified GA incorporates a neighborhood search to optimize the route frequency and evaluate fitness of solution.

(4) The key parameters, which influence the passenger demand satisfaction and fast charging station allocation, are investigated in the number experiments.

In the remainder of this paper, some need concepts, assumptions and bi-level model are presented in Section 2. Considering the problem is NP-hard, Section 3 proposes a modified genetic algorithm. Numerical example from Swiss road network is conducted in Section 4. Lastly, Section 5 contain a few concluding remarks.

II. PROBLEM OUTLINE AND NI-LEVEL MODEL

A. PROBLEM OUTLINE

At the operational level, ideally, there should be as larger batteries as possible to provide energy for BEBs, however, this is not feasible due to relatively limited bus size and the trade-off between the weight of battery pack and the seating capacity [31]. Moreover, there is a trade-off between battery capacity requirement of BEBs and deployment of charging stations. We consider a single transit route including N bus stops depicted in Fig. 1, terminals 1 and N are the starting point and ending point for the route, and the length of route is 18 km. For the diesel bus system, the dwelling time of each bus at intermediate stops and terminal stops is 1 minutes and 15 minutes. Assuming that a fleet of BEBs are operated along the route. A service loop for a BEB is a journey in which the BEB operates back and forth between the starting point and ending point, i.e., $1 \rightarrow N \rightarrow 1$. After finishing a service loop, the BEB will be fully charged at the starting point, then it starts next service loop. Assuming that the energy consumption of BEBs is 2.5 kWh/km, we analyze the following two cases of fast charging station allocation.

Case 1: Two 90 kW fast charging stations are deployed at terminals 1 and N, respectively. The BEB can add 9 km of driving range by utilizing dwelling time at ending point to quickly charge battery. In order to complete a service loop, the BEB need be equipped with a 67.5 kWh battery. Furthermore, the dwelling time of BEBs at the starting point needs to be extend from 15 minutes to 45 minutes to fully charge battery.

Case 2: Two 90 kW fast charging stations are deployed at terminals 1 and N, and five 270 kW fast charging stations are evenly deployed at intermediate stops along the route. During a service loop, the BEB can add 1.8 km of driving range at each 270 kW fast charging station. Therefore, a 22.5 kWh battery can enable BEB to complete a service loop. Furthermore, the BEB could be fully charged during 15 minutes dwelling time at the starting point.

Under Case 2, BEBs are as capable as the diesel buses in terms of operating time. Compared with Case 1, the cost of installing fast-charging stations is higher at the Case 2, but Case 2 has a lower cost of batteries and can reduce passenger waiting time significantly. So, the adoption of BEBs requires comprehensive planning on operation strategies and fast charging station deployment.

The transportation network studied in this paper is represented by a directed graph $G(Z, L)$, where nodes set $Z$ contains the candidate BEBs stops and the edges set $L$ contains links between two bus stops. We also add a dummy node 0 to facilitate the construction of model. Given origin-destination (OD) matrix and a road network, the electric transit network design problem refers to the generation of efficient electric transit network and associated deployment of fast charging station. Each bus line will be served by a fleet of BEBs, as shown in Fig. 2. A BEB cyclic operates on a line and can charge battery at the bus stops with fast charging station installed. Meanwhile, the charging time of BEBs at bus stop is limited by its dwelling time. The quality of each network is examined in terms of passenger travel time and investment cost of batteries and fast charging stations.
at the starting point so as not to delay the subsequent service loop.

The main assumptions considered in the models are:

1. If there is a fast charging station sitting in a bus stop, BEBs can employ its dwelling time at this bus stop to recharge battery.
2. BEBs will be fully charged at starting point of each route ahead of next service loop.
3. The energy consumption of BEBs on each link depends on the link length only.
4. Transit passenger demand is aggregated at bus stops and the origin-destination matrix is fixed.

**B. BI-LEVEL FORMULATION**

According to above assumptions, the optimization model for describing the electric transit route network design problem could be formulated as a bi-level model. The all notations used in this paper are listed in Table 2:

1) UPPER-LEVEL PROBLEM

\[
\begin{align*}
\min_{\{X_{ij},E,ES,e,d\}} & \ B_1 \sum_{w \in W} d^{w,a} + B_2 \left( \sum_{w \in W} \sum_{(i,j) \in L_{d}} \sum_{(i',j') \in L_{r}} \sum_{(i',j') \in L_{s}} c_{ij}X_{ij}^{w,t} \right) \\
& + \sum_{w \in W} \sum_{i \in I} \psi_{ij}^{w} + \sum_{w \in W} \sum_{(i,j) \in L_{r}} \mu_{ijr}X_{ijr}^{w,t} \\
& + B_3 \left( \max_{r=1} \sum_{i \in Z_U} \sum_{g \in G} d_{r}^{\text{charger}} \delta_{g}^{r} \right)
\end{align*}
\]

subject to

\[
\begin{align*}
\sum_{j \in U \cup \{0\}} X_{ijr} = 1, \quad \forall r = 1 \text{ to } R_{\text{max}} \\
\sum_{i \in U \cup \{0\}} X_{i0r} = 1, \quad \forall r = 1 \text{ to } R_{\text{max}} \\
\sum_{i \in U \cup \{0\}} X_{ijr} - \sum_{j \in U \cup \{0\}} X_{ijr} = 0, \\
\forall j \in Z_U, \quad r = 1 \text{ to } R_{\text{max}} \\
\sum_{i \in Z_U \cup \{0\}} X_{ijr} \leq 1, \quad \forall j \in Z_U, \quad r = 1 \text{ to } R_{\text{max}} \\
\sum_{i \in Z_U \cup \{0\}} X_{ijr} \leq 1, \quad \forall i \in Z_U, \quad r = 1 \text{ to } R_{\text{max}} \\
X_{ijr} = 0, \quad \forall j \in Z_U, \quad r = 1 \text{ to } R_{\text{max}} \\
T_r \leq T_{\text{max}}, \quad \forall r = 1 \text{ to } R_{\text{max}} \\
\max_{r=1} \sum_{i \in Z_U} \sum_{j \in U \cup \{0\}} X_{ijr} (c_{ij} + s_t) - s_t, \quad \forall r = 1 \text{ to } R_{\text{max}} \\
\sum_{r=1}^{R_{\text{max}}} \zeta_{r} (1 - X_{00r}) \leq \bar{W} \\
\zeta_{r} = [f \cdot T_r] + 1, \quad \forall r = 1 \text{ to } R_{\text{max}} \\
\min_{r=1} \left( 1 - X_{00r} \right) \leq f r, \quad \forall r = 1 \text{ to } R_{\text{max}} \\
\sum_{i \in Z_U} X_{ijr} \leq S_{\text{max}}, \quad \forall r = 1 \text{ to } R_{\text{max}} \\
\sum_{g \in G} \delta_{g}^{r} \leq 1, \quad \forall j \in Z_U \\
X_{ijr} (E_{ijr} - E_{ir} + E_{JU} - ES_{jr}) = 0, \quad \forall i \in Z_U, \quad j \in Z_U, \quad r = 1 \text{ to } R_{\text{max}}
\end{align*}
\]

**TABLE 2. Notations and parameters involved in formulating process.**

| Symbol | Description |
|--------|-------------|
| Variables | |
| $x_{ijr}^{w,t}$ | Volume of passenger flow on transit link $(i,j)$ for OD pair $w$ |
| $y_{ijr}^{w}$ | Expected arrival time of passengers at node $i$ for OD pair $w$ |
| $a_{ijr}^{w,t}$ | Sum of demand for OD pair $w$ using the transit $t$ |
| $a_{ijr}^{w,a}$ | Sum of demand for OD pair $w$ by walking |
| $X_{ijr}$ | $X_{ijr}$ = 1 if route $r$ terminates at node $i$; $X_{ijr} = 0$, otherwise |
| $X_{ijr}$ | $X_{ijr}$ = 1 if route $r$ is practically nonexistent; $X_{ijr} = 0$, otherwise |
| $X_{ijr}$ | $X_{ijr}$ = 1 if route $r$ originates at node $i$; $X_{ijr} = 0$, otherwise |
| $X_{ijr}$ | $X_{ijr}$ = 1 if route $r$ pass through node $j$ immediately after node $i$; $X_{ijr} = 0$, otherwise |
| $f_{r}$ | Frequency of route $r$ |
| $E_{ijr}$ | Battery power remaining of a BEB when it leaves stop $i$ on route $r$ |
| $E_{ijr}$ | Energy supply at station $j$ for an electric bus from route $r$ |
| $a_{r}^{w,max}$ | Battery size for electric buses on route $r$ |
| Parameters | |
| $I_{ij}$ | Frequency of transit link $(i,j)$ |
| $k_{cap}$ | Capacity of a bus |
| $c_{t}$ | Passengers’ travel time by walking |
| $\mu$ | Travel time of boarding links |
| $D_{w}$ | Total passenger demand for OD pair $w$ |
| $W_{r}$ | Input-output vector for OD pair $w$, it has only two non-zero components: the value of one component is 1 corresponding to origin $i$; the value of the other component is -1 corresponding to destination $s$ |
| $A$ | Node-link incidence matrix for the lower-level transit network |
| $B$ | In-vehicle travel time on the shortest path between stops $i$ and $j$ |
| $e_{upper}$ | Upper limit of remaining battery power of a BEB |
| $e_{lower}$ | Lower limit of remaining battery power of a BEB |
| $f_{min}$ | Minimum frequency of a route |
| $R_{\text{max}}$ | Maximum allowable number of transit routes |
| $S_{\text{max}}$ | Maximum allowable number of stops on a transit route |
| $T_{\text{max}}$ | Maximum allowable trip time of route |
| $M_{t}$ | A very large value |
| $W_{r}$ | Maximum BEBS’ fleet size |
| $P_{t}$ | Power of type $t$ charging stations |
| $s_{t}$ | Average time for stopping at a node |
| $s_{t}$ | Average time for stopping at a terminal |
| $E_{G_{ijr}}$ | Energy required to travel between nodes $i$ and $j$ for route $r$ |
| $d_{r}^{\text{battery}}$ | Amortized battery cost per kWh |
| $d_{r}^{\text{charger}}$ | Amortized installation cost of a type $g$ fast-charging station |
| $B_{1}$ | Weights associated with unsatisfied demand |
| $B_{3}$ | Weights associated with passengers’ travel time |
| $B_{5}$ | Weights associated with total operator cost |
| Functions | |
| $T_{r}$ | Trip time for a BEB on route $r$ |
| $G_{0}$ | Total number of BEBSs on route $r$ |
| Sets | |
| $w$ | Set of OD pairs |
| $G$ | Set of fast charging station types |
| $A_{t}$ | Set of nodes in the upper-level transportation network |
| $a_{t}$ | Set of transit links in the lower-level transit network |
| $I_{r}$ | Set of bus stops in the lower-level transit network |
| $U$ | Set of original nodes in the upper-level transportation network |
| $V$ | Set of terminal nodes in the upper-level transportation network |
| $L_{r}$ | Set of boarding links in the lower-level transit network |
| $L_{b}$ | Set of alighting links in the lower-level transit network |
chooses the optimal path with minimal expected total cost ofenger flow assignment, and it assumes that each passengerBased on the electric transit route network determined by2) LOWEL-LEVEL PROBLEMensures BEBs can return from ending point to starting point.

\[
\sum_{g \in G} s_{g} P_{g}^{s} g_{j} - ES_{jr} \geq -M (1 - \sum_{i \in ZU, \ j \neq j} X_{ijr}),
\]

\[
\forall j \in ZU, \ r = 1 \text{ to } R_{\text{max}}
\]

\[
X_{0ir} (E_{ir} - \epsilon^{\text{upper}} e_{r}^{\text{max}}) = 0,
\]

\[
\forall i \in ZU, \ r = 1 \text{ to } R_{\text{max}}
\]

\[
E_{ir} - EC_{ijr} - \epsilon^{\text{lower}} e_{r}^{\text{max}} \geq -M (1 - X_{ijr}),
\]

\[
\forall i \in ZU, j \in ZU, \ r = 1 \text{ to } R_{\text{max}}
\]

\[
e^{\text{upper}} e_{r}^{\text{max}} - E_{ir} \geq -M (1 - \sum_{i \in ZU \cup \{0\}} X_{ijr}),
\]

\[
\forall i \in ZU, \ r = 1 \text{ to } R_{\text{max}}
\]

\[
e_{r}^{\text{max}} \geq 0, \ \forall r = 1 \text{ to } R_{\text{max}}
\]

\[
X_{0ir} \left( \sum_{g \in G} s_{g} P_{g}^{s} g_{r} \geq (e^{\text{upper}} - \epsilon^{\text{lower}} e_{r}^{\text{max}}) \right) = 0,
\]

\[
\forall i \in ZU, \ r = 1 \text{ to } R_{\text{max}}
\]

\[
X_{ior} \left( E_{ir} - \sum_{i \in ZU \cup \{0\}} X_{ijr} + \sum_{j \in ZU} ES_{jr} \right.
\]

\[
\geq \epsilon^{\text{lower}} e_{r}^{\text{max}} \right) = 0, \ \forall i \in ZU, \ r = 1 \text{ to } R_{\text{max}}
\]

The objective function is the weighted sum of the total unsatisfied demand, total passengers’ travel time and total operator cost, where total operator cost includes the upfront cost of battery and fast charging stations.

Constraints (1) and (12) are route location constraints. Constraint (1) restricts that all the BEBs routes start from original nodes in the transportation network. Constraint (2) restricts that all the BEB routes end at a terminal node. Constraint (3) ensures that any intermediate node on a route has one preceding node and one following node. Constraints (4) and (6) require each node can be visited only once by a BEB route. Constraint (7) evaluates the trip time of BEB on a route. Constraint (9) specifies the maximum number that BEBs can be operated. Constraint (11) specifies the lower bound of frequency over each route. Constraint (12) restricts the total number of bus stops on a route.

Constraint (13) ensures that a bus stop only can get one choice of fast charging station. Constraint (14) ensures the energy balance of BEBs. Constraint (15) ensures that opportunity charging happens at a bus stop only when a fast charging station has been installed, and that the energy supply is restricted by the dwell time of BEBs. Constraint (16) determines the initial battery power. Constraints (17) and (18) dictate the lower bound and upper bound of battery remaining for BEBs. Constraint (20) ensures BEBs can be fully charged during its dwelling time at the starting point. Constraint (21) ensures BEBs can return from ending point to starting point.

2) LOWEL-LEVEL PROBLEM

Based on the electric transit route network determined by the upper-level model, the lower-level model conducts a passenger flow assignment, and it assumes that each passenger chooses the optimal path with minimal expected total cost of public transit [36]. In this paper, the transit assignment model proposed by Spiess and Florian [32] is introduced to capture the passenger path choice behavior. For modeling, we extend the electric transit route network by adding additional nodes and links.

Fig. 3 is a structure of a transit system with two transit routes, each bus stop in the new network has a corresponding boarding node, and they are connected through a pair of boarding and alighting links. The attributes of each link include travel time, capacity and frequency. Since the alighting links are for the purpose of connecting, the travel time of alighting links is set to zero, the corresponding capacity and frequency are very large. To capture the transfer penalty, the travel time of boarding links is set to a special value \( \mu \), the frequency of boarding link is set to be equal to the frequency of transit route which it connected, and the capacity of boarding link is very large. Thus, passengers are required to spend an additional boarding time whenever they transfer from one route to another. The frequency of a transit link is equal to the frequency of corresponding route, and the capacity of transit link is equal to its frequency multiplied by the passenger capacity of BEBs.

Considering the OD matrix is fixed and the link capacity is limited, some demand may not be satisfied for a given transit network. To properly serve the unsatisfied demand, we set a virtual walk link to connect each OD pair, both of capacity, frequency and trip time for virtual links are set to relatively large values. Therefore, the passenger flow on a virtual link at equilibrium state is exactly equal to the unsatisfied demand for its corresponding OD pair.
Based on the network representation, we formulate the transit assignment problem as a linear programming model:

\[
\text{Min} (x, \psi, d) \sum_{w \in W} \sum_{(i,j) \in L_d} c_{ij} x_{ij}^{w,t} + \sum_{w \in W} \sum_{i \in I} \psi_i^w + \sum_{w \in W} c_0 d_{w,a} + \sum_{w \in W} \sum_{(i,j) \in L_f} h x_{ij}^{w,t}
\]

subject to

\[
d_{w,t}^{a} + d_{w,a} = D_w, \quad \forall w \in W \tag{22}
\]

\[
Ax_{i,j}^{w,t} = H_w d_{w,t}, \quad \forall w \in W \tag{23}
\]

\[
x_{i,j}^{w,t} \geq 0, \quad \forall w \in W, \ (i,j) \in L_d \tag{24}
\]

\[
\psi_i^w \geq 0, \quad \forall i \in I, \ w \in W \tag{25}
\]

\[
x_{i,j}^{w,t} \leq f_{i,j} \psi_i^w, \quad \forall (i,j) \in L_f, \ i \in I, \ w \in W \tag{26}
\]

\[
\sum_{w \in W} x_{i,j}^{w,t} \leq f_{i,j} k_{\text{cap}}, \quad \forall (i,j) \in L_t \tag{27}
\]

The objective function is the sum of the total passengers’ in-vehicle travel time, total passengers’ waiting time, total unsatisfied demand and total passengers’ boarding time. Constraints (22) ensures that the sum of satisfied demand and unsatisfied demand is equal to the total demand from each OD pair \(w\). Constraint (23) ensures the flow balance. Constraints (24) and (25) are non-negativity conditions. Constraint (26) specifies the relationship between frequency, link flow and waiting time. Constraints (27) shows the capacity constraint.

The flow chart of the bi-level optimization structure is presented in Fig. 4, which describe the input, output and relationship between upper-level and lower-level problem.

III. SOLUTION METHOD

The proposed bi-level problem, including the transit network design and fast charging stations planning, is indeed NP-hard and intractable. In this section, a modified GA is developed to solve the bi-level model.

A. REPRESENTATION SCHEME

The solution of GA means a set of routes containing a preset number of \(R\) possible routes. It can be represented as a string of nodes with \(R\) segments, where each segment represents a route, and a node in the segment represents a stop of the corresponding route. Fig. 5 shows a solution representation scheme of GA. Since the maximum allowable number of bus stops for each route is \(S\), then a solution can be represented by a chromosome with length \(R \times S\), and a node with a positive value corresponds to a bus stop. When the number of nodes in a route is smaller than \(S\), the rest of the node values are set to zero.

B. INITIALIZATION PROCEDURE

In this paper, a Make-Small-Change procedure, introduced in Chakroborty and Wivedi [2] and extended in Fan et al. [8], is employed for generating the initial population representing route sets. First, estimate the activity level for all available bus stops, the activity level representing the total travel demand at the bus stops, then select at random a bus stops be the first bust stops for each route, the probability of a stop to be chosen is equal to its share of total travel demand. Second, for each route, the rest stops are selected from the nodes adjacent to the last stop, the selection probability of a stop is its activity level divided by total activity level of all adjacent nodes. These steps are repeated until the number of stops on each route reaches \(S\) or there is no adjacent node of last stops that has not been inserted in the current route.

C. FITNESS EVALUATION AND FREQUENCY SETTING

In this paper, we use the objective value of the upper-level model as fitness measure for the GA solution, it is a weighted
sum of total unsatisfied demand, total passengers’ travel time (TPT) and total operator cost (TOC). Whenever the fitness of a solution is evaluated, the corresponding optimal frequencies for the solution need to be found using a frequency setting heuristic method, which will be described later in this paper. Moreover, the total unsatisfied demand and TPT are calculated by solving the lower-level model, and the TOC is calculated by solving a fast charging station planning model presented by Liu et al. [23].

For rationally planning fast charging station in a transit network, we assume that the charging stations deployed at initial station and terminal station of a route can only be used by BEBs from this route. This implies that BEBs can utilize the long dwell time at initial station or terminal station to get fully charged, and avoid queuing at the charging station. For a given transit route set, let \( N \) denote the set of bus stations of all routes, \( N_r \) denotes the set of all bus stops from the route \( r \), \( e_r \) represents initial station of route \( r \). The dwell time \( s_j \) at station \( j \in N_r \) is longer than that at intermediate stations, where \( N_r \) is the set that includes the initial station and terminal station of route \( r \), \( L_r \) denotes the set of all transit links forming the route \( r \). The notations for the rest of variables of the model are listed in Table 2.

The fast charging station planning model is to determine the on-board battery sizes of BEBs, locations and types of fast charging stations for a given transit route set, such that the total construction cost including charging station and batteries is minimized. It can be formulated as follows:

\[
\text{Min} \left( E_a, e, b \right) = \sum_{r=1}^{R} d_{\text{battery}} e_{r} \\max + \sum_{i=1}^{N} \sum_{g \in G} d_{g} e_{g} \\max + \sum_{r=1}^{R} \sum_{i \in N_r} \sum_{g \in G} d_{g} e_{g} \\max \\
\text{subject to} \\
\sum_{g \in G} \delta_{g}^{i} \leq 1, \forall j \in N \\
\sum_{g \in G} \delta_{g}^{i} \leq 1, \forall i \in N_r, r = 1 \text{ to } R_{\max} \\
E_{i/r} = e_{\text{upper}} e_{r} \\max \, , \\
\forall i \in o_r, r = 1 \text{ to } R_{\max} \\
E_{i/r} = E_{i/r} - EC_{ij} + ES_{j/r}, \\
\forall (i, j) \in L_r, r = 1 \text{ to } R_{\max} \\
\sum_{g \in G} s_{j/g} P_{g} \delta_{g}^{i} \geq ES_{j/r}, \forall j \in N_r, r = 1 \text{ to } R_{\max} \\
\sum_{g \in G} s_{j/g} P_{g} \delta_{g}^{i} \geq ES_{j/r}, \forall j \in N_r, r = 1 \text{ to } R_{\max} \\
E_{i/r} - EC_{ij} \geq e_{\text{lower}} e_{r} \\max \, , \\
\forall (i, j) \in L_r, r = 1 \text{ to } R_{\max} \\
e_{\text{upper}} e_{r} \\max \geq E_{i/r}, \forall i \in N_r, r = 1 \text{ to } R_{\max} \\
e_{r} \\max \geq 0, \forall r = 1 \text{ to } R_{\max} \\
\delta_{g}^{i} \in [0, 1], \forall j \in N \\
\delta_{g}^{i} \in [0, 1], \forall i \in N_r, r = 1 \text{ to } R_{\max} 
\]

**TABLE 3. Frequency setting heuristic.**

| Algorithm 1: frequency setting heuristic method. |
|--------------------------------------------------|
| **Input:** Route set, minimum frequency and fleet size; |
| **Output:** Fitness of route set, optimal frequency of each route and deployment of fast charging station; |
| 1: Calculate the minimum number of bus required by each route: \( V_{min}^{r} = 2f_{min} T_{r} \), then allocate available buses to all routes and ensure the minimum number of bus requirement is met. |
| 2: For \( r = 1 \) to \( R_{\max} \) |
| If number of buses on route \( r \) is larger than \( V_{min}^{r} \) |
| Dispatch a bus from route \( r \) to route \( s \), calculate fitness value of the solution |
| If the fitness value is decreased, go back to step 2 |
| Otherwise, revoke this dispatch |
| If number of buses on route \( s \) is larger than \( V_{min}^{s} \) |
| Dispatch a bus from route \( s \) to route \( r \), calculate fitness value of the solution |
| If the fitness value is decreased, go back to step 2 |
| Otherwise, revoke this dispatch |
| Next \( s \) |
| Next \( r \) |
| 3: Obtain the optimal frequencies and fitness for the solution. |

After solving the transit assignment model and the fast charging station planning model, the fitness of solution \( \tilde{x} \) is calculated as:

\[
F_{\tilde{x}} = B_{1} \sum_{w \in W} d_{w,a}^{r} + B_{2} TPT_{\tilde{x}} + B_{3} TOC_{\tilde{x}},
\]

where \( TPT_{\tilde{x}} \) and \( TOC_{\tilde{x}} \) are the total passengers’ travel time and total operator cost of solution \( \tilde{x} \), respectively.

For each solution obtained in the genetic operator phase of the GA algorithm, a frequency setting heuristic method is adopted to find the optimal frequencies corresponding to the solution, which is extended from Szeto and Wu [33], Szeto and Jiang [34]. It allocates a fixed number of buses into different routes of a solution, and the frequency of route \( r \) is determined by

\[
f_{r} = V_{r}/2T_{r},
\]

where \( T_{r} \) denotes the trip time of route \( r \), \( f_{r} \), and \( V_{r} \) denote the frequency and the number of buses of route \( r \) respectively.

The steps of the heuristic method are presented in Table 3.

**D. CROSSOVER AND MUTATION OPERATIONS**

There exist two route crossover operators in proposed GA: a full route replacement from two different sets and a partial route replacement from two different routes of a route set. The first operator randomly selects two route sets from the parent population as parents, then one route is chosen at random from each parent, after that two offspring route sets are created by swapping these two routes.

Comparatively, the second crossover operator is to swap stops sequences between two routes in a solution. First, two
routes are selected randomly. Then, one of common nodes of the two routes is randomly selected as crossover site. After that, each of the routes is divided into two sections at crossover site, and two new routes are created by swapping sections between two parents. If duplicated stops exist in the same offspring route or there is no common node between two parents, two new routes will be selected randomly to repeat the crossover procedure.

To explore a large solution space, three mutation operators (insert, delete and replace) are designed for modifying the routes with a mutation rate. The insert mutation operator is realized by first choosing an inserted position of a route randomly and then inserting a feasible stop node at the position, a feasible stop node exists if the two nodes around the position on the route have one or more common nodes adjacent to them. Likewise, the replace operator attempts to replace a stop node from the route with another node. The delete operator attempts to remove a stop node from the route. If no mutation operator can be executed without violating the feasibility of the route, different routes may be chosen up to 10 times.

Fig. 6 describes the procedure of the proposed GA algorithm. The overall GA optimization procedure is presented in Table 4.

IV. NUMERICAL STUDY
The proposed model is implemented in the Mandl’s road network [25], as depicted in Fig. 7. The network includes 15 stops and 21 links, the in-vehicle travel time of bus on each link is shown in minutes. Table 5 gives the hourly passenger demand for each OD pair, while Table 6 lists the model parameters used for basic scenario.

A. BASIC SCENARIO
For the multi-objective optimization problem, the settings of weights are fundamental to strike a better balance between total unsatisfied passenger demand, total passengers’ travel time and total operator cost. In this numerical example, the weights for the total unsatisfied passenger demand, total passengers’ travel time and total operator cost, i.e., $B_1$, $B_2$
and $B_3$, are set to 1500, 100 and 1. Such combination could make the total unsatisfied demand, total passengers’ travel time and total operator cost to have the same order of magnitude. Furthermore, we do not consider solutions with nonzero unsatisfied demand to ensure the validity of the solution.

Under the frequency setting heuristic method, the BEBs fleet size remains unchanged. According to our preliminary experiments, there is no solution with zero unsatisfied demand when the fleet size is smaller than 22. On the other hand, more BEBs will contribute to a sharp increase in the total operator cost. In basic scenario, the fleet size is set to 22, which is the lowest fleet size that can satisfy all the passenger demand in most cases. The convergence process of proposed algorithm is shown in Fig. 8, the objective value is decreasing obviously as the population evolves, and it becomes stable after 150 generations.

Tables 7 and 8 summarize the computational results of the basic scenario. Results illustrate that the transit route set can serve all passenger demand in the network, and a route with longer trip time requires a larger battery for BEBs. The type 1 charging stations are deployed at both initial station and terminal station of each route, the type 2 charging stations are deployed at stations 3 and 5, which are the common intermediate stations of all transit route. Table 9 lists the charging time of BEBs at charging stations of each route. It can be seen that BEBs utilize all dwelling time at bus stops.
to recharge their batteries, while BEBs can be fully charged before running the next scheduled trip at terminals.

### B. EFFECT OF WEIGHTS

To compare the solutions of the proposed model with different weights, we keep the value of \( B_3 \) to be 1 and change the value of \( B_2 \) from 0 to 100. Each time the algorithm runs, the value of \( B_1 \) is set high enough to ensure obtained solutions without nonzero unsatisfied demand. Fig. 9 shows the objective values for 11 situations, we can observe that the total travel time and the total operator cost are conflicting objectives. The value of \( B_2 \) is set to 0 in the first situation, which means that the operator cost is not considered in the algorithm. The modified GA results the highest total travel time (2041 hours) and smallest operator cost (1.04 × 10^5 $). As the value of \( B_2 \) increases, the total travel time decreases and the total operator cost increases. When the value of \( B_2 \) is increased to 100, the modified GA gains the smallest total travel time (1530 hours) and highest operator cost (1.40 × 10^5 $). Compared with the first situation, the last situation can reduce the total travel time by 25% and increase the total operator cost by 34%. Considering the transit agencies demand to improve the level of transit service and sustainable development of bus fleet, the value of \( B_2 \) is set to 100 in subsequent experiments.

### C. EFFECT OF THE BUS FLEET SIZE

Fig. 10 and Fig. 11 depict the effect of bus fleet size in reducing the unsatisfied passenger demand, the total passengers’ travel time and total operator cost. The feasible solution is not existed when \( W < 12 \), because the requirement of minimum frequency is not met. According to Fig. 10, the unsatisfied demand decreases with the increase of fleet size for 12 ≤ \( W \) < 22, because there are more buses to be used to serve passengers. When \( W \geq 22 \), all the passenger demand can be served by BEBs system, and the constraint of fleet size is generally not binding.
For the route set listed in Table 7, Fig. 11 compares the total travel time and total operator cost under different fleet size. We can observe that the total operator cost increases as the fleet size is raised, because the BEBs system requires more batteries for BEBs. The total travel time is increased from 825 hour to 1527 hour as the number of fleet size is added from 12 to 22, because as the BEBs fleet size increases, the BEBs system has more buses to serve passengers. The increase of satisfied demand leads to the increase in total travel time. Nevertheless, the total travel time has a drop trend after fleet size exceeds 23, because all of the passenger demands between any OD pair are met and more buses mean a short waiting time. Fig. 11 also shows that the total travel time and total operator cost are conflicting when the fleet size is larger than 22. In subsequent experiments, the fleet size is set to 22.

D. SENSITIVITY ANALYSIS
To analyze the impact of battery price and dwell time on the solutions obtained, replicates of the modified GA with different parameter settings are conducted. Each modified GA runs 5 times, and the default battery price is set as $a_{\text{battery}} = 148 \ $/kWh. For easy of implement, the dwell time at initial station is set to the same value as that at terminal station, and the default dwell time at initial station or terminal station is set as $s_{t0} = 0.25 \ \text{hour}$.

1) EFFECT OF THE BATTERY PRICE
According to the reports presented in Curry [4], the average lithium-ion battery pack price was 176 $/kWh in 2018, and he expects the price to be around 94 $/kWh by 2024 and 62 $/kWh by 2030. In this paper, we allow the battery prices vary from 60 $/kWh to 180 $/kWh.

![FIGURE 12. Total travel time and total operator cost under different battery price.](image)

Fig. 12 demonstrates the variations of total travel time and total operator cost with respect to the battery price. As we can see, when battery price grows from 60 $/kWh to 180 $/kWh, total operator cost increases rapidly, meanwhile, the total travel time is relatively stationary. The reason is that, as the battery price grows, the investment cost of batteries and fast charging stations is increased to provide high quality services to passengers. The variations of total battery size, number of fast charging stations with respect to the battery price are shown in Fig. 13. As battery price grows from 60 to 180, the total battery size keeps falling, except that it has a sharp grow when $a_{\text{battery}}$ reaches 120, but it is achieved by not deploying 250 kW fast charging station. On the other hand, as the battery price grows, reducing the battery size and installing more 250 kW fast charging station become a more economical strategy.

![FIGURE 13. Number of fast charging stations and total battery size under different battery price.](image)

2) EFFECT OF THE DWELL TIME
To illustrate the effect of dwell time of BEBs at initial station or terminal station, dwell time is increased from 0.1 hour to 0.3 hour. The results are shown in Fig. 14, we can see that the number of fast charging stations decrease gradually with the increase of dwell time. Nevertheless, the total battery size has a drop when dwell time reaches 0.15, it is achieved by increasing the number of 90 kW station, and then the total battery size keeps growing as well. As the dwell time increases, reducing the number of 250 kW station and using larger batteries become a more economical strategy. It reveals the trade-off between battery capacity requirement of BEBs and deployment of charging stations. On the other hand, a longer dwell time at initial station or terminal station results in a longer trip time and a lower frequency according to equation (40), both of which will result in a longer passenger
travel time. It illustrates that the battery size, deployment of fast charging station and passenger travel time are interrelated and should be rigorously considered at the planning stage.

E. SOLUTION COMPARISON BETWEEN SEQUENTIAL APPROACH AND SIMULTANEOUS APPROACH

Additional experiment is designed through sequential solving the route network design problem and fast charging station planning problem. By eliminating the total operator cost from fitness function, the route network design problem is tackled using the GA coupled with a heuristic frequency setting method. After obtaining the transit network and associated frequencies, the fast charging station planning model is solved to minimize the total operator cost. For the sequential approach, the optimal total travel time is 1454 hours and the corresponding total operator cost is $1.604 \times 10^5$, which is not a satisfactory solution compared with the solution of simultaneous approach, because the total travel time for a decrease of 4.9% is achieved at the expense of a 14.5% increase in total operator cost. The experiment explains the necessity of addressing the transit network designing problem and fast charging station planning problem simultaneously.

F. RESULT ANALYSIS

For the operation of BBEs, the fleet size will inevitably bring influence on the solution quality. Therefore, a sensitivity analysis on fleet size is conducted and the computational results are depicted in Fig. 10 and Fig. 11. We can see that the solution quality is best when the fleet size is equal to 22, although the total travel time will reduce as the fleet size continues to grow, the solution is unacceptable because it may significantly increase the total operator cost.

After the fleet size is determined, the GA obtains the optimal solution for the Mandi’s road network under basic scenario. The results show that a route with longer trip time requires a larger battery for BBEs operation, fast charging station with 90 kW charging power can fully charge the battery of BEE during its dwelling time at bus terminal, and 250 kW fast charging stations deployed at two intermediate bus stops can provide opportunity charging for all routes.

To reveal the effects of weights on the objective values, a sensitivity analysis on weights is made by varying the value of $B_2$ from 0 to 100. Fig. 9 shows that the total travel time and the total operator cost are conflicting objectives. Compared with the situation without considering operator cost, the basic situation realizes a higher level of transit service with a large operator cost.

Impacts of battery price and dwell time on the solutions obtained are demonstrated through extensive sensitivity analysis. Fig. 12 and Fig. 13 show that the variations of battery prices affect both the investment cost and deployment of fast charging stations. By increasing the density of fast charging station, a lower battery capacity demand can be anticipated. Furthermore, a decrease in the number of charging stations can be achieved by slightly prolonging the dwelling time of BBEs at terminal.

V. CONCLUSION

This paper presents a bi-level programming framework to address the electric transit route network design problem where electric transit network designing, fast charging station planning, battery size and frequency setting are considered simultaneously. The transit route network and deployment of fast charging station are generated at upper-level, while total passengers’ travel time and unsatisfied demand are evaluated by solving the lower-level transit assignment problem. A modified algorithm based on GA is designed to solve the proposed model. Specifically, the algorithm relies on the GA to design route structures for BBEs, then fast charging station planning model and transit assignment model are solved successively in heuristic search procedure to evaluate the fitness of generated route structure.

Numerical examples from a benchmark road network are employed to illustrate the performance of the proposed algorithm and the applicability of the formulated model. A combination of weights is used to keep balance between total unsatisfied demand, total passengers’ travel time and total operator cost. Through experiment, we find that both types of fast charging are used in the transit network of BBEs, and the route with longer trip time requires larger batteries for BBEs operation. Moreover, various trade-offs between three objectives are described and sensitivity of solutions to battery price and dwell time is discussed. These results can help authorities determine the optimal transit network structure and fast charging station deployment for the BBEs system.

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