Optimally Locating Charging Stations for Electric Vehicles in Intercity Highway Networks

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ABSTRACT

It has been widely recognized that electric vehicles (EVs) represent a much more environment-friendly transportation mode than conventional gasoline vehicles (GVs). It is generally believed that, to facilitate the market penetration of EVs, electricity-charging stations must be first established to satisfy the charging demand for commuting and long-haul travels. From the perspective of en-route charging, the location of charging stations should be carefully selected so as to reduce travellers’ detour costs as much as possible, when the impact of charging station locations on the individual route choice behavior is considered. This paper focuses on developing an optimal charging station location model and method for locating charging stations for EVs in intercity highway networks with the aim of minimizing the detour cost of the driving population. We first formulate a bi-level mathematical programming model taking into account both the investment budget limit on charging infrastructure construction and the driving distance limit of EVs. This formulation is proposed on the basis of a metanetwork consisting of all candidate station location nodes and feasible shortest subpaths between these nodes. Then we develop an efficient branch and bound method to solve this optimal location problem, in which a label-correcting algorithm is adopted to solve its subproblem—the shortest path problem with relays. Finally, the effectiveness of the model and solution algorithm is demonstrated with a numerical example in an intercity highway network of the Yangtze River Delta region in China.

KEYWORDS: Facility location problem, electric vehicles, electricity-charging stations, intercity highway networks

1 INTRODUCTION

Electric vehicles (EVs) are well recognized as a promising transportation mode for enhancing social economic and environmental sustainability. EVs are superior to conventional internal combustion engine vehicles (ICEVs) in two crucial aspects. First, it can reduce overdependence on petroleum and thus decrease the exploitation and import of non-renewable energy resources. Second, it, relying on electric power, lowers emitting harmful tailpipe pollutants to the atmosphere. Therefore, EVs will inevitably have a significant impact on energy security and environmental quality if a widespread adoption can be achieved. However, there are still three major reasons impeding a massive adoption of EVs. The first one, range anxiety, which is often referred to as drivers’ mental distress or fear of being stranded on roads because the battery runs out of charge (Xie et al., 2017), no doubt affects EV drivers’ travel behaviours. The second one is overlong charging time. Based on the delay time, recharging for EVs is generally classified into three levels (He et al., 2015). The last but not the least is insufficient charging infrastructures. With innovations in battery technologies, the first
two barriers could be removed to some extent. This paper is focused on mitigating the last problem by determining proper charging station locations on the intercity highways in order to ensure travel feasibility and improve traffic efficiency of EVs.

In recent years, thanks to the rapid development and wide acceptance of EVs, facility location models have been frequently used to study the siting problem of charging infrastructures. These studies can be classified into four categories based on system optimization objectives. In the first type, these papers used real statistical data to simulate the traffic level and recommended to locate in the most frequently visited sites. Kameda and Mukai (2011) used taxi probe data to count the number of demands mapped to each node, and evaluated three indicators of riding, dropping and total number to give the optimal placement. Liu (2012) proposed a distribution model for three types of charging infrastructures and provided a service radius of fast charging stations. Wang et al. (2013) presented a quantitative model for EV charging stations by evaluating the electricity consumption and suggested that location of the charging stations is related to the conversion of petrol sales. Cai et al. (2014) evaluated and scored the taxi stops and gas stations by using trajectory data from over ten thousand taxis in Beijing, and developed station location criteria of maximum number of parking events. In these studies, the “hotspots” for charging demand are considered as the first place to serve. In a way, these methods can be used to obtain the candidate charging stations in pre-process.

The objective function of these studies in the second category was to maximize the total social welfare associated with both transportation and power networks. He et al. (2013) formulated a hierarchical modelling which merged the allocating model and the equilibrium of coupled transportation and power networks. Even though the balance of traffic and power grid was discussed in detail, but the important characteristic of EVs—driving range was not mentioned in it. He et al. (2015) based on tour-based network equilibrium model, formulated the charging station location problem as a bi-level program model whose objective function represented the total social costs including total time and missed trips. Liu and Wang (2017) paid attention to the wireless charging technology other than the traditional fixed static charging stations to assist the government planners on optimally locating multiple types of BEV recharge facilities. In order to maximize government’s economic interests, the objective function formulated in a three-level form was to minimize the public construction cost subject to a given budget.

In the third set of studies, these papers focus on minimizing various forms of transportation economic benefits, such as total travel time or driving distance, total charging station location budget, total number of missed trips and so on. Shahriaki et al. (2015) minimized the unfinished travel distance caused by recharging relay, which is equivalent as maximizing the travel mileage being electrified. Huang et al. (2015) developed a multipath refuelling location model, in which drivers would accept a moderate deviation for refuelling EVs en-route. The objective of their paper aimed to find the least cost with a reasonable deviational tolerate and considered the limited driving range into the decision-making process. Similarly, it also did not consider congestions and capacity restrict. And total number of the missed trips, Due to the recharging waiting time, EV drivers would be insufficient to complete their daily travel, Dong et al. (2014) argued to minimize the total number of the missed trips by optimizing the location of charging station based on activities.

In the last group, the locations of charging facilities are recommended to maximize the service coverage or path flow for EVs’ charging demands. Wang and Lin (2013) presented two location models (i.e., set covering and maximum covering) for capacitated multiple types of recharging stations. They concluded the mixed charging stations could provide a better service than recharging stations with a single type. Riemann et al. (2015) devised for a flow-capturing location model (FCLM) for wireless EV charging facilities, which is combined the interaction between location of charging facilities and network flow patterns associated with stochastic user equilibrium. Different from the fixed setting of charging stations, in their paper, the wireless charging facility could locate in the middle of links (centroid node) in the network to provide a convenient charging service. He et al (2016) considered the local charging station location situation for different regions of Beijing respectively. They compared three facility location models (i.e., set covering model, maximal covering location model and p-median model) subject to a supply-demand incorporating constraint and reckoned that the p-median model was more effective. He et al (2018) proposed a bi-level programming model and took into account the influence of the driving range of EVs on the location problem of charging stations. However, in this paper the EVs are limited to recharge only once during
the entire journey, it is incompatible with the charging demands that EVs travel on the intercity highways. Arslan and Karasan (2016) started studying the intercity charging station location problem for plug-in hybrid electric vehicles (PHEVs) in formulation of the flow refuelling location model (FRLM) by using a Benders decomposition algorithm. Although their research is similar to ours, but he regarded the location problem on intercity highways as a facility location problem, which was not different from the general static location problem. The impact of user travel behaviours on locations of charging stations was not reflected in his paper.

This study will therefore focus on developing a charging station location model and method for optimally locating charging stations for EVs on the intercity highways. Due to the long-haul nature of intercity highway trips, EVs may need to be recharged more than once halfway to complete their trips. It is worth noting that the purpose of locating charging stations along intercity highways is to satisfy the charging demand for en-route EVs for the purpose to accomplish their intercity trips. It should be considered that the locations of charging stations may affect the route choice for several different O-D pairs, some EV drivers may have to take a detour to recharging their EVs in order to make sure the batteries will not run out of charge in the course of their trips. Different from the most facility location studies, in which the location problem of charging stations is recognized as a static location problem, we focus on considering the impact of charging station locations on route choice results in this paper. The objective of our study is to optimize the locations of charging stations in intercity highway networks in order to minimize the total travel time derived from travel demands of EVs between each O-D trip.

The main work of this paper is a mathematical programming model and method for the charging station location problem with the requirement of en-route charging of EVs in intercity highway networks. For this purpose, the remainder of the paper is organized in the following order. In Section 2, we propose a model to and elaborate its innovation and solution properties. Section 3 presents a branch and bound method with an embedded label-correcting algorithm and details its algorithmic procedure. In Section 4, we provide a numerical example in an intercity highway network of the Yangtze River Delta region in China to demonstrate the effectiveness and efficiency of the proposed model and the algorithm. Finally, the conclusions of our study are given in Section 5.

2 PROBLEM FORMULATION

In this section, we present a novel optimization model for the charging station location problem and derive a resulting subproblem that characterize the individual travel behaviours constrained by driving range limits for EVs. The objective function is to minimize the total travel cost of electric vehicles in the network, subject to the total budget on the construction of EV charging stations.

Due to the long-haul nature of most intercity highway trips, EV’s driving range has become a concern in the driving population. In order to accomplish such long-distance trips, EV drivers must choose a route for which the distance between any two consecutive stations along the route is shorter than its driving range limit. Such a charging behaviour along routing is regarded as relay requirement and the driver’s decision making is on finding a shortest path with relays. For modelling convenience, we introduce the two definitions of subpath and feasible subpath (Xie and Jiang, 2016). A subpath is a part of path whose both head and tail node are located relay stations. And a feasible subpath means the length is no more than the driving range limit.

In order to simplify the complexity of the problem and ensure our modelling focus on the characteristics of the most essential factors, the assumptions are stated as follows:

Assumption 1: It is assumed that the travel demand population only comprises of EVs. For modelling simplicity, only one type of EVs is considered, and the same driving range limit is given in advance. Certainly, if needed, multiple types of EVs with different driving mileage limits can be easily incorporated into our model without changing the nature of the problem and the structure of the model.

Assumption 2: It is possible to hypothesis that these conditions are less likely to occur in a congested network. This is because the network of our problem is set on the intercity highways where the traffic is considered not crowded. The total travel time in our model only includes driving time on the way. Charging time and waiting time are not incorporated into the travel impedance.
Assumption 3: Without loss of generality, it could conceivably be hypothesized that every vehicle is fully charged at all origin nodes and can be fully recharged at each charging station. Moreover, the capacity of each charging station is assumed to be enough to meet the recharging requirements for EVs.

Notation

Sets
- $\mathcal{N}$: Set of nodes, where $i, j \in \mathcal{N}$
- $\mathcal{T}$: Set of the candidate charging station nodes, where $p, q \in \mathcal{T}$
- $\mathcal{A}$: Set of links connecting the points in $\mathcal{N}$, where $(i, j) \in \mathcal{A}$
- $\mathcal{\tilde{A}}$: Set of subpaths connecting two points in $\mathcal{T}$, i.e., $(p, q) \in \mathcal{\tilde{A}}$
- $\mathcal{W}$: Set of O-D pairs, $(r, s) \in \mathcal{W}$
- $\mathcal{K}_{rs}$: Set of paths $k$ between O-D pairs $(r, s)$

Variables
- $x_{ij}$: Travel flow on link $(i, j)$
- $y_{pq}$: Travel flow on subpath $(p, q)$
- $f_{rs}^k$: Travel flow on path $k$ between O-D pair $(r, s)$
- $z_t$: A decision variable indicates whether a charging station is built or not. $z_t = 1$ if a charging station is located at candidate site $t$, and $z_t = 0$ otherwise

Parameters
- $c_{ij}$: Link travel cost on link $(i, j)$
- $\bar{c}_{pq}$: Subpath travel cost on subpath $(p, q)$
- $d_{ij}$: Physical distance of link $(i, j)$
- $q_{rs}$: Travel flow between O-D pair $(r, s)$
- $Z$: Total number of charging stations
- $M$: A sufficiently large constant
- $D$: Driving range limit, i.e., the maximum distance an electric vehicle with a full charge can travel
- $\delta_{pq,k}^rs$: Path-subpath incidence indicator, where $\delta_{pq,k}^rs = 1$ if subpath $(p, q)$ is part of path $k$ between O-D pair $(r, s)$, and $\delta_{pq,k}^rs = 0$ if otherwise

Given the notations above, the charging station location model is formulated as follows:

\[
\begin{equation}
\min_y C(y) = \sum_{(p,q)\in\tilde{A}} \bar{c}_{pq}y_{pq}
\end{equation}
\]

subject to

\[
\begin{align}
\sum_t z_t &\leq Z \\
\sum_k f_{rs}^k &\geq q_{rs} & \forall (r, s) \in \mathcal{W} \\
y_{pq} &\leq Mz_{t=p,q} & \forall (p, q) \in \tilde{A} \\
y_{pq} &\leq \sum_k f_{rs}^k \delta_{pq,k}^rs & \forall (p, q) \in \tilde{A} \\
f_{rs}^k &\geq 0 & \forall (r, s) \in \mathcal{W}, \forall k \in \mathcal{K}_{rs} \\
z_t &\in \{0,1\} & \forall t \in \mathcal{T} \\
\delta_{pq,k}^rs &\in \{0,1\} & \forall (r, s) \in \mathcal{W}, \forall (p, q) \in \tilde{A}, \forall k \in \mathcal{K}_{rs}
\end{align}
\]

where

\[
\bar{c}_{pq} = \min_x \sum_{(i,j)\in\mathcal{A}} c_{ij}x_{ij}
\]

\[
\sum_{(j:\{i,j\}\in\mathcal{A})} x_{ij} - \sum_{(j:\{j,i\}\in\mathcal{A})} x_{ji} = \begin{cases} 
1, & i = p \\
0, & i \in N/\{p,q\} \\
-1, & i = q
\end{cases}
\]
The optimization problem is in a formulation of bi-level program model, in which there are four sets of decision variables in the above optimization model, including link flow $x_{ij}$, subpath flow $y_{pq}$, path flow $f_{pq}$, and location decision variable $z_t$. Obviously, this is a mixed nonlinear integer programming problem. In the upper level model, it characterizes the charging location problem. The objective function is to minimize the total travel time of EVs for all O-D trip demands in the network, which subject to the flow conservation and location budget constraints. In the lower level model, it presents a constrained shortest path problem. The problem is described in such a case that each EV cannot surpass the driving range limit due to the capacity of onboard battery. While, the objective function is to minimize the travel time with a unit flow constrained by distance limit.

Different from the formulation of network design problems with relays (Cabral, 2008; Laporte, 2011; and Smith, 2012), we introduce the term of feasible subpath directly and regard it as an effective intermediator between links and paths instead of introducing an activation parameter to indicate whether a subpath is effective or not. Therefore, the formulation of our problem is established on the basis of metanetworks. We define the metanetwork to use the set of charging station nodes as metanetwork nodes and feasible subpaths as meta-arcs. As can be seen from the above model, the feasible subpaths seem as a bridge connecting the upper and the lower level models, and it is determined by the location decision variables $z_t$ (constraint (5)) and constrained by the distance limit (constraint (11)) in the above model. Because in our problem the candidate location sites are given, the location problem can be solved as a discrete combinatorial optimization problem so the value of location decision variables can be easily obtained in each location solution. In addition, according to the assumption 1, the driving range limit of all EVs is deterministically known in advance, it is not difficult to select the specific feasible ones if a candidate location result is supposed. In a conclusion, it is reasonable to introduce the term of feasible subpaths in our problem.

The objective function (1) minimizes the total travel time of EVs for all O-D trip demands in the network. Constraint (2) is the location budget limit, which requires the total stations to be built cannot exceed the given number $Z$. Equation (3) is the flow conservation constraint. Constraint (4) describes the relationship between path flow and subpath flow. Constraint (5) indicates that only both candidate sites $p$ and $q$ are located, the subpath $(p, q)$ exists. Constraints (6)-(8) are non-negative or binary constraint of the variable, respectively. The objective function (9) minimizes a unit flow travel time on the subpath. Constraint (10) satisfies a unit flow conservation, which is decomposed into three cases: if node is an origin, there is a unit flow outflowing. Else if a destination, a unit flows into this node. Another one, inflows equal to outflows. Constraint (11) guarantees the length of subpath is no longer than the driving range limit $D$, i.e., the subpath is constrained to a feasible subpath. Constraint (12) requires the travel flow on links are binary variables.

### 3 SOLUTION ALGORITHM

It is known from the structure of the model formulated in the last section that a solution is feasible should satisfy both budget limit and distance limit. Since our network is designed to be uncongested, it is worth noting that in an uncongested network, if a location of an additional station added into a feasible solution, the new solution will also be feasible, even maybe better than the old one, i.e., the new objective value will be less than or equal to the old one. Based on the property, the solution algorithm of our model is designed as follows.

**Step 1:** Solve the charging location problem (Constraint (2)) first by the branching procedure of branch and bound method to get the candidate location solutions.

**Step 2:** In order to improve efficiency, we deal with these solutions if they satisfy the conditions as specifies in the following contents.
1) If the solution satisfies both budget limit and distance limit for all O-D pairs, this is a feasible solution simultaneously the optimal solution in this branch. No further branching is required. Solve it by label-correcting algorithm and compare with the upper bound.

2) If the solution does not satisfy the distance limit for one or more O-D pairs, this branch does not contain any feasible solution. No further search is needed thus pruning it directly.

3) If the solution satisfies the distance limit but not the budget limit, this is not a feasible solution but provides a lower bound of the objective function value for this branch. Compare this lower bound with the upper bound. If it is greater, no further search is needed for this branch, pruning it. If not, this solution requires further branching.

**Step 3:** Update the upper bound. If all feasible branches have been processed as above, the final upper bound is the optimal value of this problem. Output the upper bound and the optimal location solution.

The schematic illustration of this solution algorithm is shown in Figure 1 and details of branch and bound algorithm and label-correcting algorithm are specified as follows.

![Figure 1: Schematic Illustration of the Solution Algorithm](image_url)

3.1 **A Branch and Bound Algorithm for the Location Problem**

As discussed in the last part, the solution method of the charging station location problem can be regarded as a discrete combinatorial optimization. It can be solved easily by enumerating all feasible location solutions if the size of a given problem is sufficiently small. However, for a large-
size problem, considering all situations enumeration seems too time-consuming. Some candidate solution algorithms such as Lagrangian relaxation and Benders decomposition have been considered, but these algorithms are formulation-based. According to the complexity of our model and non-effectiveness of the above methods, we adopt an effective branch and bound method to find each feasible candidate location solution.

An operation of the branch and bound method is to iteratively divide all feasible solution spaces into smaller subsets, which is called branching. The process of calculating and determining a lower solution for relevant branches is called bounding. And after each branching, those subsets whose solution value exceed the lower bound are no longer further considered, which need be pruned. Therefore, it is the key to improve the efficiency of the branch and bound method by judging and pruning infeasible solutions as early as possible.

For obtaining a lower bound of the objective function and simplifying the branching process, we initialize all candidate locations to have a charging station located, i.e. \( z_t = 1, \forall t \in T \). The rule of branching is divided the root node into two sub-branches, one of which keeps the same solution of location as its root node for further branching. While the other is considered to cancel a candidate station node. The pseudo code for the branch and bound procedure is given as follows.

**Notation**
- \( l \): The initial node
- \( root \): The current root node
- \( left \): Left sub-branch of root node
- \( right \): Right sub-branch of root node
- \( S \): Optimal solution solved by label-correcting algorithm
- \( l \): The serial number of the current branch layer
- \( N \): Total number of the candidate charging stations
- \( Z \): The number of charging station to be built constrained by budget limit
- \( K \): The number of charging station location in the current root node
- \( U \): The upper bound of total cost
- \( C \): Minimum total cost solved by label-correcting algorithm
- \( Q \): A set containing all candidate location solutions to be checked (in FIFO order)

**Procedure**

\begin{align*}
\text{begin} & \\
& l := 0; \\
& C := \infty; \\
& l := \{1 \ldots 1\}_N; \\
& Q := \{l\}; \\
& \text{while} Q \neq \emptyset \text{ and } l \leq N \text{do} \\
& \text{begin} \\
& \text{delete the foremost element} \text{root} \text{from} \ Q; \\
& \text{if} K \leq Z \text{then solve the shortest path problem by label-correcting algorithm; } \\
& \text{if} C < U \text{then } U := C; S := root; \\
& \text{else prune root;} \\
& \text{else solve the shortest path problem by label-correcting algorithm; } \\
& \text{if} C > U \text{ then prune root;} \\
& \text{else if } l < N \text{ then left} := root; \text{ add} left \text{ into} Q; \text{root}[l] := 0; \text{right} := root; \text{ add} right \text{ into} Q; \\
& \text{if all } root \text{ on the layer } l \text{ have been branched then } l := l + 1; \\
& \text{end} \\
& \text{output} S \text{ and } U; \\
\text{end}
\end{align*}

**3.2 A Label-Correcting Algorithm for the Routing Problem**

As mentioned above, when the location solution of charging stations is given, EV drivers will make route choices and battery recharging decision to minimize their costs while making sure to complete their trips without running out of charge. Thus, the subproblem is transformed into a traffic
assignment problem with path-based constraints. Many literature have focused on this problem on congested networks following the Wardrop’s user equilibrium principle (Jiang et al (2012); Jiang et al (2014); Jiang and Xie (2014); and Wang et al (2016)). However, since our network is an uncongested network, we solve the subproblem as the shortest path problem with relays. Label-correcting algorithm taken to solve the shortest path problem with relays was early. It was first proved to be an exact fast pseudo-polynomial algorithm in Cabral et al. (2007). Soon Cabral et al (2008) used the model of shortest path problem with relays to design a wide area telecommunication network and solved it by label-correcting algorithm. Laporte and Pascoal (2011) allowed a development of label-correcting algorithm to solve a minimum cost path problem with relays. Further proved that the revised label-correcting algorithm had a faster time complexity. Smith et al (2012) incorporated replenishment arcs into the shortest path problems with a weight constraint. Label-correcting algorithm was also effectively applied to solve that problem and proved much more efficient than the network expansion algorithm. Therefore, according to the advantage of label-correcting, we adopt it to find the minimum total travel time in our subproblems.

Compared with the procedure of solving traditional shortest path problem by using label-correcting algorithm, the distinguishing feature of such a label algorithm is that each label in our problem is a two-dimensional vector including both cost and distance parameters, which requires each node maintains a set of all candidate non-dominated labels. Moreover, the method of comparison and elimination of candidate labels is following the dominated principle, which was defined in Guerriero and Musmanno (2001). The definition is said that label \( l_1 = (c_1, d_1) \) dominates label \( l_2 = (c_2, d_2) \), if \( c_1 < c_2 \) & \( d_1 \leq d_2 \), or \( c_1 \leq c_2 \) & \( d_1 < d_2 \). Below we give the Pseudo code of label-correcting algorithm to solve our subproblems.

Notation

\[ r \] Origin node
\[ (i,j) \] Link from node \( i \) to \( j \)
\[ D \] Driving range limit
\[ A \] Link set, \( (i,j) \in A \)
\[ S \] Set of the locations building charging stations
\[ c_{ij} \] Cost, i.e., travel time on link \( (i,j) \)
\[ d_{ij} \] Distance of link \( (i,j) \)
\[ c(i) \] Candidate cost of node \( i \)
\[ d(i) \] Candidate distance of node \( i \)
\[ p(i) \] Candidate predecessor of node \( i \)
\[ l(i) \] A candidate label of node \( i \), which is a two-dimensional vector with two parameters of cost and distance, i.e., \( l(i) = (c(i), d(i)) \)
\[ \tilde{c}(i) \] Updated cost of node \( i \)
\[ \tilde{d}(i) \] Updated distance of node \( i \)
\[ \tilde{p}(i) \] Updated predecessor of node \( i \)
\[ \tilde{l}(i) \] Updated label of node \( i \), \( \tilde{l}(i) = (\tilde{c}(i), \tilde{d}(i)) \)
\[ L(i) \] The label set including all candidate labels of node \( i \), i.e., \( L(i) = \{ l_1(i), l_2(i), \ldots, l_k(i) \} \), and \( k \) is the number of labels of node \( i \)
\[ Q \] A checking node set containing all nodes whose labels have changed (in FIFO order)

Procedure

\begin{verbatim}
begin
L(r) := \{(0,0)\}and p(r) := 0;
L(j) := \{(\infty, \infty)\}and p(j) := r for each node j \in N/r;
Q := \{r\};
while Q \neq \emptyset do
    delete node ifrom Q;
    for each node j, subject to(i,j) \in Aandj \neq r do
        for each(l(i)) \in L(i) do

\end{verbatim}
begin
\[ \bar{c}(j) := c(i) + c_{ij}; \]
\[ \bar{d}(j) := d(i) + d_{ij}; \]
\[ \bar{p}(j) := i; \]
if \( \bar{d}(j) \leq D \) then
  if \( j \in S \) then \( \bar{d}(j) := 0; \)
  if \( \bar{c}(j) < c(j) \) then delete \( l(j) \) from \( L(j) \) and add \( l'(j) \) into \( L(j) \);
  if \( j \notin Q \) then add \( j \) into \( Q \);
else for each \( l(j) \in L(j) \) do
  begin dominated check
    if \( l'(j) \) dominates \( l(j) \) then break;
    else add \( l'(j) \) into \( L(j) \);
    if \( l'(j) \) dominates \( l(j) \) then delete \( l(j) \) from \( L(j) \);
    if \( j \notin Q \) then add \( j \) into \( Q \);
  end
end
end
end
end

4 NUMERICAL EXAMPLE

In this section, we present a numerical example based on the topology of the intercity highway network of the Yangtze River Delta region in China. As shown in Figure 2, the transportation region is a large-size network that consists of 36 nodes and 134 undirected links, and 18 of which are origins and destinations corresponding to the city named in Figure 2. The data of free-flow travel time and distance of each link is obtained from an online map system as shown in the figure and the travel demand rates of EVs are predicted statistically from the relevant demographic and socioeconomic data. The 26 candidate station nodes are \( T = \{1, 2, 3, 4, 5, 6, 7, 8, 9, 12, 14, 15, 16, 17, 18, 19, 21, 23, 24, 25, 28, 29, 31, 33, 34, 35\} \).

![Figure 2: An Intercity Highway Network in the Yangtze River Delta Region](image-url)
In order to verify the effectiveness of our solution algorithm proposed in the last section, we choose 4 different scenarios to solve the optimal location problem. In the 4 cases, they subject to budget limits are 8 and 15, distance limits are 150 and 200, respectively. Their optimal location solutions of charging stations are shown in Figure 3, in which the determined charging station nodes are marked yellow. For the 4 cases, the minimum total travel cost is 495120, 484124, 483686 and 481518, respectively. Compared case (a) and (b) (or (c) and (d)), the two scenarios subject to the same distance limit but different budget constraints. It can be found that in an uncongested network, the minimum total travel cost may decrease as budget limit increases. It can be well understood that the network provides more en-route recharging opportunities for EVs and thus reduces unnecessary detours. From the case (a) and (c) (or (b) and (d)) those subject to the same budget limit but different distance limit, as can be seen that the minimum total cost may decrease as distance limit increases. This is because enhancing the driving range limit of EVs would improve the network performance.

![Figure 3: Optimal Charging Station Locations in Different Scenarios](image)

In addition, to capture the impact of different charging station location results on individual route choice behaviour and recharging decision, we take the O-D pair from Hefei to Shanghai as an example and solve each shortest path by label-correcting algorithm in the above 4 scenarios. As shown in Figure 3 each optimal travel path is marked as a red line. Taking case (a) as an example, the optimal travel path of the O-D pair is made up of link (32, 33), (33, 4), (4, 10), (10, 15), (15, 14), (14, 17), (17, 19), (19, 21) and (21, 23), which is distinguished from the other three. It is obvious that the optimal travel paths of the same O-D pair under different location results are distinctly different from
each other. This shows that under existing charging stations and specific driving range, EV drivers will select routes and decide battery recharging plans to minimize their costs while making sure to complete their trips without running out of charge. However, even a small magnitude of charging station location number increased or EV’s battery performance improved, the individual motorists may adopt and adjust their travel behaviours accordingly. In conclusion, the charging station location result depended on budget limit and distance limit can have a significant impact on route choice behaviour and recharging decision of EV travellers, which affects the traffic flow pattern in the network. Thus, route and location problems need to be determined simultaneously in this integrated model. In addition, based on the specific O-D pair example, it clearly demonstrates how does the minimum travel cost value changes as the budget limit and distance limit increases or decreases.

5 CONCLUSIONS

The contribution of this study is to present and solve a general optimal location problem, which determines the strategic charging station locations for EVs traveling in intercity highway networks. In this paper, we first formulated a bi-level optimization model for the location problem of charging stations taking into account the construction budget limit and limited driving ranges of EVs. Then we proposed an effective branch and bound method to solve this problem. In each branching process, a subproblem—a shortest path problem with relays was derived from a location solution. We used a label-correcting algorithm to obtain the optimal solution of the subproblem. The application of the solution algorithm for a real network example justified the effectiveness of the solution procedure. Comparing the numerical results in four different scenarios, it is found that both the budget limit for station construction and the driving distance limit of EVs have an inevitable influence on the decision of charging station locations so far as on the individual route choice and recharging choice behaviour. Figure 3 explicitly gives the optimal location results and clearly demonstrates how the route and recharging choice behaviours of individual motorists change with different locations of charging stations. In this end, we come to the conclusion that in an intercity highway network serving EVs, even a small change of the construction budget limit (on charging stations) or driving distance limit (of EVs) may have a significant impact on the traffic network performance.

This study assumes that a single driving distance limit value applies to all EVs in a transportation network. Allowing heterogeneous driving range limits implies a more realistic setting and is worth an immediate investigation. The proposed location problem is merely constrained by a budget limit. We will further extend the problem to find the optimal station locations subject to different constraints such as no detour requirement and so on. Alternatively, incorporation of other travel choice behaviours may further increase the model’s structure complexity while allowing a more sophisticated analysis on realistic travel demand and network flow patterns.

6 ACKNOWLEDGEMENTS

This research is sponsored by the National Natural Science Foundation of China (Grant No. 71471111, 71771150, 71890970/71890973).

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