Electric Vehicle Routing Problem with Charging Demands and Energy Consumption

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Abstract: An electric vehicle routing problem (EVRP) is developed to settle some operation distribution troubles such as battery energy limitation and difficulties in finding charging stations for electric vehicles (EVs). Meanwhile, in view of realistic traffic conditions and features of EVs, energy consumption with travel speed and cargo load is considered in the EVRP model. Moreover, to avoid the depletion of all battery power and ensure safe operation, EVs with insufficient battery power can be recharged at charging stations many times in transit. In conclusion, a large, realistic case study with the road network of Beijing urban, 100 customers and 30 charging stations is conducted to test the performance of the model and obtain an optimal operation scheme consisted of the routes, charging plan and driving paths. The EVRP model is solved based on the hybrid Genetic Algorithm (HGA) to get the routes and charging plan. The dynamic Dijkstra Algorithm with some improvements over the classical Dijkstra Algorithm is applied to find the driving paths called the most energy efficient paths between any two adjacent visited nodes in the routes.

1. Introduction

With the rapid development of economy and population, industrial cluster effect is further deepened. Accordingly, user consumption level and purchasing demand are increasing so that logistics activities are increasing dramatically. Therefore, logistics vehicles inevitably increase as well. The emissions and energy consumption of these logistics vehicles are far greater than passenger vehicles used for the daily travel. It is not denied that the efficient and fast modern logistics industry plays a key role in promoting economic development. Moreover, a series of problems such as energy consumption, environmental pollution and traffic problems are caused. How to apply new technologies, processes and materials to reduce negative impact of logistics activities has become one of the important issues in modern logistics industry. Recently, a new conception "green logistics" is proposed and studied by several papers (e.g., [1-6]) from ideas, methods or techniques.

Electric vehicles (EVs) powered by onboard batteries have advantages over conventional vehicles in energy savings and environment protection. The huge potential benefits have already attracted significant interest so that EVs have been applied in many public service areas such bus and taxi. Furthermore, EVs are also exploring many other development opportunities as well. As one of the short haul transportation modes, city logistic has the features of the fixed routes, short driving range, and high vehicle utilization. In addition, there are many good benefits such as the high subsidies, low electricity cost and unlimited drive for EVs in China. Therefore, the city logistics has become a new breakthrough in EV promotion. In Beijing, the results of 70 EVs introduced to the logistics industry since 2013 have been processed. As a new type of transport vehicles, EVs are facing the problem how to improve efficiency in transportation as soon as possible. The related problem is called the vehicle routing problem (VRP). The VRP, in which the multiple routes for a fleet of vehicles is determined for a set of customers to minimize the object value, is a classical problem among many distribution problems. The combination of EVs and VRP is a new extended VRP and called the electric vehicle routing problem (EVRP).

2. Literature Review

Even though EVs have been rapidly developed in the last decade, most of the current research pays attention to battery technologies [7] and charging station location problems [8]. There are few studies to focus on the EVRP. [9] allows all EVs to recharge partially (not fully) at the charging stations in transit. In this case, an EVRP model with time window is present and solved by the adaptive large neighbourhood search algorithm. The paper finally analyses the influence of the charging capacity on the results by inserting and removing the nodes including customers and charging stations. [10] mainly considers load, battery capacity, operation cost and time window to develop mix EVRP model for the mix EV fleet (EVs and conventional combustion vehicles), finally which is solved by the adaptive large-scale neighbourhood search algorithm. In EVRP with time window, [11] sets four different charging cases during mid-tour: charge with 100% capacity only once, charge with 100% capacity many times, charge only once, or charge many times. [12] pays attention to the effect of vehicle load on energy consumption to present EVRP with the minimum costs including travel cost and energy cost. [13] not only considers EVRP, but also simultaneously solves battery swap station location problem. In the location-routing problem (LRP), the paper develops an integer programming model and applies four different solution technologies based on the divided solution stages.

[14] considers energy consumption which is not assumed to a linear function of travel distance, and incorporate speed, gradient and cargo load distribution to propose an EVRP model with mixed fleet. [15] considers

some comprehensive constraints such as time windows, range, charging stations, and cargo weight to propose an EVRP model. However, the model merely focuses static traffic, so varying traffic conditions in a real road network may cause battery power to be completely depleted while in transit. For Alternative Fuel Vehicles (AFVs), [16] concentrates on the limited range and lack of refuelling stations to develop a green VRP model with the minimal total distance and applies two heuristic algorithms to solve the model. [17] simultaneously combines the charging station location problem with the EVRP to minimize the total costs including travel cost, charging cost, and location cost. In [18], because of the limited range, EVs can be recharged at special sites mid-trip. Moreover, a charging VRP model is given. Finally, the average trip length is estimated.

From the perspective of the limited range, the EVRP is likewise an extension of the distance constrained VRP (DCVRP) proposed by [19]. DCVRP requires the total distance traveled by each vehicle to be less than or equal to the maximum possible. There are different advanced algorithms to solve the DCVRP models developed by different objective functions. For example, [20] respectively considers two possible objective functions (total distance and the number of vehicles) and analyses the relationship between two obtained optimal solutions. [21] applies two approximation algorithms in solving DCVRP. [22] uses the improved branch-and-bound method in DCVRP and acquires good performance for large instances (up to 1000 customers).

Moreover, a few papers have focused on the electric bus scheduling problem which is like the EVRP. For example, [23] simply regards the limited range as only one constraint and proposed an electric bus scheduling model with battery swapping stations to minimize the total operational cost. The improved Column Generation Algorithm solves the model. [24] also studies the electric bus scheduling problem, in which all electric buses can be recharged during the period between any two shifts. Based on the request data and charging data, traffic data and weather data transmitted in real time between EVs, charging stations and server centre, [25] estimates the vehicle energy consumption and travel distance, and provides the online path planning services for electric taxi fleet in the mobile terminal or GPS navigation system.

In contrast to these previous EVRP studies, this paper focuses on EV features to consider charging demands and energy consumption. More detailed considerations in the EVRP are described as follows.

(1) In view of battery power, energy consumption can better describe the realistic travelling feature of EVs. Moreover, traffic dynamicity is considered in the road network. The situation in which EVs are directed onto excessively congested roads, which leads to rapid depletion of the battery power during mid-tour, is avoided. As a basic consideration in the EVRP, how to accurately calculate EV energy consumption is a fundamental issue.

(2) Moreover, most EVRP papers regard the limited range as one constraint in which the residual range at any node is greater than a threshold value (always 0). However, because energy consumption instead of distance is focused in the paper, the battery power constraint is correspondingly considered. An effective route must satisfy the condition that the vehicle must have sufficient battery power to arrive at any node in the route.

(3) Because of the limitation of battery technologies, any route with the initial battery power may be infeasible. EVs can be recharged at charging stations during mid-tour. Then, extra cost will then be incurred by some items such as charging time, charging cost, and excess travel time. Therefore, charging demand is also worthy of attention. At present, the large-scale popularization of the charging stations in city area has not been achieved. There are only a few network nodes to be located by the charging stations. Moreover, range anxiety, in which users are afraid that EVs will run out of battery power before reaching the destination, increases the charging demands. Therefore, how to reasonably assign the charging stations for EVs with charging demands is also a key point in this paper.

(4) Vehicle capacity is a basic constraint for VRP or variants.

(5) Finally, because the logistics companies prefer to reduce the operational cost, the object is to minimize the total costs including travel cost, charging cost, and fixed vehicle cost.

In consideration of charging demands and energy consumption, an EVRP model with the minimal total costs is developed to obtain an optimal operation scheme including routes, charging plan and driving paths. The routes answer the question how the customers are visited. The charging plan is to solve the problem of how and when the used vehicles with charging demands are recharged. The driving paths are to guide the vehicles how to drive in large road network. To accurately compute the vehicle energy consumption, a calculation method of the energy consumption with the uncertain travel speed and cargo load is present. Moreover, the most energy efficient path problem is solved by the dynamic Dijkstra Algorithm to present the driving paths.

This paper is organized as follows. Section 3 focuses on the problem description about charging demands and energy consumption. In Section 4, to solved the EVRP, the model formulation and model solution are introduced. A large realistic case study is given to analyse the results in Section 5. Finally, the conclusions and future research are presented in Section 6.

3. Problem Description

The solved results aim to provide an optimal operation scheme consisted of the routes, a charging plan and driving paths to totally fulfil customer demands, ensure EV operation safety and reduce cost to the greatest extent. A route is composed of the order of the visited nodes (possibly depots, customers or charging stations). The driving paths are regarded as the most energy efficient paths between any two adjacent visited nodes in the route. The charging plan is to solve the problem of when and where an EV with charging demands should be recharged. In other words, the EVRP is mainly divided into four sub-problems: how the vehicles visit the customers, how the vehicles run, and where and when the vehicles with charging demands are recharged. For example, we express a simple operation scheme as Fig. 1. The vehicles performing route 1 and route 2 require to be recharged respectively at nodes C1 and C2 during mid-tour. The routes are shown: depot-1-9-C1-6-depot (route 1); depot-5-4-7-8-C2-depot (route 2); depot-2-3-10-depot (route 3). Since a detailed road network is not given in Fig. 1, the most energy efficient paths are not drawn in the figure. The full results will be from A large, realistic study case in Section 5.

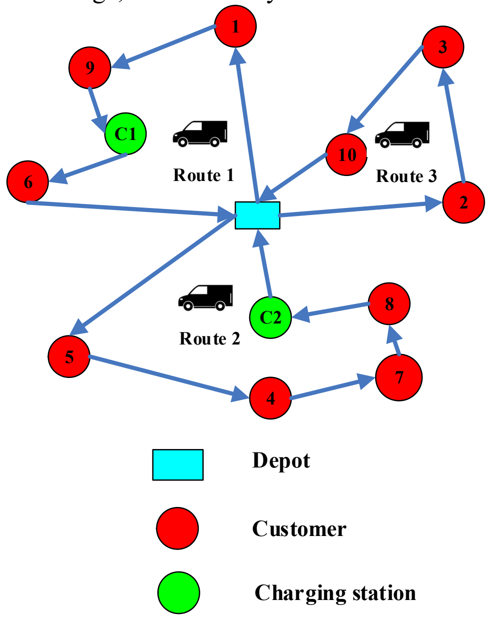

Fig. 1. An example of a simple operation scheme

As two important considerations in the EVRP, charging demands and energy consumption will be introduced as follows.

3.1. Charging Demands

In general, the logistics company with EVs has some charging spots at the depot. EVs can be recharged during idle periods (e.g., night time). When leaving depot, EVs have the full battery power. However, sometimes the trips are too long so that EVs have insufficient battery power to complete the entire trips in transit. The public charging stations provide a better choice for EVs with charging demands to recharge during mid-tour. The traditional vehicles have needs of replenishment at gas stations. However, the replenishing time is relatively less and the gas stations are located widely. Therefore, there may not be replenishment problem in the general VRP. Based on the feature of EVs, the charging demand is an essential consideration in the EVRP.

However, because of the current charging technology, there are many problems such as the lack of charging facilities and the long charging time to seriously affect the follow-up trip. How to present an optimal charging plan is one part of the solution of the EVRP.

The paper does not consider station location problem. In other words, the location information including location and number has been known. According to charging plan obtained, EVs with charging demands drive to the specified charging stations.

The activities occurring at a charging station can be divided into the queuing process and charging process (see Fig. 2). The vehicle must wait in line for the next available spot if all spots are occupied when arriving at the charging station. According to queuing theory, the queuing time is impacted by many factors such the arrival rate, service rate and number of servers. However, this paper assumes that there are enough spots (servers) at each charging station. That is, one vehicle is certainly recharged whenever reaching any charging station. The related problem in consideration of queuing time will be studied further in the future.

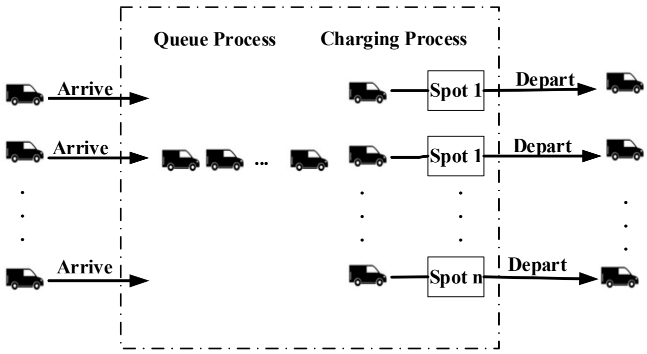

Fig. 2. The activities at a charging station

The charging process is the time an EV spends being recharged. According to Society of Automotive Engineers (SAE), there are three charging (see Table 1). Level 1 is suitable for overnight charging at home or workplace. Level 2 typically installed at private and public facilities. Level 3, also referred to as fast charging, is a high-voltage and high-current charging implementation. The charging time of Level 3 is relatively short. For example, a Level 3 charger allows a Nissan Leaf battery to be recharged to its 80% capacity in 30 min.

Table 1 Charging levels

Level	Type	Profile	Charging time (100% capacity)
Level 1	Slow charging	120 V, 15 or 20 Ah branch circuit, 1.44 kW maximum power	4–8 h
Level 2	Regular charging	240 V, 40 Ah branch circuit, 10 kW maximum power	2–3 h
Level 3	Fast charging	480 V, 60–150 kW power	30 min to 1 h

At present, most public charging stations in Beijing provide only charging Level 3 (fast charging), which can quickly complete the charging process. Moreover, this paper does not consider real recharged energy. That is, regardless of the charge level when an EV arrives at a charging station, the charging time is still regarded as a constant value (assumed to be 30 min in the paper). In addition, when recharging is undertaken, the batteries are filled to capacity.

3.2. Energy Consumption

At present, because of the battery technology issues, EVs may not travel far. The most of the EVRP studies introduce the travel distance to reflect the limited range. However, since the paper regards the battery power as one of the most outstanding features for EVs compared with conventional vehicles, the energy consumption instead of the travel distance is introduced in the EVRP model.

With the development of EVs, many papers have presented different methods for measuring or estimating the energy consumption. In addition to the views of the relatively theoretical methods, there are some practical methods such as Big Data and simulation for the analysis of the energy consumption of EVs. [26] uses SUMO (simulation of urban mobility) to simulate the energy consumption of EVs in a 3D transportation environment. In [27], a 57-mile urban/extra-urban route is analysed to obtain the lowest energy of different types of vehicles (EVs, hybrid electric vehicles and internal combustion engine vehicles). [28] analyses approximately 5 months of EV data to investigate EV performance, and an EV power estimation model was further proposed.

(1) Energy consumption formula

The energy consumption standard formula from physics and engineering used to calculate the energy consumption of EVs can be found in various books including [29] and [30]. The energy consumption is an integration of the power output at the battery terminals. For propulsion, the battery power output expressed in Eq. (1) is equal to the resistance power and any power losses in the transmission and the motor drive.

$$P_{b-out} = \frac{v(t)}{\eta}(Mgf_r\cos\alpha + Mg\sin\alpha + \frac{1}{2}\rho_a C_D A_f v(t)^2 + M\delta\frac{dv(t)}{dt}) \quad (1)$$

$Mgf_r\cos\alpha$: rolling resistance of tires on hard surfaces

$Mg\sin\alpha$: grading resistance

$\frac{1}{2}\rho_a C_D A_f v(t)^2$: aerodynamic drag

$M\delta\frac{dv(t)}{dt}$: acceleration force

The parameters and variables in Eq. (1) are shown as follows.

P_{b-out} : battery power output (W)

$v(t)$: vehicle travel speed (m/s)

η : efficiency parameter to account for all complexities of any power losses in the transmission and the motor drive (dimensionless)

M : vehicle mass (kg)

g : gravitational constant (m/s^2)

f_r : rolling resistance coefficient (dimensionless)

α : angle of the road ($-\frac{\pi}{2} \le \alpha \le \frac{\pi}{2}$, in radians)

ρ_a : air density (kg/m^3)

C_D : aerodynamic drag coefficient (dimensionless)

A_f : vehicle frontal area (m^2)

δ : mass factor (dimensionless)

$\frac{dv(t)}{dt}$: acceleration (m/s^2)

There are many variables in the energy consumption formula. Some constant variables such as the air density, gravitational constant and aerodynamic drag coefficient are determined from basic common sense. The other constant variables such as the vehicle frontal area and vehicle mass are related to the vehicle technology parameters. And the input variables such as the vehicle travel speed and acceleration are set based on the realistic assumptions. The detailed variable values will be present in Section 5.1.

The above forces are regarded as traction loads. In fact, there are also several light traction loads such as accessory loads, which comprise the energy consumed by several accessory situations including heating, conditioning, headlights and radio. However, this paper ignores the influence of these light traction loads to simplify the energy consumption formula.

As a non-traction load (auxiliary load), regenerative braking, can be produced in some cases because of EV feature and may be too significant and efficient to be ignored. The regenerative braking allows EVs to recapture most of the energy that is wasted in conventional vehicles when the brakes are applied. The regenerative braking in EVs is designed to recapture more than 90 percent of the energy normally lost and send it back to the battery pack to be stored for later use [31]. The regenerative braking power at the battery terminals can be expressed as in Eq. (2)

$$P_{b-in} = \frac{\beta v(t)}{\eta}(Mgf_r\cos\alpha + Mg\sin\alpha + \frac{1}{2}\rho_a C_D A_f v(t)^2 + M\delta\frac{dv(t)}{dt}) \quad (2)$$

Where, the acceleration $\frac{dv(t)}{dt}$ is negative. $\beta(0 < \beta < 1)$ is the percentage of the total braking energy that can be applied by the electric motor. According to Eq. (1) and Eq. (2), the energy consumption (J, 2.78×10^{-7} kWh) from batteries is

$$E = \int_{traction\ time} P_{b-out}dt + \int_{braking\ time} P_{b-in}dt . \quad (3)$$

The traction time/braking time is the period when the acceleration is positive/negative.

(2) Uncertain travel speed

The travel speed has a close relationship with energy consumption. In the realistic traffic environment, the travel speed is regarded as an uncertain value. This paper assumes that a vehicle travelling along a path is driven at the respective travel speed of each link, and when transiting from one link to the next adapts from the previous travel speed to the new (possibly higher or lower) travel speed. Therefore, the road network with travel speed information on each link is created. In addition, because the acceleration period is very short, the travel speed is assumed to be linear with time. For example, Fig. 3 shows the change in travel speed. v_1, v_2 and v_3 are the travel speeds of the vehicle over three links. l_1, l_2 and l_3 are the lengths of the respective links. The acceleration time and uniform speed time can be calculated in terms of l_1, l_2, l_3, v_1, v_2, v_3 and the acceleration value.

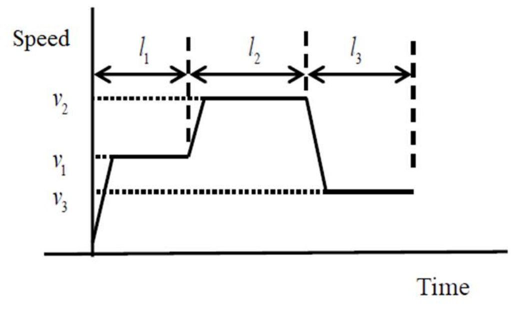

Fig. 3. *The change in travel speed*

(3) Cargo Load

When one EV visit several customers to pick-up many cargoes. With the increasing visited customers, the vehicle mass becomes bigger. According to the energy consumption formula, the vehicle mass has a greater impact on the energy consumption. Therefore, it is necessary to consider all cargo in the vehicle to calculate the energy consumption.

3.3. The Most Energy Efficient Path Problem

One route is composed of many visited nodes. Because there are massive intersections in the road network, so it is unrealistic that the vehicles drive by the straight line between any two adjacent nodes. In addition to the order of the visited nodes, the path between any two adjacent visited nodes in the route is also obtained. The problem regarding the order is settled by the model, and the path problem is separately addressed in this section. Our goal is to find the most energy efficient path in view of the benefits of considering the energy consumption.

The most energy efficient path problem is similar to the shortest path problem (SP), which consists of finding a path with the minimal cost in a directed and complete graph. Research on the SP of EVs is increasing in recent years. [32] uses the minimum travel time as the object to develop three different types of traffic network equilibrium models in terms of charging time and energy consumption. The results prove that the whole traffic network can achieve balance in the end and provide the optimal routing selection to users. The paper well integrates dynamic traffic with EV routing choices. In [33], EVs are assumed to have many charging demands along the way. To find a minimum-cost path, a dynamic program method is used to develop the model, which is solved by two algorithms. [34] regards the energy consumption as the link cost and applies the Dijkstra Algorithm to optimize the shortest path in a large network. However, because the recuperated energy of EVs during deceleration phases or when travelling downhill cause the link cost to be less than zero, Johnson potential technology was used to transform negative energy caused by deceleration or braking. Similarly, [35] considers the energy consumption as the link cost and proposes an optimal EV routing model with the least energy consumption. Finally, the model is solved by the A* Algorithm, and the results are implemented into a vehicle navigation system. Considering the uncertain characteristic of traffic time, [36] presents an energy model and uses the combination of Robust Optimization, A* Algorithm and Lagrange Relaxation to find the shortest path. [37] considers the reachable range and location problem to provide EV aid routes in each of four cases. In [38], the shortest path problem with different numbers of battery recharges/exchange stations for EVs is studied.

The best-known method for the SP is the Dijkstra Algorithm [39] which is a method to fix a single node as the source node, finds the shortest paths from the source to all other nodes in the graph, and finally produces a shortest path tree. The above-mentioned Dijkstra Algorithm is called the classical Dijkstra Algorithm. As a key factor in the classical Dijkstra Algorithm, the link weight is required to be any known and non-negative value. In other words, the link weight is not changed in solving the problem. The link weight can be regarded as travel distance, travel time, travel cost or other cost value. In the paper, the energy consumption is one of the emphasis as to be considered as the link weight. Then, the SP is named the most energy efficient path problem. However, the uncertain travel speed in the graph cause the energy consumption to be not constant and change in real time. Then, the classical Dijkstra Algorithm is not appropriate. To solve the most energy efficient path problem under the uncertain travel speed, we refer to the construction and theory of the classical Dijkstra algorithm, and make some improvements to propose a dynamic Dijkstra algorithm, where the travel time between any two nodes in the graph needs to be again computed so that the link weight is updated in real time when one node chooses the next connected node.

Because there is respective travel speed for each link, the acceleration or deceleration is sometimes produced when the vehicle transits from the last link to the current link. For example, the travel speed of link 1, link 2, link 3 and link (s,t) are, respectively 30 m/s, 20 m/s, 5 m/s and 15 m/s in the Fig. 4. Assume the acceleration or deceleration is same (2m/s^2). After calculation, the acceleration times (or deceleration times) in (a), (b) and (c) are 7.5 s, 2.5 s, 5 s, respectively. $cost(s,t)$ is defined as the energy consumption of the vehicle travelling from node s to t . To the end, small distinctions on $cost(s,t)$ with the different last connected links (link 1, link 2 and link 3) can be drawn. Therefore, the travel speed for the last connected link must be recorded in combination with the travel speed of the current link to compute the energy consumption of the current link in real time. The pseudocode is described as follows: $source$ is the origin, $target$ is the destination, $speed$ is the set of travel speeds of the links, W is the vehicle weight including curb weight and freight weight at $source$, and s is the sequence of the most energy efficient path from $source$ to $target$.

Dynamic Dijkstra Algorithm Pseudocode

```
[ S ]=Dijkstra(Graph, source , target , speed , W ):
    create node set V
    For each node v in Graph:
        dist[v] ← Infinity
        prev[v] ← Undefined
        add v to Q
    End for
    dist[source] ← 0
    u0 ← source
    While Q is not empty:
        u ← node in Q with min dist[u]
        remove u from Q
        If prev[u] is defined
        u0 ← prev[u]
        End if
        For each neighbour v of u :
            cost(u,v) ← output of Eq. (3) with speed(u0,u),
                        speed(u,v) and W
            alt ← dist[u] + cost(u,v)
            If alt < dist[v]:
                dist[v] ← alt
                prev[v] ← u
            End if
        End for
    End while
    return dist[], prev[]
    S ← empty sequence
    u ← target
    While prev[u] is defined:
        insert u at the beginning of S
        u ← prev[u]
    End while
    insert u at the beginning of S
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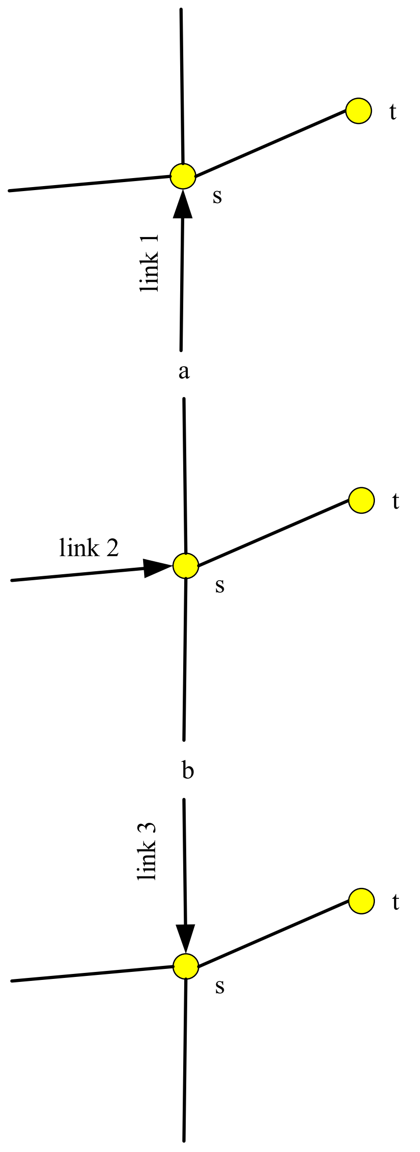

Fig. 4. *An example*
(a) *link 1—link (s,t),* ***(b)*** *link 2—link (s,t),* ***(c)*** *link 3—link (s,t)*

4. Model Formulation and Solution

4.1. Model Formulation

Since there are different types of VRPs or variants according to business requirements, to better describe and develop model the paper presents the distribution case of the EVRP. A logistics company holds only one depot and enough same EVs. There are many loads from different customers to be picked by EVs. The load weight of each customer does not exceed the vehicle load capacity. In other words, each customer is just serviced by one vehicle. The regulation requires that all used vehicles must depart from the depot to perform the distribution tasks and finally return to the depot. Moreover, in transit, these vehicles are not allowed to return to the depot. The EVs with charging demands can be recharged many times during mid-tour.

In view of the charging demands, energy consumption, range constraint and vehicle capacity constraint, the EVRP model with the minimum total cost is preset. The EVRP model is formulated as a mixed integer linear program. The variables in the model are defined as follows:

Z : total costs (yuan)
Cf_k : fixed vehicle cost of vehicle k (yuan)
Ct_k : travel cost of vehicle k (yuan)
Cr_k : charging cost of vehicle k (yuan)
c_f : per-unit fixed vehicle cost (yuan/one vehicle)
c_t : per-unit travel cost (yuan/min)
c_c : per-unit charging cost (yuan/one time)
F : a set of charging stations
O : start depot
O' : end depot
C : a set of customers
V : $O \cup C \cup F \cup O'$
Q_{jk} : battery power of vehicle k arriving at node j (kWh)
E_{ij}^k : energy consumption of vehicle k from node i to node j (kWh)
$Q_{\max}$: battery energy capacity (kWh)
W_{jk} : loading weight of vehicle k departing from node j (kg)
w_j : freight weight of node j, $\begin{cases} >0 & j \in C \\ =0 & else \end{cases}$ (kg)
$W_{\max}$: vehicle load capacity (kg)
t_{ijk} : travel time of vehicle k traveling from node i to node j (min)
T_{jk} : departure time of vehicle k at node j
t_c : charging time (min)
K : a set of all vehicles
kk : the number of all available vehicles
z_j : $\begin{cases} 1 & j \in F \\ 0 & else \end{cases}$

Decision variables:

x_{ijk} : $\begin{cases} 1 & \text{vehicle } k \text{ travels from node } i \text{ to node } j \\ 0 & \text{otherwise} \end{cases}$

y_{jk} : $\begin{cases} 1 & \text{vehicle } k \text{ is recharged at node } i \text{ to node } j \\ 0 & \text{otherwise} \end{cases}$

The model formulation is shown as follows:

$$\text{Minimize } Z = \sum_{k=1}^{K} Cf_k + Ct_k + Cr_k \tag{4}$$

where

$$Cf_k = c_f (1 - \sum_{i \in O} \sum_{j \in O'} x_{ijk}) \tag{5}$$

$$Ct_k = c_t (\sum_{i \in O'} T_{ik} - t_c \sum_{i \in F} y_{ik}) \tag{6}$$

$$Cr_k = c_c \sum_{i \in F} y_{ik} \tag{7}$$

Subject to:

$$\sum_{i \in C \cup F \cup O} x_{ijk} = 1 \qquad \forall j \in C,\ \forall k \in K \tag{8}$$

$$\sum_{j \in C \cup F \cup O'} x_{ijk} = 1 \qquad \forall i \in C,\ \forall k \in K \tag{9}$$

$$\sum_{\forall i \in C \cup F \cup O} x_{ijk} = \sum_{\forall m \in C \cup F \cup O'} x_{jmk} \qquad \forall j \in C \cup F,\ \forall k \in K \tag{10}$$

$$\sum_{\forall j \in C \cup F \cup O'} x_{Ojk} = 1 \qquad \forall k \in K \tag{11}$$

$$\sum_{\forall j \in C \cup F \cup O} x_{jO'k} = 1 \qquad \forall k \in K \tag{12}$$

$$Q_{jk} = [Q_{ik}(1-y_{ik}) + y_{ik}Q_{\max} - E_{ij}^{k}]x_{ijk} \qquad \forall j \in C \cup F \cup O' \quad \forall i \in C \cup F \cup O \quad \forall k \in K \tag{13}$$

$$Q_{jk} < Q_{\max} \qquad \forall j \in C \cup F \cup O' \ \ \forall k \in K \tag{14}$$

$$Q_{Ok} = Q_{\max} \qquad \forall k \in K \tag{15}$$

$$W_{jk} = (w_j + W_{ik})x_{ijk} \qquad \forall j \in C \cup F \cup O', \ \forall i \in C \cup F \cup O, \ \forall k \in K \tag{16}$$

$$W_{jk} = 0 \qquad \forall j \in O, \ \forall k \in K \tag{17}$$

$$W_{jk} \le W_{\max} \qquad \forall j \in V, \ \forall k \in K \tag{18}$$

$$T_{jk} = \left(T_{ik} + t_{ijk} + y_{ik}t_c\right)x_{ijk} \qquad \forall i \in C \cup F \cup O, \ \forall j \in C \cup F \cup O', \ \forall k \in K \tag{19}$$

$$T_{ik} = 0 \qquad \forall i \in O, \ \forall k \in K \tag{20}$$

$$0 \le y_{jk} \le z_j \qquad \forall j \in V, \ \forall k \in K \tag{21}$$

$$y_{jk} = \{0,1\} \qquad \forall j \in V, \ \forall k \in K \tag{22}$$

$$x_{ijk} = \{0,1\} \qquad \forall j \in C \cup F \cup O', \ \forall i \in C \cup F \cup O, \ \forall k \in K \tag{23}$$

The object given in Eq. (4) minimizes the total costs, which consist of the vehicle fixed cost, travel cost and charging cost. In Eq. (5), the used vehicles produce the vehicle fixed cost. The travel cost shown in Eq. (6) is proportional to the travel time. Eq. (7) presents the charging cost.

Eq. (8) and Eq. (9) ensure that each customer is visited by only one vehicle. Eq. (10) presents the flow conservation, in which the number of arrivals at a node must equal the number of departures for all nodes including customers and charging stations. Eq. (11) and Eq. (12) require all vehicles to leave from the start depot and return to the end depot. Because there is only one depot, the start depot and the end depot have the same location. No running vehicles pass any node except for the start depot and the end depot.

Eq. (13) expresses the residual battery power. The energy consumption E_{ij}^{k} is calculated by Eq. (3). Two vehicles consume different amounts of energy from the same path because the load weights of the two vehicles are different. The residual battery power constraint, which states that the residual battery power at any node must be larger than zero, is proposed in Eq. (14). Eq. (15) states that each vehicle at the start depot has a full battery charge (100%).

Eq. (16) is the expression of the load weight of the vehicle departing from one node. Eq. (17) states that the vehicles must pick up the loads from the customers. Eq. (18) ensures that the load weight of each vehicle does not exceed the vehicle's load capacity.

In Eq. (19), the time when the vehicle departs from one node equals to the sum of the departure time at last node, travel time between the last node and the current node, charging time, and queue time. The initial time of operation is assumed to be zero in Eq. (20).

Eq. (21) requires all vehicles to only visit the charging stations to replenish power. Eq. (22) and Eq. (23) ensure that y_{jk} and x_{ijk} are 0–1 variables. Meanwhile, the decision variables y_{jk} and x_{ijk} representing charging plans and routes.

It can be seen from the above model formulation that there are three constraints (customer service constraint, range constraint and load constraint). In consideration of the unlimited of the number of the used vehicle (the number of the used vehicle is also a optimization object), each customer can be served under load constraint. Moreover, EVs with charging demands can be recharged at charging stations many times during mid-tour so as to have enough battery power to complete the whole trip. Therefore, the solution existence can be guaranteed.

4.2. Model Solution

The solution of the EVRP model is an optimal NP-hard problem. Many methods are available to solve the problem. The exact algorithms such as Branch-and-Price Algorithm can achieve an exact solution. Although just getting a better solution faster, the heuristic algorithms have better performance in computation time. According to the features of the solved problem, the proper solution method is chosen. As several complicated considerations including battery power limitation, charging demand and path problem are involved in the EVRP model and the realistic road network is too complex, most exact algorithms which may spend much time is infeasible. Moreover, some heuristics designed for classical VRPs or variants may perform better in terms of solution quality and computation time. Therefore, a heuristic algorithm is applied in the solution of the EVRP model.

As one of the heuristic algorithms, genetic algorithm (GA) is easy to programme and has faster computation time. Moreover, GA has been widely applied in the complex VRPs or variants especially implemented in large and realistic road networks, and can obtain acceptable better solution. The hybrid Genetic Algorithm (HGA) is a combination method of GA and local search strategy to strengthen the ability of a local search based on the advantages of GA. In GA, a set number of individuals with genes are processed by selection and multiplication operators to produce new individuals. The individuals with better fitness will obtain more opportunities to survive. To ensure variety among individuals, crossover and mutation are applied in the GA procedure. For HGA, a local search strategy is performed for everyone after both crossover and mutation. The method of the local search strategy is to find more effective individuals within the neighbourhood range by partly changing the genes of the individual. Randomly exchange two different genes of one individual many times (search times), and then some new individuals within the neighbourhood range are produced. The one with the best fitness value is selected from the new individuals and the original individual as the latest individual.

The procedure of HGA is shown as follows.

Step 1: input the algorithm parameters (number of individuals N, number of generations T, number of elite individuals Ne, crossover rate P_c, mutation rate P_m) and constant variables to the model.

Step 2: design encoding method.

Step 3: produce initial population $P(gen)$.

($|P(gen)| = N$), then $gen = 0$.

Step 4: compute fitness for each individual in $P(gen)$.

Step 5: select Ne individuals from $P(gen)$ at high fitness values as elite individuals that are directly inserted into $P(gen+1)$.

Step 6: the remaining individuals are applied in the crossover.

Step 7: each individual is respectively performed by the local search strategy.

Step 8: all individuals are applied in mutation.

Step 9: each individual is respectively performed by the local search strategy.

Step 10: the processed individuals and the elite individuals are combined to form a new population $P(gen+1)$.

Step 11: if $gen < T$, gen is increased by itself, and return to step 4. Otherwise, the algorithm stops running and outputs the individual with the highest fitness value in $P(gen+1)$.

Step 12: decode the optimal individual.

To guarantee solution validity, each individual must be tested against all constraints after steps 6–10. If invalid, this step is run again.

The algorithm parameters have to some extent affect the solution. The four parameters (number of individuals, number of generations and number of elite individuals and local search times) are determined after validation with some test cases. For examples, when the generation arrives at 300 in each test case, the algorithm has been in convergence for a long time. In addition, the two parameters (crossover rate and mutation rate) are chosen in their reasonable values ranges. All algorithm parameters are listed in Table 2.

Table 2 Algorithm parameter values

Parameter	Description	Value
N	Number of individuals	50
T	Number of generations	300
Ne	Number of elite individuals	20
P_c	Crossover rate	0.9
P_m	Mutation rate	0.1
S_n	Local search times	5

5. Experiment Analysis

5.1. Experiment Data Description

A large realistic case study is conducted to reflect the performance of the proposed model and the solution technology. Several types of experimental data including road network, depot, customers and charging stations and problem parameters are determined as follows. All experiments were run on a desktop with an Intel Core i5-5200U CPU, 16 GB of RAM and a 64-bit operating system.

(1) Road Network

The case study is performed in the Beijing urban area (within the fifth ring). The realistic transportation network can better reflect the road conditions, but is very complex. If the whole transportation network is completely considered, more time will be spent on solving the problem, and the solution will possibly be feasible and inefficient. In general, the roads can be subdivided into several grades such as expressway (ring road), arterial road and branch road. Each road grade has its own respective road features in terms of design specifications. Considering simulation situation, network size, and solution effectiveness, we mainly select all expressways and arterial roads to construct a road network applied to solve the model and implement the results. In addition, we also must add the travel speed information on each link. In accordance with city road specifications and actual traffic conditions, this paper assumes that the travel speed for the fifth ring road, the fourth ring road and the remaining roads are 80 km/h, 60 km/h and 40 km/h, respectively. The road network labelled with travel speeds is given in Fig. 5. After creation, the road network is composed of 222 nodes and 943 links. Nodes and links represent road intersections and road segments, respectively.

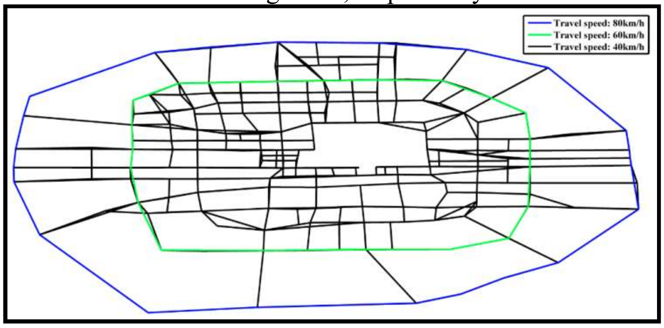

Fig. 5. *Road network labelled with travel speed*

(2) Depot, Customers and Charging Stations

There are 100 customers and 30 charging stations to be distributed in the road network. The depot is located at the centre of the road network. The freight weight of each customer is randomly generated. The comprehensive road network loading depot, customers and charging stations are shown in Fig. 6.

To examine the effectiveness and scalability of solution approach, the different number of customers or charging stations (100 customers, 50 customers, 30 customers, 15 charging stations, 30 charging stations) are considered to conduct the experiments with different problem sizes. The detailed description is showed in the analysis results (Section 5.2).

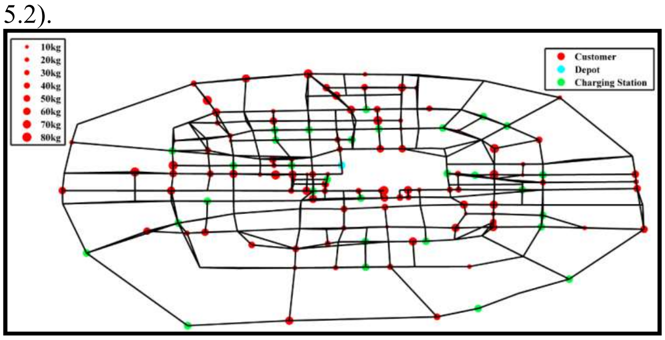

Fig. 6. *Road network loading depot, customers and charging stations*

(3) Problem Parameters

At present, EVs for logistics running in Beijing are mostly electric vans manufactured by Beijing Motor Company. The vehicle technology parameters are given in Table 3.

The values of the constant parameters in the energy consumption formula (Table 4) are determined from [29], [30] and Table 3. The constant parameters in the model (Table 5) are set based on some operation experience and Table 3. The per-unit vehicle fixed cost c_f comprehensively considers the driver wages, upkeep, vehicle idle cost, vehicle insurance cost and so on. The per-unit travel cost c_t is based on time utilization and operation efficiency. According to take advice on the logistics companies, we determine the two parameters are set to 100 yuan and 1 yuan/min, respectively. The per-unit charging cost c_c is determined by the electricity prices and charging service fee. In [40], the average industrial electricity price is 0.8 yuan/kWh. But there is no any unified standard approach for the charging service fee. Therefore, to calculate conveniently, the per-unit charging cost is valued to be 30 yuan that 21.6 yuan (the cost with 100% charge) plus 8.4 yuan (the charging service fee). The charging time t_c has been described in Section 3.1. The ten available vehicles totally satisfy the distribution demands of the study case. Moreover, because the total costs (the object) include the fixed vehicle cost, the number of used vehicles can be optimized simultaneously. The rated battery energy capacity is 27 kWh. However, because of considering the occurrence of the fear that EVs have insufficient battery power to reach the destination, so we remain 10% rated battery energy capacity and the battery energy capacity $Q_{\max}$ is set to 24.3 kWh.

Table 3 Vehicle technology parameters

Vehicle technology parameter	Value
length of frontal area (m)	1.60
wide of frontal area (m)	2.19
curb weight (including battery weight, kg)	1800
vehicle load capacity (kg)	1000
rated battery energy capacity (kWh)	27

Table 4 The values of the constant parameters in the energy consumption formula

Constant parameter	Description	Value	Constant parameter	Description	Value
ρ_a	air density (kg/m^3)	1.205	δ	mass factor (dimensionless)	1.1
C_D	aerodynamic drag coefficient (dimensionless)	0.6	g	gravitational constant (m/s^2)	9.8
A_f	vehicle frontal area (m^2)	3.504	η	energy transferring parameter (dimensionless)	80%
f_r	rolling resistance coefficient (dimensionless)	0.01	β	percentage of the restored braking energy	90%
α	the angle of the road	0			

Table 5 The values of the constant parameters in the model.

Constant parameter	Description	Value	Constant parameter	Description	Value
c_f	per-unit fixed vehicle cost (yuan/one vehicle)	100	kk	the number of available vehicles (dimensionless)	10
c_t	per-unit travel cost (yuan/min)	1	$Q_{\max}$	battery energy capacity (kWh)	24.3
c_c	per-unit charging cost (yuan/one time)	30	$W_{\max}$	vehicle load capacity (kg)	1000
t_c	charging time (min)	30			

5.2. Analysis Results

(1) Optimal Operation Scheme

Based on the foregoing experiment data, the EVRP model is solved by HGA. MATLAB R2012a is applied in the HGA implementation. The computational time of the HGA implementation is about 3.2h. Consider the model and the realistic road network are is overly complex. In addition, the result is obtained the day before the result is performed in reality. Therefore, the computational time is acceptable. The algorithm iteration process of the optimal object value in Fig. 7 shows HGA can quickly guarantee convergence and improve computational effort. Moreover, an optimal operation scheme including routes, charging plan and driving paths, are presented as follows. Table 6 summarizes all the details costs. The route information is shown in Table 7.

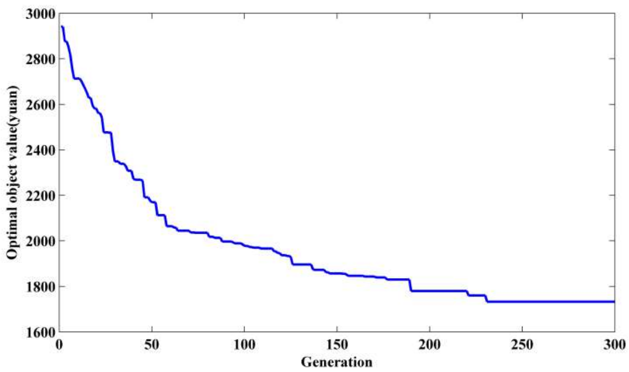

Fig. 7. *Algorithm iteration process of the optimal object value*

Table 6 The costs of the routes

Route	Fixed vehicle cost (yuan)	Travel cost (yuan)	Charging cost (yuan)	Total costs (yuan)
1	100	271.18	30	401.18
2	100	170.28	0	270.28
3	100	170.40	0	270.40
4	100	160.82	0	260.82
5	100	232.86	0	332.86
6	100	97.31	0	197.31
Total	600	1102.85	30	1732.85

To complete the distribution, 1732.85 yuan in total are spent. Moreover, six vehicles are dispatched to serve the customers. For example, the vehicle performing route 6 starts from the depot and successively visits customer 20, 10, 42, 53, 62, 69, 82, 61, 9 and, finally comes back to the depot. For route 2-6, the battery energy capacity (24.3 kWh) can totally satisfy all the energy consumption of each route so that there is no charging cost. However, because of the limitation of battery power, the vehicle performing route 1 is recharged at No. 6 charging station after visiting No. 56 customer.

To clearly show how each vehicle runs, we draw the driving path of each route on the road network (see Fig. 8). The vehicle tracks indicate that each vehicle does not cross the larger area to reduce the travel cost included by the object to the greatest extent.

In addition, the energy consumption per unit distance in kWh/km is generally used to evaluate the performance of the energy consumption. From Table 7, the total energy consumption and the total distance of all the routes are 99.55 kWh and 742.92 km, respectively. According to the calculation, the average energy consumption per unit distance is 0.134 kWh/km. This value is basically consistent with the findings of [29], who used real data to show that the lowest average amount of energy used by EVs is 0.5MJ/km (0.14kWh/km). Therefore, in view of the simplified energy consumption formula and different simulation situations, we conclude the result proves that the calculation method of the energy consumption and the simulation situation of the case are available. Moreover, the conclusion that EV with 100% charge can furthest run 200 km in the case is given.

Table 7 The detailed routes

Route	Order of the visited nodes	Energy consumption (kWh)	Distance (km)	Travel time (min)
1 (Recharged)	depot-83-4-58-22-2-64-19-11-72-55-40-79-7-37-50-81-96-95-28-33-100-56-No.6 station-depot	25.29	182.95	271.18
2	depot-78-8-80-74-57-14-15-59-16-77-12-84-97-44-48-depot	14.18	113.50	170.28
3	depot-39-76-27-23-66-99-88-94-29-13-85-89-52-75-41-34-depot	14.73	113.58	170.40
4	depot-71-60-32-1-70-92-5-24-86-49-68-43-36-93-31-30-depot	14.65	108.70	160.82
5	depot-98-17-54-91-25-21-26-47-3-67-65-73-46-63-87-35-51-45-18-38-90- depot	20.98	156.02	232.86
6	depot-20-10-42-53-62-69-82-61-9-6-depot	9.72	68.17	97.31
	Total	99.55	742.92	1102.85

(2) Energy Consumption and Distance

The cumulative energy consumption and cumulative distance at each visited node are shown in Fig. 9. Considering the number of the routes, we just choose two types of routes (recharged route and common route) as the presentation. Regardless of whether route 1 or route 2 is used, the increasingly wider gap between the cumulative energy consumption and the cumulative distance over time indicate that more loads carried during the second half of the route lead to greater energy consumption. This can also prove that there is a positive relation between the mass of the vehicle and the energy consumption in the energy consumption formula.

(3) Solution Performance

As HGA has randomness in crossover and mutation, to testify if HGA can obtain better solution the EVRP model is solved four times again. HGA takes 3.5h on average to complete the whole algorithm computation. In view of the complexity of the road network and more considerations in the model, the computation time is available. The comparison in the total costs is shown in Table 8. The total costs in Table 6 is from experiment 1. The total costs are nearly equal among five experiments. Despite some very small fluctuations in the object because of algorithm randomness, the result indicates that HGA can get an optimal solution. Therefore, HGA is a relatively common algorithm, it better guarantees computational effort.

Table 8 The comparison from five experiments in the total costs

Experiment	Total costs (yuan)
1	1732.85
2	1720.41
3	1713.15
4	1734.69
5	1728.23

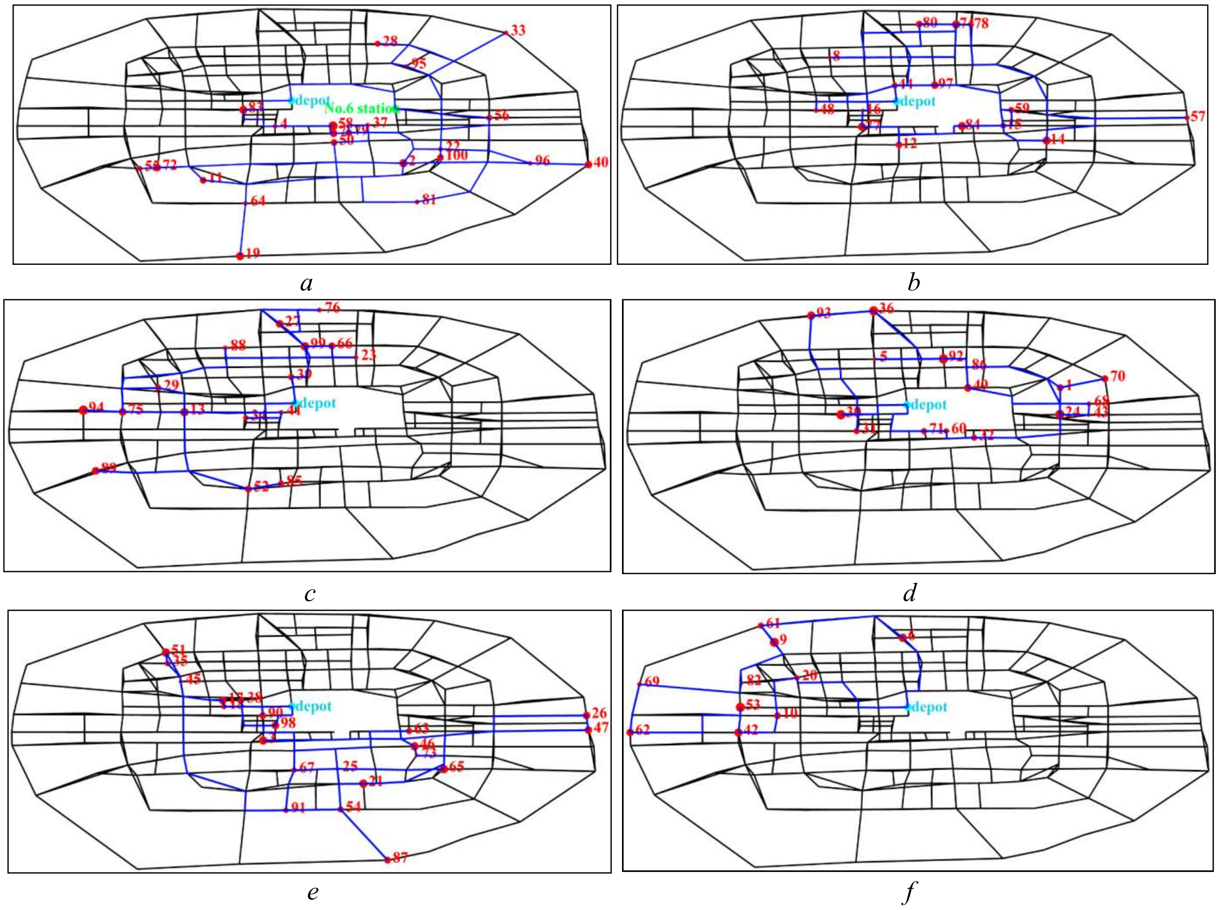

Fig. 8. The driving path of each route in the road network
***(a)** Route 1 (Recharged), **(b)** Route 2, **(c)** Route 3, **(d)** Route 4, **(e)** Route5, **(f)** Route 6*

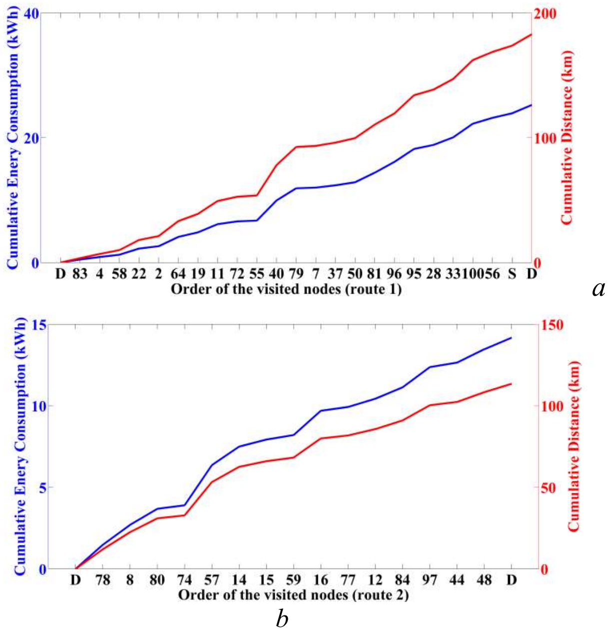

Fig. 9. The cumulative energy consumption and cumulative distance at each visited node (S and D in x-axis represent depot and charging station, respectively)
***(a)** Route 1, **(b)** Route 2*

The effectiveness and scalability of solution approach is also an evaluation index for solution performance so as to be verified by the experiments with different problem sizes. There are many considerations to reflect the different problem sizes. The paper conducts the experiments with different problem sizes by changing the number of customers and the number of charging stations. The detailed settings and result of each experiment are shown in Table 9.

The total costs are incremental over the number of customers because the increase in the number of customers. However, there are same total costs between the two experiments with different number of charging stations and same number of customer. The result indicates that HGA can find the same optimal solution between the experiments with different problem sizes. Therefore, the application of HGA in the EVRP model are superior in the aspect of effectiveness and scalability of solution approach.

Table 9 The comparison from the experiments with different problem sizes in the total costs

Total costs (yuan)		the number of charging stations	
		15	30
the number of customers	30	512.69	512.69
	50	858.81	858.81
	100	1732.85	1732.85

6. Conclusion and Future

Considering some practical comprehensive constraints such as energy consumption and charging demands, the EVRP model is developed to minimize the total costs. The EVRP model completely satisfies customer demands while reducing cost, avoiding depletion of all battery power while in transit and ensuring safe operation. Four sub-problems are solved: how the vehicles visit the customers, how the vehicles run, and where and when the vehicles with charging demands are recharged.

The energy consumption of EVs has a closer relationship to the uncertain travel speed and cargo load, which must be reflected to express EV performance realistically. Therefore, a formula that combines physics and theory is proposed to compute the EV energy consumption.

Because of the limited battery technologies, EVs sometimes are recharged at charging stations while in transit to ensure that the trips are completed. How to optimally assign the charging stations for EVs with charging demands is an advanced issue. Therefore, the EVRP model allows an EV to be recharged many times.

Finally, a large, realistic case study with Beijing urban road network, is presented. HGA is applied to solve the EVRP model to obtain an optimal operation scheme including routes, charging plan and driving paths. a dynamic Dijkstra Algorithm is proposed to find the most efficient path as the driving paths. The results indicate that HGA is superior on computation effort and solution performance.

Although the EVRP with energy consumption and charging demands has been developed and solved, our work leaves several aspects to be desired.

- The charging station location problem play a dominating role in optimizing the charging plan which is very significant for EVs with charging demands during mid-tour. Since the paper mainly focuses on the vehicle operation with the proposal data, the locations of the charging stations are assumed ahead of time. However, considering the relationship between the charging stations and the EVs activities, the EVRP associating with the charging station problem such as location problem and queuing problem will be investigated.
- Although uncertain travel speed has been considered, this paper defines only a vehicle traveling along different links at each link's travel speed. In dynamic traffic, the travel speed changes over time. To accurately calculate EV energy consumption, we place more emphasis on the driving simulation in the future.
- The optimal solution is extremely influenced by the problem parameters and algorithm parameters. The algorithm parameters are determined after many experiments. In addition, the problem parameters are set based on operation experience. Our future work will include a sensitivity analysis for these parameters.

7. Acknowledgments

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