IJNRD.ORG ISSN : 2456-4184

INTERNATIONAL JOURNAL OF NOVEL RESEARCH AND DEVELOPMENT (IJNRD) | IJNRD.ORG

An International Open Access, Peer-reviewed, Refereed Journal

ELECTRIC VEHICLE ROUTING USING VARIANTS AND ALGORITHMS

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Abstract:

Over the past decade, electric vehicles (EVs) have been considered in a growing number of models and methods for vehicle routing problems (VRPs).This study presents a comprehensive survey of EV routing problems and their many variants. We only consider the problems in which each vehicle may visit multiple vertices and be recharged during the trip. The related literature can be roughly divided into nine classes: Electric traveling salesman problem, green VRP, electric VRP, mixed electric VRP, electric location routing problem, hybrid electric VRP, electric dial-a-ride problem, electric two-echelon VRP, and electric pickup and delivery problem. For each of these nine classes, we focus on reviewing the settings of problem variants and the algorithms used to obtain their solutions.

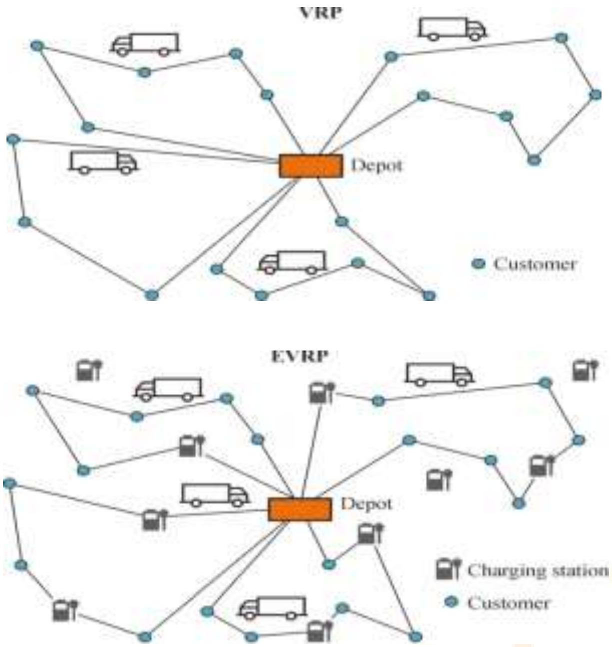
Keywords: electric vehicles, routing, recharging stations, exact algorithms, meta heuristics

1 Introduction

Burning fossil fuels generates greenhouse gas (GHG), which is a major cause of climate change and global warming, and also results in air pollution that damages human health(SchifferandWalther,2017).Transportation plays an important role in the development of economies and consumes a large portion of fossil fuels. As reported by the Environmental Protection Agency (2018), transportation activities accounted for 28.5% of GHG emissions in the US in 2016.According to Euro stat, the statistical office of the European Union (EU), fuel combustion for transportation was responsible for 25% of EU-28 GHG emissions in 2017, which has increased its contribution significantly since 1990.Governments of many countries have adopted new environmental measures and regulations to reduce GHG emissions and cut down on the consumption of fossil fuels (Keskin and Çatay, 2018).

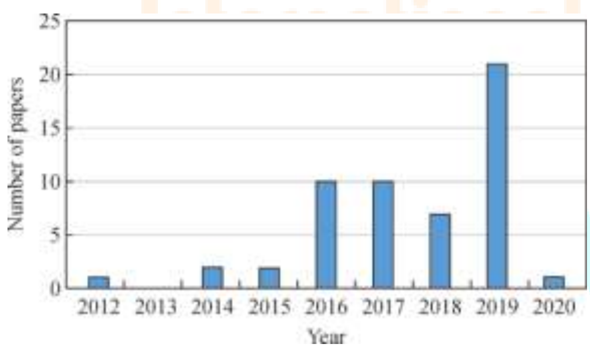
Fig.1 An example solution of the VRP.

At present, the prevalence of the EVs still face several challenges (Schneider et al., 2014;2018;Schiffer and Walther, 2017). The first challenge is the limited EV driving range whose average value is approximately 200 km so far. The maximum travel range of an EV is usually less than that of a comparable gasoline-powered vehicle. Moreover, the driving range can be decreased significantly by cold temperatures. Therefore, EV drivers must be cautious when scheduling routes to ensure that



In this study, we only review the routing problems that use EVs and consider recharging operations in the routes. In several existing studies, such as Doppstadtetal.(2016),Nejad et al. (2017),Sassi and Oulamara (2017), and Murakami (2017), the problems of routing EVs are investigated, but recharging EVs along the routes are not considered, and therefore we do not discuss them. Afroditietal.(2014)surveyed theEVRPswithindustryconstraints, but this study includes only a small number of reference papers. Recently, Erdelić and Carić (2019) reviewed the variants and solution approaches for EVRPs. The solution approaches can be roughly divided into two main streams, namely, meta heuristics and exact algorithms. However, the authors only mentioned meta heuristics for the relevant problems. According to our statistics, the number of papers on the EVRPs published in the last two years accounts for over 40% of the total number. In Erdelićand Carić(2019), only a small number of papers in the last two years were reviewed and several problem variants were not discussed. As the research on EVRPs is in an increasing stage and the relevant literature is not rich so far, the number of articles reviewed in our work is only around 50. Figures 3 and 4 show the numbers of papers published in the recent nine years and in each relevant journal, respectively.

Fig 2 Cloud diagram indicating the distribution



The rest of this paper is structured as follows. In Section 2, we review the electric traveling salesman problem (ETSP) in which only one EV is used. In Section 3, we present a thorough survey of the GVRP, which is a widely studied special case of the EVRP. In Section4,we focus on the papers about the basic EVRP as well as its extensions that consider additional features, such as charging functions and time windows. In many situations, the carriers need to simultaneously schedule various types of vehicles, which may include EVs, hybrid EVs, and conventional vehicles. Many studies have investigated the approaches for scheduling a mixed fleet of vehicles, and thus the relevant survey on the mixed EVRP (MEVRP) is given in Section 5. Subsequently, we discuss in Section 6 all papers on the electric location routing problem (ELRP) that make decisions on both the locations of recharging facilities and the routes of EVs.

2 Electric traveling sales man problem:

Traveling salesman problem (TSP) is one of the most intensively studied problems in computational mathe- matics (Gutin and Punnen, 2007). The ETSP, which extends the TSP by considering only one EV, is a special case of the EVRP. When a time window is imposed on each customer, we can obtain a variant called ETSP with time windows (ETSPTW). This problem aims to find the shortest Hamiltonian tour of a set of customers while ensuring that the time window constraints are not violated and the battery level is always positive(RobertiandWen,2016). During the tour, the electric supply for the vehicle can be recharged in recharging stations. Robertiand Wen(2016) considered in the ETSPTW two recharging policies, namely, full recharging (the battery is fully recharged at each station) and partial recharging (any amount of electricity can be recharged at each recharging station),and presented mixed integer programming(MIP) models for the problem under both recharging policies. Subsequently, they developed a three-phase heuristic to solve the ETSPTW, where the approach components need to be simply adapted to deal with different recharging policies.

In the market, various types of recharging stations exist, which use different charging technologies. As a result, the charging rate at one type of recharging station may differ from that of another. Küçükoğluetal.(2019) extended the ETSPTW by considering various charging rates and introduced a new problem called ETSPTW with mixed charging rates (ETSPTW–MCR). To solve this problem, they proposed a new and effective hybrid simulated annealing/tabu search (SA/TS) algorithm. This algorithm improved on the existing hybridization of SA and TS by employing an efficient search strategy, a modified solution acceptance criterion, and two types of tabu lists. The ETSPTW–MCR is solved by a two-state procedure. First, the hybrid SA/TS algorithm seeks the least cost solutions only considering the constraints in the TSPTW. Then, a dynamic programming algorithm is executed to obtain feasible solutions for the ETSPTW–MCR. For a given route that only contains customers, the dynamic programming algorithm generates recharging operation plans optimally by inserting the recharging stations in the customer-only route. In the experiments, the authors employed their algorithm to solve the instances of the TSPTW, ETSPTW, and ETSPTW–MCR. Compared with the existing algorithms for the TSPTW and ETSPTW, their algorithm achieved competitive results. In addition, the results generated by their algorithm is stable because the standard deviations of most of the results are zero very close to zero. The ETSP and its variants are depicted in Fig. 7, where for each arc the problem at its end is an extension of the problem at its origin.

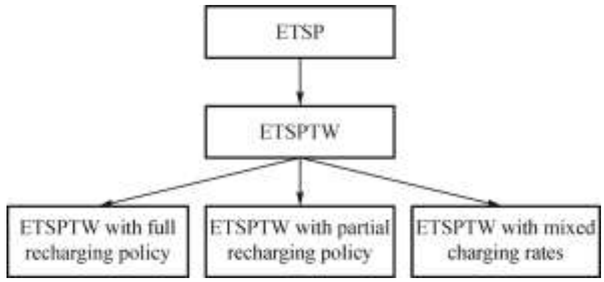


Fig 3 The ETSP and its variants.

3 Green vehicle routing problem

The GVRP, formally introduced by Erdoğan and Miller-Hooks(2012),is a special case of the EVRP that does not consider the vehicle capacity. This problem is defined on a directed graph G=(V,E),where the vertex set V=N∪F∪{0}consists of a set N={1,...,n}of n
customers, a set F ={n+1, ...,n+f}of f recharging stations, and vertex 0 representing the depot. Each customer i∈N has a service time S_i and each edge is associated with a distance $d_{i,j}$ and a travel time $t_{i,j}$. These n
customers need to be served by an unlimited number of

route-first cluster-second heuristics(Beasley,1983;Prinset al., 2014) with an optimal procedure of inserting alternative fuel stations. In the second phase, the heuristic seeks feasible GVRP solutions by solving a set-partitioning formulation based on the routes in the pool. The authors conducted experiments using 52 instances in also tested their algorithm on 52 GVRP instances presented by Erdoğan and Miller-Hooks (2012). When compared with the results in the literature, this VNS algorithm provided the best solution values for all small in stances with less computation time. For the larger instances, it also produced the best solution values for 11 out of 12 instances, and its performance is superior to the other existing heuristics in the literature.

4 Electric vehicle routing problem:

The EVRP is a straightforward extension of the classic VRP by involving EVs and the operations of recharge. This section first provides an MIP model for the standard EVRP and then introduces its several types of extensions

and variants. In the literature, the EVRP has been extended by considering many features, such as multiple types of recharging stations, minimization of the total energy

consumed, multiple depots, energy consumption uncertainty, heterogeneous EVs, time windows, and nonlinear charging functions. According to the number of articles published, we find the two main extensions of the EVRP are that with time windows (Schneider et al., 2014) and that with nonlinear charging functions (Montoya et al.,2017). The EVRP and its variants are summarized in Table 2, which shows the problem names, features considered, and solution approaches.

Here, we present the MIP model of the standard EVRP. Let $V\#$ be the set of vertices with $V\#=V\cup F\#$, where $V=\{1,...,n\}$denotes the set of n customers and $F\#$ is the set of dummy vertices related to the set F of recharging stations. Vertices 0 and n + 1 represent the exit and entrance of the depot, and each route must start from vertex

0 and end at vertex n+1.Moreover,we define

$F_0\#=F\#\cup\{0\}$,$V_0\#=V\#\cup\{0\}$,and$V_0\#_{,n+1}=V\#\cup\{0,n+1\}$. The EVRP is defined on a complete and directed graph $G=(V_0\#_{,n+1}, E)$ with these to f edges $E=\{(i,j)|i,j\in V_0\#_{,n+1},i\neq j\}$.Each edge has a distance $d_{i,j}$, a travel time $t_{i,j}$, and a constant battery consumption

rate h (perunit distance),i.e., traversing this edge

consumes $h\, d_{i,j}$ battery charge. A fleet of identical EVs

with a loading capacity of C and a battery capacity of Q is

positioned at the depot. When leaving the depot, EVs have full battery power. Each vertex $i\in V_0\#_{,n+1}$has a positive demandq_i,whichis0if$i\notin V$, and a service time

$s_i(s_0=s_{n+1}=0)$.At each recharging station, the difference between the present battery level and Q is recharged

with a charging rate of g (i.e., full recharging policy is adopted). Each customer must be visited by exactly one vehicle, i.e., split delivery is not allowed. We define decision variable τ_i as the time of arrival, decision variable u_i as the remaining cargo, and decision variable y_i as the remainingbatterylevelonarrivalatvertex$i\in V_0\#_{,n+1}$.Let $x_{i,j}(i\in V_0\#,j\in V_n\#_{+1},i\neq j)$be a binary decision variable

that equals1 if edge$(i,j)$is traversed and 0 otherwise. The objective of this problem is to minimize the total traveling distance. The MIP model for the EVRP is described as follows:

$$\min \sum_{i\in V_0\#,j\in V_n\#_{+1},i\neq j} d_{i,j}\, x_{i,j} \tag{1}$$

s.t.

$$\sum_{j\in V_n\#_{+1},i\neq j} x_{i,j}=1,6i\in V, \tag{2}$$

$$\sum_{j\in V_n\#_{+1},i\neq j} x_{i,j} £1,6i\in F\#, \tag{3}$$

$$\sum_{j\in V_n\#_{+1},i\neq j} x_{j,i}-\sum_{i\in V_0\#,i\neq j} x_{i,j}=0,6j\in V\#, \tag{4}$$

$$\tau_i+(t_{i,j}+s_i)x_{i,j}-M(1-x_{i,j})£\tau_j,$$

$$6i\in V_0,j\in V_n\#_{+1},i\neq j, \tag{5}$$

$$\tau_i+t_{i,j}x_{i,j}+g(Q-y_i)-(M+gQ)(1-x_{i,j})£\tau_j,$$

$$6i\in F,\#\ j\in V_n\#_{+1},i\neq j, \tag{6}$$

$$0£u_j£u_i- q_ix_{i,j}+ C(1-x_{i,j}),$$

$$6i\in V_0\#,j\in V_n\#_{+1},i\neq j, \tag{7}$$

$$0£u_0£C, \tag{8}$$

$$0£y_j£y_i-hd_{i,j}x_{i,j}+Q(1-x_{i,j}),$$

$$6j\in V_n\#_{+1},i\in V,i\neq j, \tag{9}$$

$$0£y_j£Q-hd_{i,j}x_{i,j},6i\in F_0\#,j\in V_n\#_{+1},i\neq j, \tag{10}$$

$$x_{i,j}\in\{0,1\},6i\in V_0\#,j\in V\#_{n+1},i\neq j. \tag{11}$$

In the above model, M is a sufficiently large positive number. Objective (1) minimizes the total traveling distance. Constraint (2) ensures that each customer must be served exactly once, and constraint (3) states that each dummy recharging station must be visited at most once. Constraint (4) represents flow conservation constraints. Constraints (5)and(6)define the relationship of u_i and u_j, which are associated with two consecutively visited vertices I and j. Constraints (7) and(8) guarantee demand fulfillment for each customer. Finally, constraints (9) and

(10) guarantee that the battery charge level never falls below 0.

4.1 **EVRP with time windows:**

Initiated the research on EVRP with time windows (EVRPTW). The MIP model of the EVRPTW can be obtained by adding time window constraints to the model (1)–(11).The authors implemented a hybrid heuristic that combines VNS algorithm and TS heuristic (henceforth called VNS/TS for brevity) to solve the EVRPTW. They conducted numerical experiments to evaluate the performance of their method. First, they compared the performance of their VNS/TS heuristic and CPLEX using small-sized instances. The results show that the VNS/TS heuristic is able to solve these small instances to optimality within only a few seconds. However, for most of these instances, CPLEX consumed much more computation times. Moreover, for 11 out of 36 small instances, CPLEX cannot produce provable optimal solutions. Second, the authors analyzed the efficiency of the algorithmic components of their hybrid heuristic based on a set of medium-size instances. Finally, they demonstrated the ability of the VNS/TS heuristic on solving the instances of the GVRP, VRPTW, and multi-depot VRP with inter depot routes (Crevier et al.,2007). Desaulnierset al. (2016) designed exact branch-and-price-and-cut algorithms for four versions of the EVRPTW, which are the following:1)each route is allowed to visit at most one recharging station and a full recharging policy is adopted,2) each route can visit multiple recharging stations and a fullrechargingpolicyisadopted,3)each route is allowed to visit at most one recharging station and a partial recharging policy is adopted, and 4) each route can visit multiple recharging stations and a partial recharging policy is adopted. Actually, the second version is exactly the same as the problem studied by Schneider et al. (2014). The branch-and-price-and-cut algorithm follows a standard framework including column generation procedure, cut- ting planes, and branching strategies. Keskin and Çatay(2016) focused on the EVRPTW with the partial recharging policy and developed an ALNS heuristic to solve it efficiently. This ALNS heuristic uses new removal and insertion mechanisms to handle the structure of the problem, which includes customer removal, recharging station removal, customer insertion, and recharging station insertion. The authors applied their heuristic to the instances of the EVRPTW with the full recharging policy and achieved new best-known solutions for four instances. Further, they showed that the partial recharging policy may improve the solutions substantially, compared with the full recharging one.

Other works in the literature focused on the extensions of the EVRPTW. Hiermann et al. (2016) extended the EVRPTW by considering heterogeneous EVs, and the resultant problem is called the heterogeneous EVRPTW (HEVRPTW). The available vehicle types differ in their load capacities, battery capacities, amount of energy consumed per distance unit, recharging time per energy unit, and acquisition costs. The authors provided two models for the HEVRPTW, namely, an arc flow model and a set-partitioning model. Then, they applied the branch- and-price algorithm to solve the set-partitioning model for the optimal solution of the problem. However, the instance size that can be optimally solved by this exact method is limited. To handle the instances of real sizes, they also developed a heuristic based on the ALNS heuristic. In this heuristic, a local search procedure is used to intensify the search process in each iteration. As the ALNS heuristic as low ability to better position the recharging stations, a post processing procedure is added to improve the selection and positioning of recharging stations for a route with the fixed customer visiting order. This post-optimization procedure is realized by a labeling algorithm and assumes that at most one recharging station can be placed between any two consecutive customers to reduce the computation time. Zhao and Lu (2019) also studied an HEVRPTW in which a full recharging policy is adopted, and the charging time of each EV type is assumed to be constant regardless of the remaining battery power of the EV. The objective of this problem is to minimize the sum of the EV acquisition, travel, charging, and waiting costs incurred by the customers and distribution center. The researchers also devised a heuristic approach based on the ALNS heuristic and the set-partitioning model to solve their problem. This heuristic first applies the ALNS heuristic to search the solution space and stores the feasible routes encountered during the search process in a route pool. Then, it constructs a set-partitioning model using the routes in the pool and solves it using an MIP solver. As the route pool is a subset of all feasible routes, the optimal solution of the set-partitioning model can only be regarded as a near- optimal solution of the problem. Yuetal. (2019b) studied a GVRP with time windows (GVRPTW) that employs heterogeneous EVs and tries to minimize the total carbon emissions. This problem considers the vehicle capacity, and thus it is essentially the HEVRPTW. The authors developed a branch-and-price algorithm to solve their problem to optimality.

Wen et al. (2016) introduced a multi-depot EVRPTW that employs the full recharging policy and considers recharging time proportional to the charged electricity. Each vertex to be served has a fixed starting time, which is equivalent to having a service time window whose starting and ending times are the same. Moreover, each depot or recharging station has a specified time window within which the EV can visit. The authors implemented an ALNS heuristic to find near-optimal solutions for their problem. Wang et al. (2019) extended the multi-depot EVRPTW by considering shared transportation resources, where the time-dependent speed and piecewise penalty costs for violating the time windows are also in corporated. There searchers proposed abi-objective model to minimize the total carbon emission and operational cost, and then designed a hybrid heuristic to solve the problem.Keskin and Çatay (2018) extended the EVRPTW by allowing partial recharging and considering three types of chargers equipped at each recharging station, namely, normal, fast, and super-fast chargers. The faster charger uses less time while the unit cost of energy is higher. This problem aims to first minimize the number of vehicles and then minimize the total cost of energy consumed. To solve this problem, the authors proposed a two-phase mat heuristic approach, where the ALNS heuristic is applied to find near-optimal solutions in the first phase and an exact method of the MIP solver is used in the second phase to further improve the solution quality. Specifically, the exact approach uses a simplified MIP model that fixes the sequence of the customers, and makes decisions based on the selection of the recharging stations and charger types, and the amount of energy charged.

Battery swapping is an alternative way to recharge EVs. Usually, the battery of the EV can be swapped with a new fully recharged one within only five minutes. Verma (2018) introduced a variant of the EVRPTW in which the recharging stations provide both chargers and batteries for swapping. To solve this problem, they designed a heuristic that consists of two steps. In the first step, the number of visits to each recharging station is fixed using a local search procedure that is combined with efficient lower and upper bounds. In the second step, this heuristic determines the routing costs of the delivery plan using a genetic algorithm. In the heuristic, the constraints on battery capacity and time windows can be violated. Vehicle load can affect the energy consumption as well as the transportation cost, which has been mentioned in several studies (Zhang et al., 2012;Luo et al., 2017).Kancharla and Ramadurai (2018) extended the EVRPTW in which energy consumption depends on the vehicle load. Actually, the electricity consumption per distance unit of an EV is a function of its speed and load. The authors applied an ALNS heuristic with several special operators to seek the near-optimal solution of their problem. Cortés- introduced a new variant of the EVRPTW that involves the concept of satellite customers. During the time for recharging the EV at any recharging station, if the

cargoes on the EV can be delivered to a certain customer by alternative transportation modes, such as walking, bicycles, and drones, such customers are called satellite customers. It is assumed that during each recharging operation, at most one satellite customer can be visited. This extended problem is solved by a hybrid heuristic consisting of iterated local search, variable neighborhood descent, and set-partitioning model.

4.2 EVRP with non linear charging function:

The majority of the existing studies on routing EVs assume that the recharging time is a linear function of the amount of electricity charged. However, the charging duration can be roughly divided into two stages, where in the first stage charging time and charged electricity have a linear relationship and in the second stage its relationship is nonlinear. To face this reality, Montoya et al. (2017) in corporate into the EVRP model the non linear feature of charging process, and thus the resultant problem is called the EVRP with non linear charging function (EVRP–NL). As shown in Fig. 8, the charging process can be approximated to a piecewise linear function. The authors provided an MIP model for the EVRP–NL and then developed a hybrid meta heuristic that combines an iterated local search algorithm and a concentration heuristic to solve it. Compared with the model used by Montoyaetal.(2017), two new MIP models were proposed by Frogeret al. (2019) for the EVRP–NL. Subsequently, they proposed a heuristic and an exact labeling algorithm to solve this problem. Extensive experiments were conducted to compare the results of directly solving the MIP models using Gurobi 7.5.0, the heuristic and exact labeling algorithm. Zuo et al. (2019) focused on formulating the EVRP–NL into new MIP models that do not use duplicated dummy vertices or edges. In this work, no tailored solution procedure is given. Through experiments, they compared the performance of their models with that of the traditional models, and demonstrated the superiority of their models.

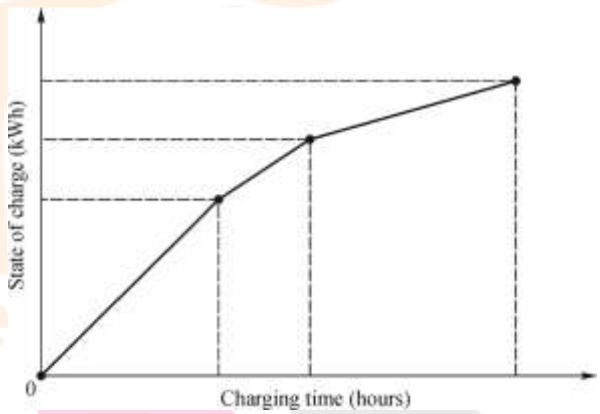


Fig. 4 Piece wise linear approximation of non linear charging function.

5 Mixed electric vehicle routing problem:

Many companies own both EVs and conventional vehicles (CVs). Therefore, routing a mixed fleet of EVs and CVs becomes necessary in many situations. The energy costs of EVs are lower, whereas labor costs may increase due to time spent on the recharging operations. Several works have investing the problems of scheduling a mixed fleet of EVs and CVs, which are presented in Table 3. Goeke and Schneider (2015) proposed an EVRP that considers time windows and a mixed fleet of EVs and CVs. The energy consumption functions of these vehicles are related to the vehicle speed, gradient, and vehicle load. The authors formulated their problem into an on linear MIP model, which cannot be directly handled by general solvers such as CPLEX and Gurobi. To find a high-quality solution for this problem, the researchers developed an ALNS heuristic that is enhanced by a local search procedure for intensifying the search process. This ALNS heuristic has three main features. First, an adaptive mechanism is used to select the number of customers to be removed by the removal operators in each iteration. Second, it uses surrogate violations to avoid the calculation of the time window and battery capacity violations. Finally, it adopts an acceptance criterion that considers the different penalty factors used when computing the solution objective value.

Hiermann et al. (2019) studied a problem that simultaneously schedules CVs, EVs, and plug-in hybrid EVs (HEVs). The HEVs have two engines, namely, an internal combustion engine and an electric engine, and thus can avoid visiting to recharging stations by switching to the internal combustion engine. The travel cost per distance unit when using the internal combustion engine is higher than that caused by the electric engine.To solve this complex problem, Hiermann et al. (2019) designed a meta heuristic consisting of a genetic algorithm, a local further improve the solutions generated by the genetic algorithm and set-partitioning model.

Macrina et al. (2019a) presented a new variant of the GVRPTW that optimizes a mixed vehicle fleet composed of EVs and CVs. The EVs can be partially recharged at any recharging station. The objective function of this problem is the sum of four terms, which are the cost of energy recharged by all EVs, fixed costs of the EVs, variable traveling costs of the EVs, and variable traveling costs of the CVs. For this problem, the authors proposed an iterated local search heuristic that mainly consists of a perturbation procedure and a local search procedure. Through experiments, they showed how the time windows and partial recharging policy affect the solution quality. Subsequently, Macrinaetal.(2019b)extended the problem by incorporating: 1) a comprehensive energy consumption function that considers speed, acceleration, deceleration, loaded cargoes, and road gradients; 2) the effects of the acceleration and braking phases; and 3) the realistic features related to the battery lifespan. Macrina et al.(2019a) only used a standard LNS heuristic to solve their problem and did not reveal the details of their approach.

5. Electric location routing problem:

Before routing EVs, we need to know the locations of recharging (or battery swapping) stations. In most of the literature, the locations of recharging stations are known in advance. However, for some situations, we need to simultaneously decide on the locations of recharging stations and schedules of EVs, which leads to the research on the ELRP. The ELRP has a single depot, a set of customers with given demands, a set of candidate locations for building recharging stations, and a fleet of identical EVs to be dispatched to delivery cargoes from the depot to the customers. Each customer can be serviced by exactly one vehicle. Each EV must start from and end at the depot, and the amount of loaded cargoes cannot exceed the vehicle capacity. A fixed construction cost exists for referred to as TS–MCWS) and a four-phase heuristic called SIGALNS. In the TS–MCWS, the tabu search algorithm is used to fix the locations of the swapping stations, and then the modified Clarke–Wright saving method is executed to decide the vehicle routes based on the given locations of the swapping stations. In the first stage of the SIGALNS, a modified sweep algorithm is invoked to generate an initial solution. In the second phase, a subset of candidate- swapping stations is selected and allocated to different routes using an iterated greedy algorithm. An ALNS heuristic is performed to route the vehicles in the third phase and solutions are further improved by a split procedure in the last phase. Hof et al. (2017) showed how to solve the ELRP by adapting the adaptive VNS (AVNS) heuristic for the VRP with intermediate stops (Schneider et al., 2015). They conducted experiments using the benchmark instances generated by Yangand Sun(2015). The AVNS heuristic significantly improved the previously best-known solutions for the majority of

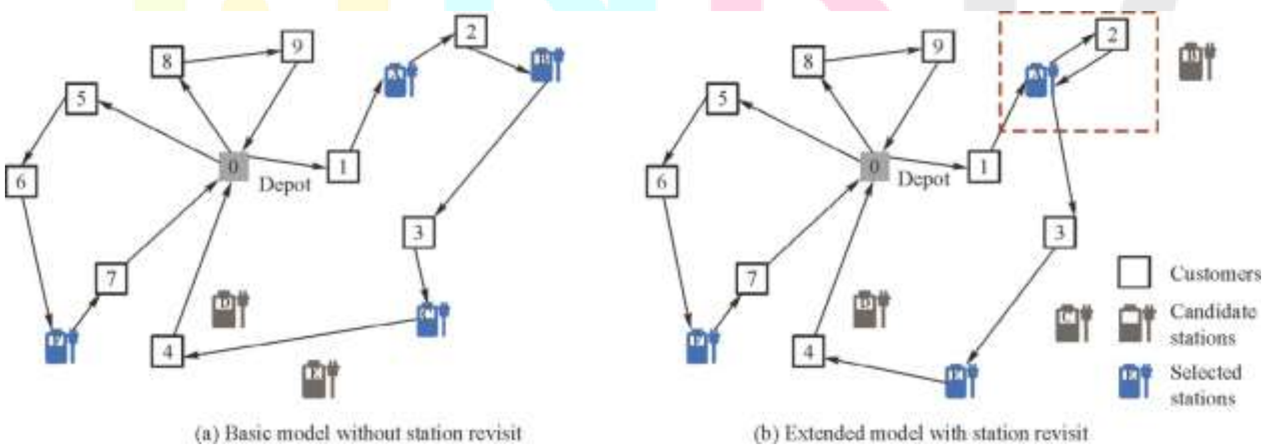


Fig.5 Comparison between allowing and not allowing revisit in ELRP

instances within reduced computation times, compared with the approaches used by Yang and Sun (2015).Moreover,theyobservedthattheAVNSheuristicisrobust based on the average solution quality, and is able to considerably reduce the number of swapping stations constructed, compared with the results in the literature.
SchifferandWalther(2017)focusedontheELRPwith timewindowsandpartialrechargingpolicy,whichisused tosupportstrategicdecisionsoftransportationcompanies. The authors formulated their problem into an MIP model andpresentedfourobjectivefunctions,eachcorresponding to one of four scenarios. Thereafter, they derived a strengthened MIP model to reduce the computation time. The authors did not provide any tailored solution procedure for their problem and only directly solvedtheir models through a general MIP solver using small instances with up to 15 customers. By experiments, they showed the advantages of their strengthened model, the benefitsbroughtaboutbythepartialrechargingpolicy,and the effect of different objective functions. Zhang et al.(2019)addressedanELRPwithstochasticdemands,with theaimtoseekamin-costsolutionthatoutputstheoptimal locations of the battery-swapping stations and optimal priori routing plan. They adapted the classical recourse policy and preventive restocking policy to consider the influences of battery capacity. The EV needs to select an optimal swapping station sequence based on its current stateofcharge.Inthisselectionprocess,theEVmustface twoconflictingobjectives,namely,minimizingthetravel- ing distance and maintaining higher battery level. The authorstriedtoidentifyaParetooptimalsettospeedupthe selectionofswappingstations.Theyimplementedahybrid heuristic composed of a binary particle swarm optimiza- tion (PSO) algorithm and a VNS heuristic to solve their problem.Intheexperiments,theauthorsdemonstratedthe performance of their proposed approach by comparing it with five other heuristics. Koç et al. (2019) presented a multi-depotELRP,whereeachcompanyrunsadistribution systemconsistingofafleetofidenticalEVs,adepot,anda preassigned set of customers. However, these companies jointly invest in installing and operating recharging stations. That is, the recharging stations are shared by these companies. This problem aims to determine the locations of the recharging stations and schedule EVs for each company. The authors implemented a multi-start ALNSheuristictosolvetheirproblemandevaluatedtheir method using self-generated test instances.

6 Other variants

In this section, we review the literature of the EVRP variants that do not appear in the a fore mentioned context. All articles except two were published in 2019 and thus, the number of articles about each type of variant is limited.

6.1 Hybrid electric vehicle routing problem:

Mancini (2017)introduced the HEVRP and assumed that the vehicle shifts to fuel propulsion mode only immediately after the power in the vehicle battery is depleted. The authors formulated this problem into an MIP model and then proposed a mat heuristic that combines a standard ALNS heuristic with as used model. The mat heuristic starts from a feasible solution. Two routes are destroyed at each iteration. Then, a simplified model is solved, which only considers two vehicles and the customers in the destroyed two routes to generate two new routes. The aforementioned two steps are iteratively executed until a termination criterion is reached.Yuetal.(2017)developed two versions of simulated annealing algorithm with a restart strategy to solve this problem. These two versions employ the Boltzmann and Cauchy functions to determine the acceptance probability of a worse solution, respectively. We refer the reader to Dascioglu and Tuzkaya(2019) for a review of the papers regarding the HEVRP published in or before 2017. In the following, we survey two most recently published papers.
Li et al. (2018) proposed a multi-objective EVRP that uses plug-in and wireless charging systems. They formulated the problem into an MIP model and solved it by CPLEX efficiently. Zhen et al. (2020) introduced a variant of the HEVRP in which vehicles can run on four types of modes. The hybrid electric vehicles (HEVs) can run as long as they have battery power or gasoline. However, in this work, the impact of the vehicle load on the electricity or gasoline consumption is neglected. This problem needs to decide which gas stations or recharging stations will be visited in the routes of the HEVs. Prices of gasoline and electricity are given, and the amounts of gasoline and electricity consumed on each edge are also known before hand. This problem has an implicit assumption that each edge can only select exactly one mode. The authors developed an improved PSO algorithm to solve their problem, which is a mixture of the PSO and VNS procedures and uses a label procedure to assign a mode to each edge.

6.2 Electric dial-a-ride problem

If the dial-a-ride problem (DARP) uses EVs and allows EVs to be recharged during the trip, then we can obtain the EDARP. The DARP consists of designing vehicle routes for a number of requests, each characterized by a pickup point(origin),a delivery point (destination), and a certain quantity of demand. For all requests, a maximal ride time exists, i.e., the difference of the pickup and delivery times must be within a given limit. For comprehensive reviews on the DARP,we refer the reader to Cordeau and Laporte(2007),Molenbruch et al. (2017), and Ho et al. (2018).
Masmoudietal.(2018)introduced the EDARP, which arises specifically in healthcare services related to

non-emergency transportation of patients. Different patients need to be transported between their homes and the clinics (orhospitals). In this problem, multiple types of EVs are considered and each EV can provide several types of resources, each with a certain capacity. The EDARP aims to plan a set of routes to fulfill all requests while minimizing the total routing cost. A feasible solution to the EDARP must satisfy the following conditions: 1) the pickup vertex must be visited before its corresponding deliveryvertex,2)the constraints of the resource capacities must be respected, 3) the service of each vertex must be startedwithinitstimewindow,4)the limitation on the ride time for each patience cannot be violated, and 5) each request must be fulfilled by exactly one EV. To solve the problem, the authors proposed three versions of the evolutionary VNS heuristic in which the VNS heuristic is integrated into the framework of the genetic algorithm. In addition, the techniques of the shuffled frog-leaping algorithm(Eusuffetal.,2006) and the bees algorithm are also used in their approaches. Shietal. (2018) also studied the EDARP in the context of ride-sharing service and formulated the problem into an MIP model.

Bongiovanni et al. (2019) extended the work of Masmoudi et al. (2018) by considering multiple starting and ending depots. Each EV can return to one of the candidate ending depots rather than return to its starting depot. The recharging stations can only be accessed by empty EVs and can provide partial recharging service.The authors formulated their problem as 3-index and 2-index MIP models, and then devised branch-and-cut algorithm with new valid inequalities derived from the problem structure. By experiments, they found that solving the

2- index model can yield better results compared with the

3- index model. The largest instances optimally solved by theirapproachescontainupto5EVsand40requests.Al-Kanjetal.(2020)addressed a comprehensive ride-hailing system that dispatches a centrally managed fleet of autonomous EVs. They used approximate dynamic programming algorithm to determine trip assignment and recharging operations.

7.1 Electric two-echelon vehicle routing problem:

Two-echelon distribution systems are common in the industry of logistics, necessitating the investigation of the two-echelon VRP(2EVRP).Inthe2EVRP,the cargoes are first transported from depot to intermediate points(called satellites) by large vehicles and then distributed from satellites to customers by small vehicles. At the satellites, the cargoes need to be transferred from large vehicles to small vehicles. Therefore, we need to simultaneously handle two VRPs, namely, routing large vehicles from a depot to a set of satellites (i.e., first echelon vehicle routing)and routing small vehicles from a satellite to a set of customers (i.e., second echelon vehicle routing). For more information with regard to2EVRP,werefer the reader to Perboli et al. (2011),Baldacci et al. (2013), and Jepsen et al. (2013). When this problem uses EVs to transport cargoes, we can obtain an extended variant called E2EVRP.Figure10providesanexampleoftheE2EVRP transportation network.

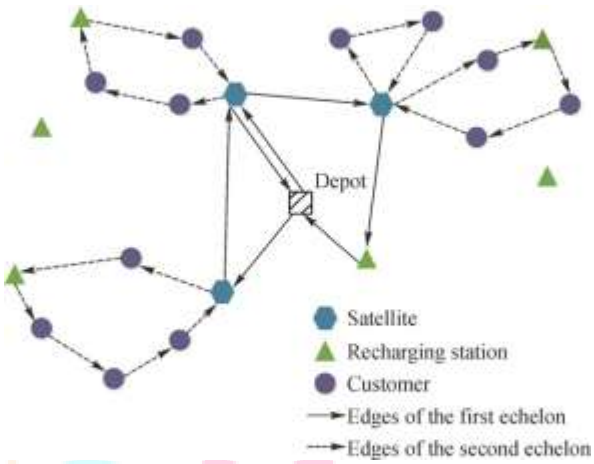


Fig.10ExampleofE2EVRPtransportationnetwork.

7.2 Electric pickup and delivery problem with time windows:

The pickup and delivery problem with time window (PDPTW)has been widely studied by many researchers. In the PDPTW, *n* transportation requests need to be fulfilled. A transportation request comprises an origin point and a destination point. A given amount of commodity is picked up from the origin point and then delivered to its corresponding destination point. Each operation has a service time and must be started within a given time.

8.Conclusions

We presented a comprehensive literature review on the routing problems concerning EVs. All the surveyed papers are extended from their corresponding vehicle routing counterparts. Two types of recharging policies, namely, full and partial recharging policy, can be adopted by the EVRPs. Thus, each problem can have two versions. The partial recharging policy is more flexible while increasing the complexity of the problem and the difficulty of the solution approach. Many studies have demonstrated the benefits resulted from the adoption of the partial charging policy. In addition, numerous papers have incorporated the battery-charging functions and energy consumption functions into their models and made their problem closer to the real practice. In terms of the solution approaches, most of the works inherited the methods for VRP and made some changes based on the properties of EVs. Further efforts have been exerted to decide the locations of the recharging (or battery-swapping) stations and when to recharge the EVs.

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