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Performance evaluation of Tabu Search method and Adaptive Large Neighborhood Search method in the Electric Vehicle Routing Problems with Time Windows

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Abstract—Transportation companies are now beginning to utilize the electric vehicles (EV) for deliveries to reduce greenhouse gas emissions. To determine the shortest tours by using the EVs, the Electric Vehicle Routing Problem with Time Windows (EVRPTW) has been established. Further, an Adaptive Large Neighborhood Search (ALNS) has been proposed as one of the methods for solving EVRPTW. Although the ALNS utilized various types of local search methods for improving the solution, our preliminary numerical experiments revealed that the ALNS had an unbalanced effect between intensification and diversification in the searching processes. To improve this problem, we proposed the ALNS with tabu search method. In addition, this method obtained smaller number of electric vehicle usage, which is the primary objective in EVRPTW, as compared to the original ALNS for simple instances of EVRPTW. In this work, we investigate the performance of our proposed method for difficult instances of EVRPTW. Numerical experiments then showed that our method also obtained good performance for various types of benchmark problems.

1. Introduction

Home delivery services have rapidly been increasing by recent developments of electric commerce markets. For transportation companies, it is desirable to minimize the number of delivery vehicles and a total distance of all vehicles. This problem of finding shorter routes with small numbers of vehicles is called a Vehicle Routing Problems (VRP). In addition, customers specifies a convenient time window to receive their goods. A VRP of considering the time window of each customer is called the Vehicle Routing Problem with Time Windows (VRPTW).

To reduce greenhouse gas emissions, transportation companies are now beginning to utilize electric vehicles (EVs) for deliveries. However, the EVs have a limited battery capacity and a shorter cruising distance than that by gasoline-powered vehicles. Therefore, the EVs must stop at any recharging stations to recharge the batteries during deliveries to customers. The electric vehicle routing problem with time window (EVRPTW) is an extension of the VRPTW where EVs with limited battery capacities can be recharged. In the EVRPTW, two recharging policies are considered: a full recharge [1] and a partial recharge [2]. The full recharge policy requires that the EV's battery is fully charged. On the other hand, for the partial charge policy, the battery will only be charged based on the amount of power required for the remaining deliveries. The problem is called EVRPTW with partial recharge (EVRPTW-PR) [2]. In this work, we treat the EVRPTW-PR.

Many heuristic methods were proposed for the EVRPTW, because the problem is a Non-deterministic Polynomial hard problem. As one of the heuristic methods, an adaptive large neighborhood search (ALNS) which uses 21 different local search methods has been proposed. Generally, a balance between intensification and diversification is important to find good solutions by the heuristic method. Diversification is an exploration of new areas of the searching space. On the other hand, intensification is an intensive search for areas close to the current good solution. To realize diversified search, the ALNS probabilistically selects one local search from 21 different local searches to shorter the length of the tour. In addition, ALNS employs a random strategy that randomly moves the current solution to a neighborhood solution to avoid local optimal solutions and search for various solutions. Therefore, the ALNS cannot find intensively search around good solutions due to this random strategy.

We have already proposed a modified ALNS that changes the random strategy to a greedy strategy [3]. In this method, neighborhood solutions were generated by three local search method: an exchange method, a CROSS-Exchange method, and a station insertion/removal method. However, the solution got stack at a local minimum if we only used the greedy search. To effectively escape from the local minima, the Tabu Search method (TS) was used in the improved method [3]. As a result, the proposed method successfully reduced the number of vehicles as compared to the ALNS. However, the benchmark instances used in the experiments were easy ones, which have a relatively tight time windows. Therefore, in this work, we investigated performance of the proposed method for benchmark instances with wide time windows. The wide time window increases the number of feasible solutions. It makes more difficult to find optimal or good near-optimal solutions. As a result of numerical simulations, the proposed method also showed higher performance than ALNS as in the cases of the wide time windows.

2. Electric Vehicle Routing Problem with Time Windows

The Electric Vehicle Routing Problem with Time Windows (EVRPTW) was first introduced by Schneider *et al.* in 2014 [1]. In this model, a battery in an EV is assumed to be full after the recharge if the EV visited a recharging station. As a model of relaxing the full recharge restriction, the EVRPTW with partial recharging (EVRPTW-PR) is formulated by Kenskin and Çatay [2]. In EVRPTW-PR, the battery is not fully charged, but is charged by any quantity.

To construct the EVRPTW-PR, a complete directed graph $G = (V', A)$ is given where $V' = \{0\} \cup V \cup F$, $\{0\}$ is a depot, V is a set of customers, F is a set of recharging stations, and $A = \{(i, j) | i, j \in V'\}$ is a set of arcs. Each arc is associated with a distance d_{ij} and a travel time t_{ij}. A customer $i \in V$ has demand $q_i > 0$, service time $s_i > 0$, and time windows $[e_i, l_i]$. The vehicle must visit customer $i \in V$ between e_i and l_i. If a vehicle arrived at customer i before e_i, the vehicle must wait until e_i.

All the EVs with fully charged batteries depart from the depot and return to the depot. A maximum load capacity and a maximum battery capacity of the EV are defined by C and Q, respectively. The EVs must recharge at the station before they run out of charge. All stations can be visited more than once. The battery charge is consumed at a rate of h. Thus, if the EV travels a distance d_{ij}, the battery will consume $h \times d_{ij}$.

We then define a binary decision variable x_{ij} that takes value 1 if the EV moved from the customer/station i to customer/station j and 0 otherwise. An objective function of EVRPTW-PR is defined as follows:

$$D = \min \sum_{i \in V'} \sum_{j \in V', i \neq j} d_{ij} x_{ij} \tag{1}$$

3. Adaptive Large Neighborhood Search

The ALNS [2] improves a solution by using 21 different local search methods. The local search methods are classified into five classes: Customer Removal (CR), Customer Insertion (CI), Station Removal (SR), Station Insertion (SI), and Route Removal (RR). Table 1 shows local search methods for each class and Figure 1 shows a flow chart of ALNS. The ALNS performs three processes depending on the iteration number (Fig. 1). If the iteration number j is divisible by N_{SR}, the ALNS performs the local search methods in the SR and SI. Further, if iteration number j is divisible by N_{RR}, the ALNS performs the local search methods in the FR and CI. Otherwise, the local search methods in CR and CI are performed. The CR and CI class mainly perform route improvement in the ALNS algorithm (Fig.1(C)). In addition, the SR and SI class produce no battery penalty solution by relocating few stations for each N_{SR} frequency. Operations of Fig. 1(B) produce broad solutions.

In each class, a local search method to be performed is probabilistically selected according to a selection probability. To calculate the selection probability for local search a, an adaptive weight w_a is given. Then, the weight w_a is updated by a score π, which is determined by the quality of the obtained solution after applying the method a. The initial weight of each algorithm is 0. The score π is added according to the three update conditions. If a new best solution is found, the score of ϕ_1 is granted to the method a. If a new solution is better than the previous solution, the score of ϕ_2 ($< \phi_1$) is granted. When a new solution is worse than the previous solution, the update of the solution is determined by the simulated annealing rule. If the worse

Table 1: Local Search Method used in ALNS

Customer Removal (CR)
Random CR, Worst-Distance CR, Worst-Time CR, Shaw Removal CR, Proximity-Based CR, Demand-Based CR, Time-Based CR, Zone Removal CR
Station Removal (SR)
Random SR, Worst-Distance SR, Worst-Charge Usage SR, Full Charge SR
Customer Insertion (CI)
Greedy CI, Regret-*k* CI, Time Based CI, Zone CI
Station Insertion (SI)
Greedy SI, Comparison SI, Best SI
Rout Removal (RR)
Random Route Removal, Greedy Route Removal

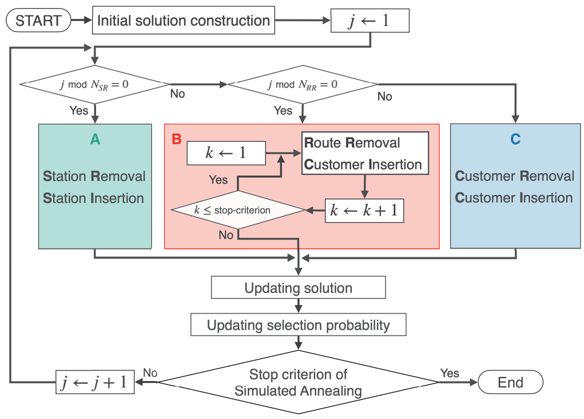


Figure 1: A flowchart of the ALNS algorithm

solution is accepted by the simulated annealing rule, the score of ϕ_3 ($< \phi_2$) is granted.

The weight of method a is updated by the following equation:

$$w_a^{s+1} = w_a^s(1-\rho) + \rho\pi_a/\theta_a, \quad (2)$$

where ρ is a roulette wheel parameter, θ_a is the number of times that the method a has been executed, and π_a is the score of the method a. The values of w_a and θ_a are reset to zero at every N_c iterations (s mod $Nc = 0$) for customer related (Fig. 1 C) and N_s iterations (s mod $N_s = 0$) for station related (Fig. 1 A).

The selecting probability of the method a at time $s+1$ is calculated by following equation:

$$P_a^{s+1} = \omega_a^s / \sum_{i=1}^{m} \omega_i^s, \quad (3)$$

where m is the number of the local search in each class. For example, m is eight for CR class.

4. Proposed Method

One of the most important issues for the VRP is to decrease the number of vehicles. Although the route removal (part B in Fig. 1) in the ALNS can decrease the number of vehicles, it does not effectively reduce the routes. Figure 2 shows the number of vehicles included in the tour by applying the route removal. As shown in Fig. 2, the number of vehicles increases rather than decreasing. In the ALNS, the current solution randomly moved to a neighborhood solution of the selected algorithm even if there is a good solution in the neighborhood solutions.

In the proposed method, we employed a greedy search, instead of the random search. However, the solution gets stack at a local minimum if we only used the greedy search. To effectively escape from the local minima, TS, which is one of the most powerful meta strategies, is introduced in the proposed method. The TS is based on a strategy of iteratively moving from one solution to the best improved solutions in the neighborhood of the solution. To escape from local minima and to avoid cycles of solution search, a previous solution is added to a tabu list and is not allowed to move back to it for a certain temporal duration called a tabu tenure. The proposed method is realized by changing the operations (Fig.1(B)) to the TS.

In the proposed method, a solution moves to the best new solution from neighborhood solutions constructed by the Exchange method, the CROSS-Exchange method, and the Station-InsertionRemoval method. The exchange method exchanges a customer/station in the same tour (Fig. 3(b)). The CROSS-Exchange replaces a partial tour i-i' in one tour with a partial tour j-j' in the other tour (Fig. 3(b)). The maximum length of the partial tours is set to three in the CROSS-Exchange method. The Station-InsertionRemoval inserts a station and deletes a visited station (Fig. 3(c)). Then, the operation performed on the best solution is memorized in the tabu list, and the same operation is prohibited

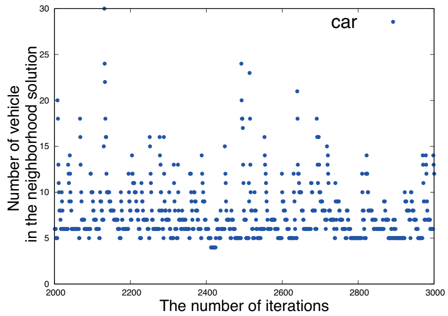


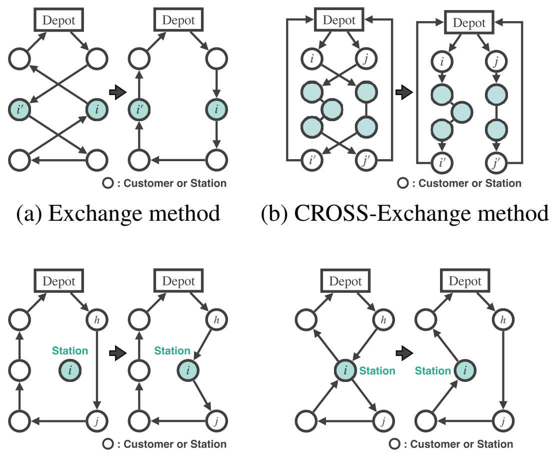
Figure 2: Temporal changing of the number of vehicles by ALNS

for a while. The information to be recorded in the tabu list for each local search method is as follows:

Exchange method: The exchanged two nodes i and i' is memorized (Fig. 3(a)). The exchange of i and i' is prohibited for a while.

CROSS-Exchange method: The four nodes (i, i', j, j') are memorized (Fig. 3(b)). The exchange of two partial tour between i and i' and j and j' is prohibited for a while.

Station-InsertionRemoval method: When a station is inserted into a tour, the two nodes where the inserted station is connecting (h and j) are memorized (Fig. 3(c)). Then, the removal of the station between h and j is prohibited for a while. When a station is removed from a tour, the two nodes (h and j) are memorized (Fig. 3(c)). Then, the insertion of the station between h and j is prohibited for a while.



(a) Exchange method (b) CROSS-Exchange method

(c) Station-InsertionRemoval

Figure 3: Local search method used in the proposed method

An improved solution by the local search methods is evaluated by an evaluation function described as follows:

$$g(s) = \sum_{i \in V'} \sum_{j \in V', i \neq j} d_{ij} x_{ij} + \sigma_1 p_t + \sigma_2 p_b + \sigma_3 p_c \quad (4)$$

where p_t denotes the total violation time of the time window, p_b denotes the total distance traveled with out-of-charge, p_c denotes the total quantity in excess of the capacity of the vehicle, σ_1, σ_2, and σ_3 are adjustment parameters for each penalty. If p_t, p_b, and p_c are equal to zero, the corresponding solution becomes feasible.

5. Numerical experiment

To investigate performances of the proposed method, we used the EVRPTW-PR benchmark problems [1]. In these numerical experiments, the maximum amount where each EV can be charged at each station is set to $0.7 \times Q$. Here, Q is the capacity of the vehicles. The values of parameters in the ALNS were set to $N_{SR} = 20$, $N_{RR} = 2000$, $N_c = 50$, $N_s = 1500$, and $\rho = 0.05$. The length of the tabu tenure in the proposed method was set to $80 \sim 100$ and the parameters in the Eq.(4) were set as follows: $\sigma_1 = \sigma_2 = \sigma_3 = 50$. The feasible solution was construct by the nearest insertion method. Usually, the nearest neighbor method first visits the nearest customer from the depot. However, in these experiments, the first customer was randomly determined to construct various initial solutions. We then constructed 30 different initial feasible solutions, and improved these solutions.

Results of the numerical experiments are shown in Table 2. In Table 2, the first column lists the instance names the second column presents the results of the proposed method, the third column indicates the results of ALNS, and the last column shows the best known solution. All the instances in the lists have wide time windows. From Table 2, the proposed method yields the same solution as the best known solutions for C201. In addition, the proposed method obtained shorter vehicle usages than those by the ALNS for C206, R201, RC201 and RC206.

Figure 4 shows a temporal changing of the total distance and the number of vehicles by the ALNS and the proposed method for the C201. From Fig. 4, the proposed method always searches for solutions with four vehicles. On the other hand, the ALNS searches the large number of vehicles and obtained long distances. From these results, we concluded that the proposed method successfully reduces the number of vehicles.

6. Conclusions

In this work, we investigated the performance of the proposed method by using tabu search for EVRPTW-PR with wide time windows. From the results, we confirmed that the proposed method obtained the same solution as the best know solution for C201. In addition, the proposed method showed higher performance than the ALNS for various instances. In future works, we will employ different types of local search methods to further improve the proposed method.

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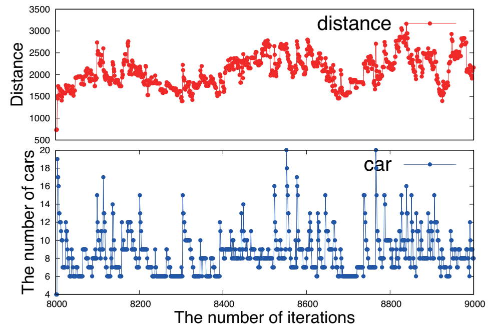
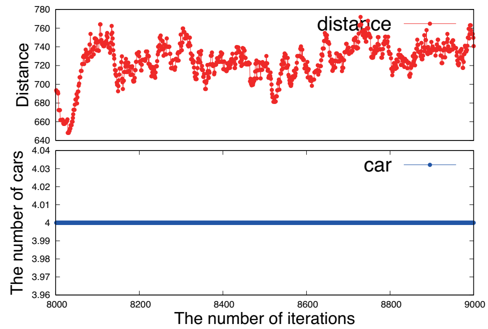
Table 2: Results of ALNS and ALNS with tabu search method (total distance and the number of using vehicles)

	ALNS&TS	ALNS	BKS
C201	**629.95 (4)**	651.83 (4)	629.95(4)
C206	**630.02 (4)**	650.11 (4)	629.95(4)
R201	**1187.26 (4)**	1221.97 (4)	1258.40(3)
R206	**980.40 (3)**	972.21 (3)	929.39(3)
RC201	**1446.73 (5)**	1595.04 (4)	1446.60(4)
RC206	**1153.54 (4)**	1198.9 (4)	1207.98(3)



(a) ALNS



(b) ALNS&TS

Figure 4: A temporal changing of the total distances and the number of vehicles for C201

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