

# A time-dependent electric vehicle routing problem with congestion tolls

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**Abstract:** Scheduling the recharging of electric vehicle fleets under different scenarios is an important but open problem. One important scenario is that vehicles travel at different speeds in different periods since traffic congestion is common in urban areas nowadays. Therefore, this paper proposes a novel time-dependent electric vehicle routing problem with congestion tolls. If a vehicle enters a peak period, a fixed congestion toll needs to be paid in this problem. A mixed integer linear programming model is established and an adaptive large neighborhood search (ALNS) heuristic is designed to solve the model. The model and solving method are validated and evaluated extensively with benchmark instances. Results indicate that a certain level of congestion tolls could prevent vehicles from entering peak periods and relieve road congestions significantly. Furthermore, the ALNS heuristic could provide much better solutions for the problem than typical optimization software such as Gurobi in much shorter running time.

**Keywords:** Adaptive Large Neighborhood Search, Congestion Toll, Electric Vehicle Routing Problem, Recharge Allocation, Time-Dependent

## 1. Introduction

Green logistics is an important research field. It was reported that transportation activities represent about 22% of the total carbon emissions; road transportation is responsible for almost 75% of the carbon emissions from transportation in the year of 2010 (refer to [1]). Freight transportation by road has caused not only environmental but also social issues. For example, serious haze-fog days

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<sup>1</sup>The work of Ruiyou Zhang and Jingmei Guo was partially supported by the National Natural Science Foundation of China (Nos. 71971050, 71831006, and 71471034), the Fundamental Research Funds for the Central Universities (No. N160404011), and National Key R&D Program of China (2017YFB0306401). The work of Junwei Wang was partially supported by the National Natural Science Foundation of China (No. 71571156), by a grant from the Research Grants Council of the Hong Kong Special Administrative Region, China (No. T32-101/15-R), by the University of Hong Kong through the Seed Fund for Basic Research (No. 201811159163), and by the open project funded by State Key Laboratory of Synthetical Automation for Process Industries of China (PAL-N201802).

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appeared widely in recent years in some countries including China. The emissions of trucks contribute the cause of such a serious atmospheric problem, more or less. Additionally, freight transportation has also aggravated traffic congestions in many cities, especially in morning and evening peak periods. The Ministry of Industry and Information Technology of People's Republic of China issued in 2019 that the use of conventional internal combustion engine vehicles would be forbidden in some cities and that the government is taking a series of measures to promote the development of alternative fuel vehicles [2]. For instance, a highway network with recharging stations has been built in the Beijing-Tianjin-Hebei zone.

Electric vehicles (EVs), as a major alternative fuel vehicle type, are becoming a hot point in the field of green logistics. It is obvious that the operating process of EVs almost does not emit carbons. The whole life-cycle really emits very few carbons if the generation of electricity is also clean. However, development of EV industries is still restricted partially because of the limited travel ranges and long recharging time of EVs [3]. Therefore, researchers are focusing on the design of EV batteries and other technologies in the viewpoint of electric engineering (refer to [4-7]), the locating of recharging stations (refer to [8-9]) and the scheduling as well as routing of EVs (refer to [10]) in the viewpoint of operations research.

Few articles investigate electric vehicle routing problems (EVRPs) considering both routing and recharging of vehicles. For example, Schneider *et al.* [10] extended EVRP introducing time window constraints resulting in EVRP with time windows (EVRPTW). They assumed that the recharging time at a station is a function of the current battery level and the battery becomes full when the vehicle departs from the station. However, this is unnecessary in most applications. The articles addressing EVRP with partial recharges are even scarce. For instance, Keskin and Çatay [11] allowed EV batteries to be recharged to any level (up to capacity of the batteries) with a linear rate.

Much attention has also been paid to traffic congestions. Vehicles travel at different speeds in different road conditions due to the existence of congestions. For example, some articles presented the shortest path problem on a time-dependent network (see, e.g., [12]). Tolling on the vehicles that pass certain roads or enter certain areas has become very popular to relieve congestions and to guide public transportation. For example, Liu *et al.* [13] studied a morning commute problem with both household and individual travels in which tolls are collected on bottleneck roads. Similar

researches could also be found in, for example, [14].

However, most articles that address EVRPs assume that EVs travel at a given constant speed between locations without considering traffic congestions (see Section 2 for a detailed review of literature). To the best of our knowledge, the model introduced by Shao *et al.* [15] was the first routing model that considers variable travel time. They considered soft time window and vehicle capacity constraints. However, they did not consider partial recharging schemes and assumed a fixed charging time in their model. Pourazarm *et al.* [16,17] took into account real-time traffic information when arranging EV routes where each EV traveled from a fixed origin to a fixed destination, which is beyond the scope of this research.

As a result, we introduce time-dependent travel speeds and congestion tolls into EVRPTW in this paper, in which a fleet of EVs deliver freight to a set of geographically scattered customers. A working day is divided into morning peak, off-peak, and evening peak periods. The speeds of EVs in different periods are different. Each EV consumes a fixed amount of electricity per travel distance and can be recharged to any level at a linear rate of time at recharging stations. If a vehicle enters a peak period, a fixed toll is collected. The problem minimizes total transportation costs including route duration related costs, recharging costs and congestion tolling costs.

The contributions made in this research could be summarized as follows. Firstly, time-dependent travel speeds and congestion tolls are introduced into EVRPs. A time-dependent EVRP with congestion tolls and time window constraints (TDEVRP-CT, for short) is mathematically modeled as a mixed integer linear programming model. Secondly, an adaptive large neighborhood search (ALNS) heuristic (refer to [11]) with an allocating algorithm of recharging amounts and an adjusting algorithm of visit-beginning time is designed to solve the TDEVRP-CT. Thirdly, the ALNS heuristic is validated with benchmark instances that were designed for EVRPTW and compared with a typical optimization software Gurobi. Finally, several primary concluding remarks are presented. The experimental results will indicate how the TDEVRP-CT help decreasing the total cost by routing and scheduling EVs in different congestion scenarios.

The remainder of this paper is organized as follows. Section 2 reviews the related literature. Sections 3 and 4 describe and mathematically model TDEVRP-CT, respectively. The ALNS heuristic is designed in Section 5 and then validated and evaluated in Section 6. Section 7

concludes this paper finally.

## 2. Literature Review

This section reviews two streams of related literature. Firstly, the research addressing EVRP, as the main topic of this research, is surveyed extensively. Secondly, we also briefly summarize the variant of VRP that considers road congestions as well as time-dependent travel speeds.

### 2.1. The Electric VRP

We only summarize electric vehicle routing problems which focus on the recharging of EVs at the operational level. The development and usage of EVs in applications also include the design of batteries to enlarge their energy density, the unification of batteries for convenient battery swaps, the centralized recharging strategy under battery swapping scenario (see, e.g., [18,19]), and the location of recharging stations (see, e.g., [20]). However, these issues are relatively far from the routing of EVs and hence beyond the scope of this article.

The research of EVRP belongs to the fields of green logistics since EVs are a type of alternative fuel vehicles. Erdoğan and Miller-Hooks [21] proposed a model of green-VRP (GVRP), which minimizes the total travel distance of involved vehicles with the constraints of given refuelling stations and restricted length of routes. They assumed that the refuelling time at a station is fixed and the tank becomes full after each time of refuelling. Neither load capacity of vehicles nor time window constraints at customers were considered. Two constructive heuristics as a modified Clarke and Wright saving heuristic and a density-based clustering algorithm, and a customized improvement technique were designed to solve GVRP. Moreover, Wang and Cheu [22] reported the operations of an electric taxi fleet. The batteries consume at a given rate per distance and can be recharged fully in a constant time at stations.

Schneider *et al.* [10] proposed EVRPTW extending GVRP. EVRPTW differs from GVRP mainly in the following aspects. Firstly, each vehicle has a limited load capacity. Secondly, each customer has a positive demand and a time window during which the service must start. Thirdly, the recharging time at a station depends on the battery level when the EV arrives at the station. Furthermore, Schneider *et al.* [10] also assumed that a battery becomes full when the EV departs from a station and the recharging rate is linear and fixed. On the other hand, EVRP is also similar to but differs from the multi-depot vehicle routing problem with inter-depot routes (MDVRPI)

described in [23]. The main difference between them is that, although the vehicles also need to visit some depots (i.e., recharging stations) during the visits of customers, the renewed amount at a depot does not depend on the demand but on the current battery level. Schneider *et al.* [24] unified EVRP and MDVRPI by using different service times in different intermediate facilities, specifically speaking, recharging time at stations or loading time at intermediate depots. They presented a hybrid algorithm of a variable neighborhood search heuristic and a tabu search heuristic to solve EVRPTW. Their method is validated with benchmark instances of GVRP as well as new instances generated from the data of [25].

Quite few articles addressing EVRP allow partial recharges. Conrad and Figliozzi [26] introduced a recharging VRP in which EVs can be recharged at some customers. The recharging time at customers is constant. The battery level after recharging depends on a given choice of recharge: full or partial. For the partial recharge case, EVs are recharged to a certain level such as eighty percent. Felipe *et al.* [27] extended GVRP in another way by allowing partial recharges using multiple power options. They considered load capacity constraints and route duration limits but not time window constraints at customers. They formulated the problem mathematically and presented several algorithms as constructive algorithms, determinate local search algorithms, and a simulated annealing algorithm to solve the problem. Koç *et al.* [28] simultaneously considered the locating of recharging stations and the routing of vehicles by allowing several companies jointly investing in and using recharging stations. They considered route duration limits but still not time window constraints at customers. They formulated the problem as a 0-1 mixed integer linear program and constructed a hybrid algorithm of ALNS and the mathematical program to solve the problem.

Quite recently, Keskin and Çatay [11] reported an EVRPTW with a partial recharge scheme. They assumed that each EV has a load capacity constraint and each customer has a time window as well as a demand. A battery can be recharged at a given rate at stations to any level up to its battery capacity. They also solved the problem based on the ALNS framework. Their article is the most similar one in existing research to this paper. This paper differs from their article mainly in the following aspects. Firstly, they assumed that travel speeds are given as a constant while we divide the working day into several time periods (i.e., morning peak, evening peak, and off-peak) and travel speed differs from period to period. Secondly, they minimized the total travel distance while

we minimize the total operating costs including route duration costs, recharging costs and congestion toll costs. Qiao and Karabasoglu [29] showed that the least-cost paths might be different from the shortest-distance or shortest-time paths when arranging the trip from a fixed origin to a fixed destination, which suggested that the research with a cost-based-objective is meaningful. Thirdly, our solving heuristic based on the ALNS framework differs from theirs especially in the decoding, feasibility and optimality of solutions due to the different problem definition.

## 2.2. Congestions and Time-dependent Speeds in VRP

This subsection briefly summarizes the topic of time-dependent travel speeds as well as road congestions in VRP. Note that this topic was introduced into the routing and recharging of EVs but not the main topic of this research. Therefore, we only survey the corresponding literature very briefly but do not present a complete review of this large topic.

Road congestions considered in VRP are caused by two types of reasons. The first type of reason is non-periodic and / or unpredictable events such as accidents, breakdowns of vehicles, bad weather events. The traveling speeds of vehicles in this scenario are usually denoted as stochastic variables. For example, Taş *et al.* [30] presented a VRP with stochastic travel times. They built two versions of mathematical models as with or without service time at customers, and solved the problem using tabu search and ALNS heuristic.

The second type of reason is periodic and predictable events such as the heavy traffic in morning or evening peak periods. Compared to the first type of reason, this type of reason results in much more traffic delays and transportation costs [31, 32]. The speeds of vehicles in this scenario are usually denoted as time-dependent. For example, Malandraki and Daskin [33] introduced a time-dependent VRP in which travel times are calculated using piecewise functions. Ichoua *et al.* [34] investigated a vehicle dispatching problem with time-dependent travel speeds. Since Ichoua *et al.* [34], most articles addressing time-dependent VRP satisfy a first-in-first-out (FIFO) property. The FIFO property indicates that if a vehicle starts from a location  $i$  earlier, it definitely arrives at a location  $j$  earlier. Furthermore, Xiao and Konak [35]-[36] studied a variant of GVRPs with time-dependent travel speeds minimizing carbon emissions as (one of) the objective functions.

Few articles consider congestion tolls when studying VRPs. For example, Wen and Eglese [37]

presented a VRP considering congestion tolls and designed a heuristic to solve it. In their model, they minimized the total costs including fuel costs, driver costs and congestion tolls. If a vehicle enters a congestion-controlled zone at any time, a fixed toll is paid. Differently from [37], we assume that if a vehicle enters a peak period, a fixed toll is paid. To the best of our knowledge, the articles addressing time-dependency and congestion tolls aforementioned do not consider the routing and recharging of EVs.

### 3. Problem Description

TDEVRP-CT considered in this paper can be described as follows. A homogeneous fleet of EVs provide delivery services in a local area. The logistic company possesses a depot, indexed as 0, and several recharging stations, say  $F$ , in the area. Note that the EVs can also be recharged at the depot. Each EV parks at the depot initially and returns to the depot finally. Each of the depot and stations, say  $i \in F \cup \{0\}$ , has a time window  $[e_i, l_i]$  ( $e_i \leq l_i$ ) representing its opening hours. Each EV has a load capacity (in volume)  $C$  and a battery capacity  $Q$ .

Assume that each vehicle consumes an amount of electricity  $r$  per unit distance of traveling. In real scenario, the electricity consumption of an EV depends on a large number of factors including total weight of the vehicle, road condition, traveling speed, and the weather condition according to [38]. It is too complicated to calculate the electricity consumption exactly and hence most factors aforementioned are seldom used when considering the scheduling and routing of EVs. For example, Goeke and Schneider [39] and Lin *et al.* [40] consider the weight of vehicles but not the driving behaviors such as acceleration and brake. Moreover, the last-mile delivery of small packages is a typical scenario of the TDEVRP-CT. The weight of packages is neglectable compared to the weight of the vehicles (see, e.g., [41]) while the total weight of a vehicle is the most important factor among all affecting factors. This is the reason for which we assume a linear consumption rate.

We further assume that any vehicle can be recharged at a rate  $g$  at any station. Actually, the recharging speed decreases significantly as the level approaches the last 10% of a battery. However, it is usually unnecessary to recharge the batteries completely especially in the scenarios where partial recharges are allowed. Therefore, linear recharging rate or piecewise linear recharging rate is widely used (see, e.g., [28,42]).

When departing from the depot, each EV has a full battery, i.e. a level of  $Q$ . The EV fleet needs to finish the delivery services to a set of customers, say  $V$ , in a scheduling horizon. Each customer  $i \in V$  has a demand  $d_i$  ( $0 \leq d_i \leq C$ ), a desired time window  $[e_i, l_i]$  ( $e_i \leq l_i$ ) during which the service has to start, and a service duration  $s_i$ . When visiting a station, an EV does not need to be recharged to a full battery level, but only to such a level that it is enough to complete its services. After finishing its services, an EV could return to the depot with any non-negative battery level because the depot can also be used for charge. Let the distance between any two locations  $i$  and  $j$  be  $d_{ij}$ ,  $i \in V \cup F \cup \{0\}$ ,  $j \in V \cup F \cup \{0\}$ .

The scheduling horizon is normally a working day. Considering different traffic conditions in different time periods, the scheduling horizon was divided into 3 time periods. The starting and ending times of the  $k$ th period are  $E_k$  and  $L_k$ , respectively,  $k = 1, 2, 3$ . The first, second, and third periods are the morning peak, off-peak, and evening peak, respectively. Considering the time continuity, we have  $L_1 = E_2$  and  $L_2 = E_3$ . The speeds of vehicles differ from period to period. EVs travel at an average speed of  $v_k$  in a period  $k$ . Moreover, once an EV enters the morning or evening peak period, the driver should pay a congestion toll of  $f_c$  (a given constant). If an EV enters both peak periods, the driver pays a double congestion toll, i.e.,  $2f_c$ . The scenario that EVs travel at night is beyond the scope of this study.

The aim of this problem is to determine a set of routes and the departure times at locations minimizing the total operating costs. Each route starts from the depot, visits a sequence of customers and stations, and finally returns to the depot, satisfying the constraints of load capacity and battery capacity of vehicles, and the time windows at variant locations. Note that the depot time window implicitly limits the route durations, i.e., the working time of drivers. As commonly done for VRPs with time window constraints (refer to [10, 11]), we assume that the EVs are enough.

The total operating costs consist of three parts. The first part depends on the total durations of all routes including the traveling time, servicing time, recharging time, and waiting time. The cost of this part is denoted as  $f_d$  (a given constant) per time unit. The second part is the recharging cost, including a fixed and a variable cost component. The fixed cost is paid each recharge that is denoted as  $v$  (a given constant) per cycle, corresponding to the cost of battery degradation. The variable cost of a recharge is proportional to the amount of electricity recharged, indicated as  $f_e$  (a

given constant) per unit. The third part is the total tolls of all drivers.

## 4. Model Formulation

This section formulates the problem TDEVRP-CT as a graph firstly and then as a mathematical model.

### 4.1. Graphical Formulation

It is not easy to directly formulate the starting and returning times of vehicles because different vehicles have different starting / returning times (refer to [43]). Therefore, we duplicate the depot as twice the number of vehicles resulting in two node sets  $O^S$  and  $O^R$ . Each node  $i \in O^S$  corresponds to the start from the depot of a vehicle. Each node  $i \in O^R$  corresponds to the return to the depot of a vehicle. Each node  $i \in O^S \cup O^R$  has the same location as the depot. Similarly, the recharging stations are also duplicated. The number of duplicated nodes of station  $i \in F$ , say  $n_i$ , is the time that station  $i$  might be visited. Let the set of these duplicated nodes of stations be  $F'$ . Note that  $n_i$  should be set as small as possible so as to reduce the size of the model, but large enough to not restrict the time of beneficial visits of station  $i$ . See Section 6.2 for more details about the setting of  $n_i$  (a similar method can also be found in [21]).

A directed graph  $G = (N, A)$  could formulate TDEVRP-CT, where

$$N = O^S \cup O^R \cup F' \cup V$$

is the node set, and

$$A = \{(i, j) | i \in N^S, j \in N^R, i \neq j\}$$

is the arc set, where  $N^S = O^S \cup F' \cup V$  and  $N^R = O^R \cup F' \cup V$ . Each node  $i \in N$  has a time window  $[e_i, l_i]$  and a demand  $d_i$ , where  $d_i = 0$  for  $i \notin V$ . Each customer node  $i \in V$  has a service time  $s_i$ . Each arc  $(i, j)$  has a distance  $d_{ij}$ .

### 4.2. Variables

The decision variables used in the model are defined as follows:

$x_{ij}$ : 1 if arc  $(i, j) \in A$  is chosen, or 0 otherwise

$x_{ijk}$ : 1 if arc  $(i, j) \in A$  is chosen in period  $k (= 1, 2, 3)$ , or 0 otherwise

$d_{ijk}$ : traveled distance of arc  $(i, j) \in A$  in period  $k (= 1, 2, 3)$   
 $\tau_i^A$ : service beginning time at node  $i \in N^R$   
 $\tau_i^D$ : departure time (i.e., service ending time) from node  $i \in N^S$

We also introduce the following auxiliary variables to build the model.

$t_{ijk}$ : traveled time of arc  $(i, j) \in A$  in period  $k (= 1, 2, 3)$   
 $q_i^A$ : battery level when arriving at node  $i \in N$   
 $q_i^D$ : battery level when departing from node  $i \in F'$   
 $c_i^{REM}$ : remaining load level when arriving at node  $i \in N$   
 $\lambda_i^S$ : 1 if vehicle  $i \in O^S$  enters the morning peak period, or 0 otherwise  
 $\lambda_i^R$ : 1 if vehicle  $i \in O^R$  enters the evening peak period, or 0 otherwise

### 4.3. Objective Function

The objective function of the mathematical model that formulates TDEVRP-CT is

$$\begin{aligned}
 \min f_d \left( \sum_{i \in O^R} \tau_i^A - \sum_{i \in O^S} \tau_i^D \right) + f_e \sum_{i \in F'} (q_i^D - q_i^A) + v \sum_{i \in N^S} \sum_{j \in F'} x_{ij} \\
 + f_c \left( \sum_{i \in O^S} \lambda_i^S + \sum_{i \in O^R} \lambda_i^R \right)
 \end{aligned} \tag{1}$$

where the first part formulates the route duration costs, the second and third parts formulate the recharging costs, and the fourth part formulates the congestion tolls.

### 4.4. Constraints for Degrees of Nodes

The model has a series of basic constraints which limit the times for which the nodes are visited as follows:

$$\sum_{j \in N^R} x_{ij} = 1, \quad i \in V \tag{2}$$

$$\sum_{j \in N^R} x_{ij} - \sum_{j \in N^S} x_{ji} = 0, \quad i \in V \cup F' \tag{3}$$

$$\sum_{j \in N^R} x_{ij} \leq 1, \quad i \in F' \cup O^S \tag{4}$$

$$\sum_{j \in N^S} x_{ji} \leq 1, \quad i \in O^R \quad (5)$$

$$\sum_{i \in O^S} \sum_{j \in V \cup F'} x_{ij} - \sum_{i \in O^R} \sum_{j \in V \cup F'} x_{ji} = 0 \quad (6)$$

Constraints (2) and (3) ensure that each customer is visited exactly once. Specifically, Constraint (2) states that one arc leaves each customer node meanwhile Constraint (3) states that the number of arcs entering a customer node equals to the number of arcs leaving the customer node. In addition, Constraint (3) also guarantees this point for duplicated station nodes. Constraint (4) ensures that each node  $i \in F' \cup O^S$  is visited at most once. Similarly, Constraint (5) states that each node  $i \in O^R$  is visited at most once. Constraint (6) ensures the consistency of the involved vehicles.

#### 4.5. Constraints for Period Consistency

The following constraints handle the consistency between time periods, which are a little similar to those in [35].

$$d_{ij}x_{ij} - \sum_{k=1}^3 d_{ijk} = 0, \quad (i, j) \in A \quad (7)$$

$$x_{ij} - x_{ijk} \geq 0, \quad (i, j) \in A, k = 1, 2, 3 \quad (8)$$

$$x_{ij} - \sum_{k=1}^3 x_{ijk} \leq 0, \quad (i, j) \in A \quad (9)$$

$$d_{ijk} - d_{ij}x_{ijk} \leq 0, \quad (i, j) \in A, k = 1, 2, 3 \quad (10)$$

$$x_{ijk} - M d_{ijk} \leq 0, \quad (i, j) \in A, k = 1, 2, 3 \quad (11)$$

Here, Constraint (7) indicates that the total distance traveled in all periods should be equal to the distance of an arc  $(i, j)$  if the arc is visited, i.e.,  $x_{ij} = 1$ ; or zero otherwise. Constraints (8) and (9) connect the variables  $x_{ij}$  and  $x_{ijk}$ . Specifically, Constraint (8) ensures that if such a period  $k$  that  $x_{ijk} = 1$  exists, we have  $x_{ij} = 1$ . Meanwhile, Constraint (9) states that if  $x_{ijk} = 0$  for all  $k = 1, 2, 3$ , i.e.,  $\sum_{k=1}^3 x_{ijk} = 0$ , we have  $x_{ij} = 0$ . Constraints (10) and (11) formulate the consistency of  $x_{ijk}$  and  $d_{ijk}$ . In detail, the traveled distance of arc  $(i, j)$  in period  $k$  is at most its full distance  $d_{ij}$  if  $x_{ijk} = 1$  or zero otherwise in Constraint (10). Constraint (11) states that an either smaller or larger distance must be traveled, that is to say,  $d_{ijk}$  must be larger than zero, if the arc is selected

to be traveled in period  $k$ , i.e.,  $x_{ijk} = 1$ , where  $M$  is a large enough constant.

#### 4.6. Constraints for Time Continuity

The following constraints formulate the time continuity of the model.

$$d_{ijk}/v_k = t_{ijk} \leq L_k - E_k, \quad (i, j) \in A, k = 1, 2, 3 \quad (12)$$

$$\tau_i^D + t_{ijk} \leq L_k + L_3(1 - x_{ijk}), \quad (i, j) \in A, k = 1, 2, 3 \quad (13)$$

$$E_k + t_{ijk} \leq \tau_j^A + L_3(1 - x_{ijk}), \quad (i, j) \in A, k = 1, 2, 3 \quad (14)$$

$$\tau_i^D + \sum_{k=1}^3 t_{ijk} \leq \tau_j^A + L_3(1 - x_{ij}), \quad (i, j) \in A \quad (15)$$

$$\tau_i^A + s_i \leq \tau_i^D, \quad i \in V \quad (16)$$

$$\tau_i^A + (q_i^D - q_i^A) / g \leq \tau_i^D \leq l_i, \quad i \in F' \quad (17)$$

$$e_i \leq \tau_i^A \leq l_i, \quad i \in N^R \quad (18)$$

$$e_i \leq \tau_i^D, \quad i \in O^S \quad (19)$$

Constraint (12) calculates the traveled time of an arc  $(i, j)$  in a given period as  $t_{ijk} = d_{ijk}/v_k$  and limits its scale by the length of the period. If  $x_{ijk} = 1$ , Constraint (13) becomes  $\tau_i^D + t_{ijk} \leq L_k$ , i.e., the departure time at node  $i$  plus the travel time in period  $k$  cannot exceed the ending time of that period. If  $x_{ijk} = 0$ , Constraint (13) is relaxed automatically because the ending time of the third period, i.e.,  $L_3$ , is large enough. Similarly, as in Constraint (13), Constraint (14) formulates the relationship between the starting time of a period  $k$  plus the traveled time of an arc in that period, and the service beginning time at node  $j$ . Constraint (15) ensures that if an arc  $(i, j)$  is selected, the departing time at node  $i$  plus the total traveling time in all periods cannot exceed the arrival time at node  $j$ . Constraint (16) guarantees the service time according to the arrival time and departure time at a customer node. Similarly, Constraint (17) calculates the battery level of an EV according to the arrival time and departure time at a station node. Constraint (18) is the time window constraint for service beginning time of node  $i \in N^R$ . Note that Constraints (17) and (18) form the double-side time window constraints for node  $i \in F'$ . Constraint (19) states the left side of time window for departure time of node  $i \in O^S$  omitting the unnecessary right side.

#### 4.7. Constraints for Load and Battery Level

The following constraints state the consistency of the remaining capacity and battery level.

$$0 \leq c_j^{REM} \leq c_i^{REM} - d_i x_{ij} + C(1 - x_{ij}), \quad (i, j) \in A \quad (20)$$

$$0 \leq c_i^{REM} \leq C, \quad i \in O^S \quad (21)$$

$$0 \leq q_j^A \leq q_i^D - r \sum_{k=1}^3 d_{ijk} + 2Q(1 - x_{ij}), (i, j) \in A \text{ and } i \in F' \quad (22)$$

$$0 \leq q_j^A \leq q_i^A - r \sum_{k=1}^3 d_{ijk} + 2Q(1 - x_{ij}), (i, j) \in A \text{ and } i \in V \cup O^S \quad (23)$$

$$0 \leq q_i^A \leq q_i^D \leq Q, \quad i \in F' \quad (24)$$

Specifically, Constraint (20) formulates the remaining load level along routes using a similar method as in (13)-(15). The remaining capacity of an EV is changed by  $d_i$  after it travels from node  $i$  to node  $j$ . Constraint (21) limits the initial capacity when an EV starts from a depot. Constraint (22) states that the battery level when an EV departs from node  $i$  minus the consumed electricity should equal to the battery level when it arrives at node  $j$ . Remembering that an EV has the same battery level when it departs from a node  $i \in V \cup O^S$  as it arrives at that node, we have Constraint (23). Constraint (24) bounds the battery level when an EV arrives at and departs from a station node.

#### 4.8. Constraints for Whether Entering Peak Periods

The following constraints determine whether a vehicle enters a peak period.

$$\lambda_i^S \geq \sum_{j \in V \cup F'} x_{ij} - \tau_i^D / L_1, \quad i \in O^S \quad (25)$$

$$\lambda_i^R \geq \tau_i^A / E_3 - \sum_{j \in V \cup F'} x_{ji}, \quad i \in O^R \quad (26)$$

We have  $\sum_{j \in V \cup F'} x_{ij} = 1$  if a vehicle departs from node  $i$ . If the departure time is earlier than the ending time of the first period, that is,  $\tau_i^D / L_1 < 1$ ,  $\lambda_i^S$  should be larger than a positive number. Its binary attribute forces it to be 1 according to Constraint (25). Otherwise,  $\tau_i^D / L_1 > 1$ ,  $\lambda_i^S$  should be larger than a negative number. The objective function forces it to be 0. Similarly, Constraint (26) ensures that a vehicle enters the evening peak period if and only if it arrives at the depot later than  $E_3$ .

## 4.9. Constraints for Variable Type

Finally, the following constraints describe the type and range of variables, where necessary.

$$x_{ij} \in \{0,1\}, x_{ijk} \in \{0,1\}, d_{ijk} \geq 0, \quad (i,j) \in A, k = 1, 2, 3 \quad (27)$$

$$\lambda_i^S \in \{0,1\}, \lambda_j^R \in \{0,1\}, \quad i \in O^S, j \in O^R \quad (28)$$

## 4.10. NP-hard Property

*Theorem 1:* The problem of TDEVRP-CT is NP-hard.

*Proof:* TDEVRP-CT degenerates to the vehicle routing problem with time windows (VRPTW) if the battery capacity  $Q$  is infinitely large. Savelsbergh [44] reported that VRPTW is NP-hard. As a result, we can conclude that TDEVRP-CT is NP-hard.  $\square$

## 5. An Adaptive Large Neighborhood Search Heuristic

The model presented in Section 4 is a mixed-integer linear programming (MILP) model. Due to its NP-hard property, existing optimization software such as Gurobi can only be used to solve small-sized instances of TDEVRP-CT. Therefore, we propose an ALNS heuristic to solve the problem.

ALNS is an extension of the large neighborhood search (LNS) framework put forward by Shaw [45]. In order to escape from a local optimum solution, Shaw [45] made large changes to a current solution instead of making very small changes as could be seen in most metaheuristics. Ropke and Pisinger [46] improved the LNS framework applying the removal and insertion operators adaptively. Recently, ALNS has been successfully applied to solve variant VRPs, see, e.g., [11], [47]-[51].

The ALNS heuristic generates an initial solution firstly. It updates the solution iteratively until a given number of iterations is reached. During each iteration, several nodes  $i \in N$  are removed from the current solution and then inserted back resulting in a new solution. The acceptance criterion of simulated annealing is used to accept or reject the generated new solution. That is, a new solution is accepted if it is better than the best-so-far solution, or accepted with a dynamic probability otherwise. The selection of removal algorithms and insertion algorithms is based on a roulette

wheel mechanism, in which the weights of the removal / insertion algorithms are updated according to their performance dynamically. Main idea and framework of the ALNS heuristic aforementioned could also be found in [11]. Therefore, we only present the differences compared to the method of [11] hereafter in this section.

### **5.1. Initial Solution**

The initial solution is obtained by sequential inserting the customers to a current route. The solution construction begins with an empty route. The insertion costs of all unassigned customer nodes to all possible existing positions of the route are determined. The best customer node is selected and inserted at the best position. If necessary, a station node  $i \in F$  is inserted using the Greedy Station Insertion algorithm. That is to say, insert the best station between the first customer node at which the battery level becomes negative and its preceding node. If this insertion is infeasible, insert the station on the preceding arc similarly. If no customer node can be inserted, the current route is finalized and a new empty route is constructed. Such a procedure is repeated until all customer nodes have been assigned.

### **5.2. Removal / Insertion Algorithms**

The removal algorithms include two classes as: customer removal and station removal. The customer removal algorithms used in the ALNS heuristic are Random Removal, Worst-Distance Removal, Shaw Removal, Random Route Removal, and Greedy Route Removal. For these customer removal algorithms, we use two more options as (a) removing customer with preceding station and (b) removing customer with succeeding station in addition to the default option as removing customer only. The station removal algorithms used in this research are Random Station Removal, Worst-Distance Station Removal, and Worst-Charge Usage Station Removal. See [11] for a detailed description of the aforementioned removal algorithms and their options.

Similarly, the insertion algorithms also include two classes: customer insertion and station insertion. The customer insertion algorithms are Greedy Insertion, Regret-2 Insertion, and Regret-3 Insertion. When calculating performance of the customer insertion algorithms, two options as (a) without noise, i.e., actual cost, and (b) with noises, are used (refer to [52]). The performance of operators with noises is defined as the actual cost plus  $0.2\lambda f_d(L_3 - E_1)$ , where  $\lambda$  is a random number between  $-1$  and  $1$ . The station insertion algorithms include Greedy Station Insertion,

Greedy Station Insertion with Comparison, and Best Station Insertion. See [11] for a detailed description of these insertion algorithms. In addition to the three station insertion algorithms aforementioned, we propose a so-called Multiple Greedy Station Insertion. That is, if inserting one station to a route cannot make it feasible, the Greedy Insertion is repeated until the route is feasible. See Section 5.3 for calculation of (actual) insertion cost of a node as well as the determination of charged amount at a station.

### **5.3. Decoding, Feasibility, and Optimality of Solutions**

The removal / insertion algorithms presented above handle node sequences only. A node sequence, i.e., a route, corresponds to the visiting of customer nodes and the recharging at stations of a vehicle. Besides node sequences, a solution of TDEVRP-CT also consists of the arrival time, departure time, and remaining load capacity at customer nodes as well as the recharging amount of electricity at stations. This section presents the determination of such information, i.e., feasibility and optimality of a route. Such determination process is executed for each route of a solution. Note that the feasibility and optimality of a route are discussed along with the decoding of the route.

Due to the difference in the mathematical model especially in the objective function (1), calculation of the insertion cost of a node to a route differs from that in [11], which is the main difference between the ALNS in [11] and the ALNS illustrated here.

#### **5.3.1 Insertion of customer nodes**

Checking the constraints of load capacity and time windows are relatively easy. Therefore, we mainly discuss the constraint of battery level given that the constraints of load capacity and time windows are satisfied. The main steps of inserting a customer node to a route are as follows.

Step 1: If the battery level when an EV arrives at some nodes in the current route is negative, let the first one among such nodes be  $i$ , go to Step 2; otherwise, go to Step 5.

Step 2: If a station node, say  $j$ , exists before  $i$  in the current route and the battery has enough capacity when the EV departs from node  $j$ , go to Step 3; otherwise, go to Step 4.

Step 3: Try to increase the recharging amount at node  $j$  (see Section 5.3.3)). If the route fails to become feasible, go to Step 4; otherwise go to Step 5.

Step 4: Try to insert a station node using the Greedy Station Insertion algorithm. If the route fails to become feasible, the insertion of the customer node is infeasible, return; otherwise, go to Step 5.

Step 5: Adjust service-beginning time in the route (see Section 5.3.4)).

### 5.3.2 Insertion of station nodes

The insertion of a station node before a node  $i$  of a route depends on cases.

**Case 1:** There is no station node before node  $i$  in the route. Select the best station among those which are reachable from the preceding node of  $i$  and insert it to the given position. If the route is feasible with respect to the time window constraints, try to allocate the recharging amount at the station (see Section 5.3.3) and then adjust the service-beginning time (see Section 5.3.4)). The insertion is infeasible either if it violates the time window constraints or if the allocation of recharging amount fails.

**Case 2:** One or more station nodes exist before node  $i$  in the route. Try to allocate the recharging amounts at the existing stations (see Section 5.3.3)) in order to make the route feasible. If this allocation fails to make the route feasible, the handling under Case 1 is executed; otherwise, the adjusting of service-beginning time is executed (see Section 5.3.4)).

### 5.3.3 Allocation of recharging amounts

Notice that a battery-infeasible route might become feasible without inserting stations. Now we try to make an infeasible route feasible without modifying the sequence of nodes. Whether the load capacity constraint is satisfied depends only on the customer nodes in the route. As a result, here we always assume that the load capacity constraint holds. In addition, the arrival and departure times at each node satisfy its time window constraint initially.

Therefore, we get the following main idea of the allocation of recharging amounts. Firstly, an EV should depart the customer nodes as early as possible initially so that it has enough time to recharge its battery. Secondly, an EV should be recharged as much as possible at stations so that it could travel a long distance. Thirdly, the time window constraint at any node cannot be violated. Fourthly, the battery level at any time can neither be negative nor higher than its battery capacity (specifically,

when the EV departs from a station node). Such an allocation succeeds if it makes a route feasible or fails otherwise.

### 5.3.4 Adjustment of service-beginning time

Now we are ready to adjust the service-beginning time at nodes in a feasible route so as to minimize operating cost of the vehicle. The summation of the operating costs of all involved EVs results in the objective value in (1). Remember that an EV should depart from the depot as early as possible in the allocation of recharging amounts as well as in the insertion of nodes aforementioned. Such an early departure might cause waits at some other nodes. We delay the departure time at the depot and the service-beginning times at the nodes as much as possible on the condition that the vehicle returns to the depot at the earliest time. The aim of this delay is to avoid waiting at nodes if possible. In such scenario, the departure time from the depot is denoted as  $\tau^{ED}$ .

**Case 1:** The EV waits at some nodes when departing the depot at  $\tau^{ED}$ .

*Proposition 1:* If the EV still waits at some nodes with departure time  $\tau^{ED}$ , then  $\tau^{ED}$  corresponds to the minimum route duration.

*Proof:* Let the first one among the waiting nodes be  $i$ . There exists a node before  $i$  whose service-beginning time is the right side of its time window. Otherwise, the EV still can postpone the departure time, which contradicts the construction of  $\tau^{ED}$ . Thus,  $\tau^{ED}$  is the latest allowed departure time. We can conclude that  $\tau^{ED}$  corresponds to the minimum route duration.  $\square$

Following Lemma 1, the operating cost can be calculated according to the departure time  $\tau^{ED}$  from the depot, the earliest return time to the depot, and whether it enters peak periods.

**Case 2:** The EV does not wait at any node. We also try to delay the departure time at the depot. However, the aim of this delay is to avoid entering peak periods if possible. Let this latest departure time of an EV be  $\tau^{LD}$ . The vehicle selects the best departure time at the depot in the range of  $[\tau^{ED}, \tau^{LD}]$ . The selecting criterion is to minimize its operating cost.

## 6. Validation and Evaluation

This section validates and evaluates the modeling and solving methodology of TDEVRP-CT. Specifically, Section 6.1 presents experiment setting and parameter tuning. Sections 6.2 and 6.3

evaluate the methodology with small-and medium-sized instances, and large-sized instances, respectively.

### 6.1 Experimental Setting and Parameter Tuning

The ALNS heuristic presented in Section 5 was coded in C++. As a comparison, small- and medium- sized instances of the MILP model were also solved using Gurobi version 6.5.2 embedded by the Matlab toolbox YALMIP. All experiments were carried out on a personal computer with 3.2 GHz Intel I5 CPU and 4 GB of RAM.

The division of the scheduling horizon into periods, the speeds of vehicles in periods, and the cost coefficients in the objective function were generated based on the instances for EVRPTW in [10], which is available at <http://evrptw.wiwi.uni-frankfurt.de>. For instances of Type C1, C2, R2, and RC2, the scheduling horizon was divided into three periods using the ratio vector [0.1, 0.8, 0.1]. The average speeds in the three periods are 0.65, 1, and 0.55, respectively. For example, the horizon in Instance C101-5D is 1236, where the letter 'D' at the end of instance names in this paper denotes the *time-dependent* property. Therefore, the morning peak is [0, 123.6], i.e.,  $E_1 = 0, L_1 = E_2 = 123.6, L_2 = E_3 = 1112.4$ , and  $L_3 = 1236$ . As a contrast, for instances of Type R1 and RC1, the horizon was divided into two periods using the ratio vector [0.1, 0.9] because they are short. The first period is the (morning) peak period with an average speed 0.75. The second period is off-peak with a speed 1. Based on the salary standard as 10 euro per hour and the recharging fees given in literature [27], the cost coefficients are generated as:  $f_d = 0.167\text{€}/\text{min}$ ,  $f_c = 5\text{€}$ ,  $f_e = 0.0098\text{€}/\text{km}$  and  $v = 1\text{€}$ .

The maximum number of iterations of the ALNS heuristic was set to be 25,000, as in most ALNS algorithms [11, 47, 49]. The lower bound and upper bound for the number of customers to be removed were set as  $0.1|V|$  and  $0.4|V|$ , respectively, where  $|V|$  denotes the size of  $V$ . Similarly, the upper bound for the number of stations to be removed was set as 0.35 times the number of stations used in the current solution. The tuning methodology of the other key parameters of the ALNS heuristic is the same as in [11], and has been widely used in literature such as [46]. Six instances, i.e., C106D, R106D, R107D, RC101D, RC104D, RC105D, were selected for parameter tuning. The initial value of each parameter was set as the optimum value of the corresponding parameter in [11]. The tuning results as well as the corresponding symbols used in [11] are shown in Table 1.

Table 1 Tuning results of parameters

Parameter (Symbol used in [11])	Value
Score of the best-so-far solution in the performance of algorithms ( $\sigma_1$ )	25
Score of the better solution in the performance of algorithms ( $\sigma_2$ )	20
Score of the worse solution in the performance of algorithms ( $\sigma_3$ )	21
Roulette wheel parameter when updating weights of algorithms ( $\rho$ )	0.25
Cooling rate of the temperature ( $\epsilon$ )	0.9994
Initial temperature control parameter of the acceptance criteria ( $\mu$ )	0.4
First Shaw parameter in Shaw Removal ( $\phi_1$ )	0.5
Second Shaw parameter in Shaw Removal ( $\phi_2$ )	13
Third Shaw parameter in Shaw Removal ( $\phi_3$ )	0.15
Fourth Shaw parameter in Shaw Removal ( $\phi_4$ )	0.25
Shaw removal determinism factor in Shaw Removal ( $\eta$ )	6
Worst removal determinism factor in Worst-Distance Removal ( $\kappa$ )	4
# of iterations between which adaptive weights of customer algorithms are updated ( $N_C$ )	200
# of iterations between which adaptive weights of station algorithms are updated ( $N_S$ )	5500
# of iterations between which station algorithms are performed ( $N_{SR}$ )	60
# of iterations between which Random Route Removal is performed ( $N_{RR}$ )	2000
# of consecutive iterations during which Random Route Removal is performed ( $n_{RR}$ )	500
Upper bound in Random Route Removal ( $m_r$ )	0.3

## 6.2 Experiments on Small- and Medium- Sized Instances

All 36 small- and medium- sized instances, each of which consists of 5, 10, or 15 customers, are solved. The instances were solved using the ALNS heuristic as well as directly by Gurobi. When an instance is solved directly, the time limit of Gurobi was set as 7200 seconds. Remember that the number of duplicated depots and that of each station should be determined before we solve the MILP model directly. The size of  $O^S$ , which is also the size of  $O^R$ , is determined as follows. We initially set it as the number of involved EVs in the corresponding instance in [11] and try to solve the model. If the model is reported to be infeasible or Gurobi cannot find even a feasible solution in the given time, we enlarge the two sets  $O^S$  and  $O^R$  by 1. Such a procedure is repeated until a feasible solution is reported. However, we stop enlarging the sets if the size of them reaches the number of EVs in the solution given by the ALNS heuristic. The number of duplicated stations is determined similarly. We initially set  $n_i$  as  $|O^S|$  for each station  $i \in F$  and try to solve the model. If all duplicated nodes of a station  $i$  are used, we increase  $n_i$  by 1. If more than one duplicated nodes of a station  $i$  are not used, we decrease  $n_i$  by 1. That is, one of the duplicated nodes of each station is not used finally.

Table 2 presents results of the two solution methods. It can be observed that Gurobi finds a solution for each of 31 instances and fails to give feasible solutions for the other 5 instances in the given time limit. Among the 31 instances, Gurobi obtains the optimum solutions for 14 instances before the time limit reaches. As a comparison, the ALNS heuristic obtains a solution for each of the 36 instances very quickly, in several seconds for most instances. For the 14 instances which optimum solutions have been found by Gurobi, the ALNS heuristic provides the same solution (with the same objective values). Among the instances which feasible but not optimum solutions are obtained by Gurobi, the ALNS heuristic provides a better solution than Gurobi for 12 instances. The average improvement is 6.16% (see the last column). For all instances which solutions (optimum or feasible) have been obtained by Gurobi, the number of involved vehicles in the solutions provided by the two methods is the same (see the column "#Veh."). As a result, the ALNS heuristic can provide the optimum solutions for smaller-sized instances or better solutions for medium-sized instances in a much shorter time than the software Gurobi. This validates the ALNS heuristic.

### 6.3 Experiments on Large-Sized Instances

We further evaluate the methodology based on large-sized instances in this subsection. Focus of the evaluation is the impact of congestion tolls. Twenty-nine instances, each of which consists of 100 customers and 21 recharging stations, were selected. We set  $f_d = 0.167$  in all instances. The value of  $f_c$  in each instance was set as 0 and then as 20 in addition to the default value of 5 as in Section 6.1. For each of the 87( $= 29 \times 3$ ) instances, the ALNS heuristic is repeated for 5 times independently and the best solution among the 5 repeats are reported. Unsurprisingly, the running time of the ALNS heuristic is much longer than the time when solving the small- and medium-sized instances in Section 6.2. The average running time is 12.46 minutes, 107.66 times larger than the average running time of the small- and medium- sized instances.

Table 2 Results on small- and medium- sized instance

Instance	Gurobi		#Veh.	ALNS		
	Obj.	CPU(s)		Obj.	CPU(s)	Obj. Improvement %
C101-5D	215.06	9.61	2	215.06	1.29	0.00
C103-5D	174.15	4.88	1	174.15	1.53	0.00
C206-5D	221.26	22.03	1	221.26	1.83	0.00
C208-5D	167.31	77.87	1	167.31	1.40	0.00
R104-5D	33.95	2.09	2	33.95	1.05	0.00
R105-5D	40.10	1.36	2	40.10	0.82	0.00

R202-5D	41.77	412.55	1	41.77	1.64	0.00
R203-5D	52.10	806.56	1	52.10	2.50	0.00
RC105-5D	63.21	7.00	2	63.21	0.95	0.00
RC108-5D	61.13	8.49	2	61.13	1.01	0.00
RC204-5D	49.32	7200.00	1	47.87	2.07	3.03
RC208-5D	45.16	278.60	1	45.16	1.82	0.00
C101-10D	406.26	463.99	3	406.26	1.79	0.00
C104-10D	279.23	7200.00	2	279.23	8.44	0.00
C202-10D	505.44	7200.00	1	505.44	6.51	0.00
C205-10D	434.64	451.04	2	434.64	2.97	0.00
R102-10D	96.14	7200.00	3	94.07	2.20	0.00
R103-10D	62.43	7200.00	2	62.07	0.58	5.39
R201-10D	95.61	521.84	1	95.61	4.02	0.00
R203-10D	94.10	7200.00	1	93.81	0.31	2.38
RC102-10D	104.59	7200.00	4	99.62	4.99	0.00
RC108-10D	87.03	7200.00	3	86.56	0.54	6.83
RC201-10D	139.34	7200.00	2	139.34	3.79	20.74
RC205-10D	119.16	7200.00	2	119.16	3.86	2.76
C103-15D	471.48	7200.00	3	432.87	9.60	8.92
C106-15D	374.42	7200.00	3	367.32	5.24	1.93
C202-15D	628.56	7200.00	2	625.99	14.86	0.41
C208-15D	479.02	7200.00	2	435.03	6.32	10.11
R102-15D	NA	7200.00	5	115.81	2.70	NA
R105-15D	99.95	7200.00	4	99.95	2.67	0.00
R202-15D	181.58	7200.00	2	161.38	22.85	12.52
R209-15D	NA	7200.00	1	111.71	17.91	NA
RC103-15D	NA	7200.00	4	107.54	3.35	NA
RC108-15D	NA	7200.00	3	102.13	3.38	NA
RC202-15D	198.72	7200.00	2	154.83	9.70	28.35
RC204-15D	NA	7200.00	1	128.87	91.18	NA

<sup>a</sup> Gurobi cannot provide a feasible solution in the given time limit 7200 seconds.

The detailed results of this evaluation are presented in the Appendix. Table 3 reports the statistical information of the results, where column #Veh. is the number of vehicles involved in the solution and #Veh.-C is the number of vehicles that enter the congestion periods in total. Besides the objective values Obj., the cost related to the congestion, the total route durations and the cost related to the recharging (See (1)), are also reported in Columns Obj.-C, Obj.-D and Obj.-E, respectively.

Table 3 Statistical results of the large-sized instances

$f_c$	#Veh.	#Veh.-C	Obj.-C	Obj.-E	Obj.-D	Obj.
0	362	223	0	480.39	24893.21	25373.63
5	367	124	765	494.72	24974.41	26234.74

20	369	99	2320	518.69	25165.34	27974.00
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Several remarks could be concluded from the results. Firstly, as the value of  $f_c$  increases from 0 to 5 and then to 20, the total congestion tolls increase, and it also pushes the total route durations to increase, in almost all instances. Table 3 summarizes the results in this viewpoint. The total congestion tolls, the recharging costs, the route duration- related costs and the objective values are increased by 203.270%, 4.85%, 0.76% and 6.63%, respectively, as  $f_c$  increases from 5 to 20. This is expected.

Secondly, it can be observed that as  $f_c$  increases, less vehicles enter peak periods although the total duration might also increase. If no congestion toll is collected, i.e.,  $f_c = 0$ , then 223 out of 362 vehicles enter peak periods totally in the 29 instances.

However, if  $f_c = 5$ , only 124 vehicles enter peak periods although 367 vehicles are involved. The number of vehicles that enter peak periods decreases to 98 if  $f_c = 20$  (See Table 3). This phenomenon is notable especially for Type C instances. For 6 out of 9 Type C instances, the times for which vehicles enter peak periods decreases as  $f_c$  increases from 0 to 5. The average relative decrease is 16.36%. Instance C109D gives the maximum decrease as 60%. If  $f_c = 0$ , the vehicle enters peak periods for 5 times. However, if  $f_c = 5$ , the vehicle enters peak periods only twice (See Column Times-C in Table A1). The result that  $f_c$  continues to increase is similar but not that significantly as the result that  $f_c$  increase from 0 to 5. The vehicles enter peak periods for less times when  $f_c$  increases from 5 to 20 in 6 out of 9 C-typed instances. This validates the motion of gathering a certain amount of congestion tolls to relieve congestions.

## 7. Conclusions and Future Research

This paper addresses TDEVRP-CT in which the scheduling horizon is divided into several periods, speeds of EVs differ from period to period, and congestion tolls are collected if a vehicle enters a peak period. A MILP model is established to formulate the problem. An ALNS heuristic is designed to solve the problem and validated with benchmark instances.

Results indicate that the ALNS heuristic could provide much better solutions than typical existing optimization software such as Gurobi in a much shorter running time. A certain amount of congestion tolls is able to decrease the number of vehicles entering peak periods and to relieve congestions. Therefore, this research is valuable and referable in both academic and industrial

fields. It can help logistic companies in routing and scheduling EVs to control the cost and to relieve traffic congestions.

Limitations of this research are as follows. We implicitly assume that the recharging poles at each station are enough. Therefore, the possible waiting of EVs at stations are not considered in this research. Secondly, we define the operating costs including the congestion tolls-related costs as the optimization criterion without considering the building costs of stations. Finally, the ALNS heuristic cannot guarantee the optimality of solutions but only provides near optimum solutions.

This research could be followed in several ways. For example, how to handle the scenarios that some roads are accessible only within certain time periods? What will happen if congestion tolls are collected based on zones, or on both periods and zones? What will happen if the waiting time at the recharging stations is introduced into the model? These are all interesting topics.

## Appendix

Table A1 reports the results of the evaluation for large-sized instances. Besides the objective values, the cost related to the total route durations, and the cost related to the recharging (See (1)), are also reported in Columns Obj.-D and Obj.-E, respectively. Furthermore, Column Times-C lists the total times that vehicles enter peak periods. Column #Veh. presents the number of vehicles involved in the solution.

Table A1 Results for large-sized instances

Ins.	$f_c$	Obj.	Obj.-D	Obj.-E	#Veh.	Times-C	CPU (min)
C101D	0	1884.03	1870.50	13.53	12	17	13.01
	5	1970.52	1872.03	13.49	12	17	13.71
	20	2230.17	1895.65	14.52	12	16	13.54
C102D	0	1886.22	1872.97	13.24	11	15	11.86
	5	1963.76	1877.63	11.13	11	15	12.94
	20	2178.97	1905.30	13.68	11	13	11.36
C103D	0	1867.56	1856.38	11.18	10	17	13.93
	5	1954.58	1863.27	11.31	10	16	13.90
	20	2004.17	1834.29	9.88	11	8	14.65
C104D	0	1767.12	1759.77	7.35	10	11	22.43
	5	1820.90	1762.49	8.41	10	10	21.67

	20	1975.52	1767.07	8.45	10	10	22.35
C105D	0	1852.82	1840.56	12.25	11	12	10.22
	5	1915.89	1842.66	13.24	11	12	10.25
	20	2061.96	1869.25	12.71	11	9	10.22
C106D	0	1832.17	1821.07	11.10	11	8	11.48
	5	1872.17	1821.07	11.10	11	8	11.47
	20	1978.85	1826.66	12.19	11	7	11.24
C107D	0	1827.04	1816.92	10.11	11	9	11.31
	5	1866.83	1815.12	11.11	11	8	11.08
	20	1970.30	1819.12	11.17	11	7	11.73
C108D	0	1877.35	1863.68	13.67	10	16	12.81
	5	1846.34	1815.16	11.18	11	4	12.82
	20	1903.39	1812.23	11.16	11	4	12.82
C109D	0	1766.77	1759.31	7.46	11	5	14.74
	5	1785.82	1766.27	9.55	11	2	15.54
	20	1832.79	1782.96	9.83	11	2	15.34
R101D	0	571.19	539.98	31.21	18	10	10.67
	5	629.68	547.04	32.64	18	10	10.94
	20	771.41	539.18	32.24	18	10	11.11
R102D	0	508.80	483.33	25.47	16	9	10.74
	5	550.21	484.97	25.24	16	8	10.74
	20	678.39	489.86	28.54	16	8	10.86
R103D	0	450.63	426.00	24.63	13	9	12.75
	5	463.11	422.82	20.28	14	4	12.86
	20	525.10	424.74	20.36	14	4	12.33
R104D	0	388.07	373.22	14.84	12	7	15.41
	5	409.17	376.21	12.96	12	4	15.49
	20	457.18	382.02	15.16	12	3	15.19
R105D	0	467.87	447.03	20.84	15	10	10.38
	5	498.35	459.10	24.25	15	3	10.68
	20	552.03	464.57	27.46	15	3	10.91
R106D	0	451.84	429.31	22.53	14	8	11.77
	5	476.39	438.61	22.78	14	3	11.43
	20	511.25	446.22	25.03	14	2	11.43
R107D	0	402.11	384.77	17.34	12	7	12.74
	5	417.75	393.00	19.75	12	1	13.00
	20	440.09	400.06	20.03	12	1	12.95
R108D	0	395.96	377.41	18.55	11	7	15.68
	5	437.01	387.09	19.92	11	6	16.67

	20	397.45	381.03	16.42	12	0	16.98
R109D	0	417.42	399.80	17.62	13	3	11.77
	5	431.97	407.95	19.03	13	1	11.64
	20	435.68	414.40	21.28	13	0	11.99
R110D	0	392.03	377.98	14.05	12	4	13.10
	5	399.07	381.84	17.23	12	0	13.68
	20	397.03	380.82	16.21	12	0	15.07
R111D	0	396.37	380.16	16.22	12	4	13.35
	5	408.10	389.49	18.61	12	0	13.87
	20	408.10	389.49	18.61	12	0	14.08
R112D	0	381.36	366.27	15.09	11	7	16.28
	5	380.54	364.80	15.74	12	0	16.70
	20	383.40	366.59	16.81	12	0	16.83
RC101D	0	517.08	495.30	21.77	16	10	8.78
	5	544.42	501.33	23.08	16	4	8.78
	20	580.73	514.45	26.28	16	2	8.82
RC102D	0	482.17	463.00	19.17	15	9	9.07
	5	504.91	475.42	19.49	15	2	9.08
	20	525.73	482.91	22.82	15	1	9.10
RC103D	0	435.49	419.07	16.43	13	7	9.55
	5	455.17	423.65	16.51	13	3	9.58
	20	489.27	448.73	20.55	13	1	9.63
RC104D	0	415.24	398.77	16.47	11	9	10.09
	5	415.67	399.44	16.23	12	0	12.88
	20	414.10	398.01	16.09	12	0	12.03
RC105D	0	470.85	451.02	19.83	14	7	10.04
	5	499.00	453.23	20.77	14	5	9.87
	20	552.43	451.50	20.92	14	4	9.76
RC106D	0	448.84	430.48	18.36	14	6	9.65
	5	462.06	437.37	19.69	14	1	9.81
	20	462.13	443.28	18.86	14	0	9.80
RC107D	0	414.57	399.57	15.00	12	7	11.07
	5	448.40	402.25	16.15	12	6	10.51
	20	449.38	441.79	17.59	12	1	10.56
RC108D	0	404.66	389.58	15.08	11	8	11.28
	5	406.95	393.10	13.85	12	0	12.45
	20	407.00	393.16	13.84	12	0	11.45

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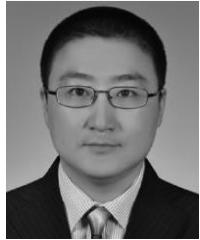
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