Modelling dynamic electric vehicle routing problem with heterogeneity and uncertainty

Abstract

CHANGE! With more and more serious issues like air pollution and traffic noise in transport sector, a fast growing number of electric vehicles has been used for various purpose in road transport, including urban freight transport. To promote the usage of electric vehicle in urban freight transport, this study investigates the dynamic vehicle routing problem with consideration of heterogeneous vehicle types and mixed-type charging facilities, as well as multiple uncertain factors in real operation. It is a challenge to incorporate charging activity into the route plan since the availability of charging station and the travel time en-route are stochastic. The decision-maker needs to assign the right vehicle type to a certain route with minimized total time to implement the routing plan. An adaptive solution approach based on multiple scenario approach and two heuristics is developed to solve the proposed model. To validate the proposed model and test the solution approach, multiple numerical experiments are conducted based on a benchmark dataset.

Keywords Electric vehicle routing problem, Heterogeneous electric vehicles, partial charging, Uncertainty, Stochastic Inputs, Dynamic approach

1 Introduction

Although road urban freight transport may cause various issues, such as traffic congestion, traffic noise, air pollution, energy consumption, and high logistics costs, it remains the primary mode of urban freight transport. The use of electric vehicles (EVs) has emerged as a promising solution to reducing such environmental and sustainable concerns. Its is evident that EVs operate more silently than conventional vehicles, and they could help reduce traffic emission significantly. Nevertheless, how to run EVs efficiently and economically under various features and limitations associated with EV, for instance, limited driving range, limited load capacity, long charging time and the scarcity of charging station (CS), is a challenge to be addressed before EVs can be used for freight transport widely.

To promote the integration and operation of EVs to freight transport, several models of electric vehicle routing problem (EVRP) have been proposed during the past few years. As optimization decision models seek to represent real-life problems, research on EVRP has introduced several variants. One of them is the heterogeneous EVRP (HEVRP). Logistics companies usually hold a fleet of diverse EVs with different acquisition cost, capacity, driving range, and energy consumption. Therefore, fleet management, i.e. selecting the right EV for a certain transportation request, is highly important. In HEVRP, it is considered that EVs differ in their capacity, battery size, and purchasing cost. Another variant of the EVRP is the stochastic EVRP (SEVRP). In real life, one or more inputs of the problem are often uncertain, and the developments in the area of algorithms and the area of information technologies, e.g. development of intelligent transportation systems (ITS), have rendered possible to freight providers the use of real-time data on the management of their operations.

CONTINUE! That is, VRP can now be solved dynamically, i.e. on real-time manner.... we consider the possibility of performing a partial recharge at a station. This implies that for each vehicle we have to decide where and when to recharge, but also how much.... However, since solving it to optimality for realistic sized instances is prohibitive, we decided to focus on heuristic approaches..... While the vehicle is traveling, the battery charge level decreases proportionally with the distance traversed and the vehicle may need to visit a recharging station in order to continue its route. The battery is recharged at any quantity and the duration of the recharge depends on the initial state of battery charge.... This waiting time varies depending on the time of the day because some time periods are more crowded due to rush hours and the demand is higher during these periods... Many different heuristics have been successfully applied to vehicle routing problems with additional constraints, providing near optimal solutions within a short computational time.... The experiments have focused on evaluating the per- formance of the proposed algorithms and analyzing some of the main characteristics of the problems considered, mainly regarding the size and geographical configuration of the instances, the number of recharge stations, the use of multiple technologies and partial recharges and the autonomy of the vehicles..... explain that there might not be enough time to compute solutions Although a diversity of EVRP models have been proposed with consideration of various factors and constraints, several key factors associated with EVs are missing, and more importantly the relationship among various factors lacks exploration.

In this paper, we introduce a model for the dynamic heterogeneous electric vehicle routing problem (DHEVRP) with consideration of heterogeneity and uncertainty. This model aims to address multiple challenges associated with EV operation in an adaptive way, i.e. sequential decision-making. Heterogeneity comes from multiple types of EVs with different loading capacity, battery capacity and energy consumption, as well as various charging rates at different CSs. Three sources of uncertainty are considered: travel time, charging station availability, and waiting time at a CS. Travel time is considered stochastic due to traffic congestion. For example, travel time is usually larger at peak hours than at non-peak hours along the same route. We assume that each CS has a probability of being available, and in case of CS is fully occupied, a stochastic waiting time will be imposed for the EV in queue. Moreover, both time window and service time are considered for each customer. Penalty cost/time will be charged if delivery occurs out of the time window. The objective function of the DHEVRP consists of en-route time and on-demand charging time. En-route includes travel time, service time, and penalty cost/time for early or late delivery whereas on-demand charging time is a function of availability of CS, waiting time at CS, charging rate, remaining and expected battery levels. To solve this problem, we proposed a dynamic solution method in which the time horizon is divided into intervals. The goal is to design a solution for how to serve customers and when/where recharge the EV within the next time interval, using both deterministic and stochastic information about the inputs.

To our best knowledge, it is the first study to consider both heterogeneous EVs and stochasticity in EVRP, and both considerations are quite practical and important in real-life EVRP. In the literature, most parameters in EVRP were either given as fixed or considered as stochastic and separate from each other. In this study, we aim to explore the connection among multiple parameters to develop interlinked conditions. For example, in our proposed model, we consider charging time as a function of a series of parameters, like remaining battery level, charging rate, and so on. Rather than fully charged setting in most studies, we consider on-demand charging, i.e. top-up charges, based on the adaptive route plan, which makes the charging strategy more flexible and economical. Last but not the least, different cases will be tested based on benchmark networks to validate the DEHVRP model and prove the efficiency of the proposed solution method.

The structure of the paper is as follows. In the next section, a review research on EVRP is briefly presented. In Section 3, the mathematical formulation of the problem is shown. The proposed solution approach is introduced in Section 4 followed by the description of the dataset in Section 5. In Section 6, we define the different cases used in the experiments. The computational results are displayed in Section 7, and the work is concluded in Section 8.

2 Literature Review

In this work, we cover two categories of the electric vehicle routing problem. A brief description of these classes together with examples of studies that have investigated them are presented as follows. Figure 1 displays these EVRP categories and studies.

The first class is the HEVRP. Although most studies on EVRP have assumed that a fleet of homogeneous EVs is available to attend all the customers (see, e.g., Zhang et al., 2018; Keskin et al., 2019, Froger et al., 2019), in real world companies usually hold a fleet of diverse electric vehicles regards to, for instance, driving range. The fleet management, i.e. selecting the right EV for a certain transportation request, is highly important when the fleet of electric vehicles is heterogeneous. This class of EVRP has been proposed to represent this situation. The HEVRP may, therefore, include many types of electric vehicles which can differ in load capacity, battery capacity, energy battery consumption, charging rate, and fixed cost. To the best of our knowledge only Hiermann et al. (2016), Penna et al. (2016), Jie et al. (2019), and Kopfer and Vornhusen (2019) have approached the HEVRP. Hiermann et al. (2016) and Penna et al. (2016) studied the electric fleet size and mix vehicle routing problem with time windows and recharging stations (E-FSMFTW). In this problem, each customer has a specific demand, a duration of the service, and must be serviced within its time window. It was assumed that the EVs vary in their transportation capacity, battery size, and purchasing costs. Jie et al. (2019) introduced the two-echelon capacitated electric vehicle routing problem with battery swapping stations (2E-EVRP-BSS) with heterogeneous EVs in different echelons. In this problem, the freight available in a depot (echelon) is transported to the transfer stations (echelon) by large EVs, and then small EVs are used to deliver the freight to the customers. The EVs operating in the different echelons have different load capacity and battery driving ranges. Kopfer and Vornhusen (2019) introduced the energy vehicle routing problem with time windows, recharge stations and vehicle classes (EVRPTW-R-VC), where the use of a heterogeneous fleet composed of differently sized EVs and combustion-powered vehicles (CVs) was investigated.

The second class is the SEVRP. In contrast to the assumptions on the deterministic nature of the problem inputs in the classical EVRP (see, e.g., Keskin and Çatay, 2016; Taş, 2020), in the real world one or more of the elements of the EVRP are uncertain. The inputs of the EVRP that have been assumed to be stochastic are customer presence (Shi et al., 2019), demands (Lu and Wang, 2019), travel time (Shao et al., 2017; Bi and Tang, 2019; Reyes-Rubiano et al., 2019), and energy consumption (Pelletier et al., 2019). Because of the importance of the time frame in the decision-making process, the SEVRP can be examined from two perspectives: static or dynamic. From a static perspective, the goal is to calculate a robust a-priori solution that undergoes minor changes during its execution to manage the fluctuations in the uncertain inputs. From a dynamic perspective, the aim is to design a route plan in an online way reporting to every vehicle what to do next. For this reason, the SEVRP can be classified either as static and stochastic EVRP (SSEVRP) or dynamic and stochastic EVRP (DSEVRP). In the SSEVRP, decisions are made at the planning phase and define actions which are implement at the execution phase, whereas in the DSEVRP decisions are made as soon as a new event occurs. In the latter, route plans are reoptimised at predefined stages with respect to both the current condition of the system and the available stochastic information. Pelletier et al. (2019) and Reyes-Rubiano et al. (2019) approached the SEVRP with a static strategy. Although in both studies the term robust refers to guaranteeing that no EV will run out of battery during the execution of its route, Pelletier et al. (2019) proposed a robust optimisation framework to the electric vehicle routing problem with energy consumption uncertainty (EVRP-ECU), while Reyes-Rubiano et al. (2019) introduced a hybrid solution approach to the electric vehicle routing problem with stochastic travel times (EVRPST). Shao et al. (2017), Lu and Wang (2019) and Bi and Tang (2019) have investigated the stochastic EVRP from a dynamic perspective. Shao et al. (2017) introduced a solution method that integrates a dynamic Dijkstra algorithm with a genetic algorithm (GA) to solve the electric vehicle routing problem with charging time and variable travel time (EVRP-CTVTT). Lu and Wang (2019) approached the dynamic capacitated electric vehicle routing problem (DCEVRP) with stochastic customers and stochastic demands by transforming the problem into a series of static problems. For solving the series of static problems, they introduced a bi-strategy based optimisation algorithm (BSOA). Bi and Tang (2019) considered the dynamic electric vehicle routing problem with battery charging and discharging and stochastic travel time and stochastic demands. The authors designed a markov decision process (MDP) model which incorporates an analytical battery model to better capture the discharging and charging pattern of the EVs. To solve this model, a hybrid rollout algorithm (HRA) which combines a pre-planning strategy and a rollout algorithm was developed.

In this work, we combine the two classes of EVRP described before and introduce the DHEVRP. Therefore, in the DHEVRP

- a fleet of heterogeneous EVs is available, and they differ based on capacity, battery capacity, energy battery consumption, charging rate, and acquisition cost;
- some of the problem inputs are uncertain, namely, travel time, charging station availability, and waiting time at a CS, and historical data is available; and
- the problem is solved using a dynamic approach.

Stochastic charging station availability means that each CS has a probability of being available. If the CS is available, the EV is promptly recharged, otherwise stochastic waiting time will be imposed. The whole period that an EV remains at a CS is called on-demand charging time. On-demand charging time is considered as a function of the parameters: availability of CS, waiting time at CS, energy consumption rate, charging rate, and remaining and target battery level. The remaining battery level is calculated based on the initial battery level

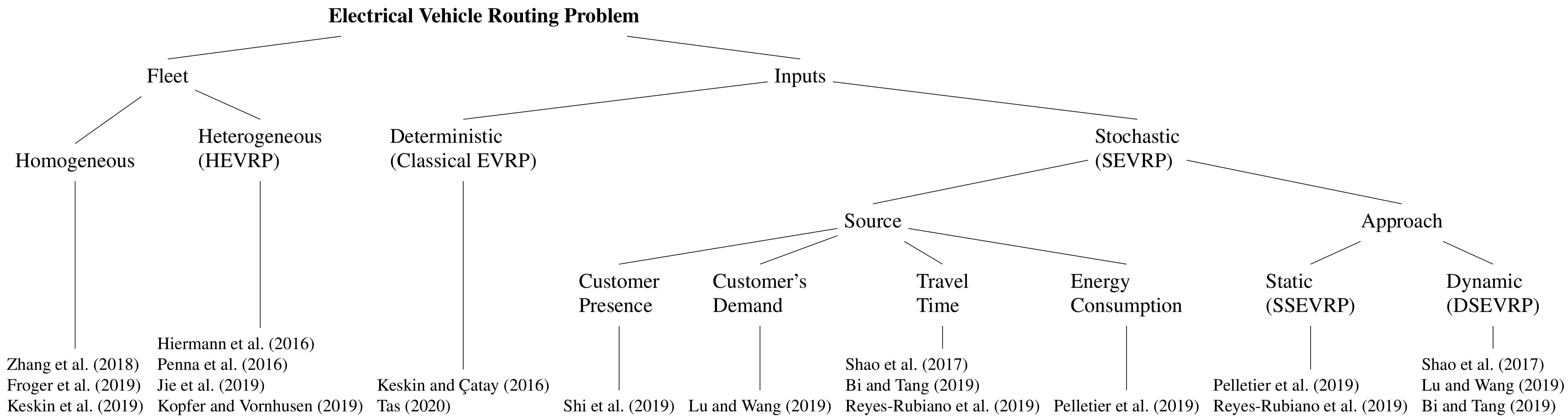

Figure 1: Papers dealing with the electrical vehicle routing problem

and en-route energy consumption. The latter is a function of the distance and energy consumption rate. The target battery level of an EV is determined based on the estimation of energy consumption on the remainder of its route. Instead of recharging the battery from empty-to-full, on-demand (partial) charging is done. That is to say, the battery is charged to a level so that the EV is able to attend its remaining customers and return to the depot.

In the dynamic approach, the decision-making process is divided into several stages. The first stage is called planning stage. In this stage, we use the stochastic information about the uncertain inputs to calculate the so-called a-priori route plan. After that, the a-priori route plan is reoptimised every time a new event occurs. An event happens when the true value of any of the stochastic inputs is disclosed. Figure 2 illustrates the difference between the stages for a single EV (route) when the true values of the stochastic travel times are revealed. At the beginning of a work day ($t = 0$), an EV starts to execute its route in accordance to the a-priori route plan (represented in grey). The a-priori route plan was designed in the previous day considering the known inputs, e.g. customers' locations, and the expected values of the uncertain inputs. In the next stage ($t = t_e$), the battery energy is consumed as the EV follows its route. Based on the a-priori route plan, the EV should consume one unit of battery power as it travels from depot to customer 1 and one unit from customer 1 to customer 2. Although the traffic was normal (black arrow), i.e. normal travel time, and one unit of battery was thus used from depot to customer 1, the traffic was congested (red arrow), i.e. higher travel time, from customer 1 to customer 2 and two units of battery were used by the EV. Hence, instead of being charged after attending customer 3 as planned in the a-priori route plan, the EV must move to a different CS right after serving customer 2. Once all the stochastic travel times are revealed, the final route plan can be seen at $t = t_f$.

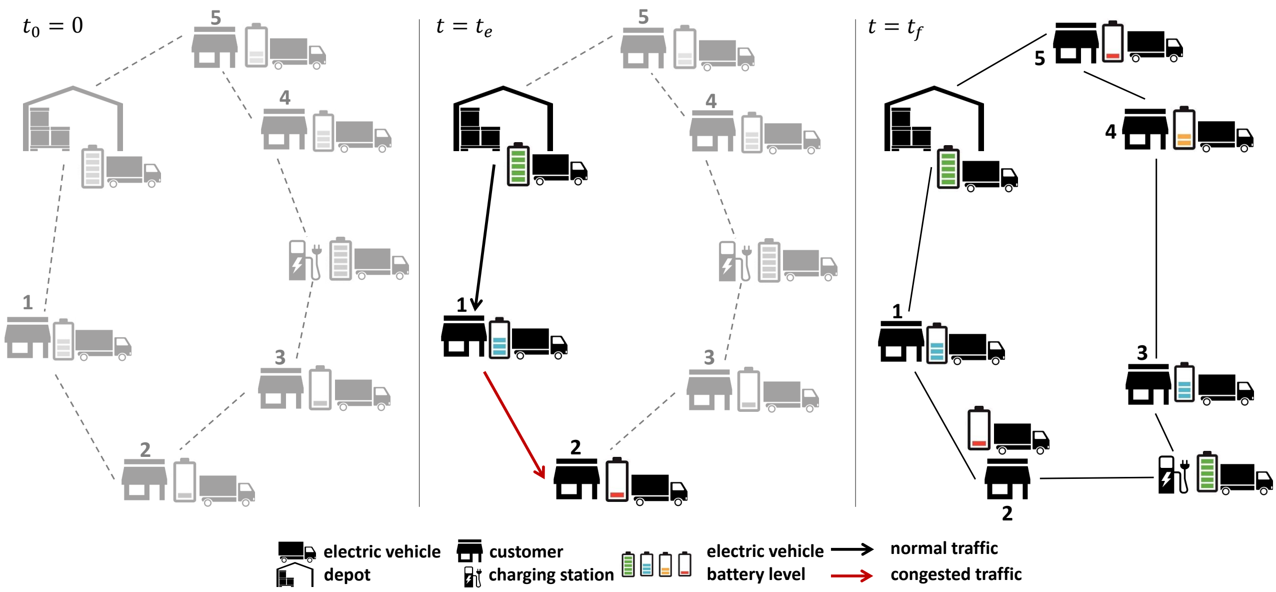

Figure 2: Example of the Dynamic electric vehicle routing problem under uncertainties

3 Static heterogeneous electric vehicle routing problem under uncertainties

As mentioned before, the DHEVRP can be studied from two perspectives, static and dynamic. In this study, we adopt a dynamic approach for dealing with the problem. We divide the time horizon into many stages such that the number of stages is equal to the number of new event occurrences. At each stage, we define an static DHEVRP by using the deterministic inputs and stochastic data on the uncertain inputs. Thus, the objective of this section is to formally introduce the static DHEVRP. We first provide the definitions and notations together with some assumptions used in the model. After that, we introduce the mathematical formulation of the static problem.

3.1 Problem description

The goal of the DHEVRP is to find a route plan to attend a set of customers with a given heterogeneous EV fleet while minimising acquisition costs, en-route time, and on-demand charging time. En-route includes travel time and service time, whereas on-demand charging time is a function of availability of CS, waiting time at CS, charging rate, and remaining and target battery level.

This problem is represented on a fully connected directed graph $G = (N, A)$, where $N = (0, 1, 2, 3 \dots n)$ is the set of nodes and $A = \{(i, j)|i, j \in N, i \neq j\}$ is the set of arcs. Therefore, there are $|A| = n.(n-1)$ arcs in the graph. Each arc $i, j \in A$ has two variables c_{ij} and t_{ij}^k associated with it. c_{ij} is the distance between the nodes i and j, and t_{ij}^k represents the travel time spent by vehicle type k in arc i, j. The travel times are are stochastic, i.e. $t_{ij} : \Omega_{ij} \rightarrow \mathbb{R}_0^+ \forall i, j \in N$ with sampling spaces Ω_{ij}, and assumed to be proportional to the distance through a coefficient p. The set of nodes is partitioned into a set of customers $C = (0, 1, 2, 3 \dots c)$ and a set of dummy nodes E', i.e. $N = C \cup U'$, where U' contains multiple charging stations of $U = (u_1, u_2, u_3, \dots u_u)$. Let n_0 and n_{n+1} represent the start and end depot nodes, respectively. For simplicity, we defined N_0 as the set of nodes with the start depot node and N_{n+1} as the set of nodes with the end depot node. $N_{0,n+1}$ portrays $N \cup \{n_0, n_{n+1}\}$. We also adopt this notation for the sets C and U' (Hiermann et al., 2016).

Since the availability of each charging station $i \in E$ is uncertain, we represented it by a stochastic variable Λ_i, i.e. $\Lambda_i : \Gamma_i \rightarrow \mathbb{R}_0^+ \forall i \in N$ with sampling spaces Γ_i. When a vehicle arrives at CS u_i and the station is available, then $\Lambda_i = 1$. In this case, the vehicle is promptly recharged. If the station is not available, i.e. $\Lambda_i = 0$, the vehicle has to wait a time interval w_i until the charging station turns available. This waiting time is also uncertain, i.e. $w_i : \alpha_i \rightarrow \mathbb{R}_0^+ \forall i \in N$ with sampling space α_i. The deterministic amount of goods that has to be delivered to (or/and collected at) customer $i \in C$ is denoted as customer's demand and is given by d_i, therefore, $d_0 = 0$. Each node $i \in N$ has a time window $[e_i, l_i]$ and a service time s_i. The true start of the service time is stored in τ_i.

There is a fleet of $K = \{1, 2, ..., k\}$ types of electric vehicles. For each vehicle type k, the variable g^k expresses the charging rate (time/energy unit) and the variable e^k expresses the battery energy consumption rate (energy unit/ kilometre). The maximum load capacity of vehicle type k is defined as Q^k, and q_i^k displays the current load of a vehicle type k in node i. The maximum energy capacity of vehicle type k is represented by Y^k, and y_i^k displays the remaining battery energy level of vehicle type k at node i. If an EV type k travels from i to j, the remaining battery energy level at j is calculated based on y_i^k and en-route energy consumption. We assume that en-route energy consumption (expressed in KWh per km) is equal to $t_{ij} \cdot e^k$. Since en-route energy consumption is proportional to the travel time, the remaining battery energy level is also stochastic, i.e. $y_i^k : \vartheta_i^k \rightarrow \mathbb{R}_0^+ \forall i \in N, \forall k \in K$ with sampling spaces ϑ_i^k. As described before, the time spent by EV type k at a charging station u_i, called on-demand charging time, depends on the availability of u_i (Λ_i), waiting time at u_i, charging rate of EV type k (g^k), target battery level at u_i (Ta_i^k), and battery energy level of the vehicle when it reaches u_i (y_i^k). The target battery level of EV type k (Ta_i^k) is determined based on the estimation of energy consumption on the remainder of its route.

An instance of the problem is defined by a complete weighted graph $G = (N, A, (c_{ij}, t_{ij}^k))$ together with the $|K|$ types of electric vehicles. M^k is defined as the acquisition cost of vehicle type k. The decision variables x_{ij}^k indicate whether or not vehicle type k travels from node i to node j. A solution $z = \{r_1, r_2, r_3, r_k\}$ to the DHEVRP, i.e. a route plan, consists of k routes. The total cost of solution z is expressed by $J(z)$, and θ expresses the unit travel time cost. A feasible route r_k is performed by one EV of type k which leaves the depot with a fully charged battery, serves a subset $B = \{i_1, i_2, \dots, i_b\} \subseteq C$ of customers, whose total demand does not exceed Q^k, recharges its battery at a charging station $u \in U'$ if necessary, and returns to the depot, i.e. $r_k = (n_0, \gamma_1^k, \gamma_2^k, u_u^k, \dots \gamma_b^k, n_{n+1})$.

3.2 Mathematical model

The static DHEVRP is presented as a three-index mixed integer programming model:

$$\begin{aligned} \min_z J(z) := \min \sum_{k \in K} M^k x_{0j}^k + \theta \Bigg(\sum_{k \in K} \sum_{i \in N_0, j \in N_{n+1}, i \neq j} E[t_{ij}^k] x_{ij}^k + \sum_{i \in U'} E[s_i] + \\ \sum_{i \in U'} E[w_i | \Lambda_i = 0] + \sum_{k \in K} \sum_{i \in U'} E[(Ta_i^k - y_i^k) g^k] \Bigg) \end{aligned} \tag{1}$$

$$\text{s.t.} \sum_{k\in K}\sum_{j\in N_{n+1}, i\neq j} x_{ij}^k = 1, \qquad \forall i \in C \tag{2}$$

$$\sum_{k\in K}\sum_{j\in N_{n+1}, i\neq j} x_{ij}^k \leq 1, \qquad \forall i \in R' \tag{3}$$

$$\sum_{i\in N_{n+1}, i\neq j} x_{ji}^k - \sum_{i\in N_0, i\neq j} x_{ij}^k = 0, \qquad \forall j \in N, \forall k \in K \tag{4}$$

$$e_j \leq E[\tau_j] \leq l_j, \qquad \forall j \in N_{0,n+1} \tag{5}$$

$$E[\tau_i] + (E[t_{ij}] + s_i)x_{ij}^k - l_0(1 - x_{ij}^k) \leq E[\tau_j], \qquad \forall k \in K, \forall i \in C_0, \forall j \in N_{n+1}, i \neq j \tag{6}$$

$$E[\tau_i] + E[t_{ij}^k]x_{ij}^k + g^k(Ta_i^k - y_i^k) - (l_0 + g^k Ta_i^k)(1 - x_{ij}^k) \leq E[\tau_j], \quad \forall K \in K, \forall i \in U', \forall j \in N_{n+1}, i \neq j \tag{7}$$

$$q_j^k \leq q_i^k - d_i x_{ij}^k + Q^k(1 + x_{ij}^k), \qquad \forall k \in K, \forall i \in N_0, \forall j \in N_{n+1}, i \neq j \tag{8}$$

$$0 \leq q_j^k \leq Q^k, \qquad \forall k \in K, \forall j \in N_{0,n+1} \tag{9}$$

$$0 \leq E[y_j^k] \leq y_i^k - (e^k c_{ij})x_{ij}^k + Ta_i^k(1 - x_{ij}^k), \qquad \forall k \in K, \forall i \in C, \forall j \in N_{n+1}, i \neq j \tag{10}$$

$$0 \leq E[y_j^k] \leq Ta_i^k - (e^k c_{ij})x_{ij}^k, \qquad \forall k \in K, \forall i \in U_0', \forall j \in N_{n+1}, i \neq j \tag{11}$$

$$y_0^k = Y^k \qquad \forall k \in K \tag{12}$$

$$x_{ij}^k \in \{0,1\} \qquad \forall i \in N_0, j \in N_{n+1}, i \neq j, \forall k \in K \tag{13}$$

This is a minimisation problem with an objective function (1) that consists of acquisition costs, en-route time and on-demand charging time. The acquisition cost is the sum of the costs of all EVs used. The en-route time corresponds to the total travel time and total service time. The on-demand charging time is formed by the total waiting time and total charging time spent at charging stations. Constraints (2) assure that each customer is visited by one incoming and one outgoing vehicle. Constraints (3) mean that a charging station is visited at most once and that it does not necessary need to be visited by a vehicle. Flow conservation is guaranteed by constraints (4). Contraints (5) ensure that the start time of a service τ_i at a node i has to be within its time window. Constraints (6) and (7) track the start time of a service and show the difference between customers and charging stations nodes regards service times. If the previous node is either a customer or the depot, constraints (6) consider the service time, while constraints (7) consider the charging time if the previous node is a charging station. Constraints (8) guarantee that the demand of every customer is satisfied. Vehicle capacity restrictions are expressed by constraints (9). Constraints (10) and (11) not only trace the battery level of the vehicle type k based on its energy consumption as it tours arc i, j but also secure that its remaining battery level is always positive in any node. Constraints (12) secure that the battery level of any vehicle is full at the depot. Finally, the domain of the decision variables is defined by constraints (13).

4 Solution approach

CONTINUE! We adopt two heuristics a greedy algorithm and a randomised variable neighbourhood search (VNS). These heuristics are explained as follows....

The greedy algorithm is used to calculate the initial solution. Its pseudocode is displayed in **Algorithm 1**. In this method, a customer $i \in C$ is allocated to the EV route r^k that has traveled time $J(r^k)$ closer to the time window of the request $[e_i; l_i]$ (Step 5). A customer's request is only added to a route when feasibility can be maintained with respect to remaining battery energy level y_i^k and EV capacity q_i^k . If customer i cannot be added to route r^k because of battery energy level feasibility (Step 6), the CS $u_j \in U'$ with lowest sum of the distance to the current customer c_{ij} plus waiting time w_j is inserted in the EV route (Step 8). This CS is then removed from the list of available CS (Step 10). Since we do not adopt fully charged setting, one has to decide how much to recharge when the EV stops at the CS. As explained before, in this paper we follow that the decision on how much to recharge the battery of any EV at any CS is based on the rest of the customers to be attend by this EV. Nevertheless, this procedure is impracticable at this stage. The initial route plan is being constructed, and not all the customers have, therefore, been assigned to the EVs. We thus create three scenarios that will guide this decision during the creation of the initial route plan. These scenarios are described in **Section 6**. If customer i cannot be allocated to route r^k due to capacity feasibility (Step 13), the EV returns to the depot and it is removed from the list of available EVs (Step 16). The greedy method repeats these steps until all the customers are designated to EV routes. The solution outputed by the greedy method z_g is improved by the VNS.

We implement a VNS modified from the VNS proposed by Mladenović and Hansen (1997). The pseudocode of the VNS is displayed in **Algorithm 2**. VNS requires the determination of three components: shaking procedure, local search procedure, and stopping criteria. For the shaking procedure, a list of neighbourhood structure must be define. The list of neighbourhood structures $M = \{m_1, m_2, m_3, \ldots, m_{max}\}$ is a finite set of neighbourhood structures whose $m_1(z')$, for instance, is the set of solutions in the 1^{st} neighbourhood of the solution z'. To define a neighbourhood of the solution z a combination of operators must be specified. We create a list of four operators $O = \{o_1, o_2, o_3, o_4\}$. The o_1 (1-0 exchange move) operator removes a customer from its original route and inserts it after other in a different route. The o_2 (1-1 exchange move) operator swaps two customers in the same route, whereas the o_3 (2-opt move) operator swaps two customers in different routes. The o_4 (CROSS-exchange) (Taillard et al., 1997) operator exchanges two arcs of different routes. All operators are used to determine the set of neighbourhood structures M. We use the randomized variable neighborhood descent (RVND) method (Hansen et al., 1997) as the local search procedure and define the number of iterations ($iterMax$ = 1000) without improvement on the current solution as the stop criteria. VNS starts by generating a neighbour z^a of the incumbent solution z' at random from the k^{th} neighbourhood ($z^a \in m_k(z')$). Following, the local procedure is applied to improve the solution z^a. In order to do so, the RVND uses a list of neighbourhood structures $V = \{v_1, v_2, v_3, \ldots, v_{max}\}$. First, one neighbourhood structure is randomly selected (Step 8). After that, the best solution in this neighbourhood structure z^b is found by using the strategy first improvement (Step 9). If z^b is better than the solution z^a (Step 10), then z^b is returned as the best solution. If not, this neighborhood structure is removed from the list (Step 14). This procedure is executed until the list V becomes empty. If the best solution found in the local procedure is not better than the imcumbent solution z', VNS starts again with a new neighbourhood structure. These steps are repeated until the stop criteria is met.

Algorithm 1 Greedy algorithm

INPUT: N, A, K
OUTPUT: z_g

1: Initialize r^k
2: $G \leftarrow C, H \leftarrow U', I \leftarrow K, z_g = \emptyset, \gamma_1^k = 0$ and $J(r^k) = 0 \; \forall k \in K, position = 1$
3: **while** $G \neq \emptyset$ **do**
4: $\quad position = position + 1$
5: $\quad$ Select customer $i \in C$ and EV type $k \in K$ based on $[e_i; l_i]$ and $J(r^k)$
6: $\quad$ **if** $y_i^k \leq 0$ **then**
7: $\quad\quad$ Compute $c_{\gamma_{(position-1)}j}$ and $w_j \; \forall j \in H$
8: $\quad\quad$ Select $u_j \in U$ with lowest $c_{\gamma_{(position-1)}j} + w_j$
9: $\quad\quad$ Allocate u_j to r^k, $J(r^k) = J(r^k) + c_{\gamma_{(position-1)}j} + w_j$
10: $\quad\quad H \leftarrow H \backslash \{u_j\}$
11: $\quad\quad$ Recharge battery of EV k according to chosen scenario
12: $\quad$ **else if then**
13: $\quad\quad$ **if** $q_i^k \leq 0$ **then**
14: $\quad\quad\quad$ Go to the depot, $\gamma_{position} \leftarrow 0$, $position \leftarrow 0$
15: $\quad\quad\quad$ Add route r^k to route plan z_g
16: $\quad\quad\quad I \leftarrow I \backslash \{k\}$
17: $\quad\quad$ **else if then**
18: $\quad\quad\quad$ Allocate customer i to r^k, $\gamma_{position} \leftarrow i$, $J(r^k) = J(r^k) + c_{(\gamma_{position-1})\gamma_{position}}$
19: $\quad\quad\quad G \leftarrow G \backslash \{i\}$
20: $\quad\quad$ **end if**
21: $\quad$ **end if**
22: **end while**

CONTINUE!....When an event occurs the route plan must be revised. The possible events are described in the following. Although each event is solely explained, many of them can happen at the same time.

Algorithm 2 Variable neighbourhood search

INPUT: z_g, N, A, K
OUTPUT: z

Initialize M, O, V
$z_{best} \leftarrow z_g, z' \leftarrow z_g$
while $iterMax \leq 1000$ **do**
  $k \leftarrow 1$
  for $k = 1$ to max **do**
    Generate a solution z^a of z' at random in $m_k(z)$
    while $V \neq \emptyset$ **do**
      $l \leftarrow U[1; |V|]$
      Find the best solution z^b in $v_l(z^a)$ via descendent method
      if $J(z^b) \leq J(z^a)$ **then**
        $z^a \leftarrow z^b$
        $z_{best} \leftarrow z^a$
      else if then
        $V \leftarrow V \backslash \{v_l\}$
      end if
    end while
    if $J(z') \leq J(z_{best})$ **then**
      $z_{best} \leftarrow z'$
      $iterMax = iterMax + 1$
      $k = k + 1$
    else if then
      $z' \leftarrow z_{best}$
    end if
  end for
  $z \leftarrow z_{best}$
end while

- **Electric vehicle arrival at customer.** When an electric vehicle type k arrives at customer $j \in C$ coming from node $i \in N$, the true values of two stochastic inputs are disclosed: travel time and remaining battery energy level.
- **Electric vehicle arrival at charging station.** Apart from the true values of the travel time and remaining battery level, the real availability of the CS is also revealed when an EV type k arrives at charging station $i \in U$ coming from customer $i \in C$.
- **Electric vehicle departure from a charging station.** The true values of both the waiting time w_i and the charging time s_i are disclosed when an EV departures from a charging station $i \in U$.

5 Dataset design

We evalute the performance of our solution approach in set of instances adapted from the dataset of Solomon (1987). We also compare our dynamic solution approach with a static solution approach in terms of quality of the solutions and computational time. Our dataset contains 56 instances. The inputs number of nodes N, customer locations C, demands d_i, travel times t_{ij}^k, and service times s_i are taken from these instances. For the representation of the uncertain travel times, we assume that the values defined in the Solomon's instances represent the expected values, and we randomly generate the variances. The same procedure is followed for the customer service times.

CHANGE! For creating the fleet of heterogeneous electric vehicles, we select some of the EVs described in NSR Compilation report (2013). Because this report does not present the charging rates of the EVs, we have to generate them. According to (Montoya et al., 2017), for a battery capacity of 22 kWh, the minimum charging time is 0.50 h, i.e. $g^k = 0.02$. Therefore, we randomly generate the charging rates in $[0.02; 0.06]$. The details of the vehicles are displayed in Table 1.

Name	Q^k (kg)	Y^k (kWh)	e^k (kWh/km)	g^k (h/kWh)
German E-Cars Pantos	1.000	38,60	0,25	0.05
Citroën Berlingo	500	23,50	0,22	0.03
Mercedes Vito E-CELL	900	36,00	0,22	0.04
Renault Kangoo Z.E.	595	22,00	0,17	0.02
Renault Kangoo Rapid Maxi Z. E.	650	22,00	0,18	0.02
Smith Electric Newton Edison	3.500	36,00	0,30	0.04
Smith Electric Newton Newton	2.800	40,00	0,80	0.05
Aixam Mega Multitruck	500	60,00	0,22	0.06

Table 1: Specifications of the available electric vehicles

For selecting the number of charging stations $|R|$, we adopt $|R| = \lfloor 0,1 \cdot |N| \rfloor$. We locate charging stations at randomly drawn nodes and one additional station at the depot. For the representation of the charging station availability and consequent waiting times, we create three scenarios. These scenarios are described in **Section 6**.

6 Cases configuration

6.1 Scenarios based on charging strategy at construction of initial route plan

charge to 1 (100%) every time an EV stops at a CS charge to 0.75 (75%) every time an EV stops at a CS charge to 0.50 (50%) every time an EV stops at a CS

6.2 Scenarios based on charging station availability

For the representation of the charging station availability, we create three scenarios. In *Scenario A.1*, the CS are always available and have long waiting times. The waiting times (hours) are assumed to be uniformed distributed $w_i \sim U[1,50;2,50]$. In *Scenario A.2*, the CS are available half of the time and have $w_i \sim U[1,00;1,50]$. In *Scenario A.3*, the charging stations are less likely to be available but have shorter waiting times ($w_i \sim U[1,50;2,50]$).

6.3 Scenarios based on initial setup

CHANGE! INITIAL BATTERY ENERGY LEVEL ($t = 0$) all values in the samples in the set of battery energy level are equal to 1 in the *Scenario B.1* In *Scenario B.2*, for initializing the set of battery energy level samples, we randomly generate the values in [0.5;1] for each electric vehicle in the fleet, i.e. $y_0^k \sim U[0.5;1]\ \forall k \in K$ Two types of scenarios. In the first scenario (*Scenario B.1*), the vehicles leave the depots with their batteries fully charged, whereas in the second scenario (*Scenario B.2*), the batteries are not fully charged when the vehicles leave the depot.

7 Computational results

8 Conclusions

Conflict of Interest

The authors declare that there is no conflict of interest regarding the publication of this paper.

References

Bi, X. and Tang, W. K. S. (2019). Logistical planning for electric vehicles under time-dependent stochastic traffic. *IEEE Transaction on Intelligent Transportation System*, 20(10):3771–3781.

Froger, A., Mendoza, J. E., Jabali, O., and Laporte, G. (2019). Improved formulations and algorithmic components for the electric vehicle routing problem with nonlinear charging functions. *Computers and Operations Research*, 104:256–294.

Hansen, P., Mladenović, N., Brimberg, J., and Moreno Pérez, J. A. M. (1997). Variable neighborhood search. In Gendreau, M. and Potvin, J., editors, *Handbook of Metaheuristics*, chapter 3, pages 61–87. Springer, 2 edition.

Hiermann, G., Puchinger, J., Ropke, S., and Hartl, R. F. (2016). The electric fleet size and mix vehicle routing problem with time windows and recharging stations. *European Journal of Operational Research*, 252(3):995–1018.

Jie, W., Yang, J., Zhang, M., and Huang, Y. (2019). The two-echelon capacitated electric vehicle routing problem with battery swapping stations: Formulation and efficient methodology. *European Journal of Operational Research*, 272:879–904.

Keskin, M. and Çatay, B. (2016). Partial recharge strategies for the electric vehicle routing problem with time windows. *Transportation Research Part C: Emerging Technologies*, 65:111–127.

Keskin, M., Laporte, G., and Çatay, B. (2019). Electric vehicle routing problem with time-dependent waiting times at recharging stations. *Computers and Operations Research*, 107:77–94.

Kopfer, H. and Vornhusen, B. (2019). Energy vehicle routing problem for differently sized and powered vehicles. *Journal of Business Economics*, 89:793–821.

Lu, J. and Wang, L. (2019). A bi-strategy based optimization algorithm for the dynamic capacitated electric vehicle routing problem. In *Proceedings of the IEEE Congress on Evolutionary Computation*, New Zealand.

Mladenović, N. and Hansen, P. (1997). Variable neighbourhood search. *Computers & Operations Research*, 24(11):1097–1100.

Montoya, A., Guéret, C., Mendoza, J. E., and Villegas, J. G. (2017). The electric vehicle routing problem with nonlinear charging function. *Transportation Research Part B: Methodological*, 103:87–110.

NSR Compilation report (2013). Comparative analysis of european examples of schemes for freight electric vehicles. http://e-mobility-nsr.eu/fileadmin/user_upload/downloads/info-pool/E-Mobility_-_Final_report_7.3.pdf. Accessed: 11-24-2019.

Pelletier, S., Jabali, O., and Laporte, G. (2019). The electric vehicle routing problem with energy consumption uncertainty. *Transportation Research Part B: Methodological*, 126:225–255.

Penna, P. H. V., Afsar, H. M., Prins, C., and Prodhon, C. (2016). A hybrid iterative local search algorithm for the electric fleet size and mix vehicle routing problem with time windows and recharging stations. *IFAC-PapersOnLine*, 49(12):955–960.

Reyes-Rubiano, L., Ferone, D., Juan, A. A., and Faulin, J. (2019). A simheuristic for routing electric vehicles with limited driving ranges and stochastic travel times. *SORT*, 43(1):3–24.

Shao, S., Guan, W., Ran, B., He, Z., and Bi, J. (2017). Electric vehicle routing problem with charging time and variable travel time. *Mathematical Problems in Engineering*, pages 1–13.

Shi, j., Gao, Y., Wang, W., Yu, N., and Ioannou, P. (2019). Operating electric vehicle fleet for ride-hailing services with reinforcement learning. *IEEE Transactions on Intelligent Transportation Systems*, pages 1–13.

Solomon, M. (1987). Algorithms for the vehicle routing and scheduling problems with time windows. *Operations Research*, 35(2):254–65.

Taillard, E., Badeau, P., Gendreau, M., Guertin, F., and Potvin, J. (1997). A tabu search heuristic for the vehicle routing problem with soft time windows. *Transportation Science*, 31(2):101–195.

Tas, D. (2020). Electric vehicle routing with flexible time windows: a column generation solution approach. *Transportation Letters*, pages 1–7.

Zhang, S., Gajpal, Y., Appadoo, S. S., and Abdulkader, M. M. S. (2018). Electric vehicle routing problem with recharging stations for minimizing energy consumption. *International Journal of Production Economics*, 203:404–413.