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# The two-echelon capacitated electric vehicle routing problem with battery swapping stations: Formulation and efficient methodology

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ABSTRACT

In this paper, we present a two-echelon capacitated electric vehicle routing problem with battery swapping stations (2E-EVRP-BSS), which aims to determine the delivery strategy under battery driving range limitations for city logistics. The electric vehicles operating in the different echelons have different load capacities, battery driving ranges, power consumption rates, and battery swapping costs. We propose an integer programming formulation and a hybrid algorithm that combines a column generation and an adaptive large neighborhood search (CG-ALNS) to solve the problem. We conducted extensive computational experiments, demonstrate the applicability of the proposed model, and show the efficiency of the CG-ALNS algorithm. In addition, we explore the interplay between battery driving range and the effectiveness of vehicle emission reduction through sensitivity analysis.

## 1. Introduction

There are a series of studies called “Green Logistics” whose aim is to increase the sustainability of transportation by considering the environmental and social issues. The usage of electric vehicles (EVs) instead of fossil fuel-based internal combustion vehicles (ICVs) is an important area of these Green Logistics studies. For example, the United States Environment Protection Agency and the National Highway Traffic Safety Administration are taking coordinated steps to enable the production of a new generation of clean vehicles, from the smallest cars to the largest trucks, to reduce greenhouse gas emissions and improve fuel use (NHTSA, 2016). The European Commission supports an urban e-mobility project called FREVUE, which seeks to demonstrate how EVs can meet the growing need for sustainable urban logistics (FREVUE, 2016). A delivery pattern of the Distripolis case in FREVUE is an example of a two-echelon transportation system. If the weight of goods is less than 200 kilograms, these goods will be transported to the urban bases located close to the main retailing districts at first (first echelon). Then, clean and quiet vehicles such as electric trucks are used for the second echelon to complete the final delivery. In accordance with the development tendency, EVs will be used more and more widely in future transportation systems. Taking into consideration the external cost of logistics associated mainly with air pollution and noise, many logistics companies have introduced EVs for their operations. In 2010, FedEx announced that it would expand its alternative-energy vehicle fleet with the first all-electric FedEx parcel delivery trucks in the United States. The electric trucks began to join more than 1800 alternative-energy vehicles already in service for FedEx around the world (FedEx, 2010; Golson, 2014). In autumn 2015, UPS announced that it would deploy 18 electric, zero-emission delivery vehicles in Texas, USA (UPS, 2015).

The two-echelon vehicle routing problem (2E-VRP) arises in two-echelon transportation systems, which is very relevant to the context of city logistics (Savelsbergh & Woensel, 2016). In this study, we specifically consider EVs in the two-echelon vehicle routing problem to increase the sustainability of transportation. In the system, the freight available in a depot is transported to the transfer stations, which we call satellites, by large EVs, and then small EVs are used to deliver the freight in the satellites to the customers. The EVs operating in the different echelons that have different battery driving ranges should visit battery swapping stations (BSSs) to swap their batteries before their battery power runs out. The battery swapping of EVs replaces the existing battery that is almost depleted by a fully charged one, which is a major and promising solution (Li, 2014). The whole operation time of battery swapping could take less than 10 minutes, which is much faster

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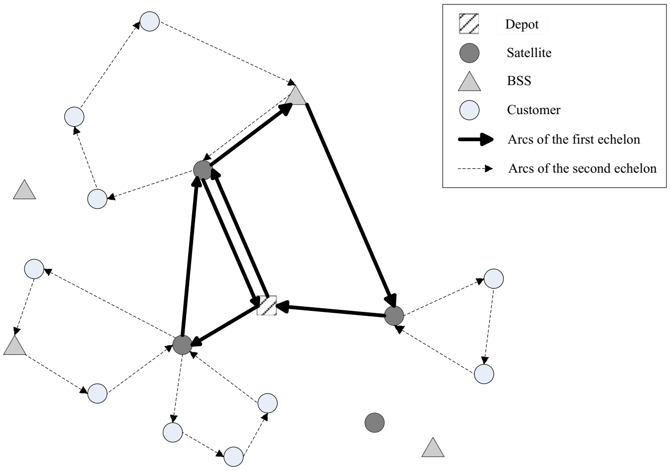

**Fig. 1.** An example of 2E-EVRP-BSS transportation network.

than battery recharging (Kim, 2011). Furthermore, depleted batteries of EVs can be charged during off-peak hours with a discounted electricity price. Owing to the limited driving range, routing and battery swapping are important to service customers promptly and fulfil orders. We name this problem as the two-echelon electric vehicle routing problem with battery swapping stations (2E-EVRP-BSS). The goal of the two-echelon EV transport system is to improve the efficiency of city logistics while keeping the emission under control.

The present paper examines the 2E-EVRP-BSS with heterogeneous EVs in different echelons. More specifically, this problem extends the traditional 2E-VRP incorporated with EV driving range limitations and battery swapping strategies. Instead of the traditional 2E-VRP, our problem considers the EVs of the first echelon to have large limited driving ranges and loading capacities, whereas the EVs of the second echelon have small limited driving ranges and loading capacities. The EVs of both echelons can share the same BSSs. All locations of depot, satellites, BSSs, and customers are given and fixed. Fig. 1 shows an example of the 2E-EVRP-BSS transportation network. Our proposed model for this problem is to determine (a) the utilization of satellites and the shipment transported to these satellites considering the loading capacity limitation, (b) the allocation of satellites or customers to EVs in each echelon, and (c) the route of each EV in both echelons with a visit to the BSSs to accomplish the delivery with sufficient energy. The contribution of the present work is multifold. First, our work is the first to study the 2E-EVRP-BSS and propose a corresponding model of the problem and provide the applicability of the examined model. Second, we propose a powerful algorithm called CG-ALNS, which is a combination of column generation (CG) and adaptive large neighborhood search (ALNS) to solve the 2E-EVRP-BSS. BSS and battery related operators are first created in the algorithm, which are been proved making important contributions to the algorithm. The performance of CG-ALNS was evaluated by a large number of computational experiments. Finally, we highlight the managerial implications of the interplay between battery driving ranges and the efficiency of vehicle emission reduction in the economic analysis. These insights may provide some decision and strategy support for a logistics corporation operating an EV transportation network.

The remainder of the paper is organized as follows. In Section 2, we review recent studies related to EV routing problems and two-echelon distribution systems. The 2E-EVRP-BSS mathematical model is presented in Section 3. In Section 4, we present the CG-ALNS algorithm and provide the details for solving the 2E-EVRP-BSS. Section 5 presents the results of the computational experiments with an extensive analysis of the heuristics performance and the efficiency of vehicle emission reduction. We conclude this study and outline the potential future directions in Section 6.

## 2. Literature review

The 2E-EVRP-BSS primarily combines two streams of research. The first stream is related to the electric vehicle routing problem (EVRP), and the other stream involves the 2E-VRP.

*Related papers on the EVRP*

As EVs have gained in popularity worldwide over the past decade, the issues related to the usage of EVs for transportation have opened up a wide range of relevant research works. Pelletier, Jabali, and Laporte (2016) provided researchers with the technological and marketing background of goods distribution with EVs and presented a review of existing research works in the EVRP field. Their overview summarized the main existing research works on EVs in transportation science, which covers three parts: fleet size and mix, vehicle routing, and optimal paths. From their work, they found that EVs have many advantages such as frequent stop-and-go movements, low travel speeds and reduced pollution, and noise in last-mile deliveries of urban logistics.

Apart from the review of main existing research works on EVs in Pelletier et al. (2016), Desaulniers, Errico, Irnich, and Schneider (2016) studied four variants of the EV routing problem with time windows, which are classified by the allowed recharge times per route and battery charge strategy (full recharges or partial recharges). Yang and Sun introduced a BSS location routing problem with capacitated EVs, which focuses on simultaneously determining the location of BSSs and the routing plan of EVs under battery driving range constraints (Yang & Sun, 2015). Moreover, the basic model they formulated allowed a BSS to be visited at most once, whereas in their extended model a BSS can be visited several times. Schiffer and Walther (2017b) considered both partial and full recharging options for EVs in their location-routing model of recharging stations, as well as time window constraints. In their objective function, they minimized not only the travel distance, but also the number of EVs and the number of recharging stations. Adler and Mirchandani (2014) presented an online routing problem of EVs, which minimizes the average delay of all vehicles by occasionally detouring them for the benefit of future ones by making battery reservations. Liao, Lu, and Shen (2016) studied the EV touring problem. Their objective is to find the route with the shortest travel time for a given road network. In the route, an EV can travel between a pair of vertices or visit a set of vertices with several stops.

Exact algorithm was used to solve the EV routing problem with time windows. According to a set partitioning formulation and a labelling algorithm, Desaulniers et al. provided branch-price-and-cut algorithms to solve four variants of their problem optimality and found solutions for instances with up to 100 customers and 21 recharging stations. In literature, the EV related problems were solved mostly by heuristics. Hof, Schneider, and Goeke (2017) showed how to extend solution methods for vehicle routing problems with intermediate stops to solve the BSS location routing problem with capacitated vehicles. Their extended AVNS algorithm improved the previously known best solutions for the instances of Yang and Sun (2015), and proved robust with regard to its average solution quality. Schiffer and Walther (2017a) studied a location routing problem with intra-route facilities and proposed an adaptive large neighborhood search algorithm with dynamic programming for it. According to their paper, the methodology can solve various problems with intra-route facilities by obtaining new best-known solutions for Yang and Sun (2015) and Schiffer and Walther (2017b).

*Related papers on the 2E-VRP*

Cuda, Guastaroba, and Speranza (2015) reviewed the foremost related papers on two-echelon distribution systems at the time. In their survey, the two-echelon location routing problem (2E-LRP), the two-echelon vehicle routing problem (2E-VRP) and the truck and trailer routing problem (TTRP) were considered. They stated that the study on the research area was still relatively unexplored despite its importance in practical applications. Li, Zhang, Lv, and Chang (2016b) introduced a short-term tactical problem named the two-echelon time-constrained vehicle routing problem in linehaul-delivery systems. They also gave a relatively comprehensive review of the 2E-VRP, 2E-LRP and TTRP.

(i) The node sets of 2E-LRP are composed of potential locations for the depots, potential locations for the satellites, and the customers. In other words, the location of the depots and the satellites to use is not determined a priori. The 2E-LRP aims at minimizing the total system cost with locating a number of depots and/or satellites among candidate sites which have specific costs. Gonzalez-Feliu (2012), and Prodhon and Prins (2014) provided the reviews on the 2E-LRP.

To the best of our knowledge, the best performing exact algorithm for the 2E-LRP is the branch-and-cut algorithm (Contardo, Hemmelmayr, & Crainic, 2012). The 2E-LRP and its variants were usually solved by heuristic algorithms. Prodhon and Prins (2014) gathered the results obtained by state-of-the-art metaheuristics on four sets of 2E-LRP instances. The adaptive large neighborhood search has the best performance on Nguyen's, Boccia's and Boccia's 2E-LRP instances (Contardo et al., 2012), and the variable neighborhood search for the 2E-LRP with several plants has the best performance on Prodhon's 2E-LRP instances (Schwengerer, Pirkwieser, & Raidl, 2012).

(ii) The 2E-VRP can be regarded as a special case of the 2E-LRP where the location of the depots and the satellites to use is given. For reviews on the 2E-VRP, we refer to Gonzalezfeliu (2011), and Cuda et al. (2015). Jacobsen and Madsen (1980) first applied the routing problem to a two-echelon system by considering the daily distribution of newspapers through transfer points. Crainic, Ricciardi, and Storchi (2009) formally defined the concept of a 2E-VRP, although the term 2E-VRP arose later in the literature. They introduced a variant of 2E-VRP with time-dependent, synchronized, multi-depot, multi-product and heterogeneous fleets of each echelon and time windows. The 2E-VRP was first introduced in Perboli, Tadei, and Vigo (2011). They provided a mathematical formulation for the 2E-VRP which is based on the flow of the freight of each arc. However, Jepsen, Spoorendonk, and Ropke (2013) pointed out that the upper bounds of the model introduced in Perboli et al. (2011) may not be correctly provided when the solution has more than two open satellites. Li, Yuan, Lv, and Chang (2016a) introduced a short-term tactical problem in linehaul-delivery systems considering carbon dioxide emissions, which named the two-echelon time-constrained vehicle routing problem. Their case study showed the applicability of the model to real-life problems. Grangier, Gendreau, Lehuédé, and Rousseau (2016) studied a variant of the 2E-VRP that integrates constraints arising in city logistics such as time window constraints, synchronization constraints, and multiple trips at the second level. Dellaert, Crainic, Van Woensel, and Saridarq (2016) studied 2E-VRP with time windows, and provided two path-based mathematical formulation of the problem. Anderluh, Hemmelmayr, and Nolz (2017) developed a two-echelon city distribution scheme with temporal and spatial synchronization between cargo bikes and vans. Li, Liu, Jian, and Lu (2018) introduced the two-echelon distribution system considering the real-time transshipment capacity varying, and proposed a mixed integer linear programming model for it.

Some exact algorithms were used to solve the 2E-VRP. Exact algorithms include those found in Jepsen et al. (2013), Baldacci, Mingozzi, Roberti, and Calvo (2013), Santos, da Cunha, and Mateus (2013), and Santos, Mateus, and da Cunha (2014). The method introduced by Baldacci et al. (2013) is considered as the best exact algorithm for the 2E-VRP, outperforming other existing exact algorithms. However, most of the 2E-VRP was solved by heuristics. The main heuristic algorithms for the 2E-VRP include math-based heuristics (Perboli & Tadei, 2010; Perboli et al., 2011), clustering-based heuristics (Crainic, Mancini, Perboli, & Tadei, 2008), GRASP (Crainic, Mancini, Perboli, & Tadei, 2011; 2013) and large neighborhood-based heuristics (Breunig, Schmid, Hartl, & Vidal, 2016; Hemmelmayr, Cordeau, & Crainic, 2012). The large neighborhood-based heuristic introduced by Breunig et al. (2016) has the best performance among these heuristic algorithms.

(iii) In the TTRP, the transport vehicles may be a truck pulling a trailer (a complete vehicle) or a single truck, some customers can be served only by a single truck and others can be reached either by a truck or by a complete vehicle (Lin, Yu, & Chou, 2009). For review on the TTRP, we refer to Drexl (2013). The capacitated TTRP is the most studied member of the class of TTRPs (Caramia & Guerriero, 2010; Villegas, Prins, Prodhon, Medaglia, & Velasco, 2013; Villegas, Prins, Prodhon, & Velasco, 2011), and some specific variants have been investigated in the literature (Derigs, Pullmann, & Vogel, 2013). To the best of our knowledge, the best performing heuristic for the capacitated TTRP is the matheuristic introduced in Villegas et al. (2013). The summary of solution algorithms and maximum size instances in each paper on TTRPs can be find in Cuda et al. (2015).

The electric vehicle routing problem and the two-echelon networks have drawn attention for academic research and practical application in literature. We first study the two-echelon routing problem in the context of electric vehicles application. In this paper, we need to determine the routing and battery swapping plan of heterogeneous EVs in both echelons simultaneously while considering the different driving ranges. From the perspective of mathematical model, loops are not allowed in the 2E-VRP model of Perboli et al. (2011) and Jepsen et al. (2013). However, in our 2E-EVRP-BSS, the same BSS can be visited several times by one vehicle, which means loops are allowed in our model. Furthermore, battery swapping costs are considered in our objective function. These settings would make more sense for a real-word routing problem. In Section 3, the construction of mathematical model for the 2E-EVRP-BSS is showed in more detail. Constraints (4) and (15) are important constraints that allow visit loops. From the perspective of algorithm, large neighborhood-based heuristics and branch-and price algorithm (a hybrid algorithm of branch and bound and column generation methods) have very good performance respectively, which are most popular algorithms to solve the EV routing problems and 2E-VRP in the literature. In consideration of their own advantages which fit into the two echelon transportation mode of 2E-EVRP-BSS, we proposed the hybrid algorithm combined ALNS and CG to solve the 2E-EVRP-BSS. In addition, according to the characteristics of this problem, several new operators are created in this algorithm. These new operators play an important role in the algorithm, which are proved in Section 5.

## 3. Model formulation

### 3.1. Problem description

In this paper, we study the 2E-EVRP-BSS, which considers the delivery of goods from a depot to the customers through a set of satellites by two types of EVs. The problem has a depot, a set of satellites, a set of customers with a given demand and a set of BSSs without any service capacity constraints for both types of EVs to share, and the locations of all these nodes are given and fixed. A large-capacity EV type with a large battery driving range for the first echelon and a small-capacity EV type with a small battery driving range for the second echelon were considered. In the first echelon, goods are delivered from the depot to the satellites by large EVs. In the second echelon, goods are delivered from the satellites to the customers by small EVs. The BSSs can provide the battery swapping service for the two types of EVs, and this operation will generate battery swapping costs. We assume that the large EVs at the depot and the small EVs at the satellites have full battery power.

Each customer must be visited exactly once by a small EV. Additionally, there is no need to use all the satellites; therefore, a satellite has two states: used or unused. Unlike the customers, a satellite can be visited several times by different large EVs to meet the demand. The capacities of both EV types cannot be exceeded, and each used EV makes a single trip. The number of large EVs available at the depot and the number of small EVs available at each satellite are limited. The unit handling cost of each satellite is specific. The objective is to minimize the sum of the EV travel costs, the battery swapping costs and the handling costs at the satellites.

### 3.2. Model

In this section, we introduce a mathematical formulation of the 2E-EVRP-BSS. According to the definition of 2E-EVRP-BSS, the freight must be delivered from the depot $v_0$ to the customer set $V_c = \{v_{c_1}, v_{c_2}, \ldots, v_{c_n}\}$. Let $q_i$ be the demand of customer $v_{c_i}$. The number of available EVs of the first echelon at the depot is $k^1$ with the same given capacity $Q^1$. The number of available EVs of the second echelon is $k^2$, and each satellite $V_{s_i}$ has $k_s^2$ vehicles. The capacity of the second echelon vehicles is $Q^2$.

In our model, the cost of the logistics distribution by EVs includes three parts:

(1) Battery swapping costs, $c_b^1$ and $c_b^2$, for each echelon per time.
(2) Costs of the arcs traveled by the EVs in both echelons, $c_{ij}^1$ and $c_{ij}^2$, for each echelon per unit distance; e.g. arcs connecting the depot to the satellites and the satellites between them in the first echelon, and arcs connecting the satellites to the customers and the customers between them in the second echelon.
(3) Handling cost of the loading and unloading operations at the satellites, $h_s$, per unit freight.

We define two sets of variables:

(1) The first set is like the traditional variables of the 2E-VRP. $x_{ijk}$ denotes whether arc $(i, j)$ is traveled by the EV $k$ at the first echelon. $z_{ijsk}$ denotes whether arc $(i, j)$ is traveled by the EV $k$ from satellite $s$ in the second echelon. $t_i$ is the decision variable that connects the two echelons, which denotes the total demand delivered to satellite $i \in V_S$ of the first echelon and also denotes the total demand of the second echelon to be served by this satellite. $w_{ik}$ is defined to control the amount of flow through the satellite $i \in V_S$ by EV $k$, $f_{ijk}^1$ and $f_{ijsk}^2$ are defined to control the amount of flow through the BBSs. $f_{ijk}^1$ and $f_{ijsk}^2$ are necessary here because they help us build a model that allows the same BSS to be visited several times by an EV, which we will specially discuss after we discuss the model.
(2) The second set represents the specific variables for EVs. $b_{ik}^{1+}$, $b_{ik}^{1-}$, $b_{isk}^{2+}$ and $b_{isk}^{2-}$ specify the remaining battery power when EV $k$ arrives at or leaves node $i$ of the two echelons.

To help the reader, we summarize the definitions of the variables and parameters in Table 1.

$$\min \sum_{k\in K^1}\sum_{(i,j)\in A_1} c_{ij}^1 x_{ijk} + \sum_{k\in K^2}\sum_{s\in V_S}\sum_{(i,j)\in A_2} c_{ij}^2 z_{ijsk} + \sum_{s\in V_S} h_s t_s + \sum_{k\in K^1}\sum_{b\in V_B}\sum_{(b,j)\in A_1} c_b^1 x_{bjk} + \sum_{k\in K^2}\sum_{s\in V_S}\sum_{b\in V_B}\sum_{(b,j)\in A_2} c_b^2 z_{bjsk} \tag{1}$$

subject to

$$\sum_{(i,j)\in A_1} x_{ijk} = \sum_{(i,j)\in A_1} x_{jik} \quad \forall i \in V_S \cup V_B, k \in K^1 \tag{2}$$

$$\sum_{(i,j)\in A_1} x_{ijk} \le 1 \quad \forall i \in V_S, k \in K^1 \tag{3}$$

$$\sum_{(i,j)\in A_1} f_{ijk}^1 = \sum_{(i,j)\in A_1} f_{jik}^1 \quad \forall i \in V_B, k \in K^1 \tag{4}$$

$$w_{ik} = \sum_{(i,j)\in A_1} f_{jik}^1 - \sum_{(i,j)\in A_1} f_{ijk}^1 \quad \forall i \in V_S, k \in K^1 \tag{5}$$

$$f_{ijk}^1 \le Q^1 x_{ijk} \quad \forall (i,j) \in A_1, k \in K^1 \tag{6}$$

$$\sum_{i\in V_S} w_{ik} \le Q^1 \quad \forall k \in K^1 \tag{7}$$

$$\sum_{k\in K^1} w_{ik} = t_i \quad \forall i \in V_S \tag{8}$$

$$\sum_{k\in K^2}\sum_{s\in V_S}\sum_{(i,j)\in A_2} z_{ijsk} = 1 \quad \forall i \in V_C \tag{9}$$

$$\sum_{(i,j)\in A_2} z_{ijsk} = \sum_{(i,j)\in A_2} z_{jisk} \quad \forall i \in V_C, s \in V_S, k \in K^2 \tag{10}$$

$$\sum_{\bar{s}\in V_S\setminus\{s\}} \left( \sum_{(s,j)\in A_2} z_{sj\bar{s}k} + \sum_{(i,s')\in A_2} z_{is'\bar{s}k} \right) = 0 \quad \forall s \in V_S, s' \in V_S', k \in K^2 \tag{11}$$

$$\sum_{k\in K^2}\sum_{s\in V_S} z_{ss'sk} = 0 \tag{12}$$

$$\sum_{k\in K^2}\sum_{(s,j)\in A_2} z_{sjsk} \le k_s^2 \quad \forall s \in V_S \tag{13}$$

$$\sum_{s\in V_S}\sum_{k\in K^2}\sum_{(s,j)\in A_2} z_{sjsk} \le k^2 \tag{14}$$

$$\sum_{(i,j)\in A_2} f_{ijsk}^2 = \sum_{(i,j)\in A_2} f_{jisk}^2 - q_i \quad \forall i \in V_C \cup V_B, s \in V_S, k \in K^2 \tag{15}$$

$$f_{ijsk}^2 \le Q^2 z_{ijsk} \quad \forall (i,j) \in A_2, s \in V_S, k \in K^2 \tag{16}$$

$$\sum_{k\in K^2}\sum_{(i,j)\in A_2} q_i z_{ijsk} = t_s \quad \forall s \in V_S \tag{17}$$

$$b_{ik}^{1-} = B^1 \quad \forall i \in V_B \cup \{v_0\}, k \in K^1 \tag{18}$$

$$b_{ik}^{1-} = b_{ik}^{1+} \quad \forall i \in V_S, k \in K^1 \tag{19}$$

$$b_{jk}^{1+} \le b_{ik}^{1-} - h^1 d_{ij} x_{ijk} + B^1(1 - x_{ijk}) \quad \forall (i,j) \in A_1, k \in K^1 \tag{20}$$

$$b_{isk}^{2-} = B^2 \quad \forall i \in V_S \cup V_B, s \in V_S, k \in K^2 \tag{21}$$

$$b_{isk}^{2-} = b_{isk}^{2+} \quad \forall i \in V_C, s \in V_S, k \in K^2 \tag{22}$$

**Table 1**
Variables and parameters of the 2E-EVRP-BSS model.

| | |
|---|---|
| $V_0$ | Depot, $V_0 = \{v_0\}$ |
| $V_0$ | Dummy depot, $V_0' = \{v_0'\}$ |
| $V_S$ | Set of satellites, $V_S = \{v_{s_1}, v_{s_2}, \ldots, v_{s_{n_s}}\}$ |
| $V_S'$ | Set of dummy satellites corresponding to $V_S$, $V_S' = \{v'_{s_1}, v'_{s_2}, \ldots, v'_{s_{n_s}}\}$ |
| $V_C$ | Set of customers, $V_C = \{v_{c_1}, v_{c_2}, \ldots, v_{c_{n_c}}\}$ |
| $V_B$ | Set of battery swap stations (BSSs), $V_B = \{v_{b_1}, v_{b_2}, \ldots, v_{b_{n_b}}\}$ |
| $A_1$ | Set of arcs in the first echelon, $A_1 = \{(i, j) \mid i \in V_0 \cup V_B \cup V_S, j \in V_B \cup V_S \cup V_0{}', i \neq j\}$ |
| $A_2$ | Set of arcs in the second echelon, $A_2 = \{(i, j) \mid i \in V_S \cup V_B \cup V_C, j \in V_B \cup V_C \cup V_S{}', i \neq j\}$ |
| $n_s$, $n_c$, $n_b$ | Number of satellites, customers, and BSSs, respectively |
| $k^1$, $k^2$ | Number of the first-echelon and of the second-echelon EVs, respectively |
| $k_s^2$ | Number of the second-echelon EVs starting from satellite $s$ |
| $K^1$, $K^2$ | Set of the first-echelon and set of the second-echelon EVs, respectively |
| $c_{ij}^1$, $c_{ij}^2$ | Cost of the first-echelon EVs from $i$ to $j$ and that of the second-echelon EVs, respectively |
| $c_b^1$, $c_b^2$ | Cost of battery swapping at the first echelon and the second echelon, respectively |
| $h_s$ | The unit handling cost of freight in satellite $s$ |
| $Q^1$, $Q^2$ | Capacity of the EVs for the first echelon and the second echelon, respectively |
| $B^1$, $B^2$ | Battery capacity of the EVs for the first echelon and the second echelon, respectively |
| $h^1$, $h^2$ | Charge consumption rate of the EVs for the first echelon and the second echelon, respectively |
| $d_{ij}$ | Distance between nodes $i$ and $j$ |
| $q_i$ | Demand of vertex $i$ |
| $x_{ijk}$ | Binary decision variable indicating whether arc $(i, j)$ is traveled by the electric vehicle $k$ in the first echelon |
| $z_{ijsk}$ | Binary decision variable indicating whether arc $(i, j)$ is traveled by the electric vehicle $k$ from satellite $s$ in the second echelon |
| $t_i$ | Decision variable specifying the total demand delivered from satellite $i \in V_S$ of the first echelon; it also denotes the total demand of customers to be served by this satellite of the second echelon |
| $w_{ik}$ | Decision variable specifying the amount of freight delivered to satellite $i \in V_S$ by vehicle $k$ |
| $f_{ijk}^1$ | Decision variable specifying the remaining cargo on arrival at $j$ from $i$ by vehicle $k$ of the first echelon |
| $f_{ijsk}^2$ | Decision variable specifying the remaining cargo on arrival at $j$ from $i$ by vehicle $k$ from satellite $s$ in the second echelon |
| $b_{ik}^{1+}$ | Specifies the remaining battery power when vehicle $k$ arrives at $i$ in the first echelon |
| $b_{ik}^{1-}$ | Specifies the remaining battery power when vehicle $k$ leaves $i$ in the first echelon |
| $b_{isk}^{2+}$ | Specifies the remaining battery power when vehicle $k$ arrives at $i$ from satellite $s$ in the second echelon |
| $b_{isk}^{2-}$ | Specifies the remaining battery power when vehicle $k$ leaves $i$ from satellite $s$ in the second echelon |

$$b_{jsk}^{2+} \leq b_{isk}^{2-} - h^2 d_{ij} z_{ijsk} + B^2(1 - z_{ijsk}) \quad \forall (i, j) \in A_2, s \in V_S, k \in K^2 \tag{23}$$

$$x_{ijk} \in \{0, 1\} \qquad \forall (i, j) \in A_1, k \in K^1 \tag{24}$$

$$z_{ijsk} \in \{0, 1\} \qquad \forall (i, j) \in A_2, s \in V_S, k \in K^2 \tag{25}$$

$$w_{ik} \geq 0 \qquad \forall i \in V_S, k \in K^1 \tag{26}$$

$$t_i \geq 0 \qquad \forall i \in V_S \tag{27}$$

$$f_{ijk}^1 \geq 0 \qquad \forall (i, j) \in A_1, k \in K^1 \tag{28}$$

$$f_{ijsk}^2 \geq 0 \qquad \forall (i, j) \in A_2, s \in V_S, k \in K^2 \tag{29}$$

$$b_{ik}^{1+}, b_{ik}^{1-} \geq 0 \qquad \forall i \in V_1, k \in K^1 \tag{30}$$

$$b_{isk}^{2+}, b_{isk}^{2-} \geq 0 \qquad \forall i \in V_2, s \in V_S, k \in K^2 \tag{31}$$

Objective function (1) minimizes the total cost including the EV shipping cost of both echelons, the loading and unloading operation costs at the satellites, and the battery swapping costs at the BSSs. Constraints (2)–(29) can be divided into four groups: Constraints (2)–(8) control the flow of goods of the first echelon. Constraints (9)–(17) control the flow of goods of the second echelon. Constraints (18)–(23) control the battery power of the EVs in both echelons. Finally, nonnegative variables and binary decision variables are defined in constraints (24)–(31).

Constraints (2) and (10) ensure the flow conservation for the EVs at each satellite in the first echelon and for each customer in the second echelon, respectively. Constraint (3) ensures that a large EV visits a satellite at most once. Constraints (4) and (15) are part of the constraints that guarantee that a BSS can be revisited more than once. Constraints (4) is for the first echelon, and constraint (15) is for the second echelon. Constraints (4) and (15) with $q_i = 0$ indicate that the sum of the remaining load of an EV entering a BSS is equal to the sum of the remaining load of an EV leaving a BSS, which not only keeps the vehicle capacity balance but also indicates that a BSS can be visited more than once by the same vehicle. Constraints (5) and (15) with $q_i \neq 0$ track the change in the remaining load level of an EV on the basis of the node sequence of satellites and customers, respectively. In this way, our model guarantees that an EV will never visit a satellite or a customer more than once. Constraints (6) and (16) are the cargo flow limitation. If $x_{ijk} = 1$, the maximal remaining load level $f_{ijk}^1$ is at most the full vehicle capacity $Q^1$. Otherwise, $f_{ijk}^1 = 0$. If $z_{ijsk} = 1$, the maximal remaining load level $f_{ijsk}^2$ is at most $Q^2$. Otherwise, $f_{ijsk}^2 = 0$. Constraint (7) ensures that the total cargo of large EVs will not exceed their capacities. Constraint (8) denotes the total shipment that is delivered to a satellite, and constraint (17) represents the total shipment that is delivered to the customers from the corresponding satellite. Constraints (8) and (17) connect the first echelon and the second echelon through the variable $t_s$, respectively. Constraint (9) ensures that each customer is visited only once. Constraint (11) eliminates the traffic between the satellites in the second echelon, which means that we cannot dispatch EVs among satellites. Constraint (12) eliminates the direct traffic between a satellite and its dummy satellite in the second echelon, in other words, these arcs should not exist. Constraints (13) and (14) restrict the number of total available small EVs at each satellite and in the second echelon, respectively.

Constraint (18) ensures that the battery power of a large EV is equal to $B^1$ when it departs from the depot or visits a BSS, and constraint (21) ensures that the battery power of a small EV is equal to $B^2$ when it departs from a satellite or visits a BSS. Constraints (19) and (22) ensure that the battery power remains the same when an EV visits a satellite and a customer, respectively. Constraints (20) and (23) keep the balance of the battery power of the large EVs and small EVs arriving at node $j$ from node $i$, respectively. They guarantee that every EV has sufficient battery power to visit the remaining satellites or customers and return to the depot or satellites. If node $j$ is visited by vehicle $k$ after node $i$ ($x_{ijk} = 1$ or $z_{ijsk} = 1$), the maximum distance that the remaining battery power allows upon arriving at node $j$ is reduced on the basis of the distance between node $i$ and node $j$.

## 4. Solution method for the 2E-EVRP-BSS

Our 2E-EVRP-BSS is solved by the CG-ALNS hybrid heuristic algorithm. CG-ALNS applies CG to solve the first echelon, which has a small or a medium number of nodes, and uses ALNS to handle the second echelon, which has a larger number of nodes. The concrete implementation of CG-ALNS will be described in the following sections.

### *4.1. Overview of the algorithmic framework*

For the first echelon of the 2E-EVRP-BSS, not all satellites need to be used and the demands of the satellites are unknown in the beginning. In addition, a satellite can be visited several times by different large EVs. These issues make it complex to solve the first echelon of the 2E-EVRP-BSS in the first place. On this occasion, our CG-ALNS starts obtaining one solution of the second echelon and then solves the first echelon on the basis of the result of the second echelon.

In the second echelon, the goods are delivered from the satellites to the customers. It can be considered as a multi-depot EV routing problem (MDEVRP) by regarding the satellites as “depots”. ALNS was first introduced by Ropke and Pisinger (2006a) for vehicle routing problems. Many research works (Laporte, Musmanno, & Vocaturo, 2010; Ribeiro & Laporte, 2012; Ropke & Pisinger, 2006a) have proved that it is successful in solving large-sized vehicle routing problems because it can provide a high diversity of solutions and improve them effectively through the use of removal and insertion operations. We applied ALNS to solve the MDEVRP in the second echelon. The solution of this part can assign each customer to one satellite for transportation service, and we call this as a customer-to-satellite assignment configuration.

In the first echelon, the goods are delivered from the depot to the satellites. On the basis of the customer-to-satellite assignment configuration generated by ALNS, we can obtain the states of the satellites (used or unused) and their demands. The decision in the first echelon can be considered as a split delivery EV routing problem (SDEVRP) when each satellite is regarded as a “customer” with the demands assigned from the second echelon. In reality, the number of satellites is not large, which is up to 15 in the literature of the 2E-VRP. CG (Desaulniers, Desrosiers, & Solomon, 2006; Jin, Liu, & Eksioglu, 2008) has been shown to be very useful in exact algorithms and has a great advantage in speed when applied to small-size routing problems. Therefore, we adopted CG to solve the SDEVRP in the first echelon.

Algorithm 1 presents the pseudocode of our CG-ALNS algorithm. During the search procedure, CG-ALNS allows infeasible solutions. At first, an initial solution $S_0^2$ for the second echelon is generated on the basis of sweep algorithm, which is described in Section 4.3. On the basis of the result of $S_0^2$, we use CG, which is presented in Section 4.4, to calculate the initial solution $S_0^1$ for the first echelon. Then, the initial solution $S_0$ of the 2E-EVRP-BSS is composed of $S_0^1$ and $S_0^2$.

**Algorithm 1** The whole CG-ALNS algorithm.

```
Require: Data of depot, satellites, customers, BSSs and EVs;
Ensure: The best-found solution $S^*$ of the 2E-EVRP-BSS;
Generate an initial solution $S_0^2$ for the second echelon by using the extended sweep algorithm (ESA);
On the basis of $S_0^2$, generate an optimal solution $S_0^1$ for the first echelon by using CG;
Obtain the initial solution $S_0 = \{S_0^1, S_0^2\}$;
$S, S^* \leftarrow S_0$;
$iter \leftarrow 0$, $T \leftarrow O(S_0) \times P_{init}$;
while $iter < OUTER^{MAX}$ and $T > T_{min}$ do
    $S' \leftarrow S$;
    Call ALNS and CG to optimize $S'$;
    Call LBO to adjust the stations of $S'$
    if $O(S') < O(S)$ then
        $S \leftarrow S'$;
    else
        Create a random number $\gamma \in [0,1]$;
        if $\gamma < e^{-(O(S')-O(S)/T)}$ then
            $S \leftarrow S'$;
        end if
    end if
    if $O(S) < O(S^*)$ then
        $S^* \leftarrow S$;
    end if
    $iter \leftarrow iter + 1$, $T \leftarrow T \times \tau$;
end while
Return $S^*$
```

Starting from $S_0$, the core CG-ALNS procedure will be executed $OUTER^{MAX}$ times. We set $OUTER^{MAX} = 400$ here. In each iteration, CG-ALNS first calls ALNS to optimize the second echelon part of the solution $S'$, calls CG to update the first echelon part of $S'$, finally, uses the label-based BSS optimization algorithm (LBO) which is a contribution of this algorithm to reduce the total cost of each route by adjusting the usage of BSSs. $O(S)$, $O(S')$ and $O(S^*)$ denote the objective function values of the current solution $S$, the neighbor solution $S'$ and the best-found solution $S^*$, respectively. In reference to some related works such as Yang and Sun (2015), our acceptance criterion of $S'$ is based on simulated annealing (SA). The criterion accepts $O(S')$ when $O(S') < O(S)$. If $O(S') \geq O(S)$, the criterion accepts $O(S')$ with a probability $e^{-(O(S')-O(S)/T)}$, where $T$ denotes the current temperature and changes by multiplying with a cooling rate $\tau$. We set the initial temperature in SA as $O(S_0) \times P_{init}$, $P_{init}$ is the initial temperature control parameter of SA.

### *4.2. Penalized objective function*

To ensure the diversity of the solution space, we allow infeasible solutions that violate the battery driving range constraints by using a penalized objective function during the search. An infeasible solution violating the battery driving range will generate a penalizing cost. Let $s_i^1$ denote the battery feasibility of node $i \in V^1$ in the first echelon, if $b_{ik}^{1+} < 0$, $s_i^1 = |b_{ik}^{1+}|$; otherwise, $s_i^1 = 0$. The definition of $s_i^2$ is similar to that of $s_i^1$. $M_1$ and $M_2$ denote very large numbers (we set $M_1 = 1000$ and $M_2 = 5000$ in the computational experiments after several calculations), and $Z$ stands for the original objective function. Then, the penalized objective function is shown as follows:

$$Z_{penalized} = Z + M_1 \sum_{i \in V^1} s_i^1 + M_2 \sum_{i \in V^2} s_i^2 \tag{32}$$

### *4.3. Preprocessing procedures and generation of the initial solution*

In this step, some preprocessing procedures are used to improve the speed of the algorithm. Following the procedures in the previous literature as Schneider, Stenger, and Goeke (2014), we remove an arc $(u, v)$ that may inevitably produce an infeasible solution with the following rules:

1. $u, v \in V_C \wedge q_u + q_v > Q^2$, which means arcs violate the capacity constraint of the second echelon.
2. $u, v \in V_S \wedge \forall i \in V_B \cup \{v_0\}, j \in V_B \cup \{v_0'\} \wedge h^1(d_{iu} + d_{uv} + d_{vj}) > B^1$, which means arcs violate the battery capacity constraints of the first echelon.
3. $u, v \in V_C \wedge \forall i \in V_B \cup V_S, j \in V_B \cup V_S' \wedge h^2(d_{iu} + d_{uv} + d_{vj}) > B^2$, which means arcs violate the battery capacity constraints of the first echelon.

Rule 1 removes an arc $(u, v)$ that violates the capacity constraint of the second echelon. Rules 2 and 3 are helpful in removing arcs that violate the battery capacity constraints in the first and the second echelons, respectively.

To generate an initial solution of the vehicle routing problem (VRP), Gillett and Miller (1974) first introduced the sweep algorithm. They claimed that this algorithm produces results better than those produced by Clarke and Wright's (1964) savings approach and by Christofides and Eilon's (1969) approach. According to the previous analysis of our problem, the initial solution $S_0$ consists of two parts: $S_0^1$ for the first echelon and $S_0^2$ for the second echelon. First, the initial solution of the second echelon $S_0^2$ is created based on the sweep algorithm. The characteristics of the 2E-EVRP-BSS are taken into account and the satellites are been inserted into each cluster in a greedy way. Then, the initial solution of the first echelon $S_0^1$ is generated by CG, which is shown in Section 4.4.

### 4.4. Column generation in the first echelon

After the solution of the second echelon is obtained, the first echelon is considered as the SDEVRP. In the SDEVRP, the demand of each used satellite can be split and delivered by one or more large EVs. CG is proposed to solve the SDEVRP, and the details are shown in the following subsections. First, we build an arc flow model for the SDEVRP. Second, we use the Dantzig–Wolfe decomposition principle to reformulate the model and transform it into a master problem on the basis of the routes and a subproblem. Third, a dynamic programming algorithm is adopted to solve the subproblem and search the routes with a negative reduced cost. A branch scheme is designed to obtain the integral solution. The CG process is shown in Algorithm 2.

**Algorithm 2** Column generation algorithm (CG).

```
Require: The solution $S^2$ of the second echelon;
Ensure: The solution $S^1$ of the first echelon;
Generate an initial route set $R_0$ on the basis of the data of $S^2$;
Create a search stack $SS \leftarrow \emptyset$, $SS \leftarrow SS \bigcup \{R_0\}$;
Create the optimal route set $R^* \leftarrow \emptyset$;
Create an upper bound limit $UB \leftarrow MAX\_VALUE$;
while $SS \neq \emptyset$ do
    $R \leftarrow pop(SS)$
    repeat
        Solve the master problem on the basis of $R$ with a simplex algorithm;
        Calculate the dual values $\pi$ and use $\pi$ to build the subproblem;
        Call the dynamic programming algorithm to search the route set denoted by $R'$;
        $R \leftarrow R \bigcup \{R'\}$
    until $R' = \emptyset$
    Obtain the cost $C(R)$;
    if $C(R) < UB$ then
        if $\exists$ fractional arc $(i, j)$ then
            Branch on arc $(i, j)$;
            Obtain two branching route sets $R^0$ and $R^1$ from $R$;
            $SS \leftarrow SS \bigcup \{R^0, R^1\}$;
        else
            $R^* \leftarrow R$, $UB \leftarrow C(R)$;
        end if
    end if
end while
Return $R^*$
```

#### 4.4.1. The arc flow model for the SDEVRP

In this section, we build the arc flow model for the SDEVRP. The model is used for the Dantzig–Wolfe decomposition in Subsection 4.4.2. Using a concept called "k-split cycles", the authors in Dror and Trudeau (1990), Dror and Trudeau (1989) and Desaulniers (2010) proposed a useful property of the optimal solution of the SDVRP, which states that "If the distances satisfy the triangle inequality, then there exists an optimal solution such that, for each pair of reverse arcs in $A(N)$, at most one of them is traversed". The detailed explanation of this property can be found in Archetti, Bianchessi, and Speranza (2011). We denote the decision variable $\omega_{ik}$ as the quantity delivered by EV $k \in K^1$ to node $i \in V_S \cup V_B$, which is a non-negative integer variable. $\bar{q}_i = min\{q_i, Q^1\}$ denotes the maximum quantity that can be delivered to node $i$ by one large EV, and the demands of BSSs are set to 0. Our arc flow model for the SDEVRP is also formulated according to this property.

$$\min \sum_{k\in K^1} \sum_{(i,j)\in A_1} c_{ij}^1 x_{ijk} + \sum_{k\in K^1} \sum_{b\in V_B} \sum_{(b,j)\in A_1} c_b^1 x_{bjk} + \sum_{i\in V_S} h_i q_i \tag{33}$$

$$\sum_{k\in K^1} \omega_{ik} = q_i \qquad \forall i \in V_S \cup V_B \tag{34}$$

$$\sum_{k\in K^1} (x_{ijk} + x_{jik}) \leq 1 \qquad \forall (i,j) \in A_1 \tag{35}$$

$$0 \leq \sum_{k\in K^1} \sum_{j\in V_S\cup V_B} x_{0jk} \leq k^1 \tag{36}$$

$$\sum_{j\in V_S\cup V_B} x_{v_0,j,k} = 1 \qquad \forall k \in K^1 \tag{37}$$

$$\sum_{(i,j)\in A_1} x_{ijk} - \sum_{(i,j)\in A_1} x_{jik} = 0 \qquad \forall k \in K^1, i \in V_S \cup V_B \tag{38}$$

$$\sum_{i\in V_S\cup V_B} x_{i,v_0',k} = 1 \qquad \forall k \in K^1 \tag{39}$$

$$\sum_{i\in V_S\cup V_B} \omega_{ik} \leq Q^1 \qquad \forall k \in K^1 \tag{40}$$

$$\sum_{(i,j)\in A_1} x_{ijk} \leq \omega_{ik} \leq \bar{q}_i \sum_{(i,j)\in A_1} x_{ijk} \qquad \forall k \in K^1, i \in V_S \cup V_B \tag{41}$$

constraints (18)–(20)

$$\omega_{ik} \geq 0, integer \qquad \forall k \in K^1, i \in V_S \cup V_B \tag{42}$$

$$x_{ijk} \in \{0, 1\} \qquad \forall k \in K^1, (i,j) \in A_1 \tag{43}$$

Objective function (33) calculates the total cost of the first echelon, which contains the travel cost, the battery swapping cost and the handling cost of freight in each satellite. Constraint (34) makes sure that the total quantity delivered to each satellite $i \in V_S$ is equal to its demand $q_i$. Constraint (35) agrees with the property mentioned above. Constraint (36) makes sure that the number of used vehicles is nonnegative and does not exceed $k^1$. Constraints (37)–(39) keep the flow balance of a route, which starts from node $v_0$ and ends at node $v_0{}'$ for each vehicle. Constraint (40) denotes the capacity constraints of the vehicles of the first echelon. Constraint (41) ensures the consistency between variables $x_{ijk}$ and variables $\omega_{ik}$. Constraints (18)–(20) are the battery constraints of the first echelon. Finally, non-negativity, integer and binary requirements are given by constraints (42) and (43).

### 4.4.2. Dantzig–Wolfe decomposition

According to the Dantzig–Wolfe decomposition principle, it is assumed that all of the feasible vehicle routes are known in advance. Then, the SDEVRP is transformed to choose the best routing combination that can satisfy all the constraints and obtain the minimum cost. Therefore, a corresponding model called the master problem model has to be built on the basis of the feasible routes for obtaining the optimal combination. However, it is almost impossible for us to get all of the feasible routes when building the master problem model. According to the duality theory and the dual values of the master problem model, the routes with a negative reduced cost can optimize the objective value by adding them to the master problem model. A subproblem model is proposed to search the routes with a negative reduced cost. Each candidate route is added as a column in the model. The detailed description of the decomposition procedure is introduced in Dantzig and Wolfe (1960).

1) Master problem

In the master problem model, we define the delivery pattern as a path where all passed satellites receive either a delivery of $\bar{q}_i$ unit or a delivery unit that is greater than 1 and less than $\bar{q}_i$. $\theta_r$ is defined as the number of EVs assigned to route $r \in R$. We used a concept called extreme delivery pattern, which was introduced in Archetti et al. (2011); it means that there is only one satellite at most in a path that can receive a partial delivery between 1 and $\bar{q}_i$ in the optimal solution. The other sets and parameters of this subsection are defined as follows:

| | |
|---|---|
| $R$ | Set of all feasible routes, which start from $v_0$ and return to $v'_0$. |
| $R^s \subseteq R$ | Set of routes that visit just one satellite. |
| $R^m \subseteq R$ | Set of routes that visit more than one satellite. |
| $c^1_r = \sum_{(i,j)\in r} c^1_{ij} +$ <br> $\sum_{b\in r\cup V_B} c^1_b$ <br> $+\sum_{s\in r\cup V_S} h_s t_s$ | Cost of route $r \in R$, including travel cost, battery swapping cost and <br> handling cost of freight in a satellite. |
| $b_{ijr}$ | Binary parameter equal to 1 if arc $(i, j) \in A_1$ is traversed by route $r \in R$ or equal to 0 otherwise. |
| $\omega_{ir}$ | Quantity delivered to satellite $i \in V_S$, $r \in R$. |

The master problem is formulated as:

$$\min \sum_{r\in R} c^1_r \theta_r \tag{44}$$

$$\sum_{r\in R} \omega_{ir}\theta_r = q_i \qquad \forall i \in V_S \cup V_B \tag{45}$$

$$\sum_{r\in R} (b_{ijr} + b_{jir})\theta_r \le 1 \qquad \forall (i, j) \in A_1 \tag{46}$$

$$0 \le \sum_{r\in R} \theta_r \le k^1 \tag{47}$$

$$\theta_r \in \{0, 1\} \qquad \forall r \in R^m \tag{48}$$

$$\theta_r, integer \qquad \forall r \in R^s \tag{49}$$

Objective function (44) calculates the total cost of the first echelon, just like (33). Constraints (45), (46), and (47) have the same function as those of constraints (34), (35), and (36). Binary and integer requirements are given in (48) and (49).

2) Subproblem

On the basis of the duality theory, we obtain the subproblem to search the routes with a negative reduced cost. The subproblem model uses the variable $x_{ij}$ as defined in the 2E-EVRP-BSS model introduced in Section 3 without the index of vehicle $k$. $\omega_i = \sum_{r\in R} \omega_{ir}$ denotes the quantity delivered to satellite $i \in V_S$. Some additional parameters for the subproblem model are denoted as follows:

| | |
|---|---|
| $\pi_i$ | Dual variable of constraint (45) for satellite $i \in V_S$. If $i \in V_B$, $\pi_i = 0$ |
| $\rho_{ij}$ | Dual variable of constraint (46) for $(i, j) \in A_1$, and $\rho_{ij} = \rho_{ji}$. |
| $\beta$ | Dual variable of constraint (47). |

Then, the subproblem can be formulated as follows:

$$\min \sum_{(i,j)\in A_1} (c^1_{ij} - \rho_{ij})x_{ij} - \sum_{i\in V_S} \omega_i \pi_i - \beta \tag{50}$$

$$\sum_{j\in V_B\cup V_S} x_{v_0,j} = 1 \tag{51}$$

$$\sum_{(i,j)\in A_1} x_{ij} - \sum_{(i,j)\in A_1} x_{ji} = 0 \qquad \forall i \in V_S \cup V_B \tag{52}$$

$$\sum_{i\in V_B\cup V_S} x_{i,v_0'} = 1 \tag{53}$$

$$\sum_{i\in V_S} \omega_i \le Q^1 \tag{54}$$

$$\sum_{(i,j)\in A_1} x_{ij} \le \omega_i \le \bar{q}_i \sum_{(i,j)\in A_1} x_{ij} \qquad \forall i \in V_S \tag{55}$$

Constraints (18)-(20) without the index of vehicles $k$

$$\omega_i \ge 0, integer \qquad \forall i \in V_S \tag{56}$$

$$x_{ij} \in \{0, 1\} \qquad \forall (i, j) \in A_1 \tag{57}$$

Objective function (50) searches the routes with the minimum negative reduced cost. Constraints (51)–(57) are the same as constraints (37)–(43), but without the index of vehicle $k$.

### 4.4.3. Dynamic programming algorithm and branching scheme

The subproblem is modeled as an elementary shortest path problem with resource constraints (SPPRC) (Feillet, Dejax, Gendreau, & Gueguen, 2010; Irnich & Desaulniers, 2005). When the search space is huge, it is cumbersome to find the candidate route paths. In the solution methods for the SPPRC, the most commonly used algorithm is the dynamic programming algorithm (Desrochers, 1988) and (Desrochers & Soumis, 1988). It can build new paths and extend these paths one by one to all feasible directions. We define an expanded graph $G' = (V', A')$. The vertex set $V'$ includes the depot $v_0$; the dummy depot $v'_0$; the vertices $v^i_g$ representing the used satellite $i$ with demand quantity g; $g = 1, \ldots, \bar{q}_i$; and the BSSs. For each used satellite $i$, $A'$ contains arcs $(v_0, v^i_g)$ with cost $c_{0i} - \rho_{0i} - \pi_i g$, arcs $(v^i_{\bar{q}_i}, v'_0)$ with cost $c_{i0} - \rho_{i0}$, arcs $(v^i_{\bar{q}_i}, v^j_g)$ with cost $c_{ij} - \rho_{ij} - \pi_j g$ and null cost arcs $(v^i_g, v^i_{\bar{q}_i})$. In addition, we do not allow paths with cycles, and a path that travels one satellite many times is forbidden.

In the dynamic programming algorithm, a labelling algorithm and dominance rules are adopted to help the search process. We denote a label of vertex $i$ as $L_i = (i, p, r, T, \lambda, C, Q)$, where $p$ is the index for accessing the previous label, $r$ is the remaining battery driving range, $T$ is the vector for recording the visited satellites, $\lambda$ is the number of split satellites visited along the path, $C$ is the current cost of the path and $Q$ is the quantity loaded on the vehicle when leaving the vertex. Through $\lambda$, we control the number of the split satellites on the path. The initial state is represented by the label $(s, -1, B^1, T[s] = 1, 0, 0, 0)$. When travelling the arc $(i, j)$, the path will create a new label from $L_i = (i, p, r, T, \lambda, C, Q)$ to $L_j = (j, p', r', T', \lambda', C', Q')$. Along arcs $(v_0, v^i_g)$, $(v^i_{\bar{q}_i}, v^j_g)$ and $(v^i_{\bar{q}_i}, v'_0)$, the extension rules are

$$r' = \begin{cases} B^1, & \text{if } j \in V_B \\ r - d_{ij} * h^1, & otherwise \end{cases} \tag{58}$$

$$T'[j] = 1 \tag{59}$$

$$\lambda' = \begin{cases} \lambda + 1, & \text{if } 1 < g < \overline{q_j} \\ \lambda, & otherwise \end{cases} \tag{60}$$

$$C' = \begin{cases} C + c^1_{ij} - \rho_{ij} - \pi_j g, & \text{if } 1 < g < \overline{q_j} \\ C + c^1_{ij} - \rho_{ij} - \pi_j \overline{q}_j, & otherwise \end{cases} \tag{61}$$

$$Q' = Q + g \tag{62}$$

If $r' \geq 0$, $T'[j] \neq 1$, $\lambda' \leq MAX_S$ and $Q' \leq Q^1$, $L_j$ resulting from this extension is deemed feasible. $MAX_S$ is the upper bound of the split satellites in one path. If $L_j$ is infeasible, delete it. We can define a dominance rule of constraints (58) – (62): Label $L_i = (i, p, r, T, \lambda, C, Q)$ dominates $L'_i = (i, p', r', T', \lambda', C', Q')$ when $r \geq r'$, $\lambda \leq \lambda'$, $C \leq C'$ and $Q \leq Q'$. If $L_i$ dominates $L'_i$ and $L_i \neq L'_i$, then $L'_i$ can be discarded. If $L_i = L'_i$, then discard one of them.

A path can be created by traversing in reverse direction the index $p$ of labels associated with the ending depot $v'_0$. The solution of the subproblem is the paths that have negative costs!'£In our CG algorithm, the dynamic programming process stops when the number of generated path results reaches the upper limit $n$. We set $n$ to twice the number of nodes in the graph. On the basis of the result, the master problem model can calculate new dual values that can update the parameters of the subproblem. The iteration between the master problem model and the subproblem stops when no negative reduced column is found and the optimal value is obtained.

The optimal value of the linear relaxation obtained above may not satisfy the integrality of the solution. In that case, a branching scheme is needed to cut off the fractional part of the solution. However, the general idea behind an effective branching scheme that is related to the variables is not suitable here because it may create an endless loop. In that case, we use a branching scheme that is based on the arc use, which was introduced in Ryan and Foster (1981). Inspired by the four branching schemes described in Jin et al. (2008), we made some improvement on the branching rule related to the arc use. At first, the fractional solution based on the route is transformed into a fractional value of its corresponding arc. $b_{rij}$ is denoted as the value of arc $(i, j)$ in route $r$. We first select the fractional value $b_{rij}$ with $Max\{b_{rij} - \lfloor b_{rij} \rfloor, r \in R\}$ and branch it to 0 and 1. When $b_{rij}$ is branched to 0, arc $(i, j)$ will be marked in the label algorithm to make sure that routes with arc $(i, j)$ will not be generated in the next route search. When $b_{rij}$ is branched to 1, the route set of the master problem model needs to delete the other routes that include arc $(i, j)$. Moreover, in the next route search of the label algorithm, route $r$ with arc $(i, j)$ will be added to a new route set first. Then, the cost of the arc $c^1_{ij}$ is set to a very large value to make sure that routes that travel on arc $(i, j)$ will not be generated.

### 4.5. ALNS framework

The ALNS heuristic algorithm is an extension of the Large Neighborhood Search (LNS) heuristic introduced by Shaw (1998). It was first introduced by Ropke and Pisinger (2006a) to solve the pickup and delivery problem. After that, ALNS has been widely used to solve several variants of the vehicle routing problem. An overview of our ALNS process is given in Algorithm 3. The removal and insertion operators are chosen by a roulette wheel mechanism on the basis of their weights. The weights of the operators are updated according to their historical performance. CG is called to re-calculate the solution of the first echelon $S^{1'}$ after the solution of the second echelon $S^{2'}$ is obtained. Then, a new solution $S'$ for the 2E-EVRP-BSS is created, and the acceptance mechanism of $S'$ is based on SA, which is the same as in Section 4.1. The iteration of ALNS will be executed $INNER^{MAX} = 500$ times.

**Algorithm 3** Adaptive large neighborhood search algorithm.

```
Require: A solution $S_0$ of the 2E-EVRP-BSS;
Ensure: An improved solution $S^*$ of the 2E-EVRP-BSS;
Initialise the weights and scores of the removal and insertion operators
$S, S^* \leftarrow S_0$;
$iter \leftarrow 0$, $T \leftarrow O(S_0) \times P_{init}$;
while $iter < INNER^{MAX}$ do
    $S' \leftarrow S$;
    Get the solution $S^{2'}$ of the second echelon from $S'$;
    Choose and apply the removal operator on $S^{2'}$
    Choose and apply the insertion operator on $S^{2'}$
    Call CG to get the solution $S^{1'}$ on the basis of $S^{2'}$
    $S' \leftarrow \{S^{1'}, S^{2'}\}$;
    if $O(S') < O(S)$ then
        $S \leftarrow S'$;
    else
        Create a random number r $\in$ [0,1];
        if $r < e^{-(O(S')-O(S)/T)}$ then
            $S \leftarrow S'$;
        end if
    end if
    if $O(S) < O(S^*)$ then
        $S^* \leftarrow S$;
    end if
    Update the weights and scores of the removal and insertion operators
    $iter \leftarrow iter + 1$, $T \leftarrow T \times \zeta$;
end while
Return $S^*$
```

#### 4.5.1. Removal and insertion operators

This subsection introduces the removal and insertion operators in our ALNS. The removal operators remove $n_r$ customers in each iteration. $n_r = (\mu_1 + (\mu_2 - \mu_1) \times r) \times n_C$, where $n_C$ is the number of customers in the graph, and $\mu_1$, $\mu_2 \in (0, 1)$, $\mu_1 \leq \mu_2$ and $r \in [0, 1]$ are randomly created parameters. There are two types of removal operators in our ALNS: the first one only affects the second echelon by removing $n_r$ customers; the second one affects both echelons of the problem, by not only removing $n_r$ customers of the second echelon, but also by changing the state of the satellites of the first echelon.

*Removal operators:*

We utilize the *random customer removal (RCR)* and related customer removal (ReCR) (Ropke & Pisinger, 2006a), *satellite closing (SC)*, *satellite opening (SO)*, *satellite swapping (SS)* and *random route removal (RRR)* operators (Hemmelmayr et al., 2012) presented in the literature. RCR selects $n_r$ customers of the second echelon at random and removes them from the current solution, it then places them into the customer pool. ReCR aims at removing the customers that are similar to the customer that has been removed. SC randomly closes one of the used satellites, removes the customers that were assigned to the satellite and places them into the customer pool. SO randomly uses one of the closed (unused) satellites. $n_r$ customers that are closest to the selected satellite are removed from their current route. SS aims at exchanging the usage states of two satellites under a certain probability. RRR randomly removes a route and places the corresponding customers into the customer pool.

*BSS-Customer Route Removal (BCRR)*: This operator aims at removing routes that visit more BSSs and fewer customers, because these routes have less contribution to the solution and produce unnecessary expenses. We denote $BCRR_r = (n^r_C + \alpha n^r_B)/(n^r_C + n^r_B)$ to calculate the contribution of route $r$, where $n^r_C$ and $n^r_B$ denote the number of customers and BSSs in route $r$ in the second echelon, respectively. $\alpha$ is a predefined parameter that controls the proportion of customers and BSSs in the removed route. $BCRR_r$ is sorted in ascending order. The larger $BCRR_r$ is, the lesser route $r$ contributes

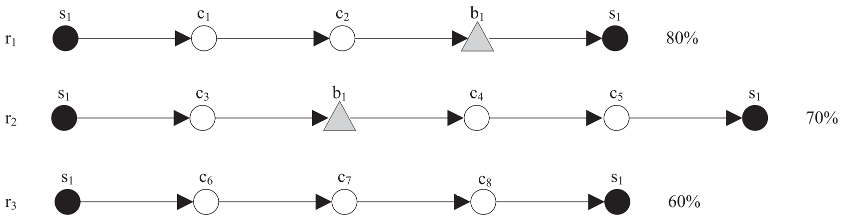

**Fig. 2.** Battery best use removal operator.

to the solution. This operator removes routes with the maximum value of $BCRR_r$ until $n_r$ customers are removed.

*BSS Proportion Route Removal (BPRR)*: This operator aims at removing routes that have a relatively large cost for visiting BSSs. We denote $BPRR_r = (\sum_{i\in V_B, j\in V_r} c_{ij} + \sum_{i\in V_r\setminus V_B, j\in V_B} c_{ij} + c_b^2 n_B^r)/c_r$ to calculate the proportion of BSS-related cost to the total cost of route $r$. $V_r$ is denoted as the nodes in route $r$. $n_B^r$ is denoted as in BCRR, and $c_r$ denotes the total cost of route $r$ of the second echelon. The larger $BPRR_r$ is, the larger the proportion of BSS-related cost to the total cost is. This operator removes routes with the maximum value of $BPRR_r$ until $n_r$ customers are removed.

*BSS Cost-Based Removal (BCBR)*: This operator aims at removing the customers that directly connect to a BSS with high travelling cost. The process helps find more suitable routes and BSSs for these removed customers. This operator first selects a BSS $b$ at random. Then, the customer $i$ that has the maximum value of $c_{bi}$ or $c_{ib}$ $(b\in V_B)$ is removed. The process is repeated until $n_r$ customers have been removed.

*Battery Best Use Removal (BBUR)*: This operator aims at making sure that EVs use their batteries optimally. First, the operator selects the route $r$ of the second echelon that returns to its satellite with the maximum value of the remaining battery driving range. Then, the customers between the satellite (terminal point of the second echelon) and the last BSS or the satellite (starting point of the second echelon) of $r$ are removed. The process is repeated until $n_r$ customers have been removed. For example, in Fig. 2, the right side denotes the remaining battery driving range of the EV in percentage form. According to BBUR, we choose route $r_1$ with 80% of battery driving range at first. However, there are no customers between the last BSS $b_1$ and $s_1$. Therefore, route $r_2$ with 70% of battery driving range will be selected, and $c_4$ and $c_5$ between the last BSS $b_1$ and $s_1$ will be removed. If the number of removed customers is less than $n_r$, route $r_3$ with 60% of battery driving range will be selected, and $c_6$, $c_7$, and $c_8$ between $s_1$ (starting point) and $s_1$ (terminal point) will be removed.

*Insertion operators:*

The insertion operators are used to insert the removed customers back into the routes of the second echelon. In the process of insertion, we do not use the closed (unused) satellites but only consider the used ones.

*Basic Greedy Insertion (BGI)*: We use the basic greedy insertion operator from the literature. In each iteration, this operator always inserts customers from the customer pool into its best position with the minimum insertion cost. The insertion cost is calculated by $Z_{cri} = c^2_{i-1,i} + c^2_{i,i+1} - c^2_{i-1,i+1}$ when inserting customer $c$ into route $r$ at position $i$. $Z_{cri} = +\infty$ when a customer $c$ cannot be inserted into route $r$. The inserting customer $c^*$ is selected as the one with the value $\min_{c\in Pool}\{\min_{r\in R^r}\{\min_{i\in Pos}\{Z_{cri}\}\}\}$, where *Pool* is the customer pool, $R^r$ is the route set of the second echelon after the removal operators are applied and *Pos* is the candidate position set in route $r$.

*Basic Regret-K Insertion (BRKI*)*: Same as BGI, this operator is applied as done in the literature, but it prefers to insert the customers with the maximum regret value in the right position repeatedly, which aims to improve BGI using a type of look-ahead mechanism when selecting a customer to insert (Pisinger & Ropke, 2007). The regret value is the sum of the cost differences among the top $K$ best insertion positions, where $K$ is a user-defined parameter and $K\geq 2$. Every time we choose the customer $c^*$ with value $\max_{c\in Pool}\{\sum_{j=2}^{K}(Z_{cj} - Z_{c1})\}$ to insert. $Z_{cj}$ represents the $j_{th}$ lowest insertion cost after customer $c$ is reinserted into the solution. In our implementation, we just consider the situations of $K = 2$ and $K = 3$, which are named Basic Regret-2 Insertion (BR2I) and Basic Regret-3 Insertion (BR3I), respectively.

*Advanced Greedy Insertion (AGI)*: After a customer is inserted, not only the travelling distance increases, but also the feasibility of the current solution will change. Unlike that in BGI, the insertion cost is changed to $Z_{cri} = \eta(c^2_{i-1,i} + c^2_{i,i+1} - c^2_{i-1,i+1}) + (1 - \eta)(\sum_{v\in V} s_c^2 - \sum_{v\in V'} s_c^2) + c_{penalty}$ when customer $c$ is inserted in the $i$th position of route $r$, $\eta\in[0,\ 1]$ (Yang & Sun, 2015). $s_c^2$ represents the feasibility state of customer $c$ that we already defined in Section 4.2. $V$ and $V^{'}$ denote the vertex set of route $r$ before and after the insertion, respectively. $c_{penalty} = M_c max\{(\sum_{c\in r} q_c - Q^2), 0\}$ denotes the penalty of exceeding vehicle capacity, where $M_c$ denotes a very large value. On the basis of the new calculation formula of the insertion cost, the operator prefers to select the best insertion that satisfies both the battery driving range limitation and the vehicle capacity constraints.

*Advanced Regret-K Insertion (ARKI*)*: Customer $c = arg\max_{c\in Pool}\{\sum_{j=2}^{K}(Z_{crj} - Z_{cr1})\}$ is selected by this operator to its best inserting position. ARKI is similar to BRKI, but it replaces the regret value with $Z_{crj}$. In our algorithm, we consider the situations of $K = 2$ and $K = 3$.

### 4.5.2. Adaptive selection of operators

In this section, we show the mechanism of the operator selection, which is based on the weights of the operators. In our ALNS, the weights of the operators are automatically adjusted according to their historical performance. We divide the search into a number of segments of 100 consecutive iterations, like what Ropke and Pisinger did in Ropke and Pisinger (2006a). The operators are selected by a roulette wheel mechanism in each iteration. Then, the selection probability of operator $i$ in segment $m$ is $p_{im} = w_i/\sum_{im\in OP} w_{im}$, where $OP$ is the set of removal or insertion operators and $w_{im}$ stands for the weight of the operator $i$ in segment $m$. We set the initial value of weight $w_{init} = 0$. After 100 iterations, the weights of the operators are updated according to the score obtained during the segment. $w_{i,m+1} = \begin{cases} (1-\theta)\times w_{im} + \theta\times \eta_{im}/N_{im}, & \text{if } N_{im}\neq 0 \\ w_{i,m}, & otherwise \end{cases}$, where $\theta$ is the reaction factor, $N_{im}$ denotes the times operator $i$ is used in segment $m$ and $\eta_{im}$ denotes the score of operator $i$ in the $m$ segment. We set $\eta_{im} = 0$ initially, and it increases on the basis of the historical performance of operator $i$ at iteration $h$. If the new solution is a new best-found solution, $\sigma_1$ is added to the score; if it is a new improving solution, $\sigma_2$ is added; if it is an accepted deteriorating solution, $\sigma_3$ is added; otherwise, 0 is added.

### 4.6. Label-based BSS optimization algorithm

The aforementioned approaches primarily focus on the optimization of satellites and customers, but not on BBSs. Therefore, in this section, a label-based BSS optimization algorithm (LBO) is proposed to optimize the use of the BBSs for each route. Since the choices of many BBSs and the constraints of the battery driving range are considered, this problem is not simple to solve exactly with a dynamic programming approach or to find an approximate solution with a constrained shortest path algorithm. Therefore, the main idea of LBO is to use a label algorithm to select and insert the best candidate BSSs into routes at high speed and high quality. First, the LBO removes all of the BSSs in each route and the order of customers will be fixed. In this case, the battery driving range constraints may be violated. Second, the LBO finds the possible insertion locations for each route and selects the BSSs with the minimum insertion costs to insert into the corresponding routes. This procedure will be stopped until all routes satisfy the battery driving range constraints. An overview of our LBO process is given in Algorithm 4, and the specific implementation details are described in the following part.

**Algorithm 4** Label-Based BBS Optimization Algorithm (LBO).

```
Require: A solution $S_0$ of the 2E-EVRP-BSS;
Ensure: An improved solution $S^*$ of the 2E-EVRP-BSS;
1: Get the route set $R$ from solution $S$;
2: Create a route set $R^* \leftarrow \emptyset$;
3: for $r \in R$ do
4:     Create the current best route $r^* \leftarrow r$;
5:     Remove all the stations of route $r$;
6:     Create a route TreeSet $TR \leftarrow \emptyset$;
7:     $TR \leftarrow TR \bigcup \{r\}$;
8:     Create a counter $c = 0$;
9:     while $TR \neq \emptyset$ and $c < n_{max}$ do
10:        $r' \leftarrow pollFirst(TR)$;
11:        Calculate $B_{min}$, $v^*$ and $L$ for $r'$;
12:        if $B_{min} < 0$ then
13:            for $v \in L$ do
14:                copy a new route $r'_v$ from $r'$;
15:                insert the BSS with the minimum insertion cost in front of $v$ of $r'_v$;
16:                $TR \leftarrow TR \bigcup \{r'_v\}$;
17:            end for
18:        else
19:            $c = c + 1$;
20:            if $r' > r^*$ then
21:                $r^* \leftarrow r'$;
22:            end if
23:        end if
24:    end while
25:    $R^* \leftarrow R^* \bigcup \{r^*\}$;
26: end for
27: On the basis of $R^*$, create a solution $S^*$;
28: Return $S^*$;
```

We can get a route set $R$ from a known solution $S$ of the 2E-EVRP-BSS (line 1). For each route $r$ in $R$, some nodes may be unreachable because of the removal of all the BSSs in it. We need to extend the route by reinserting the BSSs into the appropriate locations. For a large number of new extended routes, a comparison mechanism based on label ($f$, $c$, $n_s$, $b$, $l$) is helpful to choose the best candidate route for the next extension, where $f$ represents the feasibility, $c$ denotes the travel cost, $n_s$ denotes the number of BSSs in the route, $b$ is the amount of violated battery level and $l$ is the location of the first node that violates the battery driving range constraints. If the route is feasible, $f = 1$; otherwise, $f = 0$. Label ($f$, $c$, $n_s$, $b$, $l$) is better than label ($f'$, $c'$, $n'_s$, $b'$, $l'$) for the next extension when $f \geq f'$, $c \leq c'$, $n_s \leq n'_s$ and $l \geq l'$. We use an automatic sorting collection called TreeSet in Java to collect the new extended routes and to sort the routes on the basis of their labels (line 6). In the search procedure of route $r$, $r^*$ is defined to record the current best route and $TR$ is the collection of routes that need to be extended. For one candidate route $r'$ in $TR$, we calculate the remaining battery power $B_v$ for each node (line 11). $v$ is unreachable when $B_v < 0$. $B_{min}$ denotes the minimum value of the remaining battery power for all nodes. $r'$ is feasible when $B_{min} \geq 0$. If $B_{min} < 0$, $r'$ is unfeasible. Then, $v^*$ is defined as the first unreachable node. We need to find suitable insertion positions of the BSSs in $L$, where $L$ is denoted as the set of the candidate insertion positions before $v^*$ (line 12–16). If route $r'$ is feasible, $r'$ is assigned to $r^*$ when $r'$ is better than $r^*$ ($r' > r^*$) (line 18–23). This extension process continues until $TR = \emptyset$ or the number of iterations get $n_{max}$. Finally, a new route set $R^*$ is created after optimizing all of the routes in $R$, and an improved solution $S^*$ of the 2E-EVRP-BSS is generated.

## 5. Computational experiments

This section presents the results of the numerical experiments performed to evaluate the performance of our CG-ALNS algorithm. First, we used newly designed small instances that can be solved by CPLEX 12.6 to assess the quality of our CG-ALNS solution. Second, we conducted tests on larger instances to assess the performance of CG-ALNS in the 2E-EVRP-BSS. Third, we demonstrate the strong performance concerning solution quality and runtime of our CG-ALNS on available benchmark instances of the related problem, i.e. 2E-VRP. Finally, economic analysis was performed to assess the effect on the result and the emission reduction efficiency (ERE) of improving battery performance in the future.

Instances of the 2E-EVRP-BSS are generated as described in Section 5.1. In Section 5.2 we tune the values of the parameters using the instances of the 2E-EVRP-BSS and analyze the performance of each operator in CG-ALNS. Computational results of the 2E-EVRP-BSS and the 2E-VRP instances are showed in Section 5.3. The ERE and specific conclusions are given in Section 5.4.

### 5.1. Generation of 2E-EVRP-BSS benchmark instances

As the 2E-EVRP-BSS is the first model of this type, there are no available benchmark instances to evaluate the solution methods for this problem at present. Hence, we created small-sized instances of the 2E-EVRP-BSS named Set 1 that were based on the 2E-VRP instances in Perboli et al. (2011). Set 2 to Set 6 of the instances for the 2E-EVRP-BSS are created on the basis of the 2E-VRP instances used in Crainic, Perboli, Mancini, and Tadei (2010), Perboli et al. (2011), Hemmelmayr et al. (2012), and Baldacci et al. (2013). Breunig et al. gave a summary of the 2E-VRP instances in Breunig et al. (2016). We named the new generated instances of the 2E-EVRP-BSS after them.

In our 2E-EVRP-BSS, the instances we made consisted of the following data: number and locations of the BSSs, battery swapping cost, battery driving range and battery consumption rates of both types of EVs. Without loss of generality, the location of the BSSs was generated randomly and the number of BSSs was set to be 1/5 of the nodes in the network, like Schneider, Andreas and Goeke did in Schneider et al. (2014). The unit battery swapping fee was set to 2 for the first echelon and 1 for the second echelon. Let $d_{max}$ denote the maximum Euclidean distance between any two points on the network. The battery driving ranges of the large EVs and the small EVs were defined in a simple way as in Schneider et al. (2014). We set $B^1 = \lceil 1.6 d_{max} \rceil$ and $B^2 = \lceil 0.8 d_{max} \rceil$, respectively. We set the EV consumption rate in both echelons to 1 per kilometre.

Table 2 provides a summary of the generated instances, including the number of instances (Inst.) in the set and subset with the number of customers ($n_C$), satellites ($n_S$), BSSs ($n_B$), EVs of the first-echelon ($k^1$), EVs of the second-echelon ($k^2$), EVs of satellite $s$ of the second-echelon($k^1_s$), travelling cost of each echelon ($c^1_{ij}$ and $c^2_{ij}$), battery swapping cost of both echelons ($c^1_b$ and $c^2_b$), battery consumption rate of both echelons ($h^1$ and $h^2$) and unit handling cost

**Table 2**
Characteristics of the 2E-EVRP-BSS instances.

| Set | Inst. | $n_C$ | $n_S$ | $n_B$ | $k^1$ | $k^2$ | $k_s^2$ | $c_{ij}^1$ | $c_{ij}^2$ | $c_b^1$ | $c_b^2$ | $h^1$ | $h^2$ | $h_s$ |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | 66 | 7 | 2 | 5 | 3 | 4 | – | 1 | 1 | 2 | 1 | 1 | 1 | 0 |
| 1 | 66 | 12 | 2 | 5 | 3 | 4 | – | 1 | 1 | 2 | 1 | 1 | 1 | 0 |
| 2a | 6 | 21 | 2 | 6 | 3 | 4 | – | 1 | 1 | 2 | 1 | 1 | 1 | 0 |
|  | 6 | 32 | 2 | 6 | 3 | 4 | – | 1 | 1 | 2 | 1 | 1 | 1 | 0 |
| 2b | 6 | 50 | 2 | 10 | 3 | 5 | – | 1 | 1 | 2 | 1 | 1 | 1 | 0 |
|  | 3 | 50 | 4 | 10 | 4 | 5 | – | 1 | 1 | 2 | 1 | 1 | 1 | 0 |
| 2c | 6 | 50 | 2 | 10 | 3 | 5 | – | 1 | 1 | 2 | 1 | 1 | 1 | 0 |
|  | 3 | 50 | 4 | 10 | 4 | 5 | – | 1 | 1 | 2 | 1 | 1 | 1 | 0 |
| 3a | 6 | 21 | 2 | 6 | 3 | 4 | – | 1 | 1 | 2 | 1 | 1 | 1 | 0 |
|  | 6 | 32 | 2 | 6 | 3 | 4 | – | 1 | 1 | 2 | 1 | 1 | 1 | 0 |
| 3b | 6 | 50 | 2 | 10 | 3 | 5 | – | 1 | 1 | 2 | 1 | 1 | 1 | 0 |
| 3c | 6 | 50 | 2 | 10 | 3 | 5 | – | 1 | 1 | 2 | 1 | 1 | 1 | 0 |
| 4a | 18 | 50 | 2 | 10 | 3 | 6 | – | 1 | 1 | 2 | 1 | 1 | 1 | 0 |
|  | 18 | 50 | 3 | 10 | 3 | 6 | – | 1 | 1 | 2 | 1 | 1 | 1 | 0 |
|  | 18 | 50 | 5 | 10 | 3 | 6 | – | 1 | 1 | 2 | 1 | 1 | 1 | 0 |
| 4b | 18 | 50 | 2 | 10 | 3 | 6 | 4 | 1 | 1 | 2 | 1 | 1 | 1 | 0 |
|  | 18 | 50 | 3 | 10 | 3 | 6 | 3 | 1 | 1 | 2 | 1 | 1 | 1 | 0 |
|  | 18 | 50 | 5 | 10 | 3 | 6 | 2 | 1 | 1 | 2 | 1 | 1 | 1 | 0 |
| 5 | 6 | 100 | 5 | 20 | 5 | [15,32] | – | 1 | 1 | 2 | 1 | 1 | 1 | 0 |
|  | 6 | 200 | 10 | 20 | 5 | [17,35] | – | 1 | 1 | 2 | 1 | 1 | 1 | 0 |
|  | 6 | 200 | 10 | 20 | 5 | [30,63] | – | 1 | 1 | 2 | 1 | 1 | 1 | 0 |
| 6a | 9 | 50 | [4,6] | 10 | 2 | 50 |  | 1 | 1 | 2 | 1 | 1 | 1 | 0 |
|  | 9 | 75 | [4,6] | 15 | 3 | 75 |  | 1 | 1 | 2 | 1 | 1 | 1 | 0 |
|  | 9 | 100 | [4,6] | 20 | 4 | 100 |  | 1 | 1 | 2 | 1 | 1 | 1 | 0 |
| 6b | 9 | 50 | [4,6] | 10 | 2 | 50 |  | 1 | 1 | 2 | 1 | 1 | 1 | $\neq 0$ |
|  | 9 | 75 | [4,6] | 15 | 3 | 75 |  | 1 | 1 | 2 | 1 | 1 | 1 | $\neq 0$ |
|  | 9 | 100 | [4,6] | 20 | 4 | 100 |  | 1 | 1 | 2 | 1 | 1 | 1 | $\neq 0$ |

**Table 3**
Notation and description of the parameters.

| Parameter | Notation and description |
|---|---|
| $\tau$ | Cooling rate of SA of CG-ALNS |
| $P_{init}$ | Initial temperature control parameter of SA |
| $\zeta$ | Cooling rate of SA of ALNS |
| $\mu_1$, $\mu_2$ | Control Parameters of the number of removed customers |
| $\alpha$ | Parameter of BSS-customer route removal operator(BCRR) |
| $\eta$ | Parameter of advanced greedy insertion operator(AGI) |
| $\theta$ | Reactor factor in adaptive selection of operators |
| $\sigma_1$ | Score of a new best found solution |
| $\sigma_2$ | Score of a new improving solution |
| $\sigma_3$ | Score of an accepted deteriorating solution |

of freight in the satellites ($h_s$). All of these instances were generated according to the procedures done in Prins, Prodhon, and Wolfler-Calvo (2004), Crainic et al. (2010), Perboli et al. (2011), and Hemmelmayr et al. (2012).

### 5.2. Parameter tuning and operator analyses

In line with the tuning method in the literature (Ribeiro & Laporte, 2012; Ropke & Pisinger, 2006b), we selected ten instances from Set 2 to Set 6 (two instances from each set) and performed 10 runs by considering up to seven values for each parameter. Set 1 was omitted here because the size of the instance was too small and provided less reference value. For each parameter value, we calculated the average percent deviation from the the best-found solutions. Then, the value that had the least average percent deviation was chosen to conduct the following calculation. The process was repeated until all the parameters had been tuned. The initial values of some parameters were set according to Hemmelmayr et al. (2012); the others were set according to several experiments. Table 3 summarizes the notations of the parameters, and Table 4 gives their considered values and corresponding deviations. The final values of the parameters are marked in bold.

The sensitivity analysis of the removal operators operators were conducted by keeping one of them used in the experiments but all insertion operators are involved, like the authors did in Yang and Sun (2015). We conducted a similar analysis for the insertion operators. The results are showed in Tables A.1 and A.2 of the Appendix A.1. The BPRR, RCR, BCBR, SO, BBUR, BCRR, SR, BGI, BR2I, BR3I, AGI, AR2I and AR3I are selected for the following computational experiments. Table 5 provides further analysis about their contributions to diversifying the structure of the solutions and escaping local optima. The second column gives the average solution deviation without this operator under several computational experiments. The algorithm was conducted by excluding each of the corresponding operators while keeping the others. The BSS-customer route removal operator had the largest deviation, followed by the BSS proportion route removal and the random customer removal. In the third column of Table 5, we show the average number of times a new best solution was found by each operator. The random customer removal operator had the largest value of column 3, followed by the battery best use removal and the basic regret-3 insertion. From several experiments, the operators with smaller value in Table 5 helped in diversifying the structure of the solutions and escaping local optima. Therefore, we kept these operators in the following experiments.

### 5.3. Computational results

This subsection presents the results of the numerical experiments performed to demonstrate the applicability of our models and to evaluate the performance of our CG-ALNS heuristic.

#### 5.3.1. Performance of CG-ALNS on small 2E-EVRP-BSS instances

We used the generated small 2E-EVRP-BSS test instances (Set 1) to analyse the performance of our CG-ALNS algorithm. In the first 14 instances of the test, we randomly selected five nodes among the customers as BSSs, and these nodes were no longer considered as customers. In the last five instances of the test, we randomly selected five nodes among the customers as both BSSs and customers. Therefore, according to the benchmark instance, Set 1 had two kinds of instances: the first one with 7 customers, 2 satellites and 5 BSSs; the other one with 12 customers, 2 satellites and 5

**Table 4**
Parameter tuning.

| Parameter | | Initial value | Values tested | | | | | |
|---|---|---|---|---|---|---|---|---|
| $\tau$ | Value | 0.995 | **0.992** | 0.993 | 0.994 | 0.996 | 0.997 | 0.998 |
| | dev% | 0.51 | 0.37 | 0.49 | 0.44 | 0.53 | 0.41 | 0.43 |
| $P_{init}$ | Value | 1.5 | **1.2** | 1.3 | 1.4 | 1.6 | 1.7 | 1.8 |
| | dev% | 0.62 | 0.58 | 0.73 | 0.68 | 0.85 | 0.69 | 0.77 |
| $\zeta$ | Value | 0.995 | 0.992 | **0.993** | 0.994 | 0.996 | 0.997 | 0.998 |
| | dev% | 0.53 | 0.48 | 0.43 | 0.58 | 0.52 | 0.61 | 0.61 |
| $\mu_1$ | Value | **0.1** | 0.04 | 0.08 | 0.06 | 0.12 | 0.16 | 0.2 |
| | dev% | 0.32 | 0.41 | 0.37 | 0.57 | 0.45 | 0.33 | 0.34 |
| $\mu_2$ | Value | 0.3 | **0.24** | 0.26 | 0.28 | 0.32 | 0.34 | 0.36 |
| | dev% | 0.36 | 0.22 | 0.28 | 0.34 | 0.4 | 0.39 | 0.44 |
| $\alpha$ | Value | 2 | 1 | 1.5 | **2.5** | 3 | 3.5 | 4 |
| | dev% | 0.55 | 0.43 | 0.47 | 0.32 | 0.38 | 0.64 | 0.43 |
| $\eta$ | Value | 0.5 | 0.2 | 0.3 | 0.4 | 0.6 | **0.7** | 0.8 |
| | dev% | 0.42 | 0.56 | 0.44 | 0.4 | 0.41 | 0.37 | 0.51 |
| $\theta$ | Value | 0.7 | 0.3 | 0.4 | 0.5 | 0.6 | **0.8** | 0.9 |
| | dev% | 0.81 | 1.1 | 0.66 | 0.64 | 0.74 | 0.59 | 0.71 |
| $\sigma_1$ | Value | 33 | 27 | 29 | 31 | **35** | 37 | 39 |
| | dev% | 0.93 | 0.72 | 0.84 | 0.77 | 0.62 | 0.88 | 0.82 |
| $\sigma_2$ | Value | 21 | 15 | 17 | 19 | **23** | 25 | 27 |
| | dev% | 0.86 | 0.82 | 0.79 | 0.92 | 0.64 | 0.88 | 0.72 |
| $\sigma_3$ | Value | 6 | 0 | 2 | 4 | **8** | 10 | 12 |
| | dev% | 0.59 | 0.61 | 0.74 | 0.67 | 0.52 | 0.65 | 0.58 |

**Table 5**
Analysis on the removal and insertion operators.

| Operator | Solution degradation without this operator | Average number of new best solutions found by the operator |
|---|---|---|
| Random customer removal | 0.05 | 15.23 |
| Satellite removal | 0.01 | 2.84 |
| Satellite opening | 0.04 | 1.8 |
| BSS-customer route removal | 0.1 | 1.33 |
| BSS proportion route removal | 0.07 | 3.93 |
| BSS cost based removal | 0.03 | 6.35 |
| Battery best use removal | 0.01 | 10.48 |
| Basic greedy insertion | 0.02 | 2.74 |
| Basic regret-2 insertion | 0.03 | 4.5 |
| Basic regret-3 insertion | 0.03 | 10.05 |
| Advanced greedy insertion | 0.03 | 2.45 |
| Advanced regret-2 insertion | 0.03 | 5.33 |
| Advanced regret-3 insertion | 0.04 | 9.2 |

BSSs. We solved the instances with CG-ALNS and compared the obtained results to the optimal or near-optimal solution found by the MIP solver of CPLEX 12.6 using the 2E-EVRP-BSS formulation presented in Section 3.

Table 6 gives the instance description and part of results of the test. The columns "$n_C$", "$n_S$" and "$n_B$" present the number of customers, satellites and BSSs of each instance, respectively. The column "t(seconds)" denotes the computing time (in seconds) of CPLEX and CG-ALNS separately. The column "Best" and "Avg. 10" provides the best results obtained with CPLEX and the average result found in 10 runs by CG-ALNS. The best result of CPLEX was received either from the optimal solution or from the best upper bound (marked by an underscore) found within 7200 seconds. The percentage deviation between the total cost found by CPLEX and that by CG-ALNS is provided by $\%dev^1$.

It can be observed from Table 6 that the average computation time of our CG-ALNS for 19 instances was 33.37 seconds, which is significantly faster than that of CPLEX, which was 2917.58 seconds. These clearly show the performance of our CG-ALNS algorithm in solving small-sized 2E-EVRP-BSS instances to optimality in only a few seconds. These results show that our CG-ALNS is capable of determining the highly efficient EV routes of the 2E-EVRP-BSS and is reasonable for application to larger instances.

### 5.3.2. Performance of CG-ALNS on larger 2E-EVRP-BSS instances

Tables 7–13 show the results of the computational experiments on the new larger 2E-EVRP-BSS instances of Set 2 to Set 6. These tables show the objective values of our CG-ALNS with stopping conditions of 200$K$ iterations and 2000$K$ iterations, $K = 1000$. In these tables, column 1 gives the name of each instance; column "Best" gives the results that were found in longer runtimes, we set the longer runtime of CG-ALNS iterations equal to 2200K; column "$\%dev^2$" shows the percentage deviation of the "CG-ALNS 200$K$ " solution from that of "Best"; column "$\%dev^3$" shows the percentage deviation of the "CG-ALNS 2000$K$ " solution from that of "Best"; column "T(seconds) 200$K$" and column "T*(seconds) 200$K$" give the total runtime and the time when the best solution in 200$K$ iterations was found in seconds.

These tables show that we can obtain good results at moderate computing times. "$\%dev^2$" and "$\%dev^3$" increased with increasing data size, which indicates that longer runtimes and more iterations are needed for better solutions. For the largest data size of Set 5 with 100 and 200 customers, the average value of "$\%dev^2$" was 0.90 and the average value of "$\%dev^3$" was 0.17, which are acceptable at certain runtimes.

### 5.3.3. Performance of CG-ALNS on 2E-VRP instances

We can consider the classic 2E-VRP as the 2E-EVRP-BSS with a relaxation of the battery driving range constraints when the

**Table 6**
Comparison of results obtained with CPLEX and CG-ALNS on the small-sized 2E-EVRP-BSS instances.

| Instance | Description | | | CPLEX | | CG-ALNS | | $\%dev^1$ |
|---|---|---|---|---|---|---|---|---|
| | $n_C$ | $n_S$ | $n_B$ | Best | t(seconds) | Avg. 10 | t(seconds) | |
| E-n13-k4-1-c7 | 7 | 2 | 5 | 203 | 1785 | 203 | 13 | 0 |
| E-n13-k4-2-c7 | 7 | 2 | 5 | 203 | 2715 | 203 | 19 | 0 |
| E-n13-k4-10-c7 | 7 | 2 | 5 | 203 | 290 | 203 | 4. | 0 |
| E-n13-k4-12-c7 | 7 | 2 | 5 | 221 | 1963 | 221 | 22 | 0 |
| E-n13-k4-15-c7 | 7 | 2 | 5 | 217 | 465 | 221 | 8 | 0 |
| E-n13-k4-22-c7 | 7 | 2 | 5 | 257 | 4023 | 257 | 22 | 0 |
| E-n13-k4-26-c7 | 7 | 2 | 5 | 257 | 2342 | 257 | 21 | 0 |
| E-n13-k4-35-c7 | 7 | 2 | 5 | 271 | 2304 | 271 | 5 | 0 |
| E-n13-k4-36-c7 | 7 | 2 | 5 | 271 | 1821 | 271 | 7 | 0 |
| E-n13-k4-39-c7 | 7 | 2 | 5 | 214 | 1242 | 214 | 16 | 0 |
| E-n13-k4-43-c7 | 7 | 2 | 5 | 214 | 156 | 214 | 13 | 0 |
| E-n13-k4-48-c7 | 7 | 2 | 5 | 217 | 44 | 217 | 9 | 0 |
| E-n13-k4-57-c7 | 7 | 2 | 5 | 257 | 43 | 257 | 11 | 0 |
| E-n13-k4-62-c7 | 7 | 2 | 5 | 277 | 233 | 277 | 6 | 0 |
| E-n13-k4-1-c12 | 12 | 2 | 5 | 340 | 7200 | 335 | 88 | −1.49 |
| E-n13-k4-2-c12 | 12 | 2 | 5 | 361 | 7200 | 350 | 93 | −3.14 |
| E-n13-k4-17-c12 | 12 | 2 | 5 | 354 | 7200 | 346 | 148 | −2.31 |
| E-n13-k4-32-c12 | 12 | 2 | 5 | 363 | 7200 | 342 | 31 | −6.14 |
| E-n13-k4-58-c12 | 12 | 2 | 5 | 477 | 7200 | 441 | 98 | −8.16 |
| Avg. | – | – | – | – | 2917 | – | 33.37 | −1.12 |

**Table 7**
Results and runtimes for Set 2 for the 2E-EVRP-BSS by CG-ALNS.

| Instance | Best | CG-ALNS 200K | $\%dev^2$ | CG-ALNS 2000K | $\%dev^3$ | T(seconds)200K | T*(seconds)200K |
|---|---|---|---|---|---|---|---|
| **Set2a** | | | | | | | |
| E-n22-k4-s6-17 | 433.15 | 434.09 | 0.22 | 433.15 | 0.00 | 35 | 23 |
| E-n22-k4-s8-14 | 395.58 | 396.47 | 0.22 | 395.58 | 0.00 | 28 | 19 |
| E-n22-k4-s9-19 | 494.09 | 494.39 | 0.06 | 494.39 | 0.06 | 58 | 31 |
| E-n22-k4-s10-14 | 371.50 | 371.50 | 0.00 | 371.50 | 0.00 | 43 | 30 |
| E-n22-k4-s11-12 | 440.03 | 442.10 | 0.47 | 441.11 | 0.24 | 44 | 30 |
| E-n22-k4-s12-16 | 401.90 | 401.90 | 0.00 | 401.90 | 0.00 | 79 | 52 |
| E-n33-k4-s1-9 | 754.67 | 754.67 | 0.00 | 754.67 | 0.00 | 302 | 229 |
| E-n33-k4-s2-13 | 745.38 | 745.38 | 0.00 | 745.38 | 0.00 | 463 | 303 |
| E-n33-k4-s3-17 | 715.48 | 717.21 | 0.24 | 715.48 | 0.00 | 230 | 180 |
| E-n33-k4-s4-5 | 802.22 | 807.62 | 0.67 | 805.31 | 0.38 | 243 | 176 |
| E-n33-k4-s7-25 | 779.13 | 779.13 | 0.00 | 779.13 | 0.00 | 261 | 239 |
| E-n33-k4-s14-22 | 795.31 | 800.12 | 0.60 | 797.68 | 0.30 | 199 | 172 |
| Avg. | 594.04 | 595.38 | 0.21 | 594.61 | 0.08 | 165.42 | 123.67 |
| **Set2b** | | | | | | | |
| E-n51-k5-s2-17 | 597.49 | 602.12 | 0.77 | 597.49 | 0.00 | 99 | 53 |
| E-n51-k5-s4-46 | 710.81 | 713.14 | 0.33 | 711.76 | 0.13 | 143 | 83 |
| E-n51-k5-s6-12 | 583.04 | 587.49 | 0.76 | 585.83 | 0.48 | 201 | 179 |
| E-n51-k5-s11-19 | 600.56 | 605.19 | 0.77 | 602.58 | 0.34 | 277 | 159 |
| E-n51-k5-s27-47 | 583.54 | 583.54 | 0.00 | 583.54 | 0.00 | 59 | 31 |
| E-n51-k5-s32-37 | 747.76 | 753.68 | 0.79 | 752.93 | 0.69 | 107 | 79 |
| E-n51-k5-s2-4-17-46 | 600.18 | 602.55 | 0.39 | 600.18 | 0.00 | 249 | 178 |
| E-n51-k5-s6-12-32-37 | 585.54 | 588.80 | 0.55 | 586.33 | 0.13 | 159 | 125 |
| E-n51-k5-s11-19-27-47 | 539.14 | 540.74 | 0.30 | 540.38 | 0.23 | 247 | 201 |
| Avg. | 616.45 | 619.69 | 0.52 | 617.89 | 0.22 | 171.22 | 120.89 |
| **Set 2c** | | | | | | | |
| E-n51-k5-s2-17 | 624.32 | 630.74 | 1.02 | 627.18 | 0.46 | 114 | 77 |
| E-n51-k5-s4-46 | 764.22 | 764.22 | 0.00 | 764.22 | 0.00 | 96 | 58 |
| E-n51-k5-s6-12 | 612.48 | 630.10 | 2.80 | 617.58 | 0.83 | 160 | 126 |
| E-n51-k5-s11-19 | 684.31 | 701.26 | 2.42 | 688.74 | 0.64 | 305 | 266 |
| E-n51-k5-s27-47 | 583.54 | 583.54 | 0.00 | 583.54 | 0.00 | 127 | 103 |
| E-n51-k5-s32-37 | 814.63 | 822.76 | 0.99 | 814.63 | 0.00 | 224 | 185 |
| E-n51-k5-s2-4-17-46 | 862.18 | 870.39 | 0.94 | 870.39 | 0.94 | 348 | 273 |
| E-n51-k5-s6-12-32-37 | 626.45 | 650.83 | 3.75 | 626.45 | 0.00 | 236 | 192 |
| E-n51-k5-s11-19-27-47 | 582.36 | 588.64 | 1.07 | 585.61 | 0.55 | 184 | 132 |
| Avg. | 683.83 | 693.61 | 1.44 | 686.48 | 0.38 | 199.33 | 156.89 |

**Table 8**
Results and runtimes for Set 3 for the 2E-EVRP-BSS by CG-ALNS.

| Instance | Best | CG-ALNS 200K | %$dev^2$ | CG-ALNS 2000K | %$dev^3$ | T(seconds)200K | $T^*$(seconds)200K |
|---|---|---|---|---|---|---|---|
| **Set3a** | | | | | | | |
| E-n22-k4-s13-14 | 532.79 | 532.79 | 0.00 | 532.79 | 0.00 | 124 | 82 |
| E-n22-k4-s13-16 | 521.40 | 523.15 | 0.33 | 522.15 | 0.14 | 123 | 73 |
| E-n22-k4-s13-17 | 496.38 | 498.43 | 0.41 | 498.06 | 0.34 | 62 | 49 |
| E-n22-k4-s14-19 | 507.12 | 508.31 | 0.23 | 507.12 | 0.00 | 88 | 61 |
| E-n22-k4-s17-19 | 512.80 | 513.76 | 0.19 | 512.80 | 0.00 | 72 | 59 |
| E-n22-k4-s19-21 | 528.58 | 530.58 | 0.38 | 528.58 | 0.00 | 81 | 63 |
| E-n33-k4-s16-22 | 748.58 | 751.53 | 0.39 | 748.58 | 0.00 | 57 | 48 |
| E-n33-k4-s16-24 | 747.99 | 752.71 | 0.63 | 749.01 | 0.14 | 134 | 107 |
| E-n33-k4-s19-26 | 680.36 | 685.01 | 0.68 | 682.52 | 0.32 | 331 | 261 |
| E-n33-k4-s22-26 | 693.40 | 699.11 | 0.82 | 696.39 | 0.43 | 163 | 142 |
| E-n33-k4-s24-28 | 684.98 | 689.49 | 0.65 | 686.77 | 0.26 | 108 | 76 |
| E-n33-k4-s25-28 | 684.98 | 684.98 | 0.00 | 684.98 | 0.00 | 103 | 85 |
| Avg. | 611.61 | 614.15 | 0.39 | 612.48 | 0.14 | 120.50 | 92.17 |
| **Set3b** | | | | | | | |
| E-n51-k5-s12-18 | 759.65 | 766.24 | 0.86 | 761.03 | 0.18 | 142 | 121 |
| E-n51-k5-s12-41 | 732.98 | 741.23 | 1.11 | 737.51 | 0.61 | 245 | 174 |
| E-n51-k5-s12-43 | 852.07 | 859.22 | 0.83 | 852.07 | 0.00 | 182 | 163 |
| E-n51-k5-s39-41 | 899.35 | 903.04 | 0.41 | 899.36 | 0.00 | 214 | 163 |
| E-n51-k5-s40-41 | 964.47 | 968.71 | 0.44 | 964.82 | 0.04 | 179 | 162 |
| E-n51-k5-s40-43 | 915.26 | 924.30 | 0.98 | 918.06 | 0.30 | 205 | 183 |
| Avg. | 853.96 | 860.46 | 0.77 | 855.48 | 0.19 | 194.50 | 161.00 |
| **Set3c** | | | | | | | |
| E-n51-k5-s13-19 | 679.59 | 702.72 | 3.29 | 684.27 | 0.68 | 217 | 183 |
| E-n51-k5-s13-42 | 656.74 | 662.41 | 0.86 | 656.74 | 0.00 | 192 | 166 |
| E-n51-k5-s13-44 | 710.76 | 722.81 | 1.67 | 722.81 | 1.67 | 314 | 268 |
| E-n51-k5-s40-42 | 909.32 | 931.42 | 2.37 | 920.78 | 1.24 | 284 | 223 |
| E-n51-k5-s41-42 | 970.52 | 1012.93 | 4.19 | 995.43 | 2.50 | 236 | 197 |
| E-n51-k5-s41-44 | 925.63 | 987.85 | 6.30 | 964.93 | 4.07 | 265 | 214 |
| Avg. | 808.76 | 836.69 | 3.11 | 824.16 | 1.70 | 251.33 | 208.50 |

battery driving range is large enough and no BSSs are required. Tables 14–20 show the best solutions of the benchmark instance calculated by CG-ALNS. Columns “HCC Avg. 5” and “HCC (Best)” show the average results for five runs and the best solution found at longer runtimes given by Hemmelmayr et al. (2012), respectively, whose ALNS algorithm has been proven to have a good performance; columns “BSHV Avg. 5” and “BSHV (Best 5)” show the average results for five runs and the best solution found for these five runs given by Breunig et al. (2016), respectively, whose algorithm is known as the best performing heuristic so far; column “BKS” shows the best-known solution found in the literature, which is summarized in Breunig et al. (2016), and the solutions marked with asterisks were proven to be optimal; column “CG-ALNS (Avg. 5)” gives the average solution calculated by CG-ALNS for five runs; column “CG-ALNS (Best 5)” gives the best solutions found in these five runs; column “T(seconds)” and column “T*(seconds)” give the average overall runtime of CG-ALNS and the average time that the best solution was found in the five runs, respectively. Our solutions by CG-ALNS are marked in bold if they are equal to those of the BKS.

From Tables 14–20, for the instances with $n_C \leq 50$ (Set 2a and Set 3a), we obtained the same results as those of the BKS; for the instances of $n_C = 50$ (Set 2b, Set 2c, Set 3b, Set 3c Set 4a and Set 4b), our results obtained by CG-ALNS only had a slight deviation from those of the BKS. Our $T(seconds)$ and $T^*(seconds)$ were larger than the corresponding time in Hemmelmayr et al. (2012) and Breunig et al. (2016). This is because CG-ALNS is not specifically tailored to the classic 2E-VRP. When we use CG-ALNS to solve the classic 2E-VRP, the battery driving range is set large enough to avoid visiting BSSs. However, from the view of the execution of CG-ALNS, CG-ALNS still need to decide whether the battery driving ranges is violated in each iteration, and it is time consuming. In summary, we can obtain good results of 2E-VRP with moderate computing time.

### 5.4. Economic analysis and specific conclusions

In this section, we analyse two parts: the first one is the sensitivity of the result to the battery driving range of EVs of each echelon, and the other is the ERE by using EVs instead of ICVs. To analyse the sensitivity of the result to the battery driving range, we changed the battery driving range of one echelon by fixing the battery driving range of the other echelon. CG-ALNS was performed five times for each instance, and the default parameter configuration and the best results were reported. Columns “$B^1$” and “$B^2$” give the variation percentage to the base value of the battery driving range in each echelon, respectively. Columns “$n_{b1}$” and “$n_{b2}$” give the number of BSSs visited in the result of the first echelon and the second echelon, respectively. Columns “$n_{k1}$” and “$n_{k2}$” give the number of routes in the result of the first echelon and the second echelon, respectively. Columns “$L^1$” and “$L^2$” give the length of the longest route in the result of the first echelon and the second echelon, respectively. Column “Obj.” gives the objective values of the instances. Columns 11–12 provide the result of the ERE of nitrogen oxides (NOx) and particulate emission. ERE is defined as $(Best - BKS)/(Er_x{}^1 * BKS^1 + Er_x{}^2 * BKS^2)$, which calculates the marginal cost of reducing the emission. $BKS^1$ and $BKS^2$ denote the first echelon part value and the second echelon part value of BKS, respectively. $(Best - BKS)$ is the increased cost when adopting EVs instead of diesel vehicles, and $(Er_x{}^1 * BKS^1 + Er_x{}^2 * BKS^2)$ is the total emission of diesel vehicles in the best-known solutions. Based on the research by Zhang et al. (2016), the emission of gaseous and particulate pollutants exhaust are influenced by the speed,

**Table 9**
Results and runtimes for Set 4a for the 2E-EVRP-BSS by CG-ALNS.

| Instance | Best | CG-ALNS 200K | %$dev^2$ | CG-ALNS 2000K | %$dev^3$ | T(seconds)200K | T*(seconds)200K |
|---|---|---|---|---|---|---|---|
| Instance50-1 | 1785.52 | 1799.57 | 0.78 | 1789.52 | 0.22 | 212 | 185 |
| Instance50-2 | 1446.90 | 1453.57 | 0.46 | 1450.13 | 0.22 | 245 | 211 |
| Instance50-3 | 1789.08 | 1798.83 | 0.54 | 1789.08 | 0.00 | 164 | 128 |
| Instance50-4 | 1462.04 | 1469.14 | 0.48 | 1465.67 | 0.25 | 135 | 110 |
| Instance50-5 | 2204.30 | 2213.53 | 0.42 | 2210.34 | 0.27 | 67 | 48 |
| Instance50-6 | 1339.48 | 1350.92 | 0.85 | 1344.21 | 0.35 | 379 | 326 |
| Instance50-7 | 1526.48 | 1538.35 | 0.77 | 1533.19 | 0.44 | 229 | 176 |
| Instance50-8 | 1541.63 | 1546.27 | 0.30 | 1541.63 | 0.00 | 484 | 396 |
| Instance50-9 | 1609.18 | 1614.32 | 0.32 | 1609.18 | 0.00 | 77 | 54 |
| Instance50-10 | 1446.92 | 1470.04 | 1.57 | 1452.77 | 0.40 | 180 | 157 |
| Instance50-11 | 2166.48 | 2185.13 | 0.85 | 2176.36 | 0.45 | 235 | 184 |
| Instance50-12 | 1432.77 | 1445.35 | 0.87 | 1443.75 | 0.76 | 1003 | 914 |
| Instance50-13 | 1560.52 | 1593.49 | 2.07 | 1572.34 | 0.75 | 114 | 82 |
| Instance50-14 | 1531.81 | 1542.65 | 0.70 | 1535.89 | 0.27 | 189 | 145 |
| Instance50-15 | 1710.4 | 1725.46 | 0.87 | 1710.40 | 0.00 | 143 | 86 |
| Instance50-16 | 1416.28 | 1423.16 | 0.48 | 1416.28 | 0.00 | 127 | 91 |
| Instance50-17 | 2354.27 | 2367.43 | 0.56 | 2358.99 | 0.20 | 148 | 124 |
| Instance50-18 | 1232.61 | 1242.41 | 0.79 | 1234.92 | 0.19 | 133 | 105 |
| Instance50-19 | 1868.48 | 1880.12 | 0.62 | 1874.42 | 0.32 | 940 | 883 |
| Instance50-20 | 1348.74 | 1357.71 | 0.66 | 1356.47 | 0.57 | 587 | 485 |
| Instance50-21 | 1591.01 | 1598.05 | 0.44 | 1594.59 | 0.22 | 525 | 479 |
| Instance50-22 | 1347.45 | 1350.68 | 0.24 | 1347.45 | 0.00 | 842 | 695 |
| Instance50-23 | 1816.34 | 1816.34 | 0.00 | 1816.34 | 0.00 | 1330 | 1064 |
| Instance50-24 | 1500.66 | 1512.32 | 0.77 | 1504.76 | 0.27 | 206 | 176 |
| Instance50-25 | 1705.64 | 1713.23 | 0.44 | 1705.64 | 0.00 | 344 | 282 |
| Instance50-26 | 1270.85 | 1273.16 | 0.18 | 1270.85 | 0.00 | 726 | 683 |
| Instance50-27 | 1752.40 | 1752.40 | 0.00 | 1752.40 | 0.00 | 482 | 410 |
| Instance50-28 | 1259.63 | 1263.62 | 0.32 | 1260.65 | 0.08 | 1494 | 1187 |
| Instance50-29 | 1814.92 | 1830.36 | 0.84 | 1814.92 | 0.00 | 472 | 430 |
| Instance50-30 | 1239.07 | 1251.68 | 1.01 | 1244.86 | 0.47 | 639 | 564 |
| Instance50-31 | 1562.14 | 1589.73 | 1.74 | 1586.11 | 1.51 | 1559 | 1371 |
| Instance50-32 | 1244.64 | 1246.28 | 0.13 | 1244.64 | 0.00 | 685 | 589 |
| Instance50-33 | 1706.62 | 1714.99 | 0.49 | 1712.49 | 0.34 | 1662 | 1217 |
| Instance50-34 | 1240.30 | 1242.78 | 0.20 | 1240.30 | 0.00 | 347 | 258 |
| Instance50-35 | 1770.54 | 1790.22 | 1.10 | 1784.46 | 0.78 | 1195 | 857 |
| Instance50-36 | 1249.77 | 1250.23 | 0.04 | 1249.87 | 0.01 | 430 | 361 |
| Instance50-37 | 1544.83 | 1546.82 | 0.13 | 1544.83 | 0.00 | 497 | 442 |
| Instance50-38 | 1247.04 | 1261.71 | 1.16 | 1258.49 | 0.91 | 1549 | 1190 |
| Instance50-39 | 1576.00 | 1579.00 | 0.19 | 1577.94 | 0.12 | 1317 | 922 |
| Instance50-40 | 1246.92 | 1250.18 | 0.26 | 1246.92 | 0.00 | 452 | 406 |
| Instance50-41 | 1697.44 | 1706.35 | 0.52 | 1703.62 | 0.36 | 1008 | 825 |
| Instance50-42 | 1272.99 | 1276.12 | 0.25 | 1272.99 | 0.00 | 1534 | 1421 |
| Instance50-43 | 1495.40 | 1505.68 | 0.68 | 1502.57 | 0.48 | 648 | 603 |
| Instance50-44 | 1122.76 | 1124.70 | 0.17 | 1122.76 | 0.00 | 259 | 223 |
| Instance50-45 | 1560.20 | 1570.15 | 0.63 | 1566.83 | 0.42 | 1604 | 1487 |
| Instance50-46 | 1118.46 | 1127.17 | 0.77 | 1121.25 | 0.25 | 1480 | 1292 |
| Instance50-47 | 1601.27 | 1603.49 | 0.14 | 1601.27 | 0.00 | 1635 | 1277 |
| Instance50-48 | 1136.90 | 1148.45 | 1.01 | 1140.38 | 0.31 | 398 | 365 |
| Instance50-49 | 1511.17 | 1516.17 | 0.33 | 1511.17 | 0.00 | 1541 | 1213 |
| Instance50-50 | 1153.52 | 1160.30 | 0.58 | 1156.46 | 0.25 | 856 | 772 |
| Instance50-51 | 1588.65 | 1590.78 | 0.13 | 1588.65 | 0.00 | 584 | 510 |
| Instance50-52 | 1148.61 | 1152.37 | 0.33 | 1150.41 | 0.16 | 671 | 586 |
| Instance50-53 | 1588.82 | 1593.12 | 0.27 | 1588.82 | 0.00 | 477 | 426 |
| Instance50-54 | 1144.20 | 1153.88 | 0.84 | 1146.64 | 0.21 | 572 | 492 |
| Avg. | 1511.13 | 1520.00 | 0.58 | 1514.78 | 0.24 | 663.17 | 554.91 |

acceleration and engine load of vehicles. They calculated the average NOx emission rate and particulate emission rate of heavy duty diesel truck ($Er_x{}^1$) was 7.29 and 0.60 (grams/kilometers), respectively. The average NOx emission rate and particulate emission rate of light duty diesel truck ($Er_x{}^2$) was 5.53 and 0.14 (grams/kilometers), respectively. Based on the data, the ERE in Table 21 are obtained.

Based on the BSS, the 2E-EVRP-BSS aims to introduce the EVs into 2E-VRP and enrich the application of EVs in practice. Some constraints on the battery driving range are given special consideration. Although the algorithm parameters and the computational instances affect the computational results, some specific conclusions are generalized as follows.

1) The battery driving range of EVs is an important factor to reduce the two-echelon distribution costs of logistics enterprises. From Table 21, if the battery driving range of the first echelon decreases by 10% of the base value, the objective value increases, whose increase rates are 2.1%, 1.8%, 0.1% and 1.1%. If the battery driving range of the first echelon increases by 10% of the base value, the objective value reduces, whose reduce rates are −0.8%,

**Table 10**
Results and runtimes for Set 4b for the 2E-EVRP-BSS by CG-ALNS.

| Instance | Best | CG-ALNS 200K | $\%dev^2$ | CG-ALNS 2000K | $\%dev^3$ | T(seconds)200K | T*(seconds)200K |
|---|---|---|---|---|---|---|---|
| Instance50-1 | 1785.52 | 1799.57 | 0.78 | 1789.52 | 0.22 | 158 | 89 |
| Instance50-2 | 1446.90 | 1453.57 | 0.46 | 1450.13 | 0.22 | 282 | 172 |
| Instance50-3 | 1789.08 | 1798.83 | 0.54 | 1789.08 | 0.00 | 87 | 72 |
| Instance50-4 | 1462.04 | 1469.14 | 0.48 | 1465.67 | 0.25 | 102 | 84 |
| Instance50-5 | 2204.30 | 2213.53 | 0.42 | 2210.34 | 0.27 | 79 | 62 |
| Instance50-6 | 1339.48 | 1350.92 | 0.85 | 1344.21 | 0.35 | 459 | 354 |
| Instance50-7 | 1504.02 | 1514.75 | 0.71 | 1510.32 | 0.42 | 158 | 129 |
| Instance50-8 | 1532.94 | 1544.83 | 0.77 | 1539.21 | 0.41 | 342 | 277 |
| Instance50-9 | 1583.29 | 1607.97 | 1.53 | 1588.43 | 0.32 | 98 | 62 |
| Instance50-10 | 1410.42 | 1423.71 | 0.93 | 1413.63 | 0.23 | 201 | 187 |
| Instance50-11 | 2132.93 | 2146.97 | 0.65 | 2138.42 | 0.26 | 147 | 102 |
| Instance50-12 | 1432.77 | 1445.35 | 0.87 | 1443.75 | 0.76 | 1189 | 812 |
| Instance50-13 | 1553.71 | 1568.32 | 0.93 | 1556.83 | 0.20 | 86 | 44 |
| Instance50-14 | 1531.81 | 1542.65 | 0.70 | 1535.89 | 0.27 | 108 | 91 |
| Instance50-15 | 1671.15 | 1680.01 | 0.53 | 1675.28 | 0.25 | 86 | 74 |
| Instance50-16 | 1410.42 | 1413.63 | 0.23 | 1410.57 | 0.01 | 174 | 153 |
| Instance50-17 | 2354.27 | 2367.43 | 0.56 | 2358.99 | 0.20 | 81 | 51 |
| Instance50-18 | 1232.61 | 1242.41 | 0.79 | 1234.92 | 0.19 | 103 | 84 |
| Instance50-19 | 1852.76 | 1867.32 | 0.78 | 1859.80 | 0.38 | 1086 | 836 |
| Instance50-20 | 1348.74 | 1357.71 | 0.66 | 1356.47 | 0.57 | 606 | 527 |
| Instance50-21 | 1591.01 | 1598.05 | 0.44 | 1594.59 | 0.22 | 446 | 341 |
| Instance50-22 | 1347.45 | 1350.68 | 0.24 | 1347.45 | 0.00 | 711 | 528 |
| Instance50-23 | 1805.99 | 1808.41 | 0.13 | 1806.02 | 0.00 | 1188 | 863 |
| Instance50-24 | 1456.87 | 1468.30 | 0.78 | 1460.92 | 0.28 | 159 | 105 |
| Instance50-25 | 1674.23 | 1688.52 | 0.85 | 1679.44 | 0.31 | 257 | 178 |
| Instance50-26 | 1270.85 | 1273.16 | 0.18 | 1270.85 | 0.00 | 584 | 495 |
| Instance50-27 | 1732.86 | 1745.62 | 0.73 | 1739.01 | 0.35 | 620 | 572 |
| Instance50-28 | 1259.63 | 1263.62 | 0.32 | 1260.65 | 0.08 | 1608 | 1264 |
| Instance50-29 | 1778.61 | 1792.04 | 0.75 | 1784.76 | 0.34 | 511 | 396 |
| Instance50-30 | 1239.07 | 1251.68 | 1.01 | 1244.86 | 0.47 | 518 | 445 |
| Instance50-31 | 1538.11 | 1540.83 | 0.18 | 1538.11 | 0.00 | 1831 | 1422 |
| Instance50-32 | 1244.64 | 1246.28 | 0.13 | 1244.64 | 0.00 | 542 | 357 |
| Instance50-33 | 1701.88 | 1714.99 | 0.76 | 1708.95 | 0.41 | 1508 | 1038 |
| Instance50-34 | 1240.30 | 1242.78 | 0.20 | 1240.30 | 0.00 | 214 | 179 |
| Instance50-35 | 1598.66 | 1607.72 | 0.56 | 1599.18 | 0.03 | 1343 | 971 |
| Instance50-36 | 1249.77 | 1250.23 | 0.04 | 1249.87 | 0.01 | 304 | 203 |
| Instance50-37 | 1544.83 | 1546.82 | 0.13 | 1544.83 | 0.00 | 478 | 298 |
| Instance50-38 | 1220.76 | 1221.99 | 0.10 | 1221.85 | 0.09 | 1364 | 1063 |
| Instance50-39 | 1576.00 | 1579.00 | 0.19 | 1577.94 | 0.12 | 1429 | 1238 |
| Instance50-40 | 1221.31 | 1222.86 | 0.13 | 1221.31 | 0.00 | 366 | 296 |
| Instance50-41 | 1681.04 | 1699.85 | 1.11 | 1686.21 | 0.31 | 894 | 639 |
| Instance50-42 | 1266.00 | 1272.48 | 0.51 | 1271.00 | 0.39 | 1090 | 821 |
| Instance50-43 | 1489.03 | 1496.54 | 0.50 | 1493.38 | 0.29 | 791 | 534 |
| Instance50-44 | 1117.42 | 1118.57 | 0.10 | 1117.42 | 0.00 | 365 | 257 |
| Instance50-45 | 1552.81 | 1563.64 | 0.69 | 1559.92 | 0.46 | 1943 | 1346 |
| Instance50-46 | 1115.58 | 1117.46 | 0.17 | 1115.58 | 0.00 | 1735 | 1392 |
| Instance50-47 | 1588.48 | 1600.81 | 0.77 | 1588.54 | 0.00 | 1580 | 1112 |
| Instance50-48. | 1134.57 | 1148.45 | 1.21 | 1137.85 | 0.29 | 531 | 414 |
| Instance50-49 | 1511.17 | 1516.17 | 0.33 | 1511.17 | 0.00 | 1409 | 1041 |
| Instance50-50 | 1150.26 | 1156.96 | 0.58 | 1154.96 | 0.41 | 665 | 492 |
| Instance50-51 | 1584.37 | 1590.57 | 0.39 | 1587.01 | 0.17 | 366 | 221 |
| Instance50-52 | 1147.17 | 1149.21 | 0.18 | 1147.61 | 0.04 | 478 | 341 |
| Instance50-53 | 1554.58 | 1567.73 | 0.84 | 1556.06 | 0.10 | 460 | 338 |
| Instance50-54 | 1144.82 | 1151.35 | 0.57 | 1144.99 | 0.01 | 408 | 372 |
| Avg. | 1498.32 | 1506.89 | 0.55 | 1501.46 | 0.20 | 635.70 | 478.41 |

−1.4%, −1.0% and −0.2%. If the battery driving range of the second echelon decreases by 10% of the base value, the objective value increases, whose increase rates are 0.7%, 0.9%, 3.2% and 1.3%. If the battery driving range of the second echelon increases by 10% of the base value, the objective value reduces, whose reduce rates are −6%, −0.8%, −1.2% and −0.3%.

For saving the cost of the two-echelon distribution system, when logistics enterprises try to introduce EVs to deliver goods, they need to give priority to EVs with larger battery driving range. Meanwhile, considering that different logistics enterprises have different service scope and volume, the configuration of vehicle types especially the purchase cost of EVs and battery driving range should be well-balanced according to their business condition and demand network characteristics.

2) Logistics enterprises should focus on the number of needed BSSs to support current business. In our experiments, the location of the BSSs was generated randomly and the number of BSSs was set to be 1/5 of the nodes in the network, like Schneider, Andreas and Goeke did in Schneider et al. (2014). From Table 21, the number of visited BSSs shows little change when battery driving range varies. The battery driving range does not much affect the number of needed BSSs. The reason maybe be-

**Table 11**
Results and runtimes for Set 5 for the 2E-EVRP-BSS by CG-ALNS.

| Instance | Best | CG-ALNS 200K | %*dev*$^2$ | CG-ALNS 2000K | %*dev*$^3$ | T(seconds)200K | T*(seconds)200K |
|---|---|---|---|---|---|---|---|
| 100-5-1 | 1825.67 | 1846.01 | 1.10 | 1831.05 | 0.29 | 4931 | 4127 |
| 100-5-1b | 1559.31 | 1599.25 | 2.50 | 1559.93 | 0.04 | 4482 | 3036 |
| 100-5-2 | 1478.62 | 1479.93 | 0.09 | 1478.62 | 0.00 | 3501 | 2964 |
| 100-5-2b | 930.34 | 933.53 | 0.34 | 932.68 | 0.25 | 1323 | 1021 |
| 100-5-3 | 1183.31 | 1190.31 | 0.59 | 1184.55 | 0.10 | 3656 | 2847 |
| 100-5-3b | 981.43 | 981.43 | 0.00 | 981.43 | 0.00 | 1032 | 823 |
| 100-10-1 | 1354.26 | 1374.22 | 1.45 | 1355.29 | 0.08 | 13902 | 9927 |
| 100-10-1b | 1052.81 | 1060.72 | 0.75 | 1056.01 | 0.30 | 13729 | 9906 |
| 100-10-2 | 1095.28 | 1103.79 | 0.77 | 1103.79 | 0.77 | 14284 | 11220 |
| 100-10-2b | 936.08 | 944.42 | 0.88 | 939.48 | 0.36 | 6283 | 5092 |
| 100-10-3 | 1272.10 | 1286.07 | 1.09 | 1272.10 | 0.00 | 17249 | 13257 |
| 100-10-3b | 1002.85 | 1012.10 | 0.91 | 1005.10 | 0.22 | 8214 | 6972 |
| 200-10-1 | 1937.70 | 1950.11 | 0.64 | 1938.79 | 0.06 | 4255 | 3710 |
| 200-10-1b | 1522.16 | 1541.86 | 1.28 | 1524.31 | 0.14 | 15876 | 13442 |
| 200-10-2 | 1786.55 | 1796.30 | 0.54 | 1788.21 | 0.09 | 20998 | 17620 |
| 200-10-2b | 1228.48 | 1241.12 | 1.02 | 1228.48 | 0.00 | 30191 | 27546 |
| 200-10-3 | 2113.42 | 2130.23 | 0.79 | 2114.25 | 0.04 | 15297 | 10384 |
| 200-10-3b | 1502.12 | 1523.35 | 1.39 | 1507.94 | 0.39 | 12076 | 9903 |
| Avg. | 1375.69 | 1388.60 | 0.90 | 1377.89 | 0.17 | 10626.61 | 8544.28 |

**Table 12**
Results and runtimes for Set 6a for the 2E-EVRP-BSS by CG-ALNS.

| Instance | Best | CG-ALNS 200K | %*dev*$^2$ | CG-ALNS 2000K | %*dev*$^3$ | T(seconds)200K | T*(seconds)200K |
|---|---|---|---|---|---|---|---|
| A-n51-4 | 836.40 | 838.25 | 0.22 | 836.40 | 0.00 | 367 | 303 |
| A-n51-5 | 781.22 | 784.54 | 0.42 | 781.22 | 0.00 | 429 | 385 |
| A-n51-6 | 852.26 | 860.64 | 0.97 | 856.35 | 0.48 | 273 | 241 |
| A-n76-4 | 1704.64 | 1718.47 | 0.80 | 1715.42 | 0.63 | 1249 | 1184 |
| A-n76-5 | 1635.95 | 1649.20 | 0.80 | 1642.86 | 0.42 | 1887 | 1662 |
| A-n76-6 | 1922.92 | 1938.77 | 0.82 | 1927.42 | 0.23 | 2238 | 1945 |
| A-n101-4 | 2176.48 | 2190.78 | 0.65 | 2183.35 | 0.31 | 3951 | 3301 |
| A-n101-5 | 2348.53 | 2378.90 | 1.28 | 2366.94 | 0.78 | 4272 | 3849 |
| A-n101-6 | 2317.42 | 2355.27 | 1.61 | 2320.69 | 0.14 | 4406 | 4160 |
| B-n51-4 | 710.84 | 736.62 | 3.50 | 715.35 | 0.63 | 384 | 349 |
| B-n51-5 | 852.23 | 869.31 | 1.96 | 854.48 | 0.26 | 463 | 427 |
| B-n51-6 | 742.30 | 753.08 | 1.43 | 749.37 | 0.94 | 459 | 410 |
| B-n76-4 | 1837.93 | 1851.43 | 0.73 | 1841.24 | 0.18 | 2379 | 2158 |
| B-n76-5 | 1661.81 | 1674.18 | 0.74 | 1667.04 | 0.31 | 1741 | 1505 |
| B-n76-6 | 1568.40 | 1585.60 | 1.08 | 1574.01 | 0.36 | 2402 | 2180 |
| B-n101-4 | 2053.28 | 2100.72 | 2.26 | 2061.51 | 0.40 | 4065 | 3819 |
| B-n101-5 | 1886.74 | 1913.52 | 1.40 | 1894.38 | 0.40 | 5257 | 4934 |
| B-n101-6 | 2142.34 | 2158.42 | 0.74 | 2150.85 | 0.40 | 5077 | 4826 |
| C-n51-4 | 810.40 | 816.47 | 0.74 | 814.62 | 0.52 | 306 | 280 |
| C-n51-5 | 881.94 | 885.39 | 0.39 | 883.05 | 0.13 | 394 | 362 |
| C-n51-6 | 898.45 | 904.24 | 0.64 | 901.50 | 0.34 | 375 | 328 |
| C-n76-4 | 1824.40 | 1830.23 | 0.32 | 1826.68 | 0.12 | 1891 | 1573 |
| C-n76-5 | 1760.18 | 1766.48 | 0.36 | 1763.05 | 0.16 | 3048 | 2529 |
| C-n76-6 | 1806.25 | 1813.42 | 0.40 | 1808.73 | 0.14 | 2152 | 1806 |
| C-n101-4 | 2057.81 | 2082.47 | 1.18 | 2073.25 | 0.74 | 4593 | 4155 |
| C-n101-5 | 1994.90 | 2110.72 | 5.49 | 2105.44 | 5.25 | 5022 | 4610 |
| C-n101-6 | 2162.17 | 2190.95 | 1.31 | 2174.03 | 0.55 | 4850 | 4331 |
| Avg. | 1564.01 | 1583.63 | 1.19 | 1573.68 | 0.55 | 2367.78 | 2133.78 |

cause both types of EVs can share BSSs and a BSS can be visited more than one time by the same EV. So, if the BSSs could be located in a more suitable location, we believe the number of needed BSSs and operational cost may be reduced, but not much. And we will study this strategy in the future research.

3) Logistics enterprises need to evaluate the tradeoffs between reducing carbon emissions and the cost of using EVs. In order to control the carbon emission, the government mostly has three policies when dealing with carbon emission, setting carbon cap, carbon taxes, the platform of cap-and-trade. If logistics enterprises use traditional vehicles, they may emit more pollution than using EVs, their carbon emissions may exceed the carbon cap. It will cost more on carbon taxes or buying carbon off-sets. However, if logistics enterprises use EVs, they need to pay the cost of EV detours, battery swapping costs, time cost (because of the detours and battery swapping) and more purchase cost instead of pollution cost. From Table 21, we provide the ERE to help logistics enterprises to

**Table 13**
Results and runtimes for Set 6b for the 2E-EVRP-BSS by CG-ALNS.

| Instance | Best | CG-ALNS 200K | $\%dev^2$ | CG-ALNS 2000K | $\%dev^3$ | T(seconds)200K | T*(seconds)200K |
|---|---|---|---|---|---|---|---|
| A-n51-4 | 838.36 | 838.36 | 0.00 | 838.36 | 0.00 | 385 | 324 |
| A-n51-5 | 876.29 | 876.29 | 0.00 | 876.29 | 0.00 | 287 | 241 |
| A-n51-6 | 985.74 | 990.18 | 0.45 | 985.74 | 0.00 | 331 | 294 |
| A-n76-4 | 1625.97 | 1655.62 | 1.79 | 1631.18 | 0.32 | 1082 | 935 |
| A-n76-5 | 1803.49 | 1847.80 | 2.40 | 1803.49 | 0.00 | 2190 | 1857 |
| A-n76-6 | 1910.42 | 1957.53 | 2.41 | 1924.84 | 0.75 | 1437 | 944 |
| A-n101-4 | 2180.04 | 2275.94 | 4.21 | 2261.15 | 3.59 | 4228 | 3149 |
| A-n101-5 | 1953.29 | 1991.42 | 1.91 | 1976.06 | 1.15 | 3842 | 3321 |
| A-n101-6 | 2099.73 | 2147.40 | 2.22 | 2125.36 | 1.21 | 4511 | 3984 |
| B-n51-4 | 708.35 | 726.14 | 2.45 | 712.60 | 0.60 | 462 | 410 |
| B-n51-5 | 812.17 | 827.76 | 1.88 | 814.29 | 0.26 | 365 | 304 |
| B-n51-6 | 928.61 | 950.22 | 2.27 | 932.72 | 0.44 | 507 | 437 |
| B-n76-4 | 1248.90 | 1274.27 | 1.99 | 1253.89 | 0.40 | 1942 | 1677 |
| B-n76-5 | 1497.04 | 1521.33 | 1.60 | 1502.84 | 0.39 | 2490 | 2152 |
| B-n76-6 | 1569.41 | 1579.95 | 0.67 | 1573.52 | 0.26 | 2208 | 1866 |
| B-n101-4 | 2111.58 | 2118.78 | 0.34 | 2114.26 | 0.13 | 3643 | 3159 |
| B-n101-5 | 1977.67 | 1996.23 | 0.93 | 1982.47 | 0.24 | 5048 | 4741 |
| B-n101-6 | 2013.63 | 2104.4 | 4.31 | 2081.05 | 3.24 | 4155 | 3763 |
| C-n51-4 | 967.55 | 992.62 | 2.53 | 984.25 | 1.70 | 291 | 254 |
| C-n51-5 | 1125.45 | 1150.42 | 2.17 | 1136.39 | 0.96 | 359 | 296 |
| C-n51-6 | 1187.86 | 1214.65 | 2.21 | 1195.31 | 0.62 | 304 | 268 |
| C-n76-4 | 1716.48 | 1731.14 | 0.85 | 1725.47 | 0.52 | 968 | 840 |
| C-n76-5 | 2014.84 | 2087.52 | 3.48 | 2042.26 | 1.34 | 2551 | 2072 |
| C-n76-6 | 1920.49 | 1968.72 | 2.45 | 1942.18 | 1.12 | 1751 | 1585 |
| C-n101-4 | 2337.15 | 2426.34 | 3.68 | 2401.51 | 2.68 | 1489 | 1105 |
| C-n101-5 | 2337.45 | 2354.27 | 0.71 | 2349.03 | 0.49 | 4624 | 4301 |
| C-n101-6 | 2308.94 | 2350.62 | 1.77 | 2316.60 | 0.33 | 3747 | 3229 |
| Avg. | 1594.70 | 1628.00 | 1.91 | 1610.49 | 0.84 | 2044.33 | 1759.56 |

**Table 14**
Results and runtimes for Set 2 for the 2E-VRP by CG-ALNS.

| Instance | BKS | HCC | | | BSHV | | | CG-ALNS | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | | Avg. 5 | T(seconds) | T*(seconds) | Avg. 5 | T(seconds) | T*(seconds) | Avg. 5 | Best5 | T(seconds) | T*(seconds) |
| **Set 2a** | | | | | | | | | | | |
| E-n22-k4-s6-17 | 417.07* | **417.07** | 37 | 0 | **417.07** | 60 | 1 | **417.07** | **417.07** | 27 | 19 |
| E-n22-k4-s8-14 | 384.96* | **384.96** | 34 | 0 | **384.96** | 60 | 1 | **384.96** | **384.96** | 27 | 20 |
| E-n22-k4-s9-19 | 470.60* | **470.60** | 35 | 0 | **470.60** | 60 | 1 | **470.60** | **470.60** | 47 | 33 |
| E-n22-k4-s10-14 | 371.50* | **371.50** | 37 | 0 | **371.50** | 60 | 2 | **371.50** | **371.50** | 25 | 18 |
| E-n22-k4-s11-12 | 427.22* | **427.22** | 31 | 0 | **427.22** | 60 | 2 | **427.29** | **427.22** | 31 | 24 |
| E-n22-k4-s12-16 | 392.78* | **392.78** | 36 | 0 | **392.78** | 60 | 1 | **392.78** | **392.78** | 66 | 45 |
| E-n33-k4-s1-9 | 730.16* | **730.16** | 74 | 0 | **730.16** | 60 | 1 | **730.16** | **730.16** | 159 | 108 |
| E-n33-k4-s2-13 | 714.63* | **714.63** | 64 | 0 | **714.63** | 60 | 1 | **714.63** | **714.63** | 102 | 76 |
| E-n33-k4-s3-17 | 707.48* | **707.48** | 58 | 0 | **707.48** | 60 | 1 | **707.48** | **707.48** | 186 | 141 |
| E-n33-k4-s4-5 | 778.74* | **778.74** | 77 | 0 | **778.74** | 60 | 1 | **778.74** | **778.74** | 237 | 152 |
| E-n33-k4-s7-25 | 756.85* | **756.85** | 53.00 | 3 | **756.85** | 60 | 1 | **756.85** | **756.85** | 205 | 177 |
| E-n33-k4-s14-22 | 779.05* | **779.05** | 85 | 0 | **779.05** | 60 | 1 | **779.31** | **779.05** | 184 | 121 |
| Avg. | 577.59 | 577.59 | 51.75 | 0.25 | 577.59 | 60 | 1 | 577.59 | 577.59 | 108 | 77.83 |
| **Set 2b** | | | | | | | | | | | |
| E-n51-k5-s2-17 | 597.49* | **597.49** | 100 | 7. | **597.49** | 60 | 1 | **597.49** | **597.49** | 88 | 45 |
| E-n51-k5-s4-46 | 530.76* | **530.76** | 173 | 0 | **530.76** | 60 | 4 | **530.76** | **530.76** | 138 | 78 |
| E-n51-k5-s6-12 | 554.81* | **554.80** | 149 | 2 | **554.80** | 60 | 3 | 556.03 | **554.81** | 104 | 72 |
| E-n51-k5-s11-19 | 581.64* | **581.64** | 182 | 6 | **581.64** | 60 | 3 | 582.12 | **581.64** | 179 | 135 |
| E-n51-k5-s27-47 | 538.22* | **538.22** | 136 | 1 | **538.22** | 60 | 1 | 538.37 | **538.22** | 40 | 29 |
| E-n51-k5-s32-37 | 552.28* | **552.28** | 141 | 1 | **552.28** | 60 | 2 | **552.28** | **552.28** | 89 | 58 |
| E-n51-k5-s2-4-17-46 | 530.76* | **530.76** | 154 | 1 | **530.76** | 60 | 3 | **530.76** | **530.76** | 251 | 201 |
| E-n51-k5-s6-12-32-37 | 531.92* | **531.92** | 150 | 0 | **531.92** | 60 | 4 | **531.92** | **531.92** | 152 | 102 |
| E-n51-k5-s11-19-27-47 | 527.63* | **527.63** | 147 | 1 | **527.63** | 60 | 2 | **527.63** | **527.63** | 206 | 188 |
| Avg. | 549.50 | 549.50 | 148.00 | 2.11 | 549.50 | 60 | 2 | 549.71 | 549.50 | 138.56 | 100.89 |
| **Set 2c** | | | | | | | | | | | |
| E-n51-k5-s11-19 | 617.42 | | | | **617.42** | 60 | 3 | 620.16 | 619.81 | 215 | 176 |
| E-n51-k5-s11-19-27-47 | 530.76 | | | | **530.76** | 60 | 1 | **530.76** | **530.76** | 189 | 162 |
| E-n51-k5-s2-17 | 601.39 | | | | **601.39** | 60 | 3 | 605.62 | 605.62 | 96 | 71 |
| E-n51-k5-s2-4-17-46 | 601.39 | | | | **601.39** | 60 | 4 | **601.39** | **601.39** | 337 | 162 |
| E-n51-k5-s27-47 | 530.76 | | | | **530.76** | 60 | 3 | 532.86 | **530.76** | 59 | 37 |
| E-n51-k5-s32-37 | 752.59 | | | | **752.59** | 60 | 5 | 756.82 | 755.28 | 77 | 32 |
| E-n51-k5-s4-46 | 702.33 | | | | **702.33** | 60 | 4 | **702.33** | **702.33** | 155 | 83 |
| E-n51-k5-s6-12 | 567.42 | | | | **567.42** | 60 | 5 | 569.36 | **567.42** | 95 | 47 |
| E-n51-k5-s6-12-32-37 | 567.42 | | | | **567.42** | 60 | 6 | **567.42** | **567.42** | 151 | 99 |
| Avg. | 607.94 | | | | 607.94 | 60 | 4 | 609.64 | 608.98 | 152.67 | 96.56 |

**Table 15**
Results and runtimes for Set 3 for the 2E-VRP by CG-ALNS.

| Instance | BKS | HCC | | | BSHV | | | CG-ALNS | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | | Avg. 5 | T(seconds) | T*(seconds) | Avg. 5 | T(seconds) | T*(seconds) | Avg. 5 | Best5 | T(seconds) | T*(seconds) |
| **Set 3a** | | | | | | | | | | | |
| E-n22-k4-s13-14 | 526.15* | **526.15** | 43 | 0 | **526.15** | 60 | 2 | **526.15** | **526.15** | 103 | 81 |
| E-n22-k4-s13-16 | 521.09* | **521.09** | 44 | 0 | **521.09** | 60 | 2 | **521.09** | **521.09** | 107 | 79 |
| E-n22-k4-s13-17 | 496.38* | **496.38** | 49 | 0 | **496.38** | 60 | 1 | **496.38** | **496.38** | 56 | 33 |
| E-n22-k4-s14-19 | 498.80* | **498.80** | 43 | 0 | **498.80** | 60 | 1 | **498.80** | **498.80** | 75 | 54 |
| E-n22-k4-s17-19 | 512.80* | 512.81 | 26 | 0 | **512.80** | 60 | 4 | 512.81 | 512.81 | 89 | 49 |
| E-n22-k4-s19-21 | 520.42* | **520.42** | 34 | 0 | **520.42** | 60 | 2 | **520.42** | **520.42** | 68 | 44 |
| E-n33-k4-s16-22 | 672.17* | **672.17** | 76 | 3 | **672.17** | 60 | 4 | **672.17** | **672.17** | 58 | 39 |
| E-n33-k4-s16-24 | 666.02* | **666.02** | 77 | 0 | **666.02** | 60 | 1 | **666.02** | **666.02** | 115 | 83 |
| E-n33-k4-s19-26 | 680.36* | **680.36** | 84 | 0 | **680.36** | 60 | 1 | **680.36** | **680.36** | 200 | 162 |
| E-n33-k4-s22-26 | 680.36* | 680.37 | 77 | 0 | **680.36** | 60 | 1 | 680.37 | 680.37 | 121 | 87 |
| E-n33-k4-s24-28 | 670.43* | **670.43** | 88 | 0 | **670.43** | 60 | 2 | **670.43** | **670.43** | 88 | 51 |
| E-n33-k4-s25-28 | 650.58* | **650.58** | 63 | 0 | **650.58** | 60 | 1 | **650.58** | **650.58** | 86 | 53 |
| Avg. | 591.30 | 591.30 | 58.67 | 0 | 591.30 | 60 | 2 | 591.30 | 591.30 | 97.17 | 67.92 |
| **Set3b** | | | | | | | | | | | |
| E-n51-k5-s12-18 | 690.59 | **690.59** | 147 | 4 | **690.59** | 60 | 8 | **690.59** | **690.59** | 116 | 82 |
| E-n51-k5-s12-41 | 683.05 | **683.05** | 133 | 38 | **683.05** | 60 | 11 | 683.89 | **683.05** | 123 | 97 |
| E-n51-k5-s12-43 | 710.41 | **710.41** | 217 | 1 | **710.41** | 60 | 5 | **710.41** | **710.41** | 177 | 135 |
| E-n51-k5-s39-41 | 728.54 | **728.54** | 155 | 18 | **728.54** | 60 | 7 | **728.54** | **728.54** | 216 | 172 |
| E-n51-k5-s40-41 | 723.75 | **723.75** | 154 | 17 | **723.75** | 60 | 5 | **723.75** | **723.75** | 177 | 159 |
| E-n51-k5-s40-43 | 752.15 | **752.15** | 158 | 15 | **752.15** | 60 | 12 | 753.19 | 753.19 | 199 | 139 |
| Avg. | 714.75 | 714.75 | 160.67 | 16.00 | 714.75 | 60 | 8 | 715.06 | 714.92 | 119.54 | 87.73 |
| **Set3c** | | | | | | | | | | | |
| E-n51-k5-s13-19 | 560.73 | | | | **560.73** | 60 | 10 | **560.73** | **560.73** | 148 | 107 |
| E-n51-k5-s13-42 | 564.45 | | | | **564.45** | 60 | 3 | **564.45** | **564.45** | 87 | 62 |
| E-n51-k5-s13-44 | 564.45 | | | | **564.45** | 60 | 2 | **564.45** | **564.45** | 105 | 91 |
| E-n51-k5-s40-42 | 746.31 | | | | **746.31** | 60 | 5 | 747.37 | **746.31** | 193 | 149 |
| E-n51-k5-s41-42 | 771.56 | | | | **771.56** | 60 | 15 | **771.56** | **771.56** | 132 | 116 |
| E-n51-k5-s41-44 | 802.91 | | | | **802.91** | 60 | 16 | 804.23 | 804.23 | 99 | 52 |
| Avg. | 668.40 | | | | 668.40 | 60 | 9 | 668.80 | 668.62 | 127.33 | 96.17 |

**Table 16**
Results and runtimes for Set 4a for the 2E-VRP by CG-ALNS.

| Instance | BKS | BSHV | | | | CG-ALNS | | | |
|---|---|---|---|---|---|---|---|---|---|
| | | Avg. 5 | Best 5 | T(seconds) | T*(seconds) | Avg.5 | Best 5 | T(seconds) | T*(seconds) |
| Instance50-1 | 1569.42* | **1569.42** | **1569.42** | 60 | 4 | **1569.42** | **1569.42** | 184 | 93 |
| Instance50-2 | 1438.33* | **1438.32** | **1438.32** | 60 | 16 | 1444.33 | 1444.33 | 139 | 116 |
| Instance50-3 | 1570.43* | **1570.43** | **1570.43** | 60 | 8 | **1570.43** | **1570.43** | 82 | 47 |
| Instance50-4 | 1424.04* | **1424.04** | **1424.04** | 60 | 7 | **1424.04** | **1424.04** | 136 | 114 |
| Instance50-5 | 2193.52* | **2193.52** | **2193.52** | 60 | 10 | 2199.11 | 2195.26 | 91 | 77 |
| Instance50-6 | 1279.87* | **1279.89** | **1279.89** | 60 | 0 | **1279.87** | **1279.87** | 152 | 131 |
| Instance50-7 | 1458.63* | **1458.60** | **1458.60** | 60 | 2 | 1503.72 | 1498.00 | 104 | 88 |
| Instance50-8 | 1363.74* | **1363.76** | **1363.76** | 60 | 29 | **1363.76** | **1363.76** | 160 | 137 |
| Instance50-9 | 1450.27* | **1450.25** | **1450.25** | 60 | 5 | **1450.27** | **1450.27** | 76 | 59 |
| Instance50-10 | 1407.64* | **1407.65** | **1407.65** | 60 | 6 | **1407.65** | **1407.65** | 147 | 118 |
| Instance50-11 | 2047.46* | 2052.21 | **2047.43** | 60 | 3 | 2054.42 | 2050.00 | 87 | 63 |
| Instance50-12 | 1209.42* | **1209.46** | **1209.46** | 60 | 8 | **1209.42** | **1209.42** | 142 | 125 |
| Instance50-13 | 1481.83* | **1481.80** | **1481.80** | 60 | 7 | 1527.16 | 1513.60 | 69 | 44 |
| Instance50-14 | 1393.61* | **1393.64** | **1393.64** | 60 | 1 | **1393.61** | **1393.61** | 125 | 119 |
| Instance50-15 | 1489.94* | **1489.92** | **1489.92** | 60 | 16 | 1497.34 | 1492.88 | 74 | 31 |
| Instance50-16 | 1389.17* | **1389.20** | **1389.20** | 60 | 2 | **1389.20** | **1389.20** | 192 | 104 |
| Instance50-17 | 2088.49* | **2088.48** | **2088.48** | 60 | 15 | **2088.49** | **2088.49** | 124 | 83 |
| Instance50-18 | 1227.61* | **1227.68** | **1227.68** | 60 | 1 | 1227.81 | 1227.73 | 115 | 82 |
| Instance50-19 | 1564.66* | **1564.66** | **1564.66** | 60 | 3 | **1564.66** | **1564.66** | 213 | 155 |
| Instance50-20 | 1272.97* | **1272.98** | **1272.98** | 60 | 25 | **1272.97** | **1272.97** | 217 | 158 |
| Instance50-21 | 1577.82* | **1577.82** | **1577.82** | 60 | 2 | **1577.82** | **1577.82** | 84 | 63 |
| Instance50-22 | 1281.83* | **1281.83** | **1281.83** | 60 | 3 | **1281.83** | **1281.82** | 164 | 118 |
| Instance50-23 | 1807.35* | **1807.35** | **1807.35** | 60 | 8 | **1807.35** | **1807.35** | 295 | 246 |
| Instance50-24 | 1282.69* | **1282.69** | **1282.69** | 60 | 0 | **1282.68** | **1282.68** | 144 | 108 |
| Instance50-25 | 1522.42* | **1522.40** | **1522.40** | 60 | 4 | 1551.40 | 1537.10 | 68 | 60 |
| Instance50-26 | 1167.46* | **1167.47** | **1167.47** | 60 | 1 | **1167.46** | **1167.46** | 152 | 107 |
| Instance50-27 | 1481.57* | **1481.56** | **1481.56** | 60 | 42 | 1483.48 | **1482.92** | 205 | 183 |
| Instance50-28 | 1210.44* | **1210.46** | **1210.46** | 60 | 3 | **1210.44** | **1210.44** | 177 | 129 |
| Instance50-29 | 1722.04 | 1722.06 | **1722.00** | 60 | 31 | 1723.03 | **1722.00** | 394 | 287 |
| Instance50-30 | 1211.59* | **1211.63** | **1211.63** | 60 | 12 | 1212.40 | 1212.40 | 185 | 148 |
| Instance50-31 | 1490.34 | **1490.32** | **1490.32** | 60 | 7 | **1490.34** | **1490.34** | 179 | 163 |
| Instance50-32 | 1199.00* | **1199.05** | **1199.05** | 60 | 24 | **1199.13** | **1199.00** | 143 | 112 |
| Instance50-33 | 1508.30 | **1508.32** | **1508.32** | 60 | 14 | **1508.30** | **1508.30** | 186 | 149 |
| Instance50-34 | 1233.92* | **1233.96** | **1233.96** | 60 | 7 | **1233.92** | **1233.92** | 311 | 220 |
| Instance50-35 | 1718.41 | **1718.42** | **1718.42** | 60 | 41 | **1718.42** | **1718.42** | 124 | 83 |

(*continued on next page*)

**Table 16** (*continued*)

| Instance | BKS | BSHV | | | | CG-ALNS | | | |
|---|---|---|---|---|---|---|---|---|---|
| | | Avg. 5 | Best 5 | T(seconds) | T*(seconds) | Avg.5 | Best 5 | T(seconds) | T*(seconds) |
| Instance50-36 | 1228.89* | **1228.95** | **1228.95** | 60 | 0 | 1235.10 | 1231.72 | 172 | 105 |
| Instance50-37 | 1528.73* | **1528.73** | **1528.73** | 60 | 25 | **1528.73** | **1528.73** | 254 | 209 |
| Instance50-38 | 1169.21* | **1169.20** | **1169.20** | 60 | 15 | **1169.20** | **1169.20** | 247 | 213 |
| Instance50-39 | 1520.92* | **1520.92** | **1520.92** | 60 | 17 | **1520.95** | **1520.92** | 436 | 337 |
| Instance50-40 | 1199.42* | **1199.42** | **1199.42** | 60 | 2 | **1199.42** | **1199.42** | 291 | 215 |
| Instance50-41 | 1667.96* | **1667.96** | **1667.96** | 60 | 9 | **1667.96** | **1667.96** | 582 | 437 |
| Instance50-42 | 1194.54* | **1194.54** | **1194.54** | 60 | 19 | **1195.94** | **1195.28** | 360 | 254 |
| Instance50-43 | 1439.67* | **1439.67** | **1439.67** | 60 | 14 | 1442.82 | 1440.88 | 233 | 181 |
| Instance50-44 | 1045.13* | **1045.14** | **1045.14** | 60 | 24 | 1047.23 | 1045.74 | 192 | 163 |
| Instance50-45 | 1450.96* | **1451.48** | **1450.95** | 60 | 3 | 1457.48 | 1452.61 | 437 | 384 |
| Instance50-46 | 1088.77* | **1088.79** | **1088.79** | 60 | 2 | 1090.10 | **1088.79** | 293 | 241 |
| Instance50-47 | 1587.29* | **1587.29** | **1587.29** | 60 | 15 | 1597.29 | 1597.29 | 411 | 365 |
| Instance50-48 | 1082.20* | **1082.21** | **1082.21** | 60 | 23 | **1082.20** | **1082.20** | 385 | 297 |
| Instance50-49 | 1434.88* | **1434.88** | **1434.88** | 60 | 14 | 1438.62 | **1434.88** | 138 | 114 |
| Instance50-50 | 1083.12* | **1083.16** | **1083.16** | 60 | 23 | **1084.13** | **1083.77** | 227 | 176 |
| Instance50-51 | 1398.05* | **1398.03** | **1398.03** | 60 | 21 | 1402.18 | 1400.22 | 344 | 268 |
| Instance50-52 | 1125.67* | **1125.69** | **1125.69** | 60 | 6 | 1126.37 | **1125.93** | 275 | 220 |
| Instance50-53 | 1567.77* | **1567.79** | **1567.79** | 60 | 21 | **1567.79** | **1567.79** | 401 | 354 |
| Instance50-54 | 1127.61* | **1127.66** | **1127.66** | 60 | 15 | **1127.66** | **1127.66** | 304 | 258 |
| Avg. | 1419.94 | 1420.05 | 1419.95 | 60 | 12 | 1423.46 | 1422.20 | 212 | 165 |

**Table 17**
Results and runtimes for Set 4b for the 2E-VRP by CG-ALNS.

| Instance | BKS | HCC | | | | BSHV | | | | CG-ALNS | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | Avg 5 | Best | T(seconds) | T*(seconds) | Avg. 5 | Best 5 | T(seconds) | T*(seconds) | Avg.5 | Best 5 | T(seconds) | T*(seconds) |
| Instance50-1 | 1569.42* | **1569.42** | **1569.42** | 235 | 6 | **1569.42** | **1569.42** | 60 | 15 | **1569.42** | **1569.42** | 131 | 84 |
| Instance50-2 | 1438.33* | 1441.02 | **1438.33** | 155 | 43 | **1438.32** | **1438.32** | 60 | 6 | 1444.33 | 1444.33 | 151 | 71 |
| Instance50-3 | 1570.43* | **1570.43** | **1570.43** | 183 | 3 | **1570.43** | **1570.43** | 60 | 7 | **1570.43** | **1570.43** | 74 | 50 |
| Instance50-4 | 1424.04* | **1424.04** | **1424.04** | 130 | 11 | **1424.04** | **1424.04** | 60 | 7 | **1424.04** | **1424.04** | 94 | 50 |
| Instance50-5 | 2193.52* | **2194.11** | **2194.11** | 614 | 63 | **2193.52** | **2193.52** | 60 | 18 | 2199.11 | 2195.26 | 83 | 53 |
| Instance50-6 | 1279.87* | **1279.87** | **1279.87** | 99 | 2 | **1279.89** | **1279.89** | 60 | 0 | **1279.87** | **1279.87** | 119 | 86 |
| Instance50-7 | 1408.57* | 1458.63 | 1458.63 | 169 | 6 | **1408.58** | **1408.58** | 60 | 17 | 1454.17 | 1446.00 | 125 | 72 |
| Instance50-8 | 1360.32* | **1360.32** | **1360.32** | 205 | 5 | **1360.32** | **1360.32** | 60 | 8 | **1360.77** | **1360.32** | 129 | 82 |
| Instance50-9 | 1403.53* | 1450.27 | 1450.27 | 204 | 46 | **1403.53** | **1403.53** | 60 | 11 | 1447.84 | 1409.00 | 84 | 62 |
| Instance50-10 | 1360.56* | **1360.56** | **1360.56** | 174 | 1 | **1360.54** | **1360.54** | 60 | 1 | **1360.56** | **1360.56** | 176 | 127 |
| Instance50-11 | 2047.46* | 2059.88 | 2059.88 | 648 | 101 | 2054.60 | **2047.43** | 60 | 2 | 2054.42 | 2050.00 | 109 | 73 |
| Instance50-12 | 1209.42* | **1209.42** | **1209.42** | 205 | 44 | **1209.46** | **1209.46** | 60 | 20 | **1209.42** | **1209.42** | 71 | 51 |
| Instance50-13 | 1450.93* | 1481.83 | 1481.83 | 220 | 25 | **1450.95** | **1450.94** | 60 | 10 | 1468.32 | 1459.94 | 54 | 34 |
| Instance50-14 | 1393.61* | **1393.61** | **1393.61** | 189 | 6 | **1393.64** | **1393.64** | 60 | 3 | **1393.61** | **1393.61** | 116 | 76 |
| Instance50-15 | 1446.83* | 1489.94 | 1489.94 | 173 | 9 | **1466.84** | **1466.84** | 60 | 2 | 1468.01 | **1466.83** | 86 | 55 |
| Instance50-16 | 1387.83* | **1387.83** | **1387.83** | 147 | 6 | **1387.85** | **1387.85** | 60 | 12 | **1388.46** | **1388.14** | 162 | 131 |
| Instance50-17 | 2088.49* | **2088.49** | **2088.49** | 625 | 165 | **2088.48** | **2088.48** | 60 | 13 | **2088.49** | **2088.49** | 87 | 59 |
| Instance50-18 | 1227.61* | **1227.61** | **1227.61** | 94 | 3 | **1227.68** | **1227.68** | 60 | 5 | **1227.81** | **1227.73** | 91 | 67 |
| Instance50-19 | 1546.28* | **1546.28** | **1546.28** | 171 | 25 | **1546.28** | **1546.28** | 60 | 34 | **1546.28** | **1546.28** | 150 | 117 |
| Instance50-20 | 1272.97* | **1272.97** | **1272.97** | 99 | 12 | **1272.98** | **1272.98** | 60 | 11 | **1272.97** | **1272.97** | 229 | 174 |
| Instance50-21 | 1577.82* | **1577.82** | **1577.82** | 155 | 61 | **1577.82** | **1577.82** | 60 | 16 | **1577.82** | **1577.82** | 91 | 52 |
| Instance50-22 | 1281.83* | **1281.83** | **1281.83** | 127 | 2 | **1281.83** | **1281.83** | 60 | 4 | **1281.83** | **1281.82** | 185 | 132 |
| Instance50-23 | 1652.98* | **1652.98** | **1652.98** | 175 | 5 | **1652.98** | **1652.98** | 60 | 4 | **1652.98** | **1652.98** | 241 | 197 |
| Instance50-24 | 1282.68* | **1282.68** | **1282.68** | 110 | 2 | **1282.69** | **1282.69** | 60 | 1 | **1282.68** | **1282.68** | 132 | 84 |
| Instance50-25 | 1408.57* | 1440.84 | 1440.68 | 154 | 53 | **1408.58** | **1408.58** | 60 | 20 | 1447.98 | 1440.50 | 95 | 59 |
| Instance50-26 | 1167.46* | **1167.46** | **1167.46** | 96 | 0 | **1167.47** | **1167.47** | 60 | 16 | **1167.46** | **1167.46** | 103 | 76 |
| Instance50-27 | 1444.50* | 1447.79 | **1444.50** | 163 | 12 | **1444.49** | **1444.49** | 60 | 20 | **1445.79** | **1445.57** | 154 | 109 |
| Instance50-28 | 1210.44* | **1210.44** | **1210.44** | 143 | 7 | **1210.46** | **1210.46** | 60 | 6 | **1210.44** | **1210.44** | 142 | 105 |
| Instance50-29 | 1552.66* | 1561.81 | 1559.82 | 178 | 102 | **1552.66** | **1552.66** | 60 | 39 | 1563.82 | **1552.66** | 487 | 320 |
| Instance50-30 | 1211.59* | **1211.59** | **1211.59** | 132 | 5 | **1211.63** | **1211.63** | 60 | 5 | **1212.40** | **1212.40** | 135 | 94 |
| Instance50-31 | 1440.86* | **1440.86** | **1440.86** | 144 | 37 | **1440.85** | **1440.85** | 60 | 15 | **1440.86** | **1440.86** | 115 | 76 |
| Instance50-32 | 1199.00* | **1199.00** | **1199.00** | 102 | 11 | **1199.05** | **1199.05** | 60 | 21 | **1199.13** | **1199.00** | 121 | 89 |
| Instance50-33 | 1478.86* | **1478.86** | **1478.86** | 159 | 16 | **1478.87** | **1478.87** | 60 | 15 | **1478.86** | **1478.86** | 165 | 139 |
| Instance50-34 | 1233.92* | **1233.92** | **1233.92** | 93 | 4 | **1233.96** | **1233.96** | 60 | 11 | **1233.92** | **1233.92** | 201 | 172 |
| Instance50-35 | 1570.72* | **1570.80** | **1570.72** | 182 | 116 | **1570.73** | **1570.73** | 60 | 10 | **1570.72** | **1570.72** | 131 | 99 |
| Instance50-36 | 1228.89* | **1228.89** | **1228.89** | 123 | 6 | **1228.95** | **1228.95** | 60 | 6 | 1235.10 | 1231.72 | 143 | 98 |
| Instance50-37 | 1528.73 | **1528.81** | **1528.73** | 143 | 55 | **1528.73** | **1528.73** | 60 | 27 | **1528.73** | **1528.73** | 276 | 218 |
| Instance50-38 | 1163.07* | **1163.07** | **1163.07** | 88 | 15 | **1163.07** | **1163.07** | 60 | 17 | **1163.07** | **1163.07** | 222 | 190 |
| Instance50-39 | 1520.92* | **1520.92** | **1520.92** | 158 | 33 | **1520.92** | **1520.92** | 60 | 25 | **1520.95** | **1520.92** | 399 | 243 |
| Instance50-40 | 1163.04* | 1165.24 | **1163.04** | 84 | 20 | **1163.04** | **1163.04** | 60 | 5 | 1168.04 | 1168.04 | 357 | 208 |
| Instance50-41 | 1652.98* | **1652.98** | **1652.98** | 150 | 12 | **1652.98** | **1652.98** | 60 | 14 | **1652.98** | **1652.98** | 624 | 469 |
| Instance50-42 | 1190.17* | **1190.17** | **1190.17** | 95 | 31 | **1190.17** | **1190.17** | 60 | 9 | **1190.90** | **1190.49** | 324 | 167 |
| Instance50-43 | 1406.11* | 1408.95 | **1406.11** | 151 | 60 | 1407.09 | **1406.10** | 60 | 13 | 1414.11 | 1413.38 | 291 | 151 |
| Instance50-44 | 1035.03* | **1035.32** | **1035.03** | 109 | 30 | **1035.05** | **1035.05** | 60 | 42 | **1036.98** | **1036.25** | 278 | 181 |
| Instance50-45 | 1401.87* | 1406.43 | 1403.10 | 144 | 104 | **1401.87** | **1401.87** | 60 | 21 | 1413.19 | 1405.19 | 384 | 296 |

(*continued on next page*)

**Table 17** (*continued*)

| Instance | BKS | HCC | | | | BSHV | | | | CG-ALNS | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | Avg 5 | Best | T(seconds) | T*(seconds) | Avg. 5 | Best 5 | T(seconds) | T*(seconds) | Avg.5 | Best 5 | T(seconds) | T*(seconds) |
| Instance50-46 | 1058.11* | 1058.97 | **1058.11** | 74 | 17 | **1058.10** | **1058.10** | 60 | 16 | 1063.11 | **1058.29** | 345 | 255 |
| Instance50-47 | 1552.66* | 1564.41 | 1559.82 | 185 | 103 | **1552.66** | **1552.66** | 60 | 24 | 1558.48 | **1553.48** | 466 | 370 |
| Instance50-48 | 1074.50* | **1074.50** | **1074.50** | 83 | 2 | **1074.51** | **1074.51** | 60 | 4 | **1074.50** | **1074.50** | 237 | 104 |
| Instance50-49 | 1434.88 | **1435.28** | **1434.88** | 140 | 81 | **1434.88** | **1434.88** | 60 | 9 | 1438.62 | **1434.88** | 152 | 101 |
| Instance50-50 | 1065.25* | **1065.25** | **1065.25** | 92 | 16 | **1065.30** | **1065.30** | 60 | 33 | **1065.25** | **1065.25** | 160 | 125 |
| Instance50-51 | 1387.51* | **1387.72** | **1387.51** | 138 | 46 | **1387.51** | **1387.51** | 60 | 19 | 1391.07 | **1388.06** | 322 | 203 |
| Instance50-52 | 1103.42* | **1103.76** | **1103.42** | 102 | 47 | **1103.47** | **1103.47** | 60 | 17 | **1104.31** | **1103.42** | 376 | 301 |
| Instance50-53 | 1545.73* | **1545.73** | **1545.73** | 148 | 37 | **1545.76** | **1545.76** | 60 | 21 | **1545.73** | **1545.73** | 320 | 287 |
| Instance50-54 | 1113.62* | **1113.62** | **1113.62** | 90 | 2 | **1113.66** | **1113.66** | 60 | 5 | **1113.17** | **1113.17** | 266 | 150 |
| Avg. | 1397.04 | 1401.39 | 1400.96 | 169.43 | 32.07 | 1397.21 | 1397.06 | 60.00 | 13.56 | 1401.36 | 1399.22 | 199 | 139 |

**Table 18**
Results and runtimes for Set 5 for the 2E-VRP by CG-ALNS.

| Instance | BKS | HCC | | | | BSHV | | | | CG-ALNS | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | Avg. 5 | Best | T(seconds) | T*(seconds) | Avg. 5 | Best 5 | T(seconds) | T*(seconds) | Avg. 5 | Best 5 | T(seconds) | T*(seconds) |
| 100-5-1 | 1564.46* | 1588.73 | 1565.45 | 353 | 116 | 1566.87 | **1564.46** | 900 | 201 | 1572.35 | 1570.97 | 1699 | 1302 |
| 100-5-1b | 1108.62 | 1126.93 | 1111.34 | 397 | 45 | 1111.93 | **1108.62** | 900 | 176 | 1111.99 | **1108.65** | 2305 | 1981 |
| 100-5-2 | 1016.32* | 1022.29 | **1016.32** | 406 | 117 | 1017.94 | **1016.32** | 900 | 75 | 1023.56 | **1017.33** | 2346 | 865 |
| 100-5-2b | 782.25 | 789.05 | **782.25** | 340 | 170 | 783.07 | **782.25** | 900 | 152 | 794.44 | **782.67** | 1289 | 921 |
| 100-5-3 | 1045.29* | 1046.67 | **1045.29** | 352 | 80 | **1045.29** | **1045.29** | 900 | 131 | 1046.67 | **1045.29** | 1796 | 1025 |
| 100-5-3b | 828.54 | 828.99 | 828.99 | 391 | 127 | **828.54** | **828.54** | 900 | 62 | 834.30 | 834.21 | 1777 | 821 |
| 100-10-1 | 1124.93 | 1137.00 | 1130.23 | 429 | 136 | 1132.11 | 1124.93 | 900 | 567 | 1139.21 | 1127.04 | 10382 | 9912 |
| 100-10-1b | 916.25 | 928.01 | 916.48 | 476 | 262 | 922.85 | **916.25** | 900 | 424 | 925.35 | **916.22** | 11142 | 9563 |
| 100-10-2 | 990.58 | 1009.49 | **990.58** | 356 | 232 | 1014.61 | 1002.15 | 900 | 471 | 1011.42 | 997.82 | 12056 | 10314 |
| 100-10-2b | 786.61 | 773.58 | **768.61** | 432 | 157 | 786.64 | 774.11 | 900 | 416 | 769.26 | **768.61** | 5962 | 4392 |
| 100-10-3 | 1043.25 | 1055.28 | **1043.25** | 415 | 209 | 1053.55 | 1048.53 | 900 | 105 | 1056.22 | 1047.74 | 15746 | 10247 |
| 100-10-3b | 850.92 | 861.88 | **850.92** | 418 | 29 | 858.72 | 854.90 | 900 | 175 | 866.10 | 851.36 | 6559 | 5923 |
| 200-10-1 | 1556.79 | 1626.83 | 1574.12 | 888 | 207 | 1598.46 | **1556.79** | 900 | 730 | 1586.43 | 1585.08 | 3177 | 2821 |
| 200-10-1b | 1187.62 | 1239.79 | 1201.75 | 692 | 374 | 1217.23 | **1187.62** | 900 | 588 | 1221.25 | 1206.32 | 12943 | 9328 |
| 200-10-2 | 1365.74 | 1416.87 | 1374.74 | 1072 | 496 | 1406.16 | **1365.74** | 900 | 534 | 1407.88 | 1383.12 | 19832 | 15320 |
| 200-10-2b | 1002.85 | 1018.57 | 1003.75 | 1058 | 221 | 1016.05 | **1002.85** | 900 | 721 | 1014.50 | **1002.84** | 28240 | 23318 |
| 200-10-3 | 1787.73 | 1808.24 | **1787.73** | 916 | 305 | 1809.44 | 1793.99 | 900 | 675 | 1811.99 | 1803.77 | 13021 | 10044 |
| 200-10-3b | 1197.90 | 1208.38 | 1200.74 | 1217 | 478 | 1206.85 | **1197.90** | 900 | 523 | 1215.76 | 1209.02 | 10932 | 7361 |
| Avg. | 1118.81 | 1138.14 | 1121.81 | 589.33 | 208.94 | 1132.02 | 1120.62 | 900 | 373.7 | 1133.82 | 1125.45 | 8955.78 | 6969.89 |

**Table 19**
Results and runtimes for Set 6a for the 2E-VRP by CG-ALNS.

| Instance | BKS | BSHV | | | | CG-ALNS | | | |
|---|---|---|---|---|---|---|---|---|---|
| | | Avg. 5 | Best 5 | T(seconds) | T*(seconds) | Avg.5 | Best 5 | T(seconds) | T*(seconds) |
| A-n51-4 | 652.00 | **652.00** | **652.00** | 60 | 19 | **652.00** | **652.00** | 214 | 181 |
| A-n51-5 | 663.41 | **663.41** | **663.41** | 60 | 37 | **663.41** | **663.41** | 163 | 147 |
| A-n51-6 | 662.51 | **662.51** | **662.51** | 60 | 23 | 674.28 | 674.28 | 185 | 156 |
| A-n76-4 | 985.95 | 985.98 | **985.95** | 900 | 128 | 993.17 | 993.17 | 459 | 382 |
| A-n76-5 | 979.15 | 981.19 | **979.15** | 900 | 286 | 982.64 | **979.15** | 373 | 322 |
| A-n76-6 | 970.20 | 971.65 | **970.20** | 900 | 233 | 974.32 | **970.20** | 506 | 474 |
| A-n101-4 | 1194.17 | 1194.38 | **1194.17** | 900 | 267 | 1221.61 | 1215.05 | 1267 | 1105 |
| A-n101-5 | 1211.40 | 1215.89 | 1211.40 | 900 | 414 | 1231.38 | 1228.64 | 1526 | 1372 |
| A-n101-6 | 1155.96 | 1161.91 | **1155.97** | 900 | 154 | 1174.23 | 1170.48 | 1352 | 1136 |
| B-n51-4 | 563.98 | **563.98** | **563.98** | 60 | 6 | 567.84 | 567.84 | 217 | 184 |
| B-n51-5 | 549.23 | **549.23** | **549.23** | 60 | 55 | **549.23** | **549.23** | 172 | 160 |
| B-n51-6 | 556.32 | **556.32** | **556.32** | 60 | 39 | **556.32** | **556.32** | 249 | 213 |
| B-n76-4 | 792.73 | **793.97** | **792.73** | 900 | 320 | 805.15 | 802.27 | 345 | 284 |
| B-n76-5 | 784.19 | **784.27** | **784.19** | 900 | 190 | 790.81 | 788.49 | 273 | 249 |
| B-n76-6 | 774.17 | 775.75 | **774.17** | 900 | 160 | 799.72 | 792.34 | 406 | 353 |
| B-n101-4 | 939.21 | **939.79** | **939.21** | 900 | 377 | 1048.35 | 1044.91 | 1027 | 983 |
| B-n101-5 | 969.13 | 971.27 | 969.13 | 900 | 161 | 989.49 | 985.74 | 1335 | 1146 |
| B-n101-6 | 960.29 | 961.91 | **960.29** | 900 | 88 | 1290.4 | 1187.43 | 1293 | 1014 |
| C-n51-4 | 689.18 | **689.18** | **689.18** | 60 | 13 | **689.18** | **689.18** | 228 | 194 |
| C-n51-5 | 723.12 | **723.12** | **723.12** | 60 | 19 | **723.12** | **723.12** | 186 | 154 |
| C-n51-6 | 697.00 | **697.00** | **697.00** | 60 | 46 | **697.00** | **697.00** | 272 | 249 |
| C-n76-4 | 1054.89 | 1055.61 | **1054.89** | 900 | 339 | 1140.62 | 1132.47 | 436 | 370 |
| C-n76-5 | 1115.32 | **1115.32** | **1115.32** | 900 | 113 | 1182.44 | 1176.61 | 517 | 489 |
| C-n76-6 | 1060.52 | 1066.88 | **1060.52** | 900 | 474 | 1178.21 | 1173.35 | 450 | 428 |
| C-n101-4 | 1302.16 | 1305.94 | **1302.16** | 900 | 236 | 1369.77 | 1364.43 | 1425 | 1362 |
| C-n101-5 | 1305.82 | 1307.24 | **1305.82** | 900 | 141 | 1391.92 | 1382.40 | 1604 | 1341 |
| C-n101-6 | 1284.48 | 1292.1 | **1284.48** | 900 | 446 | 1342.38 | 1337.62 | 1499 | 1247 |
| Avg. | 910.98 | 912.51 | 910.98 | 620 | 177 | 951.07 | 944.34 | 665.89 | 581.30 |

**Table 20**
Results and runtimes for Set 6b for the 2E-VRP by CG-ALNS.

| Instance | BKS | BSHV | | | | CG-ALNS | | | |
|---|---|---|---|---|---|---|---|---|---|
| | | Avg. 5 | Best 5 | T(seconds) | T*(seconds) | Avg.5 | Best 5 | T(seconds) | T*(seconds) |
| A-n51-4 | 744.24 | **744.24** | **744.24** | 60 | 17 | **744.24** | **744.24** | 237 | 186 |
| A-n51-5 | 811.52 | **811.51** | **811.51** | 60 | 49 | **811.51** | **811.51** | 301 | 266 |
| A-n51-6 | 930.11 | **930.11** | **930.11** | 60 | 31 | 932.58 | 932.58 | 259 | 212 |
| A-n76-4 | 1385.51 | **1385.51** | **1385.51** | 900 | 26 | 1395.39 | 1395.39 | 475 | 418 |
| A-n76-5 | 1519.86 | **1519.86** | **1519.86** | 900 | 71 | **1519.86** | **1519.86** | 334 | 294 |
| A-n76-6 | 1666.06 | 1666.28 | **1666.06** | 900 | 533 | 1671.44 | 1671.44 | 512 | 483 |
| A-n101-4 | 1881.44 | 1884.48 | 1883.79 | 900 | 283 | 1930.20 | 1924.30 | 1173 | 962 |
| A-n101-5 | 1709.06 | 1723.06 | 1711.95 | 900 | 318 | 1738.19 | 1734.86 | 1329 | 1184 |
| A-n101-6 | 1777.69 | 1795.36 | 1791.44 | 900 | 100 | 1885.17 | 1880.63 | 1281 | 1094 |
| B-n51-4 | 653.09 | **653.09** | **653.09** | 60 | 21 | **653.09** | **653.09** | 322 | 261 |
| B-n51-5 | 672.10 | **672.10** | **672.10** | 60 | 51 | 677.65 | 677.65 | 278 | 262 |
| B-n51-6 | 767.13 | **767.13** | **767.13** | 60 | 58 | **767.13** | **767.13** | 426 | 385 |
| B-n76-4 | 1094.52 | **1094.52** | **1094.52** | 900 | 44 | **1094.52** | **1094.52** | 474 | 451 |
| B-n76-5 | 1218.13 | **1218.12** | **1218.12** | 900 | 19 | 1224.74 | 1224.74 | 393 | 314 |
| B-n76-6 | 1326.76 | 1328.90 | **1326.76** | 900 | 329 | 1333.05 | 1331.12 | 376 | 331 |
| B-n101-4 | 1500.55 | 1500.80 | **1500.55** | 900 | 82 | 1520.58 | 1516.41 | 1441 | 1254 |
| B-n101-5 | 1395.32 | 1398.05 | **1395.32** | 900 | 317 | 1417.25 | 1410.40 | 1273 | 1006 |
| B-n101-6 | 1450.39 | 1455.05 | 1453.54 | 900 | 460 | 1478.75 | 1471.29 | 1214 | 1113 |
| C-n51-4 | 866.58 | **866.58** | **866.58** | 60 | 22 | **866.58** | **866.58** | 268 | 232 |
| C-n51-5 | 943.12 | **943.12** | **943.12** | 60 | 12 | **943.12** | **943.12** | 482 | 411 |
| C-n51-6 | 1050.42 | **1050.42** | **1050.42** | 60 | 18 | 1066.71 | 1066.71 | 352 | 287 |
| C-n76-4 | 1438.96 | 1439.39 | **1438.96** | 900 | 84 | 1441.22 | 1441.22 | 652 | 436 |
| C-n76-5 | 1745.39 | 1745.49 | **1745.39** | 900 | 281 | 1750.29 | 1748.18 | 584 | 462 |
| C-n76-6 | 1756.54 | 1759.40 | **1756.54** | 900 | 358 | 1761.62 | 1761.62 | 779 | 621 |
| C-n101-4 | 2064.86 | 2076.36 | **2064.86** | 900 | 378 | 2081.68 | 2070.44 | 1489 | 1105 |
| C-n101-5 | 1964.63 | 1974.39 | **1964.63** | 900 | 285 | 1983.36 | 1975.11 | 1266 | 965 |
| C-n101-6 | 1861.50 | 1867.45 | **1861.50** | 900 | 401 | 1877.14 | 1872.42 | 1524 | 1018 |
| Avg. | 1340.57 | 1343.36 | 1341.39 | 620 | 172.1 | 1354.34 | 1352.09 | 722 | 593.07 |

**Table 21**
Sensitivity analysis of battery driving range and emission reduction efficiency (ERE).

| Instance | $B^1$ | $B^2$ | $n_{b^1}$ | $n_{b^2}$ | $n_{k^1}$ | $n_{k^2}$ | $L^1$ | $L^2$ | Obj. | ERE | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | | | | | | | | *NOx* | Particulate emission |
| E-n51-k5-s4-46 | −10% | 0% | 3 | 4 | 3 | 6 | 65.12 | 128.86 | 728.49 | 0.0642 | 1.7605 |
| | 0% | −10% | 2 | 4 | 2 | 5 | 119.42 | 118.13 | 719.10 | 0.0611 | 1.6769 |
| | 0% | 0% | 2 | 4 | 2 | 5 | 119.42 | 124.10 | 713.41 | 0.0593 | 1.6262 |
| | 10% | 0% | 2 | 4 | 2 | 5 | 119.42 | 146.38 | 707.59 | 0.0574 | 1.5744 |
| | 0% | 10% | 2 | 2 | 2 | 5 | 65.12 | 122.43 | 675.93 | 0.0471 | 1.2925 |
| E-n51-k5-s6-12 | −10% | 0% | 2 | 3 | 2 | 5 | 24.08 | 136.38 | 598.20 | 0.0137 | 0.4027 |
| | 0% | −10% | 2 | 5 | 2 | 6 | 28.28 | 116.78 | 592.81 | 0.0120 | 0.3526 |
| | 0% | 0% | 2 | 3 | 2 | 5 | 24.08 | 124.54 | 587.49 | 0.0103 | 0.3033 |
| | 10% | 0% | 2 | 3 | 3 | 5 | 24.08 | 151.25 | 579.19 | 0.0077 | 0.2263 |
| | 0% | 10% | 2 | 2 | 3 | 5 | 28.28 | 117.46 | 582.42 | 0.0087 | 0.2563 |
| E-n51-k5-s6-12-32-37 | −10% | 0% | 2 | 3 | 2 | 5 | 24.08 | 136.38 | 589.58 | 0.0192 | 0.6315 |
| | 0% | −10% | 2 | 4 | 3 | 5 | 59.67 | 117.31 | 607.60 | 0.0252 | 0.8287 |
| | 0% | 0% | 2 | 3 | 2 | 5 | 24.08 | 151.25 | 588.80 | 0.0189 | 0.6229 |
| | 10% | 0% | 1 | 3 | 3 | 5 | 28.28 | 117.46 | 582.42 | 0.0168 | 0.5530 |
| | 0% | 10% | 2 | 3 | 2 | 5 | 24.08 | 120.87 | 581.64 | 0.0165 | 0.5444 |
| E-n51-k5-s11-19-27-47 | −10% | 0% | 2 | 3 | 3 | 5 | 29.53 | 109.56 | 547.11 | 0.0065 | 0.2177 |
| | 0% | −10% | 2 | 4 | 3 | 5 | 29.53 | 109.33 | 548.16 | 0.0069 | 0.2295 |
| | 0% | 0% | 2 | 3 | 3 | 5 | 29.53 | 119.98 | 540.74 | 0.0044 | 0.1465 |
| | 10% | 0% | 0 | 3 | 2 | 5 | 4.47 | 119.98 | 539.34 | 0.0039 | 0.1309 |
| | 0% | 10% | 2 | 3 | 3 | 5 | 29.53 | 119.98 | 539.14 | 0.0039 | 0.1287 |

compare the cost between using EVs and using traditional vehicles. In addition, Table 21 show that the value of ERE decreases with increasing battery driving range of both echelons. Therefore, logistics enterprises could evaluate their green vehicles plan for two echelon city logistics according to this indicator ERE obtained from our problem.

## 6. Conclusion and future work

In this paper, we presented the 2E-EVRP-BSS that considers the limited battery driving ranges and the battery swapping strategy at available BSSs. Furthermore, vehicle capacity constraints were also incorporated into the 2E-EVRP-BSS model to represent real-world requirements. We developed a hybrid CG-ALNS heuristic that uses the strong accuracy effect of CG and involves an ALNS heuristic to efficiently search a large neighborhood. To assess the performance of the proposed solution approach, we conducted experiments on the basis of the benchmark instances of the literature. We demonstrated the strong performance of our algorithm by computational experiments on newly designed 2E-EVRP-BSS instances. The quality of our method was further substantiated by very convincing results on test instances of the related problem of the 2E-VRP. Finally, in the economic analysis, we performed several experiments to highlight the managerial implications of the interplay between battery driving ranges and the efficiency of vehicle emission reduction.

Our manuscript did not consider all realistic situations in the problem. Future work should extend the 2E-EVRP-BSS model by considering the battery recharging time and customer service time window. The capacity limitation of satellites and BSSs should be incorporated also into the 2E-EVRP-BSS.

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## Appendix A.1

In the two tables, “Call” presents the number of times an operator has been used, “Weight” presents the average value of the final weight of each operator, the column “Filename” presents the names of the corresponding instances, and column “Avg.” denotes the average value of each instance. The results better than the average value are marked in bold, and was selected for the following computational experiments.

**Table A.1**
Sensitivity analysis of the removal operators.

| Param. | Filename | BPRR | RCR | ReCR | BCBR | SO | SS | BBUR | BCRR | RRR | SR | Avg. |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Call | E-n22-k4-s10-14 | **20018** | 19963 | **20052** | **20038** | **20062** | **20081** | 18878 | **20111** | 19703 | **21094** | 20000 |
| | E-n22-k4-s11-12 | **20037** | **20112** | 19718 | **20137** | 19974 | 19964 | **20021** | **20036** | 19918 | **20083** | 20000 |
| | E-n22-k4-s12-16 | **20050** | **20104** | 19786 | **20204** | **20028** | 19840 | **21025** | **20087** | 18849 | **20027** | 20000 |
| | E-n22-k4-s6-17 | **20140** | **20259** | **20067** | **20130** | **20082** | **20013** | **20007** | **20067** | 19205 | **20030** | 20000 |
| | E-n22-k4-s8-14 | **20027** | **20126** | **20061** | **20039** | 18971 | **20056** | 19970 | **21021** | 19714 | **20015** | 20000 |
| | E-n22-k4-s9-19 | **20054** | **20149** | 19852 | **20231** | **21009** | 18870 | **20140** | **20047** | 19560 | **20088** | 20000 |
| | E-n33-k4-s1-9 | **20271** | **21112** | 18794 | **20222** | **20016** | 19814 | **20088** | **20163** | 19677 | 19843 | 20000 |
| | E-n33-k4-s14-22 | **20273** | **20262** | 19476 | **20241** | **20125** | 19592 | **20085** | **20090** | 19551 | **20305** | 20000 |
| | E-n33-k4-s2-13 | **20168** | **20189** | 19924 | **20185** | **20014** | 19892 | **20061** | **20106** | 19275 | **20186** | 20000 |
| | E-n33-k4-s3-17 | **21283** | **20161** | 19831 | **20262** | **20019** | 18610 | **20049** | **20019** | 19630 | **20136** | 20000 |
| | E-n33-k4-s4-5 | **20150** | **20172** | 19795 | **20297** | 19992 | 19941 | 19927 | **20140** | 19516 | **20070** | 20000 |
| | E-n33-k4-s7-25 | **20189** | **20130** | 19697 | **20255** | **20234** | 19706 | 19887 | **20091** | 19524 | **20287** | 20000 |
| | E-n51-k5-s11-19-27-47 | **20081** | **20094** | 19859 | 19995 | **20084** | 19769 | **20131** | **20301** | 19698 | 19988 | 20000 |
| | E-n51-k5-s11-19 | **20342** | **20289** | 19476 | **21362** | **20058** | 18463 | **20102** | **20133** | 19636 | **20139** | 20000 |
| | E-n51-k5-s2-1 | **20094** | **20114** | 19622 | **20160** | **20050** | 19681 | **20204** | **20164** | 19929 | 19982 | 20000 |
| | E-n51-k5-s2-4-17-46 | **21184** | **20070** | 19743 | **20264** | **20020** | 18731 | **20043** | **20148** | 19703 | **20094** | 20000 |
| | E-n51-k5-s27-47 | **20329** | **20274** | 19434 | **20316** | **20146** | 19431 | **20096** | **20339** | 18533 | **21102** | 20000 |
| | E-n51-k5-s32-37 | **20409** | **20131** | 19316 | **20345** | **21185** | 19273 | **20193** | **20229** | 18537 | **20382** | 20000 |
| | E-n51-k5-s4-46 | **20437** | **21159** | 18578 | **20171** | **20038** | 19626 | **20039** | **20162** | 19647 | **20143** | 20000 |
| | E-n51-k5-s6-12-32-37 | **20219** | **20099** | 19860 | **20202** | **20155** | 19527 | **20103** | **20139** | 19826 | 19870 | 20000 |
| | E-n51-k5-s6-12 | **20179** | **20036** | 19576 | **20239** | **20053** | 19525 | **20096** | **20116** | **20050** | **20130** | 20000 |
| Weight | E-n22-k4-s10-14 | **11.53** | 10.72 | **13.08** | 11.14 | **11.19** | **13.06** | **11.31** | 10.15 | 8.09 | 11.40 | 11.17 |
| | E-n22-k4-s11-12 | 11.14 | **12.13** | 9.56 | **12.27** | 9.86 | 9.70 | 10.79 | **13.78** | **11.79** | 10.97 | 11.20 |
| | E-n22-k4-s12-16 | **11.15** | **11.83** | 7.79 | **11.93** | **11.30** | 6.95 | **10.14** | **10.87** | 6.07 | **10.43** | 9.85 |
| | E-n22-k4-s6-17 | **11.56** | **11.75** | **10.20** | **10.64** | **11.64** | 9.10 | 9.05 | **11.92** | 0.00 | **10.34** | 9.62 |
| | E-n22-k4-s8-14 | **10.48** | **12.12** | **10.66** | **11.54** | **10.96** | 9.40 | **10.95** | **11.33** | 7.85 | **10.89** | 10.62 |
| | E-n22-k4-s9-19 | **11.18** | **12.01** | 8.71 | **13.59** | **11.43** | 9.99 | **11.51** | **12.79** | 5.56 | **11.35** | 10.81 |
| | E-n33-k4-s1-9 | **12.69** | **11.95** | 8.82 | **13.67** | **10.60** | 7.71 | **12.46** | **11.59** | 3.18 | **10.85** | 10.35 |
| | E-n33-k4-s14-22 | **14.43** | **12.32** | 3.37 | **12.98** | **11.66** | 7.99 | **11.62** | **13.97** | 6.87 | **13.11** | 10.83 |
| | E-n33-k4-s2-13 | **12.74** | **12.84** | 7.76 | **12.21** | **11.19** | 5.51 | **9.98** | **14.02** | 0.00 | **12.33** | 9.86 |
| | E-n33-k4-s3-17 | **13.47** | **12.24** | 6.50 | **14.12** | **12.03** | 9.37 | 7.95 | **12.15** | 5.47 | **11.24** | 10.45 |
| | E-n33-k4-s4-5 | **12.59** | **13.66** | 6.88 | **13.55** | **11.83** | 10.44 | **10.93** | **14.09** | 2.28 | **13.14** | 10.94 |
| | E-n33-k4-s7-25 | **10.64** | **9.48** | **9.18** | **12.17** | **11.31** | 4.61 | 7.44 | **11.77** | 1.17 | **11.76** | 8.95 |
| | E-n51-k5-s11-19-27-47 | **14.09** | **12.01** | 8.43 | **14.84** | **12.11** | 6.55 | **12.46** | **16.08** | 8.23 | **12.04** | 11.68 |
| | E-n51-k5-s11-19 | **15.02** | **12.98** | 3.99 | **14.89** | **13.03** | 2.11 | **13.01** | **12.92** | 3.91 | **14.49** | 10.64 |
| | E-n51-k5-s2-17 | **14.83** | **13.21** | 2.20 | **14.09** | **11.25** | 5.39 | **15.23** | **15.23** | 8.19 | **12.45** | 11.21 |
| | E-n51-k5-s2-4-17-46 | **15.91** | **12.79** | 9.18 | **15.72** | 11.43 | 7.38 | **13.74** | **12.87** | 7.77 | **14.20** | 12.10 |
| | E-n51-k5-s27-47 | **14.12** | **12.43** | 3.99 | **14.41** | **11.93** | 2.34 | **12.50** | **12.88** | 2.93 | **12.36** | 9.99 |
| | E-n51-k5-s32-37 | **14.07** | **10.87** | 0.00 | **13.92** | **11.73** | 0.00 | **11.92** | **12.69** | 3.80 | **13.23** | 9.22 |
| | E-n51-k5-s4-46 | **16.69** | **14.56** | 3.48 | **13.49** | **11.12** | 6.72 | **13.95** | **13.31** | 4.33 | **11.91** | 10.96 |
| | E-n51-k5-s6-12-32-37 | **16.60** | **13.29** | 9.22 | **15.38** | **13.28** | 5.69 | **15.26** | **13.75** | 6.22 | **12.05** | 12.07 |
| | E-n51-k5-s6-12s | **14.03** | **11.72** | 4.12 | **14.86** | **13.01** | 4.62 | **14.69** | **13.05** | **11.24** | **14.00** | 11.53 |

**Table A.2**
Sensitivity analysis of the insertion operators.

| Param. | Filename | BGI | BR2I | BR3I | BR4I | AGI | AR2I | AR3I | AR4I | Avg. |
|---|---|---|---|---|---|---|---|---|---|---|
| Call | E-n22-k4-s10-14 | 24241 | **25470** | **25102** | 24407 | **25026** | **25809** | **25108** | 24837 | 25000.00 |
| | E-n22-k4-s11-12 | **26117** | **25119** | 23902 | 24955 | 24928 | **25212** | 24917 | 24850 | 25000.00 |
| | E-n22-k4-s12-16 | **25038** | **25103** | **25113** | 24874 | 24988 | **25039** | **25019** | 24826 | 25000.00 |
| | E-n22-k4-s6-17 | **25106** | **25040** | **26001** | 23625 | **25137** | **25243** | **25073** | 24775 | 25000.00 |
| | E-n22-k4-s8-14 | **25109** | **25048** | **25048** | 24087 | **25813** | **25026** | **25050** | 24819 | 25000.00 |
| | E-n22-k4-s9-19 | **25090** | **25036** | **25031** | **25022** | 23993 | **25043** | **26022** | 24763 | 25000.00 |
| | E-n33-k4-s1-9 | **25038** | 24946 | **25019** | 24698 | **25109** | **25215** | 24936 | **25039** | 25000.00 |
| | E-n33-k4-s14-22 | **24972** | **25198** | **25189** | 24721 | **25139** | **25079** | **25023** | 24679 | 25000.00 |
| | E-n33-k4-s2-13 | **25012** | **25123** | **25132** | 24811 | **25021** | **25226** | **25088** | 24587 | 25000.00 |
| | E-n33-k4-s3-17 | **25243** | **25113** | **25178** | 24765 | **25014** | **25020** | **25066** | 24601 | 25000.00 |
| | E-n33-k4-s4-5 | 24194 | **25919** | **25189** | 24639 | **25117** | **25023** | **25198** | 24721 | 25000.00 |
| | E-n33-k4-s7-25 | **25028** | **25107** | 24740 | **25067** | **25152** | **25081** | **25064** | 24761 | 25000.00 |
| | E-n51-k5-s11-19-27-47 | **25289** | **25063** | **25144** | 24589 | **25003** | **25109** | **25191** | 24612 | 25000.00 |
| | E-n51-k5-s11-19 | **25002** | **25009** | **25029** | 24904 | **25055** | **25019** | **26011** | 23971 | 25000.00 |
| | E-n51-k5-s2-17 | **25099** | **25042** | **25010** | 24821 | **25147** | **25006** | 24809 | 25066 | 25000.00 |
| | E-n51-k5-s2-4-17-46 | **25107** | **25098** | **25076** | 23822 | **25097** | **26005** | **25050** | 24745 | 25000.00 |
| | E-n51-k5-s27-47 | **25010** | **25100** | **25004** | **26021** | **25051** | **25015** | **25050** | 23749 | 25000.00 |
| | E-n51-k5-s32-37 | **26096** | **25156** | **25050** | 24924 | **25047** | **25077** | **25027** | 23623 | 25000.00 |
| | E-n51-k5-s4-46 | **25016** | **25004** | **25821** | **25008** | **25019** | **25063** | **25064** | 24005 | 25000.00 |
| | E-n51-k5-s6-12-32-37 | **25193** | 24972 | 24884 | 24847 | **25065** | **25021** | **25295** | 24723 | 25000.00 |
| | E-n51-k5-s6-12 | 24824 | **26066** | **25053** | 24845 | 24925 | 23908 | **25354** | **25025** | 25000.00 |
| Weight | E-n22-k4-s10-14 | 10.12 | **12.25** | 10.59 | 10.11 | **12.63** | **12.77** | **12.12** | 7.23 | 10.98 |
| | E-n22-k4-s11-12 | **11.05** | **12.08** | 9.11 | 8.92 | 9.52 | **11.55** | 9.61 | 9.23 | 10.13 |
| | E-n22-k4-s12-16 | **11.72** | **11.31** | **12.13** | 10.37 | 10.33 | **12.35** | **11.45** | 5.82 | 10.69 |
| | E-n22-k4-s6-17 | **12.65** | **11.59** | **11.86** | 6.21 | **10.62** | **13.24** | 9.08 | 7.66 | 10.36 |
| | E-n22-k4-s8-14 | 9.56 | **11.85** | **10.71** | 8.24 | 8.79 | **11.90** | **10.34** | 9.32 | 10.09 |
| | E-n22-k4-s9-19 | **10.86** | **11.23** | 9.63 | 10.42 | **11.84** | **10.93** | **10.81** | 9.23 | 10.62 |
| | E-n33-k4-s1-9 | 9.67 | **11.64** | **11.07** | 9.83 | **10.98** | **12.27** | 10.34 | **11.61** | 10.93 |
| | E-n33-k4-s14-22 | **11.37** | **13.34** | **12.08** | 8.79 | 10.64 | **12.71** | **13.23** | 10.83 | 11.62 |
| | E-n33-k4-s2-13 | 9.89 | **13.51** | 9.92 | 8.02 | 8.87 | **13.36** | **10.28** | 7.86 | 10.21 |
| | E-n33-k4-s3-17 | **11.58** | **12.33** | **11.98** | 8.22 | **11.84** | **13.12** | **11.91** | **11.29** | 11.53 |
| | E-n33-k4-s4-5 | **10.87** | **14.02** | **13.41** | 6.85 | **11.59** | **10.84** | **11.07** | 6.76 | 10.68 |
| | E-n33-k4-s7-25 | **10.61** | **11.03** | **10.31** | **10.93** | 8.99 | **10.34** | 9.28 | 8.58 | 10.01 |
| | E-n51-k5-s11-19-27-47 | 8.46 | **12.26** | **13.65** | 7.97 | **11.47** | **11.50** | **13.59** | 9.34 | 11.03 |
| | E-n51-k5-s11-19 | **11.98** | **13.22** | **11.63** | 10.49 | **11.96** | 11.22 | **13.07** | 8.36 | 11.49 |
| | E-n51-k5-s2-17 | **12.03** | **13.15** | **12.59** | 9.37 | **13.28** | **14.54** | **12.54** | 9.74 | 12.16 |
| | E-n51-k5-s2-4-17-46 | **10.93** | **12.45** | **12.48** | 8.68 | 9.81 | **13.11** | **13.39** | 6.47 | 10.92 |
| | E-n51-k5-s27-47 | **11.85** | **12.37** | **12.29** | 11.37 | **12.41** | **11.56** | **13.32** | 6.51 | 11.46 |
| | E-n51-k5-s32-37 | **11.36** | **12.89** | **12.48** | 9.48 | 11.13 | **11.87** | **12.88** | 8.63 | 11.34 |
| | E-n51-k5-s4-46 | 10.24 | **12.73** | **12.53** | 8.86 | **12.32** | **12.02** | **11.56** | **11.76** | 11.50 |
| | E-n51-k5-s6-12-32-37 | 9.21 | **12.28** | **12.49** | 10.84 | **11.86** | **13.72** | **12.97** | 6.53 | 11.24 |
| | E-n51-k5-s6-12 | **12.63** | **13.06** | **13.19** | 7.86 | **13.71** | **13.56** | **13.76** | **12.97** | 12.59 |

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