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A Branch-and-Price Algorithm for a Green Two-Echelon Capacitated Location Routing Problem

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KEY WORDS: ***Two-echelon system; Electric vehicles; Location routing problem; Branch-and-price***

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Abstract

In this paper, we present a new green two-echelon capacitated location routing problem (G-2E-CLRP), which aims to determine simultaneous decisions on locating satellites and routing electric vehicles for city logistics delivery system. The first echelon consists of round trips from the depot to open satellites, the second echelon consists of tours from these satellites to the end customers, whereas battery swapping operations are only allowed at the depot or satellites. The problem is formulated as an arc-based formulation and then we propose a set-partitioning formulation in which routes are defined as second-echelon tours. We develop an branch-and-price (B&P) algorithm to solve this problem and propose a column generation procedure that combines modified Clarke Wright (MCW) savings method and pulse algorithm to provide feasible tours efficiently. The proposed algorithm is validated using extensive computational experiments and is found to perform well when compared against commercial branch-and-bound/cut solvers such as CPLEX. Based on these results, we assess the benefits of integrating locations of satellites and routes of electric vehicles in this new green two-echelon logistics system.

Keywords: Two-echelon system; Electric vehicles; Location routing problem; Branch-and-price

1 Introduction

Green logistics attempts to trade off economic and environmental efficiency in production and distribution processes. Recently, there is a trend to use electric vehicles (EVs) instead of conventional internal combustion engine vehicles in city logistics, since EVs can significantly reduce emissions of CO_2, NOx, and are quieter than conventional vehicles. Despite high acquisition costs, limited range and lengthy recharging, EVs are proving attractive for city logistics because they are quiet and generate no street-level emissions. For example, UPS (2018) continues to expand its use of electric vehicles and works with a wide array of manufacturers, DPDHL (2017) aims to double production of its electrically powered "StreetScooter" delivery vehicles by opening a second manufacturing plant in Germany, and FedEx (2019) also expands the size of its EV fleet to minimize environmental impacts.

The two-echelon distribution network is very relevant to the context of city logistics (Savelsbergh and Van Woensel (2016)), because of legal restrictions on the use of large trucks within the city centre and the convenience of sorting and consolidating freight before final deliveries. EVs require a two-echelon transport system, due to their limited driving ranges, posing new challenges to transport planning and routing. With current technology, battery-swapping (BS) is a promising option to recharging, which replaces the existing battery by a fully charged one in ten minutes (Li (2014) and Kim (2011)). It can improve the productivity of vehicles by mitigating disadvantages of recharging, like longer time and battery degradation. Furthermore, drivers can take a break during this time, and depleted batteries can be charged during off-peak hours with a discounted electricity price (Jie et al. (2019)). Therefore, EVs in two echelons which swap their batteries at their start nodes (the depot or satellites) before battery power runs out is an attractive and sensitive option. Actually, charging only at start stations not en-route is also used in practical logistics due to the improvement of charging technology. In 2018, DPD(UK) opened its first all-electric last-mile delivery satellite in Westminster, London. In their system, the freight available in the London City depot is transported by the 7.5-tonners eCanters (primary EVs) to the micro delivery depots (satellites), and then Nissan eNV200s and Paxsters (secondary EVs) serve the final customers. Both EVs do not need additional recharging during deliveries.

In the express delivery industry, logistics companies need to establish and refurbish facilities for the EVs by themselves, since the public charging infrastructure is not sufficient and the battery standards for different EVs are not unified (Yang and Sun (2015)). For example, DPD(UK) has spent £500,000 to prepare a new charging system for their fleet of EVs at the satellite in Westminster, London. Hence, optimizing the number and location of facilities with battery swapping or recharging infrastructure could improve the efficiency of EV operations in city logistics. In addition, tactical routing decisions in both echelons depend on the open satellites, so interdependencies between location and routing decisions have to be regarded simultaneously.

Against this background, our work aims to suggest an arc-based formulation of this new green two-

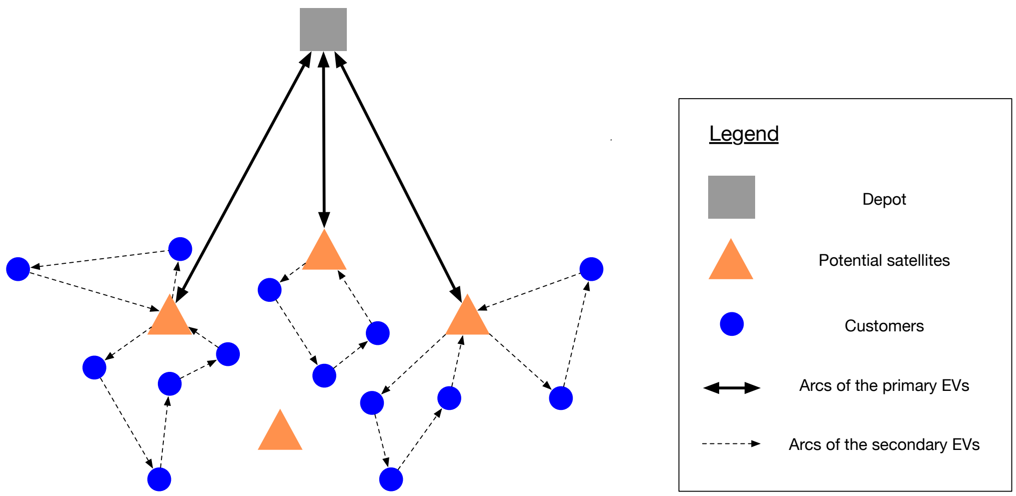

Figure 1: An example of the G-2E-CLRP distribution network.

echelon capacitated location routing problem (G-2E-CLRP) with the goal of choosing which satellites to open and determining the service frequencies for primary EVs and routing plans for secondary EVs with respect to loading capacities and battery driving range constraints. Instead of the traditional 2E-LRP, our problem considers EVs with different battery consumption rates, battery driving ranges and battery swapping costs in different echelons, and focuses on the location decision of satellites, like a typical secondary facility location-routing problem (Mancini (2017)) or a two-echelon capacitated location-routing problem with a single depot (Cuda et al. (2015)). All locations of the depot and customers are given and fixed. Figure 1 shows an example of the G-2E-CLRP distribution network. Our proposed model for this problem is to determine a) the number and location of satellites, b) the allocation and size of primary EVs which do the round trips and swap batteries at the depot, c) the tours of secondary EVs which accomplish customer demand and swap batteries at their start satellites.

The contribution of the present work is multifold. First, our work is the first to incorporate location decisions of satellites with routing decisions with limited EV driving ranges and battery swapping operations in a two-echelon system. Second, the related problem is rarely treated from an exact optimization point of view. In this paper, we firstly develop a specialized branch-and-price (B&P) algorithm in which the column generation procedure is based on a modified Clarke Wright (MCW) savings method (heuristic) and pulse algorithm (exact algorithm). The numerical experiments demonstrate the power of the proposed B&P algorithm and its root-node solutions exhibit good optimality gaps (below 4% on average) in run times. Finally, we highlight the importance and advantages of studying an integrated location and routing problem for a logistics company using EVs in a two-echelon distribution network.

The remainder of the paper is organized as follows. In Section 2, we review recent literature related to green or electric vehicle routing problems, and two-echelon distribution systems. The arc-based G-2E-CLRP mathematical model is firstly introduced in Section 3. The overall design of the B&P algorithm is discussed in Section 4. Section 5 presents computational experiments and analyzes the results obtained. Finally, conclusions and potential future directions are given in Section 6.

2 Literature review

The G-2E-CLRP primarily combines two streams of research. The first stream is related to the green vehicle routing problem (G-VRP) or electric vehicle routing problem (E-VRP), and the second stream involves the two-echelon location and routing problem (2E-LRP).

2.1 Related papers on G-VRP/E-VRP

During the last decades, there has been a huge growth in the number of the G-VRP/E-VRP tackled both by the research community and by practitioners. Early studies share a similar focus on the routing vehicles with an initial limited fuel budget (Ichimori et al. (1983)) or with limited driving ranges (Conrad and Figliozzi (2011)). More recently, Erdoan and Miller-Hooks (2012) introduced the G-VRP and proposed the first model considering charging facilities on routes. Conrad and Figliozzi (2011) firstly investigated the routing and recharging of EVs, although recharging is only allowed at customer vertices. For recent surveys of the G-VRP/E-VRP and related technological and marketing background of EVs, we refer the reader to Pelletier et al. (2016).

Regarding the potential improvement of charging strategies, some studies apply facility location problem (FLP) techniques for locating charging infrastructure include vertex-based and flow-based planning approaches (e.g., An et al. (2014) and Lee and Han (2017)). However, both G-VRP/E-VRP and FLP lack the interdependencies between routing of vehicles and charging station location decisions. Several contributions have emerged in recent years that focus on related integrated models from a LRP perspective. Yang and Sun (2015) presented a battery swapping station (BSS) location routing problem with capacitated EVs under battery driving range constraints. Schiffer et al. (2016) showed the benefit of integrated planning of charging station location and EV routing decisions by studying a real-world case. In addition, Schiffer and Walther (2017a) proposed a LRP with intra-route facilities covering both charging stations and freight replenishing facilities. Schiffer and Walther (2017b) considered both partial and full recharging options for electric routing problems with time windows (E-VRPTW).

Several heuristic solution methods have recently been investigated for solving the G-VRP/E-VRP. Erdoan and Miller-Hooks (2012) developed two customized heuristic algorithms including a modified Clarke and Wright savings algorithm and a density-based clustering algorithm. Felipe et al. (2014) considered recharging operations performed with different technologies, such as partial battery recharges and overnight depot charging. Then, several heuristics based on a simulated annealing framework are provided. Schneider et al. (2014) focused on E-VRPTW with recharging stations and combined variable neighborhood search (VNS) and tabu search to solve their problem. Hof et al. (2017) considered battery swap station location-routing problem with capacitated electric vehicles and intermediate stops. They extended an adaptive variable neighborhood search (AVNS) algorithm and achieved significantly improvements. Montoya et al. (2017) investigated nonlinear charging functions in E-VRP and developed a hybrid meta-heuristic combining an iterated local search (ILS) and a heuristic concentration (HC). Hiermann et al. (2019) introduced fleet size and mix into the E-VRP and developed a hybrid genetic algorithm based on layered route evaluation procedures.

Because of the complexity of the problem, only a limited number of exact algorithms for the G-VRP/E-VRP are proposed in the literature. Desaulniers et al. (2016) developed branch-price-and-cut (B&P&C) algorithms to solve four variants of their problem to optimality. Hiermann et al. (2016) provided both exact and heuristic algorithms for VRPTW considering a heterogeneous electric fleet. Their exact algorithm is a B&P framework using a labeling algorithm and a heuristic algorithm based on an adaptive large neighborhood search (ALNS). Recently, Andelmin and Bartolini (2017) modeled a G-VRP based on a multigraph for en route recharging options and presented a B&P&C algorithm. According to the above review, Table 1 summarizes the main contributions to the G-VRP/E-VRP literature.

2.2 Related papers on 2E-LRP

Multi-echelon logistics systems are common in practice, since they allow for freight sorting and consolidating to the city centre (Savelsbergh and Van Woensel (2016)). Recently, a number of papers deal with multi-echelon systems, especially for two-echelon structures. Cuda et al. (2015) provided an extensive overview and classified the related literature into three classes: the two-echelon location-routing problems (2E-LRP), the two-echelon vehicle-routing problems (2E-VRP) and the truck and trailer routing problems (TTRP). Furthermore, Schiffer et al. (2019) gave a detailed review of vehicle routing problems (VRPs) and location routing problems (LRPs) with intermediate stops, dedicated to replenishment and unloading, refueling or idling.

Integrated location and routing decisions is of benefit for designing distribution systems (Salhi and Rand (1989)). Prodhon and Prins (2014) and Drexl and Schneider (2015) review the foremost related papers on the LRP and also identify future directions for this area of research. The 2E-LRP is a generalization of LRP, in which the satellites are connected by first echelon trips, and the location of the depots and the satellites needed to be determined. Compared to the classical LRP, 2E-LRP has only been studied by a few researchers. Except for some recent papers focusing on the location decisions of both stages (Crainic et al. (2011b); Contardo et al. (2012); Schwengerer et al. (2012)), most of papers on 2E-LRP only consider one stage location decisions, usually the second stage (Jacobsen and Madsen (1980); Laporte (1987); Madsen (1983)). The capacitated 2E-LRP (2E-CLRP) is the most studied problem among the 2E-LRP, firstly formalized in Boccia et al. (2010). According to the notation of Laporte and Nobert (1988) and Cuda et al. (2015), our problem is corresponding to the $3/R/\overline{T}$ problem with a single depot, where only return trips are allowed between the depot and open satellites, and only the location decisions of satellites is considered. To the best of our knowledge, the best performing exact and heuristic algorithm for the 2E-CLRP is the branch-and-cut (B&C) algorithm and the Adaptive Large Neighborhood Search (ALNS), respectively (Contardo et al. (2012)).

Although green or electric two-echelon logistics systems have been applied in real world, the two-echelon systems with EVs have drawn little attention for academic research in the literature. There has been little research related to this problem. Soysal et al. (2015) is the first paper to consider CO_2 emissions in the VRP as the objective, and many realistic factors were taken into account in their formulation, such as multiple time zones, vehicle type and size, and travel distance. Later, Li et al. (2016) extended the above problem by considering many-to-many demands in the two-echelon line-haul level. Both papers focus on the environmental impact. Breunig et al. (2019) presented a natural extension of the 2E-VRP in which electric vehicles are used in the second echelon. They developed a large neighborhood search (LNS) meta-heuristic as well as an exact mathematical programming algorithm to produce optimal or near-optimal solutions for their problem. Macrina et al. (2019) considered an electric two-echelon vehicle routing problem with recharging operations in each echelon and also proposed both exact and meta-heuristic algorithms. In particular, Jie et al. (2019) presented a two-echelon capacitated electric vehicle routing problem with battery swapping stations (2E-EVRP-BSS) and developed a hybrid algorithm by combining a column generation and adaptive large neighborhood search (CG-ALNS) to solve the problem.

Our G-2E-LRP developed within this paper differs from above related studies in two main ways: First, our G-2E-CLRP just considers battery swapping strategies at start nodes other than en route recharging operations. Second, a B&P algorithm is proposed for our G-2E-CLRP by designing a set-partitioning formulation and pricing subproblems, which is described detailed in Section 4.

3 Model formulation

3.1 Problem description

In this paper, we study the G-2E-CLRP which considers a two-echelon delivery network composed of a depot, potential locations for the satellites and the customers, respectively. The depot and the customers are situated at given and fixed locations. On the other hand, the location of candidate satellites is determined a priori but not which satellites to open. In this two-echelon delivery network, two types of EVs have been considered with different load capacities, battery driving ranges, power consumption rates and battery swapping costs. The primary EVs can only serve one satellite and go back to the depot in the first echelon, and the secondary EVs can serve more than one customer in the second echelon and go back to the starting satellite.

Only the depot and the satellites can provide the battery swapping service for each type of EV, at a different cost, respectively. The capacities of both EV types cannot be exceeded, and the swapping operation times of primary EVs at the depot and of secondary EVs at each satellite are limited. Each open satellite has to be visited by exactly one primary vehicle. Similarly, each customer has to be served by exactly one secondary vehicle that starts from an open satellite (i.e., customer demand cannot be split).

This model aims to find the optimal set of sites for the satellites as well as the optimal set of primary trips and secondary routes that satisfy the customer demands and do not violate the battery capacity and load capacity constraints. The objective is to minimize the sum of the fixed cost of open satellites, the EV travel costs, and the battery swapping costs at the depot and the satellites.

3.2 Arc-based formulation

According to the above definition, the G-2E-CLRP may be described as the following problem. Let us consider a directed graph $G = (V, A)$, where $V = V_0 \cup V_s \cup V_c$ is the set of vertices, where $V_0 = \{v_0\}$ represents the depot, $V_s = \{v_{s_1}, v_{s_2}, \ldots, v_{s_{n_s}}\}$ is the set of potential satellite locations, and $V_c = \{v_{c_1}, v_{c_2}, \ldots, v_{c_{n_c}}\}$ is the customer set. These three sets of vertices are pairwise disjoint. The arc set A is defined as $A = A^1 \cup A^2$ is the set of arcs (i, j) such that arc set $A^1 = \{(i, j) : i, j \in V_0 \cup V_s,\ (i, j) \notin V_s \times V_s\}$ includes the arcs connecting the depot to the satellites. Arc set $A^2 = \{(j, k) : j, k \in V_s \cup V_c,\ (j, k) \notin$

Table 1: Summary of the G-VRP/E-VRP contributions in the scientific literature.

References	Routing	Location	TW	Mixed fleet	Recharging	BS	Algorithm
Contreras et al. (2011)	✓				✓		Heuristic
Erdoan and Miller-Hooks (2012)	✓				✓		Heuristic
Felipe et al. (2014)	✓				✓		Heuristic
Schneider et al. (2014)	✓		✓		✓		Heuristic
Sassi et al. (2014)	✓		✓	✓	✓		Heuristic
Goeke and Schneider (2015)	✓			✓	✓		Heuristic
Sassi et al. (2015)	✓			✓	✓		Heuristic
Yang and Sun (2015)	✓	✓				✓	Heuristic
Doppstadt et al. (2016)	✓			✓			Heuristic
Desaulniers et al. (2016)	✓		✓		✓		Exact
Hiermann et al. (2016)	✓		✓	✓	✓		Heuristic and Exact
Keskin and Çatay (2016)	✓		✓		✓		Heuristic
Liao et al. (2016)	✓					✓	Heuristic
Andelmin and Bartolini (2017)	✓				✓		Exact
Barco et al. (2017)	✓				✓		Case study
Hof et al. (2017)	✓	✓			✓		Heuristic
Lee and Han (2017)		✓			✓		Exact
Mancini (2017)	✓			✓	✓		Heuristic
Montoya et al. (2017)	✓				✓		Heuristic
Schiffer and Walther (2017a)	✓	✓			✓		Heuristic
Schiffer and Walther (2017b)	✓	✓	✓		✓		Heuristic
Wang et al. (2017)	✓				✓		Case study
Keskin and Çatay (2018)	✓		✓		✓		Heuristic
Dukkanci et al. (2019)	✓	✓	✓				Heuristic
Hiermann et al. (2019)	✓			✓	✓		Heuristic
This work	✓	✓				✓	Exact

Table 2: Definitions and Notations

Notation	Meaning
V_0	Depot, $V_0 = \{v_0\}$
V_s	Set of satellites, $V_s = \{v_{s_1}, v_{s_2}, \ldots, v_{s_{n_s}}\}$
V_c	Set of customers, $V_c = \{v_{c_1}, v_{c_2}, \ldots, v_{c_{n_c}}\}$
n_s, n_c	Number of satellites and customers, respectively
A^1	Set of arcs in the first echelon, $A^1 = \{(i,j) : i,j \in V_0 \cup V_s,\ (i,j) \notin V_s \times V_s\}$
A^2	Set of arcs in the second echelon, $A^2 = \{(j,k) : j,k \in V_s \cup V_c,\ (j,k) \notin V_s \times V_s\}$
m^1	The maximum number of primary EVs battery swaps at the depot
m^2_s	The maximum number of secondary EVs battery swaps at the satellite s
K^1, K^2	Load 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
q_i	Demand required by customer i
d_{ij}	Distance between node i to node j
c^1_{ij}, c^2_{ij}	Cost of the primary EVs from node i to node j and that of the secondary EVs, respectively
c^1_b, c^2_b	Cost of battery swapping or recharging at the first echelon and the second echelon, respectively
f_s	Cost of opening a satellite s
y_s	Binary decision variable indicating whether or not satellite s opens
z_{ijs}	Binary decision variable indicating whether a secondary EV from satellite s travels arc (i,j)
x_{ij}	Integer decision variable specifying the frequency of primary EVs using arc (i,j)
f_{ijs}	Decision variable specifying the load on a secondary EV from satellite s when leaving node i to node j
t_s	Decision variable specifying the total demand of customers to be served by satellite s
b^+_i	Specifies the remaining battery power when a secondary vehicle arrives at node i
b^-_i	Specifies the remaining battery power when a secondary vehicle leaves at node i

$V_s \times V_s\}$ comprises the arcs connecting satellites to the customers, as well as those connecting pairs of customers.

A rental cost f_i is given for each satellite $i \in V_s$. Each customer $k \in V_c$ has a known and deterministic demand q_k. The load capacity of the two types EVs associated with the echelons are given as K^1 and K^2 with battery capacity B^1 and B^2 and charging consumption rate h^1 and h^2, respectively. m^1 is the maximum number of primary EVs battery swaps or recharges at the depot. m_s^2 is the maximum number of secondary EVs battery swaps or recharges at the satellite s. The EVs travel cost of arcs $(i, j) \in A^1$ and arcs $(i, j) \in A^2$ is given as c_{ij}^1 and c_{ij}^2, respectively. We assume, throughout this paper, that the travel costs satisfy the triangle inequality. The battery swapping costs for each echelon per time is c_b^1 and c_b^2, respectively.

Table 2 provides the definitions of variables and parameters used in formulations introduced in this paper. Then, this arc-based model can be cast as the following Mixed Integer Linear Programming (MILP) model as follows.

$$\min \sum_{j \in V_s} f_j y_j + \sum_{(i,j) \in A^1} c_{ij}^1 x_{ij} + \sum_{i \in V_0} \sum_{j \in V_s} c_b^1 x_{ij} + \sum_{s \in V_s} \sum_{(i,j) \in A^2} c_{ij}^2 z_{ijs} + \sum_{s \in V_s} \sum_{(s,j) \in A^2} c_b^2 z_{sjs} \tag{1}$$

$$\text{s.t.} \sum_{i \in V_o} \sum_{j \in V_s} x_{ij} \leq m^1 \tag{2}$$

$$x_{ij} \leq m^1 y_j \qquad \forall (i,j) \in A^1 \tag{3}$$

$$x_{ij} = x_{ji} \qquad \forall (i,j) \in A^1 \tag{4}$$

$$[h^1(d_{ij} + d_{ji}) - B^1] y_j \leq 0 \qquad \forall (i,j) \in A^1 \tag{5}$$

$$t_s \leq K^1 \sum_{i \in V_0} x_{is} \qquad \forall s \in V_s \tag{6}$$

$$t_s = \sum_{(i,j) \in A^2} q_j z_{ijs} \qquad \forall s \in V_s \tag{7}$$

$$\sum_{s \in V_s} \sum_{j \in V_c \cup \{s\}} z_{ijs} = 1 \qquad \forall i \in V_c \tag{8}$$

$$\sum_{j \in V_c \cup \{s\}} z_{ijs} = \sum_{j \in V_c \cup \{s\}} z_{jis} \qquad \forall i \in V_c, \forall s \in V_s \tag{9}$$

$$\sum_{j \in V_c} z_{sjs} = \sum_{j \in V_c} z_{jss} \qquad \forall s \in V_s \tag{10}$$

$$\sum_{\bar{s} \in V_s \setminus \{s\}} \Big(\sum_{j \in V_c \cup \{s\}} z_{sj\bar{s}} + \sum_{i \in V_c \cup \{s\}} z_{is\bar{s}} \Big) = 0 \qquad \forall s \in V_s \tag{11}$$

$$\sum_{j \in V_c \cup \{s\}} z_{sjs} \leq m_s^2 y_s \qquad \forall s \in V_s \tag{12}$$

$$f_{ijs} \leq K^2 z_{ijs} \qquad \forall (i,j) \in A^2, \forall s \in V_s \tag{13}$$

$$\sum_{s \in V_s} \sum_{j \in V_c \cup \{s\}} f_{jis} = \sum_{s \in V_s} \sum_{j \in V_c \cup \{s\}} f_{ijs} + q_i \qquad \forall i \in V_c \tag{14}$$

$$b_s^- = B^2 \qquad \forall s \in V_s \tag{15}$$

$$b_i^- = b_i^+ \qquad \forall i \in V_c \tag{16}$$

$$b_j^+ \leq b_i^- - h^2 d_{ij} z_{ijs} + B^2(1 - z_{ijs}) \qquad \forall (i,j) \in A^2, \forall s \in V_s \tag{17}$$

$$y_j \in \{0,1\} \qquad \forall j \in V_s \tag{18}$$

$$x_{ij} \in Z \qquad \forall (i,j) \in A^1 \tag{19}$$

$$t_j \geq 0 \qquad \forall j \in V_s \tag{20}$$

$$z_{ijs} \in \{0,1\} \qquad \forall (i,j) \in A^2, \forall s \in V_s \tag{21}$$

$$f_{ijs} \geq 0 \qquad \forall (i,j) \in A^2, \forall s \in V_s \tag{22}$$

$$b_i^-, b_i^+ \geq 0 \qquad \forall i \in V_s \cup V_c \tag{23}$$

The objective function (1) minimizes the total cost including the fixed cost of open satellites, the EV travel cost of both echelons, and the battery swapping cost at the depot or satellites. Constraints (2) and (12) restrict the number of battery swapping operations for primary EVs at the depot and secondary EVs at satellites (notice that constraints limit at the same time the freight capacity of the satellites as well). Constraints (3) indicate that any primary EV should be assigned to an open satellite. Constraints (4) ensure each primary EV is required to go back to the depot after serving one satellite. Constraints (5) ensure the open satellites could be visited and go back within the battery power of a primary EV. Constraints (15) indicate that the battery capacity of a secondary EV is equal to B^2 when it departs from an open satellite. Constraints (16) ensure that the battery power remains the same when a secondary EV visits a customer. Constraints (17) keep the balance of the battery power of the secondary EVs arriving at node j from node i. Similarly, they guarantee that every secondary EV has sufficient battery power to visit the remaining customers and return to the satellites.

The capacity constraints are formulated in (6) and (13) for the first echelon and the second echelon, respectively. Constraints (14) and (7) indicate that the flow' balance on each customer node is equal to the demand of this node, and the flow is equal to the demand assigned to the open satellites at the second echelon. Constraints (8) assign each customer to only one open satellite, and constraints (9) ensure the flow conservation for the secondary EVs. Moreover, constraints (10) force each route in the second echelon to begin and end at the same open satellite, while implying that the outgoing and the incoming routes associated to each satellite are equal. Constraints (11) forbid the presence of sub-tours containing different satellites, which means that we cannot dispatch secondary EVs among satellites. Finally, constraints (18)-(23) specify the domains of the variables. In particular, notice that while the arc variables z_{ijs} can be defined as Boolean, each customer being served by at most one secondary EV, the first echelon arc variables x_{ij} must be a non-negative integer.

Actually, the model formulation is identical for the pickup problem where K^1 and K^2 are redefined as the remaining load capacity of the EVs in first echelon and second echelon, f_{ijs} denotes the remaining load capacity on a secondary EV from satellite s when leaving node i to node j. Constraints (14) need some tweaking to ensure the flow' balance for each customer. In addition, battery swapping operations also can be replaced by recharging operations depending on the real case, and related parameters change accordingly.

The above model has a polynomial-size number of variables and constraints, but provides a poor lower bound and a long run time. These issues are common and discussed for similar formulations (see Crainic et al. (2011a)). The numerical evaluation of this formulation will be presented in Section 5. Then, we develop an efficient B&P algorithm in Section 4 to solve the G-2E-CLRP to optimality for larger size instances.

4 Branch-and-price algorithm

We first formulate the G-2E-CLRP as a set partitioning formulation (Section 4.1) using the Danzig-Wolfe decomposition method (Dantzig and Wolfe (1960)) as a master problem (MP), and its continuous relaxation is called the linear master problem (LMP). Pricing subproblems are defined to search the secondary routes with negative reduced costs (Section 4.2). As the number of column variables in MP grows exponentially with the problem-instance size, it would be difficult for commercial solvers such as CPLEX to solve the MP directly so a B&P algorithm (Algorithm 1) is developed instead with a new column generation (CG) procedure in Section 4.3.

In our B&P algorithm, an initial feasible solution is firstly generated by a heuristic algorithm based on a modified Clarke Wright (MCW) savings method described in Section 4.6. Then, a restricted MP (RMP) involving a small subset of variables is considered at each branch node, and then its continuous relaxation (RLMP) is solved to optimality using CPLEX. Based on the resulting and dual solutions of RLMP, the CG procedure is called (Section 4.3) to generate a set of new columns with negative reduced costs to the current RLMP, and updated RLMP is solved again until no new column exists.

Then, we can obtain the optimal solution of LMP (that is, the final solution of the RLMP). If it is fractional, some branching rules (Section 4.5) are applied to generate two complementary subproblems and the same procedure is called to solve each of them until an optimal integer solution is found or the problem is found to be infeasible. A best first search strategy is implemented in the branch-and-bound tree. It is worth noting that a similar aggregate-based lower bound $LB_{AG}(\mathbf{y}, \mathbf{x})$ proposed by Dellaert et al. (2018) was implemented in our B&P framework, as detailed in Section 4.4. Algorithm 1 outlines this modified procedure.

4.1 Set partitioning formulation

We denote R as the set of all feasible secondary routes. Each secondary route $r \in R_s$ starts from an open satellite s, visits one or several customers in V_c, and ends at s, and $\sum_{s \in V_s} R_s = R$. Note that secondary routes traverse only arcs in A^2. Let $\alpha_{ri} \in \{0, 1\}$ be a binary parameter equal to 1 if customer i is visited in route r, and 0 otherwise. The cost of each route $r \in R$ is p_r. Finally, given a secondary route $r \in R$, let $q_r = \sum_{i \in V_c} \alpha_{ri} q_i \leq K^2$ denote the total demand of customers visited. Hence, each secondary route $r \in R$ does not violate the vehicle capacity by construction. Furthermore, the path-based G-2E-CLRP reformulation uses an additional set of variables. Let z_r be a binary variable that takes value 1 if route $r \in R$ belongs to the solution, and 0 otherwise. Then, the arc-based formulation can be reformulated as the following set-partitioning problem.

MP:

$$\min_{\mathbf{y}, \mathbf{x}, \mathbf{z}} \sum_{j \in V_s} f_j y_j + \sum_{(i,j) \in A^1} c^1_{ij} x_{ij} + \sum_{i \in V_0} \sum_{j \in V_s} c^1_b x_{ij} + \sum_{r \in R} p_r z_r \tag{24}$$

s.t. constraints (2)-(5) and (18)-(19)

$$\sum_{r \in R_s} z_r q_r \leq K^1 \sum_{i \in V_o} x_{is} \qquad \forall s \in V_s \tag{25}$$

$$\sum_{r \in R} \alpha_{ri} z_r = 1 \qquad \forall i \in V_c \tag{26}$$

$$\sum_{r \in R_s} z_r \leq m^2_s y_s \qquad \forall s \in V_s \tag{27}$$

$$z_r \in \{0, 1\} \qquad \forall r \in R \tag{28}$$

Objective (24) is the same as objective (1). Constraints (25) guarantee that the total customer demand served by the same satellite s does not exceed its capacity supported by primary EVs. Constraints (26) ensure that all customers can be visited only once. Constraints (27) state that at most m^2_s

Algorithm 1: B&P algorithm

Comment: Let Ω be the list of all active nodes in the B&P tree;
Comment: Let ω_r be the solution of continuous relaxation of node ω;
$Best \leftarrow$ The constructed initial solution presented by heuristic algorithm (Section 4.6);
Initialize RMP at root node $\bar{\omega}$ using routes in $Best$ and compute $\bar{\omega}_r$ by CG, $\Omega \leftarrow \{\bar{\omega}\}$;
while $\Omega \neq \varnothing$ **do**
    $\omega \leftarrow$ The node in Ω with the minimum lower bound, $\Omega \leftarrow \Omega \backslash \omega$;
    if ω_r is better than $Best$ **then**
        if ω_r is feasible (integral) **then**
            $Best \leftarrow \omega_r$;
        else
            Branching on ω according to Section 4.5;
            if branching location variables **then**
                Modify V_s to V_s' based on the results of branching;
                Generate new columns by using heuristic algorithm (Section 4.6) for each satellite $s \in V_s'$;
                Add these feasible columns to corresponding RLMP to make sure them feasible;
            end
            if location variables $\mathbf{y}$ and frequency variables of primary EVs $\mathbf{x}$ are both integral **then**
                Calculate the aggregate-based lower bound $LB_{AG}(\mathbf{y}, \mathbf{x})$;
                if node cost of $\omega_r < LB_{AG}(\mathbf{y}, \mathbf{x})$ **then**
                    Construct ω^1 and ω^2 which obtained from branching on ω;
                    Compute ω_r^1 and ω_r^2 by CG;
                    $\Omega \leftarrow \Omega \cup \{\omega^1, \omega^2\}$;
                end
            else
                Construct ω^1 and ω^2 which obtained from branching on ω;
                Compute ω_r^1 and ω_r^2 by CG;
                $\Omega \leftarrow \Omega \cup \{\omega^1, \omega^2\}$;
            end
        end
    end
end

times the secondary EVs can swap battery at satellite s. Moreover, constraints (28) impose integrality restrictions on the decision variables.

Then, the linear MP (LMP) can be strengthened by the following two valid inequalities:

$$\sum_{s\in V_s} y_s \geq \lceil \sum_{i\in V_c} q_i/K^2 \rceil / \max_{s\in V_s}\{m_s^2\} \tag{29}$$

$$\sum_{i\in V_o}\sum_{j\in V_s} x_{ij} \geq \lceil \sum_{i\in V_c} q_i/K^1 \rceil \tag{30}$$

Constraint (29) indicates a minimum number of satellites that need to be open to satisfy the total demand. Constraint (30) imposes a minimum number of primary EVs that need to be on duty to ship the total demand to the satellites. From now on, the formulation of LMP includes constraints (29) and (30).

4.2 Pricing subproblem

The pricing subproblem constructs a feasible secondary route with a minimum reduced cost, using the dual values obtained from the RLMP. If the constructed route has negative reduced cost, its corresponding column is added to the RLMP. Otherwise, the LP procedure terminates with an optimal solution to the current MP. Specifically, let $\mathbf{u}$, $\mathbf{v}$, and $\boldsymbol{\tau}$ be the dual variables of the constraints (25)-(27), respectively. Then, the reduced cost of decision variable z_r to open satellite $s \in V_s$ is equal to

$$\tilde{p}_r = p_r - \sum_{i\in V_c} \alpha_{ri}(u_i + q_i v_s) - \tau_s \tag{31}$$

Thus, the optimality condition for any feasible route is given by

$$p_r - \sum_{i\in V_c} \alpha_{ri}(u_i + q_i v_s) - \tau_s \leq 0 \tag{32}$$

By substituting α_{ri} by $\sum_{j\in V_c\cup\{s'\}, j\neq i} z_{ij}$ and letting s' be the dummy satellite corresponding to s, the optimality condition can be stated as

$$\sum_{i\in V_c\cup\{s\}}\sum_{j\in V_c\cup\{s'\}, j\neq i} c_{ij}^2 z_{ij} + \sum_{j\in V_c} c_b^2 z_{sj} - \sum_{i\in V_c}\sum_{j\in V_c\cup\{s'\}, j\neq i} (u_i + q_i v_s) z_{ij} - \tau_s \leq 0 \tag{33}$$

Therefore, given the values of $\mathbf{u}$, $\mathbf{v}$, and $\boldsymbol{\tau}$ obtained by solving RLMP, the pricing subproblem (PP-s) corresponding to open satellite $s \in V_s$ is presented as follows:

PP-s:

$$\min \sum_{i\in V_c}\sum_{j\in V_c\cup\{s'\}, j\neq i} (c_{ij}^2 - u_i - q_i v_s) z_{ij} + \sum_{j\in V_c} c_{sj}^2 z_{sj} + c_b^2 - \tau_s \tag{34}$$

$$\text{s.t.} \sum_{j \in V_c} z_{sj} = 1 \tag{35}$$

$$\sum_{j \in V_c} z_{js'} = 1 \tag{36}$$

$$\sum_{j \in V_c \cup \{s\}, j \neq i} z_{ji} = \sum_{j \in V_c \cup \{s'\}, j \neq i} z_{ij} \qquad \forall i \in V_c \tag{37}$$

$$\sum_{i \in V_c} q_i \sum_{j \in V_c \cup \{s'\}, j \neq i} z_{ij} \leq K^2 \tag{38}$$

$$b_j \leq b_i - h^2 d_{ij} z_{ij} + B^2(1 - z_{ij}) \qquad \forall i \in V_c, \forall j \in V_c \cup \{s'\}, j \neq i \tag{39}$$

$$b_j \leq B^2 - h^2 d_{sj} z_{sj} \qquad \forall j \in V_c \tag{40}$$

$$z_{ij} \in \{0,1\} \qquad \forall i \in V_c \cup \{s\}, \forall j \in V_c \cup \{s'\}, j \neq i \tag{41}$$

$$b_i \geq 0 \qquad \forall i \in V_c \cup \{s'\} \tag{42}$$

The objective function (34) minimizes the reduced cost of the constructed column with respect to z_{ij}. Constraints (35)-(36) are associated with the routing decision for this satellite s, where constraints (37) ensure the flow balance. Constraints (38) relate to the total secondary EV tour capacity. Constraints (39)-(40) enforce sub-tour elimination constraints using the cumulative battery capacity consumed upon visiting a particular customer node.

It can be shown that the pricing subproblem is modeled as an elementary shortest path problem with resource constraints (ESPPRC) which is NP-hard in the strong sense (Dror (1994)) and is computationally challenging to find feasible paths. Therefore, it is crucial to seek a more efficient solution methodology to generate feasible columns in order to solve larger size instances for the G-2E-CLRP, as detailed in next subsection.

4.3 Column generation procedure

For the detailed CG procedure, it first invokes a two-phase column generation (Section 4.3.2) to iteratively provide as much as possible columns with negative reduced costs to the RLMP. If above heuristic procedure fails to construct a new column, then the pulse algorithm (Section 4.3.1) is used globally, as a last resort. When there is also no feasible column constructed, then the CG terminates and the LMP is known to be solved to optimality (Desaulniers et al. (2006)).

4.3.1 Pulse algorithm (Exact)

For our pricing subproblems, battery capacity and load capacity are key resource constraints. Traditionally, ESPPRC are most solved with labeling algorithms. Feillet et al. (2004) proposed a label correcting algorithm which is the first exact approach for the ESPPRC. Then, Lozano et al. (2015) developed a pulse algorithm based on bounding and pruning strategies to discard partial paths, which do not rely on dominance rules and performed well against state-of-the-art algorithms for the ESPPRC on VRPTW instances. Furthermore, we refer the reader to Costa et al. (2019) for a comprehensive review on exact algorithms for the ESPPRC and VRP.

In order to handle subproblems efficiently, we present a tailored pulse algorithm by reconstructing a battery used window for each node. That is, each node $i \in V_s \cup V_c$ is served within its battery consumed window $[a_{is}, b_{is}]$ from open satellite s, where $a_{is} = h^2 c_{si}$ and $b_{is} = B^2 - h^2 c_{is}$. We create a new label $L = (P_l, R_l, Q_l, B_l)$ for each partial path, which comprises the following elements: (i) P_l the corresponding partial path; (ii) R_l the cumulative reduced cost; (iii) Q_l the cumulative load capacity consumption; (iv) B_l the cumulative battery capacity consumption. An overview of our pulse algorithm is given in Algorithms 2 and 3, and implementation details are refer to Lozano et al. (2015).

4.3.2 Two-phase column generation (Heuristic)

For two-phase column generation procedure, the main idea is to use savings to decompose the pricing subproblem into two phases. For each open satellite $s \in V_s'$ and its reachable customers Z_s in terms of branching results and battery capacity constraints, the saving pair of customer i and j is $s^2_{ijs} = c^2_{sj} + c^2_{is'} - c^2_{ij}$, $\forall i \in Z_s, j \in Z_s, j \neq i$. Then, the objective (34) can also be expressed as

$$\min \sum_{i \in Z_s} (c^2_{si} + c^2_{is'} - u_i - q_i v_s) \sum_{j \in Z_s \cup \{s'\}, j \neq i} z_{ij} - \sum_{i \in Z_s} \sum_{j \in Z_s, j \neq i} s^2_{ijs} z_{ij} + c^2_b - \tau_s \tag{43}$$

where $\sum_{j \in Z_s \cup \{s'\}, j \neq i} z_{ij}$ can be regarded as an assign decision that if customer i in route $r \in R$ is served by satellite s or not. Apparently, the cost of dual variables $\mathbf{u}$, $\mathbf{v}$ and $\boldsymbol{\tau}$ only affect this assign decision not secondary route decision. Hence, the first phase is to generate a customer assignment problem (CAP-s) based on the dual values from RLMP, to decide which customers are assigned to satellite s. Substituting $\sum_{j \in V_c \cup \{s'\}, j \neq i} z_{ij}$ by a new decision variable δ_{is}, the formulation of CAP is the following:

CAP-s:

$$\sum_{i \in Z_s} (c^2_{si} + c^2_{is'} - u_i - q_i v_s) \delta_{is} - \tau_s \tag{44}$$

$$\text{s.t.} \sum_{s \in V_s'} \delta_{is} \leq 1 \qquad \forall i \in Z_s \tag{45}$$

$$\delta_{is} \in \{0,1\} \qquad \forall i \in Z_s, \forall s \in V_s', j \neq i \tag{46}$$

The objective function (44) minimizes the reduced cost of assigning customers to open satellite s, while constraints (45) ensure that each customer is served at most once. Note that CAP-s is an integer programming problem. It is easy to see that the continuous relaxation of CAP-s has an integral polyhedron.

Based on the assignment result of the first phase, the second phase is to construct feasible columns for each satellite $s \in V_s'$ using parallel version of modified Clarke Wright (MCW) algorithm and pulse algorithm in sequence, where Clarke Wright (CW) algorithm is firstly proposed for the classical VRP(Clarke and Wright (1964)) and extended for a new variant of VRP called green-VRP (Erdoan and Miller-Hooks (2012)). Then, iteratively adds a set of columns satisfying optimality condition (32) to the RMP, until no column is found, then the two-phase column generation procedure terminates.

4.4 Lower bound

Actually, it would be slow convergence in column generation process when the solution is near the optimum. Hence, after ensuring integrality of location decisions $\mathbf{y}$ and frequency decisions $\mathbf{x}$ of primary EVs, we implement an aggregate-based lower bound $LB_{AG}(\mathbf{y}, \mathbf{x})$ (ideas come from Dellaert et al. (2018)) in B&P tree to mitigate this tailing-off effect.

We first solve a simple set partitioning problem (SPP-s) to obtain the minimal cost for serving a customer i from an open satellite s, in which satellite $s \in V_s'$ is considered as the depot with unlimited capacity. Then, SPP-s is developed as follows:

SPP-s:

$$\min \sum_{r \in R_s} p_r z_r \tag{47}$$

$$\text{s.t.} \sum_{r \in R_s} \alpha_{ri} z_r = 1 \qquad \forall i \in V_c \tag{48}$$

$$z_r \in \{0,1\} \qquad \forall r \in R_s \tag{49}$$

The pulse algorithm is used to generate feasible columns to solve the LP-relaxation of SPP-s to optimality. Define γ_{is} as the dual values associated with constraints (48), which can be considered as the minimal cost of serving customer i from satellite s. For customers which could not been served directly by any satellite, this value is set to infinity. Then, for an integral solution $(\mathbf{y}, \mathbf{x})$ of a child node in B&P tree, we can obtain the aggregate-based lower bound as follows:

$$LB_{AG}(\mathbf{y}, \mathbf{x}) = \sum_{j \in V_s'} f_j y_j + \sum_{(i,j) \in A^1} c_{ij}^1 x_{ij} + \sum_{i \in V_0} \sum_{j \in V_s'} c_b^1 x_{ij} + \sum_{i \in V_c} \min_{s \in V_s'} \{\gamma_{is}\} \tag{50}$$

Algorithm 2: Pulse algorithm (Main)

Comment: Battery consumed window $[\underline{\beta},\ \bar{\beta}]$, battery step Δ, node $i \in V_c \cup \{s\}$;
bound(Δ, $[\underline{\beta},\ \bar{\beta}]$);
pulse(s, L);
return optimal path P^*;

Algorithm 3: Pulse(i, L)

Comment: $\Gamma^+(i) = \{j \in V_c \cup \{s\} \mid (i,j) \in A^2\}$ the set of next reachable nodes from node i;
Comment: $r_{sj} = c_{sj}^2 + c_b^2 - \tau_s$, $r_{ij} = c_{ij}^2 - u_i - q_i v_s, i \neq s$ reduced cost contribution;
Comment: $\beta_{ij} = h^2 d_{ij}$ battery consumption;
if isFeasible(i, L) = true **then**
    if checkBounds(i, L) = false **then**
        if rollback(i, L) = false **then**
            $P_l \leftarrow P_l \cup \{i\}$;
            $Q_l \leftarrow Q_l + q_i$;
            for $j \in \Gamma^+(i)$ **do**
                $R_l \leftarrow R_l + r_{ij}$;
                $B_l \leftarrow \max\{a_j,\ B_l + \beta_{ij}\}$;
                pulse (j, L);
            end
        end
    end
end

4.5 Branching rules

If the optimal solution of the LMP (which is the solution to the last RLMP) is fractional, a branching decision is required. Branching on location variables is given higher priority since it results empirically in the best improvement in the lower bound. Then, the following four branching rules are applied in order to create two new child nodes.

Branching on the location of satellites. If there is a satellite $s \in V_s$ with a most fractional (closer to 0.5) variable y_s, apply the dichotomy branching by enforcing $y_s = 0$ on one branch and $y_s = 1$ on the other. At the same time, valid inequality $x_{is} \leq 0$ could be added into left branch. Note that there is no need to solve the pricing subproblem corresponding to closed satellite s.

Branching on the number of primary EVs. If there is a satellite $s \in V_s$ whose number of primary EVs $\hat{x}_{is}$ is most fractional, then consider the constraint $x_{is} \leq \lfloor \hat{x}_{is} \rfloor$ on one branch, and $x_{is} \geq \lceil \hat{x}_{is} \rceil$ on the other.

If a column variable z_r, $r \in R_s$ is most fractional, there must exist other columns (routes) serving at least one common customer in column r. According to the definition in Danna and Le Pape (2005), find the other satisfied column r' and the first common customer i.

Branching on the assignment of customers to the open satellites. If column r and r' are from different satellites, that means customer i is served partially. Let L_i be the set of all columns that visit customer i belonging to satellite s. Then, consider $\sum_{r \in L_i} z_r = 0$ on one branch, and $\sum_{r \in L_i} z_r = 1$ on the other.

Branching on arcs. If route r and r' are from the same satellite s, that means at least one arc in route r is served partially. Find the branch arc (i, j) in terms of the procedure in Danna and Le Pape (2005). Let H_{ij} be the set of all columns that visit the routing arc $(i, j) \in A^2$. Then, consider $\sum_{r \in H_{ij}} z_r = 0$ on one branch and $\sum_{r \in H_{ij}} z_r = 1$ on the other.

4.6 Initial Solution

This subsection describes a heuristic algorithm that constructs an initial solution for any feasible instance of the G-2E-CLRP. The main idea is to minimize the number of open satellites and ensure that the load and battery capacity of EVs. The overall heuristic framework is outlined as follows.

Step 1 *(Candidate satellites list (CSL) generation phase).*

Step 1.1: First choose potential satellites from V_s to $\bar{V}_s$, in terms of the battery capacity constraints of primary EVs.

Step 1.2: Create a list CSL as the set of candidate satellites to open with corresponding customers, in which satellites in $\bar{V}_s$ sequenced in a decreasing order of the number of times that customers choose as the nearest satellite.

Step 2 *(Customer assignment list (CAL) generation phase).*

Step 2.1: Calculate the minimum number of satellites to open, denoted by N', is defined as follows: $N' = \max\{1, \lceil \frac{\sum_{i \in V_c} q_i}{K^2} \rceil * \frac{1}{\max_{s \in \bar{V}_s} m_s^2}\}$.

Step 2.2: Choose first N' satellites in CSL to create a List CAL.

Step 2.3: Check each satellite s in CAL is in its capacity $m_s^2 K^2$ or not. If yes, go to *Step* 2.5; otherwise, choose this satellite s and its customer k with most demand and go to *Step* 2.4.

Step 2.4: Reassign customer k to other satellites in CAL and ensure the capacity of chosen satellite. If success, update CAL and continue *Step* 2.3; otherwise, update $N' = N' + 1$ and go back to *Step* 2.2.

Step 2.5: Check if there exists customer k in V_c is not been served. If yes, go back to *Step* 2.4; otherwise, go to *Step* 3.

Step 3 *(Modified Clarke Wright algorithm (MCW) phase).*

Generate electric vehicle routes for each satellite in CAL by using modified Clarke Wright (MCW) algorithm, which is designed to consider EVs driving range limitation from parallel version of CW algorithm (Paessens (1988)).

Step 4 *(Verify solution phase).*

Check secondary routes for each satellite s in CAL is in its maximum number m_s^2 or not. If yes, go to *Step* 5; otherwise, update $N' = N' + 1$ and go back to *Step* 2.2.

Step 5 *(Termination phase).*

Stop the heuristic algorithm and return current objective function value and optimal solution.

5 Computational experiments

In this section, we conduct numerical experiments with two aims. First, we evaluate the performance of our exact B&P algorithm for different types of instance. Second, we measure the benefit of integrated location and routing planning for this new green two-echelon system, and economic analysis is analyzed to assess the impact of EVs using in city logistics. All experiments are coded by JAVA and run on a computer with a 8GB RAM and 2.3 GHz CPU.

5.1 Generation of G-2E-CLRP benchmark instances

Our benchmark instances for the G-2E-CLRP are natural extensions of the 2E-VRP instances known as Set 1 to Set 3 by Perboli et al. (2011). In our G-2E-CLRP instances, new information is: rental cost of satellites, battery swapping cost, battery driving ranges and battery consumption rates of both types of EVs. The unit battery swapping fee is set to 2 for the first echelon and 1 for the second echelon. The battery driving ranges of the large EVs and the small EVs are defined in a simple way, that is, each EV can serve the most distant satellite or customer node and then go back to the depot or satellite within the battery capacity limitation. Let d_{max} denote the maximum Euclidean distance between any two points on the network. We set $B^1 \geq \lceil 2 * \max_{i \in V_0} \min_{j \in V_s} \{d_{ij}\} \rceil$, $B^2 \geq \lceil 2 * \max_{i \in V_s} \min_{j \in V_c} \{d_{ij}\} \rceil$, and $B^1 \geq B^2$, the rental cost of satellites is set $\lceil 0.5 * B^1 \rceil$ in terms of Yang and Sun (2015). We set the EV consumption rate in both echelons to 1 per kilometre. Furthermore, the depot, satellites and customers locations are unchanged. In our pulse algorithm, the lower bound procedure is run with $\Delta = 15$ and $\underline{\beta} = \lfloor 0.5 * B^2 \rfloor$.

Table 3 provides a summary of generated instances which includes the name of instances (Inst.), the number of satellites(n_s) and customers (n_c), the rental cost (f_s), the maximum number of primary EVs battery swaps at the depot (m^1) and secondary EVs battery swaps at open satellite s (m_s^2), traveling cost of each echelon (c_{ij}^1 and c_{ij}^2), battery swapping cost of both echelons (c_b^1 and c_b^2), battery consumption rate of both echelons (h^1 and h^2), battery driving ranges of both echelons (B^1 and B^2) and load capacity of both EVs (K^1 and K^2).

Table 3: Characteristics of the G-2E-CLRP instances

#	Inst.	n_c	n_s	f_s	m^1	m_s^2	c_{ij}^1	c_{ij}^2	c_b^1	c_b^2	h^1	h^2	B^1	B^2	K^1	K^2
1	10	12	3	50	3	2	1	1	2	1	1	1	100	80	15000	6000
	5	12	4	50	3	2	1	1	2	1	1	1	100	80	15000	6000
2	3	21	3	75	3	2	1	1	2	1	1	1	150	130	15000	6000
	3	21	4	75	3	2	1	1	2	1	1	1	150	130	15000	6000
3	3	21	3	75	3	2	1	1	2	1	1	1	150	130	15000	6000
	3	21	4	75	3	2	1	1	2	1	1	1	150	130	15000	6000

5.2 Performance of B&P algorithm

In this section, we use the generated test instances of Set 1 to Set 3 to evaluate the computational performance of our B&P algorithm, and compare it against the arc-based formulation (Section 3.2) using the B&C algorithm of CPLEX 12.7. All runs were performed with a time limit of 3600 CPU seconds.

Tables 4 and 5 give the instance description and report the results of the test. In these tables, column 1 shows the name of each instance. The column "Description" stands for the set of potential satellites. The column "T(s)" presents the computing time (in seconds) of CPLEX and B&P algorithm, respectively. The best results (optimal solutions or best upper bound found within 3600 seconds) obtained with CPLEX and B&P algorithm are provided by column "Best". The column "Gap(%)" provides the optimality gap found by CPLEX and by B&P algorithm at termination or at the root-node within a time limit of 3600 seconds. Columns 6-8 report the root-node performance of B&P algorithm. The column "LB" means the lower bound obtained by our column generation. Columns 9-12 focus on the overall of performance of B&P algorithm. The column "B&B N." indicates the number of B&P nodes explored.

As shown in Table 4, our B&P algorithm can solve small instances of Set 1 in only two seconds, which is significantly faster than CPLEX that took an average of 400 seconds to compute. Table 5 reports that the results on medium instances of Set2 and Set3, containing 21 customers and at most 4 candidate satellites . The results clearly show that our B&P algorithm also gives a notable improvement in computational time by solving medium instances to optimality in only a few seconds. Moreover, our B&P root node solutions exhibit an optimality gap of 3.4% on average and are achieved within about 2 seconds.

5.3 Profit of integrated planning for the G-2E-CLRP

In order to show the large benefits of integrated planning in our G-2E-CLRP, we compare our integration approach to the sequential approach where the long-term strategic location decisions are determined first, and other tactical decisions such as routing plans, are decided later. Here, heuristic procedure talked about in Section 4.6 is used to offer sequential results, whose locations of open satellites and the set of customers assigned to each open satellite are determined first.

Table 6 displays the relative savings obtained by using our integration approach that simultaneously consider location and routing over the sequential procedure. The average savings are 21.6%, 41.3%,

Table 4: Comparison of results obtained with CPLEX and B&P algorithm on instances with 12 customers

Instance	Description	CPLEX			B&P algorithm						
	Satellites	Best	Gap(%)	T(s)	Root-node B&P			Overall B&P algorithm			
					LB	Gap(%)	T(s)	Best	Gap(%)	T(s)	B&B N.
Set 1											
En13s3-1	1,2,3	462	15.4	3604.5	407.9	6.4	0.4	436	0.0	0.9	27.0
En13s3-2	2,5,10	354	0.0	28.8	319.8	9.7	0.4	354	0.0	0.9	27.0
En13s3-3	3,4,8	366	0.0	45.9	344.4	5.9	0.4	366	0.0	0.6	7.0
En13s3-4	4,5,6	356	0.0	24.1	337.1	5.3	0.4	356	0.0	0.5	5.0
En13s3-5	5,7,9	362	0.0	11.5	351.4	2.9	0.5	362	0.0	0.6	5.0
En13s3-6	6,7,12	392	0.0	8.3	385.2	1.7	0.4	392	0.0	1.7	47.0
En13s3-7	7,8,9	400	0.0	12.2	396.2	1.0	0.6	400	0.0	0.6	5.0
En13s3-8	8,10,11	452	0.0	135.8	439.9	2.7	0.4	452	0.0	0.6	11
En13s3-9	9,11,12	496	0.0	715.0	483.7	2.5	0.5	496	0.0	0.5	3.0
En13s3-10	10,11,12	486	0.0	173.4	467.2	3.9	0.5	486	0.0	0.5	5.0
En13s4-1	1,2,3,4	398	0.0	1155.7	362.4	8.9	0.4	398	0.0	1.4	47.0
En13s4-2	3,4,5,6	354	0.0	26.8	333.9	5.7	0.6	354	0.0	1.1	11.0
En13s4-3	1,4,7,11	346	0.0	43.7	314.8	9.0	0.5	346	0.0	0.9	17.0
En13s4-4	2,3,6,12	340	0.0	15.4	333.0	2.1	0.5	340	0.0	0.6	5.0
En13s4-5	5,7,10,11	362	0.0	18.6	351.4	2.9	0.5	362	0.0	0.6	7.0
Average			1.0	401.3		4.7	0.5		0.0	0.8	

Table 5: Comparison of results obtained with CPLEX and B&P algorithm on instances with 21 customers

Instance	Description	CPLEX			B&P algorithm						
	Satellites	Best	Gap(%)	T(s)	Root-node B&P			Overall B&P algorithm			
					LB	Gap(%)	T(s)	Best	Gap(%)	T(s)	B&B N.
Set 2											
En22s3-1	6,8,17	564.2	0.0	160.3	558.7	1.0	1.6	564.2	0.0	1.6	3
En22s3-2	9,14,19	565.8	0.0	320.4	532.6	5.9	1.8	565.8	0.0	4.0	23
En22s3-3	10,11,12	624.8	0.0	1334.7	609.9	2.4	1.9	624.8	0.0	3.6	23
En22s4-1	6,8,11,12	573.8	0.0	441.0	560.8	2.3	1.9	573.8	0.0	2.0	5
En22s4-2	9,14,16,17	562.7	0.0	505.4	524.2	6.8	2.2	562.7	0.0	5.4	29
En22s4-3	9,10,12,16	538.1	0.0	220.7	524.7	2.5	2.3	538.1	0.0	2.9	7
Average			0.0	497.1		3.5	1.9		0.0	3.2	
Set 3											
En22s3-1	13,14,16	562.7	0.0	257.6	550.1	2.2	1.6	562.7	0.0	2.1	5
En22s3-2	14,17,19	587.2	5.8	3600.0	575.2	2.0	1.4	587.2	0.0	1.8	9
En22s3-3	13,17,21	597.9	4.8	3600.0	592.4	0.9	1.6	597.9	0.0	5.2	31
En22s4-1	13,14,16,17	562.7	0.0	602.0	548.8	2.5	2.2	562.7	0.0	2.6	5
En22s4-2	14,17,19,21	587.2	7.9	3600.0	575.2	2.0	1.7	587.2	0.0	3.3	23
En22s4-3	13,16,19,21	585.2	2.2	3600.0	575.1	1.7	1.9	585.2	0.0	3.8	25
Average			3.4	2543.3		1.9	1.7		0.0	3.1	

48.8% for instances of Set 1, Set 2 and Set3, respectively. The extreme savings are 85.9% for instance En22s4-2 of Set 3. These results clearly show why logistics company should incorporate routing decisions into determining location decisions when they design a green two-echelon delivery system.

Table 6: Comparison of the integration and sequential results of our G-2E-CLRP

Instance	Optimal objective			Instance	Optimal objective			Instance	Optimal objective		
Set 1	Sequntial	Integration	Savings	Set 2	Sequntial	Integration	Savings	Set 3	Sequntial	Integration	Savings
En13s3-1	468	436	7.3	En22s3-1	847.8	564.2	50.3	En22s3-1	739.1	562.7	31.3
En13s3-2	439	354	24.0	En22s3-2	684.7	565.8	21.0	En22s3-2	960.5	587.2	63.6
En13s3-3	511	366	39.6	En22s3-3	814.0	624.8	30.3	En22s3-3	735.7	597.9	23.1
En13s4-1	468	398	17.6	En22s4-1	956.5	573.8	66.7	En22s4-1	763.9	562.7	35.8
En13s4-2	354	354	0.0	En22s4-2	783.9	562.7	39.3	En22s4-2	1091.3	587.2	85.9
En13s4-3	489	346	41.3	En22s4-3	753.6	538.1	40.1	En22s4-3	897.8	585.2	53.4
Average			21.6				41.3				48.8

5.4 Sensitivity analysis for the G-2E-CLRP

In this section, we analyze the sensitivity of the result to the rental cost and the battery driving range. Table 7 shows the impact of the rental cost of satellites and the battery driving range of each echelon. The column "Instance" stands for the name of each instance. The group of columns shows the description of the instances: the rental cost of satellites (f_s) and the battery driving range B^1 and B^2 in each echelon, respectively. The next group of columns reports the results of the instances: the number of open satellites (n_s), the number of tours in the second echelon (n_r^2), the final rental cost (RC), the final travel cost and battery swapping cost (tactical cost, TC) and the overall cost (Best).

These experiments highlight the significant impact of the rental cost of satellites and EV battery capacity in each echelon in the instances under study. First of all, as the rental cost of satellites grows, both the number of open satellites and the tactical cost slightly decrease: e.g., in the instance En22s4-2 of Set 2, the number of satellites to open from 3 to 2, the corresponding tactical cost from 422.7 to 428.8 and the overall cost from 422.7 to 578.8 when the battery driving range in each echelon fixed at 130 and 110, respectively. Moreover, the number of open satellites show little change when battery driving range varies. The battery driving ranges actually affect the number of open satellites in our G-2E-CLRP. In these conditions, the location of satellites is a key strategy for logistics enterprises to support EVs in their two-echelon system.

The battery driving range of EVs has an even larger impact to reduce the two-echelon distribution costs of logistics enterprises. For considered instances, if the battery driving range of the first echelon increases, the number of open satellites and the number of secondary tours maybe decrease, and both the tactical cost and the overall cost will decrease: e.g., in the instance En22s3-2 of Set 2, the tactical cost from 446.8 to 428.8, the overall cost from 671.8 to 578.8 when the battery driving range of secondary EVs from 90 to 110 and the rental cost fixed at 75. The reason maybe because customers could be served by less satellites when the battery driving range is improved and the rental cost is high. It is worth mentioning that the larger battery driving range is also helpful for reducing the times of swapping batteries. Therefore, the location of satellites and the configuration of EVs, especially the battery driving range of secondary EVs, should be well-balanced for logistics enterprises in terms of their infrastructures (with different rental and refurbishing costs) and demand network to enrich the application of EVs in practice.

6 Conclusion and future work

In this paper, we present the G-2E-CLRP that considers the locations of satellites, different types of EVs and battery swapping operations at start nodes in a two-echelon delivery network. Furthermore, the capacity limitation of satellites and the load and battery capacity of EVs are also incorporated into the G-2E-CLRP model to represent real-world requirements. We introduce a compact arc-based formulation, propose a set partitioning formulation and develop an efficient B&P algorithm for the G-2E-CLRP. In the pricing subproblems, we design a new column generation procedure embedded into a branch-and-bound framework to generate feasible columns for the RLMPs. It consists of a two-phase heuristic column generation procedure where first using the CAP to choose customers for each open satellites and followed by Modified Clarke Wright (MCW) algorithm and pulse algorithm to generate feasible secondary routes, and an exact pulse algorithm by reconstructing battery capacity constraints to battery consumption windows for each node to solve RLMPs exactly.

To assess the performance of the proposed B&P algorithm, we conduct experiments on the basis of the benchmark instances in the literature. We demonstrate the strong performance of our algorithm in comparison with the MIP solver CPLEX. This approach is able to solve to optimality small- and medium-size instances, and provides tight lower bounds at the root-node. Finally, in the economic analysis, we perform several experiments to highlight the importance of integrating location and routing decisions, and the managerial implications of using EVs in a two-echelon logistics system.

The future research perspectives are multiple. Inclusion of stochastic elements in the G-2E-CLRP

Table 7: Sensitivity analysis of rental costs and battery driving ranges

Instance	Description			G-2E-CLRP					Instance	Description			G-2E-CLRP				
Set2	f_s	B^1	B^2	n_s	n_r^2	FC	TC	Best	Set3	f_s	B^1	B^2	n_s	n_r^2	FC	TC	Best
En22s3-2	0	110	90	3	5	0	430.4	430.4	En22s3-3	0	110	110	3	6	0	853.0	853.0
	30	110	90	3	5	90	430.4	520.4		30	110	110	3	6	90	853.0	943.0
	75	110	90	3	5	225	430.4	655.4		75	110	110	3	5	225	853.0	1078.0
	0	110	110	2	4	0	428.8	428.8		0	130	110	3	6	0	853.0	853.0
	30	110	110	2	4	60	428.8	488.8		30	130	110	3	6	90	853.0	943.0
	75	110	110	2	4	150	428.8	578.8		75	130	110	3	5	225	853.0	1078.0
	0	130	110	2	4	0	428.8	428.8		0	130	130	2	4	0	447.9	447.9
	30	130	110	2	4	60	428.8	488.8		30	130	130	2	4	60	447.9	507.9
	75	130	110	2	4	150	428.8	578.8		75	130	130	2	4	150	447.9	597.9
	0	130	130	2	3	0	415.8	415.8		0	150	130	2	4	0	447.9	447.9
	30	130	130	2	4	60	415.8	475.3		30	150	130	2	4	60	447.9	507.9
	75	130	130	2	4	150	415.8	565.8		75	150	130	2	4	150	447.9	597.9
	0	150	130	2	3	0	415.8	415.8		0	150	150	2	4	0	445.4	445.4
	30	150	130	2	4	60	415.8	475.3		30	150	150	2	4	60	445.4	505.4
	75	150	130	2	4	150	415.8	565.8		75	150	150	2	4	150	445.4	595.4
En22s4-2	0	110	90	3	6	0	445.7	445.7	En22s4-2	0	110	110	3	6	0	705.6	705.6
	30	110	90	3	6	90	445.7	535.7		30	110	110	3	6	90	705.6	795.6
	75	110	90	3	5	225	446.8	671.8		75	110	110	3	6	225	705.6	930.6
	0	110	110	3	6	0	422.7	422.7		0	130	110	3	6	0	705.6	705.6
	30	110	110	2	4	60	428.8	488.8		30	130	110	3	6	90	705.6	795.6
	75	110	110	2	4	150	428.8	578.8		75	130	110	3	6	225	705.6	930.6
	0	130	110	3	6	0	422.7	422.7		0	130	130	2	4	0	437.2	437.2
	30	130	110	2	4	60	428.8	488.8		30	130	130	2	4	60	437.2	497.2
	75	130	110	2	4	150	428.8	578.8		75	130	130	2	4	150	437.2	587.2
	0	130	130	2	4	0	412.7	412.7		0	150	130	2	4	0	437.2	437.2
	30	130	130	2	4	60	412.7	472.7		30	150	130	2	4	60	437.2	497.2
	75	130	130	2	4	150	412.7	562.7		75	150	130	2	4	150	437.2	587.2
	0	150	130	2	4	0	412.7	412.7		0	150	150	2	4	0	437.2	437.2
	30	150	130	2	4	60	412.7	472.7		30	150	150	2	4	60	437.2	497.2
	75	150	130	2	4	150	412.7	562.7		75	150	150	2	4	150	437.2	587.2

is a meaningful direction in order to derive robust long-term network structures, such as modeling demand uncertainty. Other promising topics include exploring the adaptive large neighborhood search (ALNS) meta-heuristic to solve pricing subproblems for larger scale problems, and investigating the G-2E-CLRP with special aspects such as tours in first echelon, or customer time windows.

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