Two-echelon electric vehicle routing problem with e-cargo bikes considering carbon emission minimization

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1 Introduction & related works

Sustainable two-echelon electric vehicle (EV)-based parcel distribution systems have received considerable attention recently due to the increasing demand for sustainable and efficient last-mile delivery solutions. With rapid urbanization and the expansion of e-commerce, traditional logistics networks face challenges such as congestion, high operational costs, and carbon emissions. The two-echelon EV routing problem (2E-EVRP), first formulated by Breunig et al. (2017), offers a practical solution by introducing intermediate satellite facilities where goods can be transferred from larger trucks to smaller, more agile ones for final delivery. The 2E-EVRP is a logistics optimization problem where deliveries occur in two distinct phases. In the first echelon, larger trucks transport parcels from a central depot to satellite facilities. Smaller delivery EVs, such as e-cargo bikes, in the second echelon distribute these parcels to final customers.

Despite some works on 2E-EVRP, one deficiency is that they did not consider sustainability objectives. While many studies focus on cost minimization or service level improvements, none have incorporated carbon emissions as a primary optimization objective. Given the increasing global emphasis on reducing logistics' environmental impact, there is a need to integrate sustainability considerations into 2E-EVRP models. One way to address this deficiency is by introducing an objective function that explicitly minimizes carbon emissions. This paper presents the 2E-EVRP with e-cargo bikes and carbon emission minimization (2E-EVRP-EB-CEM). The proposed model aims to optimize parcel delivery by reducing carbon emissions while ensuring efficient logistics operations in urban settings. To achieve this, we propose a mixed-integer linear programming (MILP) model that optimizes first-echelon truck routes and second-echelon e-cargo bike deliveries while considering cargo load and battery constraints, satellite storage limitations, and charging station (CS) availability. We also reported how much savings in carbon emission can be achieved via this delivery system compared to truck-based parcel delivery.

The addressed problem in this paper is a variant of the 2E-EVRP, initially introduced by Breunig et al. (2017). So, here, we focused on 2E-EVRP-related works. Breunig et al. (2017) introduced 2E-EVRP as a general case of two-echelon VRP (2EVRP) (Cuda et al., 2015), in which EVs were assumed in the second echelon of the delivery problem. In addition, CS-related infrastructure planning was also considered in the second echelon of the 2E-EVRP. They developed a large neighborhood search (LNS)-based heuristic to solve the problem. Next, Breunig et al. (2019) formulated the problem and proposed a mathematical programming-based algorithm, adapted from Baldacci et al. (2013) while proposing an LNS metaheuristic. They assumed there were limited fleet sizes of 1st- and 2nd-echelon vehicles while minimizing the total routing costs. Also, Agárdi et al. (2019) tacked the 2E-EVRP with a limited number of 1st- and 2nd-echelon vehicles. Similar to Breunig et al. (2017, 2019), they consider the minimization of the routing costs of the vehicles; however, they assume that each satellite (intermediate depots) has a limited storage capacity, satisfying a limited number of demands. They developed a genetic algorithm (GA) to tackle the large instances.

Moreover, Jie et al. (2019) studied the 2E-EVRP with battery swapping stations (2E-EVRP-BSS), where two types of EVs existed across two echelons. Battery swapping stations (BSSs) are located at fixed points with no service limitations, serving both types of EVs. Also, Caggiani et al. (2021) proposed a 2E-EVRP that includes time windows and partial recharging (2E-EVRPTW-PR), modeled as a mixed-integer program. Wang et al. (2019) introduced a 2E-EVRP with time windows and BSSs (2E-EVRPTW-BSS). Each satellite has a time window for delivery, and EVs may visit BSSs to swap batteries. Affi (2020) also developed a general variable neighbor search (GVNS) to tackle the 2E-EVRP. Wang et al. (2021) proposed a 2E-EVRPTW-BSS model with two logistics tiers. EVs must recharge at BSSs during delivery due to battery limitations. Recently, Akbay et al. (2022) studied the

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2E-EVRP, which incorporates customer demands, time windows, and CS for efficient EV recharging. The model is formulated as a three-index integer programming problem to accommodate different vehicle types. Also, Zijlstra et al. (2021) introduced an extended LNS heuristic for solving the 2E-EVRP with non-linear charging functions and partial recharging. The methodology has two phases: replicating the original LNS algorithm proposed by Breunig et al. (2019) (without local search enhancements) and extending it to include charging costs. In addition, Akbay et al. (2023) introduced the 2E-EVRP with simultaneous pickup and delivery (SPD). Wu and Zhang (2023) developed a branch-and-price exact algorithm to solve the 2E-EVRP while mining the route cost of vehicles and their usage costs. The present work differs from the related studies in the literature regarding the objective function, where we optimize the carbon emission from the 1st- and 2nd-echelon vehicles. We also compared the carbon emission of the 2E-EVRP-EB delivery system and two-echelon truck-based delivery in which no e-bikes exist.

2 Problem statement & formulation

In the 2E-EVRP-EB-CEM, 1st-echelon trucks (with large load capacity) start their journeys at the central depot, distributing packages to specific satellite sites. Multiple first-echelon trucks can service a single satellite. These satellites are located within the urban area closer to populated regions. After a satellite is chosen and packages are dropped off, 2nd-echelon e-cargo bikes (with smaller cargo capacity compared to trucks) are loaded with these packages and set out to deliver them to final customers. E-bikes can be recharged at designated CSs if needed. Each customer must be serviced by exactly one e-bike. However, there are no fixed costs associated with opening satellites. The goal is to find the least-carbon-emission truck and e-bike routes to transport parcels from the main depot to satellites in the first echelon and then to customers in the last mile. There is a load capacity related to the 1st-echelon trucks and 2nd-echelon e-bikes; however, the driving range of the e-bikes is limited by a maximum battery capacity. Also, the storage capacity of the satellites is limited, and there is a limited number of e-bikes at each satellite.

The 2E-EVRP-EB-CEM can be represented as a graph $G = (V, A)$, where V denotes the set of all nodes, categorized as $V = D \cup C \cup F \cup S$. The central depot, represented by $D = \{0\}$, houses a fleet of 1st-echelon trucks denoted as K^1, which begin their trips from this location. Each first-echelon truck has a maximum load capacity Q^1 and carbon emission rate per unit distance λ^1. The customer nodes, denoted by C, each have an associated demand q_i, which an e-bike must fulfill. The CSs are represented by F, where second-echelon e-bikes can recharge their batteries to a full capacity of B^2. The set S includes satellite locations acting as intermediary transfer points. Each satellite $s \in S$ can deploy a maximum of $|K_s^2|$ second-echelon e-bikes, each characterized by a maximum load capacity Q^2, battery capacity B^2, carbon emission rate per unit distance λ^2, and energy consumption rate per unit distance h^2. The set of directed arcs in the graph is denoted as $A = A^1 \cup A^2$. The 1st-echelon arcs A^1 represent the directed edges between the central depot and the satellites, expressed as $A^1 = \{(i,j)|i,j \in D \cup S, i \neq j\}$. Similarly, the 2nd-echelon arcs A^2 connect the satellites to customers and CSs, formulated as $A^2 = \{(i,j)|i,j \in C \cup S \cup F, i \neq j\}$. Additionally, the total demand a satellite $s \in S$ can satisfy is constrained by a capacity limit Q'_s.

The following decision variables are defined for 2E-EVRP-EB-EM: x_{ijk}: Binary variable indicating whether a 1st-echelon truck travels along arc $(i,j) \in A^1$ (1 if yes, 0 otherwise). y_{ijks}: Binary variable indicating whether a 2nd-echelon e-bike $k \in K^2$ deployed from satellite $s \in S$ travels along arc $(i,j) \in A^2$ (1 if yes, 0 otherwise). λ_s: Represents the total number of parcels assigned to satellite $s \in S$. w_{sk}: Denotes the total number of parcels delivered to satellite s by 1st-echelon truck $k \in K^1$. f_{ijk}: Tracks the remaining cargo load on 1st-echelon truck $k \in K^1$ while traveling along arc $(i,j) \in A^1$. f'_{ijks}: Tracks the remaining cargo load on 2nd-echelon e-bike $k \in K^2$ launched from satellite s while traveling along arc $(i,j) \in A^2$. b_{isk}^{2+}: Battery level of 2nd-echelon vehicle $k \in K^2$ (deployed from satellite $s \in S$) upon entering node i in the second echelon. b_{isk}^{2-}: Battery level of 2nd-echelon e-bike $k \in K^2$ upon leaving node i in the second echelon. The objective of the probe (minimizing the consumed energy by trucks and e-bikes) must be achieved while adhering to various operational constraints. Based on these formulations, the MILP model is presented as follows.

$$Min. \quad \sum_{(i,j)\in A^1} \sum_{k\in K^1} \lambda^1 d_{ij} x_{ijk} + \sum_{(i,j)\in A^2} \sum_{k\in K^2} \sum_{s\in S} \lambda^2 d_{ij} y_{ijks} \tag{1}$$

subject to,

$$\sum_{j\in D\cup S: j\neq i} x_{ijk} = \sum_{j\in D\cup S: j\neq i} x_{jik}, \qquad \forall i \in D \cup S, \forall k \in K^1 \tag{2}$$

$$\sum_{j\in D\cup S: j\neq s} x_{sjk} \leq 1, \qquad \forall s \in S, \forall k \in K^1 \tag{3}$$

$$w_{sk} = \sum_{j\in D\cup S: j\neq i} f_{jsk} - \sum_{j\in D\cup S: j\neq i} f_{sjk}, \qquad \forall s \in S, \forall k \in K^1 \tag{4}$$

$$f_{ijk} \leq Q^1 x_{ijk} \qquad \forall i, j \in D \cup S, i \neq j, \forall k \in K^1 \tag{5}$$

$$\sum_{s \in S} w_{sk} \leq Q^1, \qquad \forall k \in K^1 \tag{6}$$

$$\sum_{k \in K^1} w_{sk} = \lambda_s, \qquad \forall s \in S \tag{7}$$

$$\sum_{k \in K^2} \sum_{s \in S} \sum_{j \in C \cup S \cup F : j \neq i} y_{ijks} = 1, \qquad \forall i \in C \tag{8}$$

$$\sum_{j \in C \cup S \cup F : j \neq i} y_{ijks} = \sum_{j \in C \cup S \cup F : j \neq i} y_{jiks}, \qquad \forall i \in C \cup S \cup F, \forall s \in S, \forall k \in K^2 \tag{9}$$

$$\sum_{\hat{s} \in S : \hat{s} \neq s} (\sum_{j \in C \cup S \cup F : j \neq s} y_{sjk\hat{s}} + \sum_{i \in C \cup S \cup F : i \neq s} y_{isk\hat{s}}) = 0, \forall s \in S, \forall k \in K^2 \tag{10}$$

$$\sum_{j \in C \cup F} \sum_{k \in K^2} y_{sjks} \leq |K_s^2|, \qquad \forall s \in S \tag{11}$$

$$\sum_{j \in C \cup S \cup F : j \neq i} \sum_{s \in S} \sum_{k \in K^2} f'_{ijks} = \sum_{j \in C \cup S \cup F : j \neq i} \sum_{s \in S} \sum_{k \in K^2} f'_{jiks} - q_i, \qquad \forall i \in C \tag{12}$$

$$\sum_{j \in C \cup S \cup F : j \neq i} \sum_{s \in S} \sum_{k \in K^2} f'_{ijks} = \sum_{j \in C \cup S \cup F : j \neq i} \sum_{s \in S} \sum_{k \in K^2} f'_{jiks}, \qquad \forall i \in F \tag{13}$$

$$f'_{ijks} \leq Q^2 y_{ijks}, \qquad \forall i, j \in C \cup S \cup F, i \neq j, \forall s \in S, \forall k \in K^2 \tag{14}$$

$$\sum_{i,j \in C \cup S \cup F : i \neq j} \sum_{k \in K^2} q_i y_{ijks} = \lambda_s, \qquad \forall s \in S \tag{15}$$

$$\sum_{i,j \in C \cup S \cup F : i \neq j} \sum_{k \in K^2} q_i y_{ijks} \leq Q'_s, \qquad \forall s \in S \tag{16}$$

$$b_{isk}^{2-} = B^2, \qquad \forall s \in S, \forall i \in S \cup F, \forall k \in K^2 \tag{17}$$

$$b_{isk}^{2-} = b_{isk}^{2+}, \qquad \forall s \in S, \forall i \in C, \forall k \in K^2 \tag{18}$$

$$b_{jsk}^{2+} \leq b_{isk}^{2-} - h^2 d_{ij} y_{ijks} + B^2 (1 - y_{ijks}), \qquad \forall (i, j) \in A^2, s \in S, k \in K^2 \tag{19}$$

$$x_{ijk} \in \{0, 1\}, f_{ijk} \geq 0, \qquad \forall (i, j) \in A^1, \forall k \in K^1 \tag{20}$$

$$y_{ijks} \in \{0, 1\}, f'_{ijks} \geq 0, \qquad \forall (i, j) \in A^2, \forall k \in K^2 \tag{21}$$

$$\lambda_s, w_{sk} \geq 0, \qquad \forall s \in S, \forall k \in K^1 \tag{22}$$

$$b_{isk}^{2-}, b_{isk}^{2+} \geq 0, \qquad \forall s \in S, \forall i \in S \cup C \cup F, \forall k \in K^2 \tag{23}$$

The objective function 1 minimizes the total carbon emitted from the 1st-echelon trucks and 2nd-echelon e-bikes. Constraint (2), is the vehicle flow balance constraint in the first echelon. Constraint (3) enforces that each 1st-echelon vehicle can only be used once. Constraint (4) maintains the balance of cargo levels before and after delivery to a satellite. Constraint (5) ensures that the load capacity of the 1st-echelon vehicles is not exceeded. Constraint (6) prevents a 1st-echelon vehicle from delivering more parcels to a satellite than its maximum capacity allows. Constraint (7) calculates the total number of parcels delivered to each satellite. Constraints (8)-(11) govern vehicle flow in the second echelon. Constraints (12)-(15) regulate the cargo levels of 2nd-echelon EVs while they visit customer and satellite nodes. Constraints (17)-(19) monitor the battery or energy levels of 2nd-echelon EVs during travel. Finally, constraints (20)-(23) define the types and domains of the model's decision variables.

3 Computational results & conclusion

We solved the developed MILP model via Gurobi implemented in Python language programming. We modified the EVRP instances (Schneider et al., 2014) by adding new parameters defined in Section 2. The results of the 2E-EVRP-EB-CEM were compared to truck-only delivery, i.e., 2E-VRP with carbon emission minimization (2E-VRP-CEM), as shown in table 1. To compare with 2E-VRP-CEM, we assume that instead of e-bikes, multiple vans with larger fuel ranges are located on the satellites, and they do the last-mile delivery. The average execution time for Gurobi to optimally solve the 2E-EVRP-EB-CEM instances with sizes of five to fifteen customers was 15.23 seconds, indicated by T. TCE, TCE_t, TCE_e, and $\zeta\%$ represent the total carbon emitted, carbon emitted by trucks, the carbon emitted by e-bikes, and the gap between TCE of the 2E-EVRP-EB-CEM and 2E-VRP-CEM. By using e-bikes as the 2nd-echelon vehicles, total carbon emission is reduced by 83.81% on average in all instances, showing the effectiveness of the proposed approach in suitability considerations. We conclude that green vehicles (e.g., e-bikes) can reduce carbon-related pollution in last-mile delivery, particularly in a two-echelon parcel distribution system. Future works can study cost-related objectives besides carbon emission as multi-objective problems and develop heuristics methodologies for real case studies with larger networks.

Table 1: Comparison of the of 2E-EVRP-EB-CEM with 2E-VRP-CEM

Instance	**2E-EVRP-EB-CEM**				**2E-VRP-CEM**			**2E-EVRP-EB-CEM**				**2E-VRP-CEM**	
	TCE	TCE_t	TCE_e	T	TCE	$\zeta\%$	**Instance**	TCE	TCE_t	TCE_e	T	TCE	$\zeta\%$
r104C5	5.10	4.70	0.41	0.21	20.22	-74.76	*c205C10*	4.00	3.32	0.68	3.97	33.09	-87.92
r105C5	5.10	4.70	0.40	0.14	21.11	-75.84	*rc102C10*	4.21	3.32	0.89	9.67	36.85	-88.58
r202C5	5.08	4.70	0.39	0.16	18.51	-72.53	*rc108C10*	4.18	3.32	0.86	1.87	37.86	-88.95
r203C5	5.22	4.70	0.52	0.19	24.19	-78.43	*rc201C10*	4.04	3.32	0.72	3.24	32.27	-87.48
c101C5	3.81	3.32	0.49	0.15	27.48	-86.14	*rc205C10*	4.17	3.32	0.85	2.92	37.03	-88.73
c103C5	3.76	3.32	0.44	0.16	24.76	-84.83	*r102C15*	8.23	7.57	0.66	31.82	30.40	-72.93
c206C5	3.89	3.32	0.57	0.53	26.77	-85.48	*r105C15*	8.25	7.57	0.68	23.65	31.27	-73.62
c208C5	3.81	3.32	0.49	0.38	20.58	-81.47	*r202C15*	8.28	7.57	0.71	24.71	32.24	-74.32
rc105C5	3.91	3.32	0.59	0.18	28.32	-86.21	*r209C15*	8.27	7.57	0.70	77.88	32.07	-74.21
rc108C5	3.95	3.32	0.63	0.20	29.79	-86.74	*c103C15*	2.88	2.10	0.78	18.10	29.41	-90.20
rc204C5	3.84	3.32	0.52	0.42	26.46	-85.49	*c106C15*	2.71	2.10	0.61	23.81	23.32	-88.38
rc208C5	3.80	3.32	0.48	0.21	30.34	-87.48	*c202C15*	2.99	2.10	0.89	97.76	32.72	-90.87
r102C10	5.23	4.70	0.53	2.47	24.80	-78.93	*c208C15*	2.82	2.10	0.72	26.55	27.32	-89.66
r103C10	5.11	4.70	0.42	0.69	19.89	-74.29	*rc103C15*	2.92	2.10	0.82	39.27	30.85	-90.52
r201C10	5.20	4.70	0.51	1.26	22.74	-77.13	*rc108C15*	3.04	2.10	0.94	26.24	34.84	-91.29
r203C10	5.32	4.70	0.63	2.78	27.24	-80.46	*rc202C15*	2.94	2.10	0.84	22.79	31.56	-90.67
c101C10	4.07	3.32	0.75	4.77	33.66	-87.91	*rc204C15*	2.93	2.10	0.83	93.53	30.95	-90.55
c104C10	4.04	3.32	0.72	1.12	32.13	-87.43	**Average (all)**	4.47	3.83	0.65	15.23	28.70	-83.81
c202C10	3.96	3.32	0.64	4.47	30.18	-86.87							

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