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Reconfiguration of last-mile supply chain for parcel delivery using machine learning and routing optimization

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ABSTRACT

Last-mile delivery has several negative environmental impacts in urban areas because of its high levels of greenhouse gas emissions and air pollution, as well as traffic congestion. These issues motivate decision-makers to redesign the delivery networks and make them more sustainable and efficient. A well-planned territory design can reduce total travel times and distances in urban distribution systems, in addition to balancing the workload between drivers. In this study, a two-echelon parcel distribution network modeled as the two-echelon vehicle routing problem with territory design and satellite location decisions is considered. A three-stage decomposition algorithm is proposed to solve this problem. In the first stage, a non-supervised machine learning clustering method is applied, followed by an algorithm based on the nearest-neighbor routing procedure, to find a set of routes for the second and first echelons. An improvement heuristic was also applied to improve the results in terms of the second echelon routing, considering the computational complexity of a large-scale instance. A case study based on real data from a delivery company in the city of Paris, France is adopted to perform the experiments. The outcomes of this paper show an improvement of 22.6% in travel time and distance. This reduction is also assessed with performance indicators like land use, fixed costs, energy consumption, carbon dioxide equivalent, and fine particles emissions.

1. Introduction

More than 50% of the world's population resides in urban areas (Bac & Erdem, 2021). As the world population increases, the demand for parcels and commodities will increase. Moreover, in the last few years, an expansion of e-commerce has been taking place worldwide, reaching a growth of approximately 21% (Statista, 2020). Numerous products are available, and deliveries can be received at the customer's home, office, or mailbox (Kull et al., 2007). Although the transportation and mobility sectors are essential for meeting the increase in demand, last-mile delivery accounts for up to 28% of the total delivery costs (Wang et al., 2016). In addition, urban parcel delivery activities are the source of approximately 25% of CO_2 emissions, 30% of NOx emissions, 40% of energy consumption, and 50% of particle matter (Dablanc, 2011; Schoemaker et al., 2006). According to the World Health Organization (WHO), no less than 91% of the world's population is exposed to poor air quality that exceeds WHO guideline limits (Tahami et al., 2020). All these externalities highlight the need for sustainable urban delivery planning (Pamucar et al., 2022).

Different city logistics initiatives and strategies have been developed and modeled to improve efficiency, relieve traffic congestion, and reduce greenhouse gas (GHG) emissions (i.e., the addition of satellite distribution centers and urban logistic centers) (Crainic & Sgalambro, 2014; Meza-Peralta et al., 2020). Two-echelon distribution is the most common model used to design last-mile supply networks. It consists of delivering parcels from a depot to a set of satellites, and from there, to a set of geographically dispersed customers. Practitioners and academics frequently approach this logistics distribution problem as a two-echelon

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vehicle routing problem (2E-VRP) (Crainic et al., 2004). Owing to the high computational complexity of the problem, many researchers are motivated to design and propose approximate algorithms (heuristics and metaheuristics) to solve it.

Moreover, territory design (TD) or districting involves the grouping of small geographic zones into larger areas, called territories. These territories must accomplish a set of planning criteria according to the given context. Planning criteria, such as contiguity and compactness, are widely used to reduce distances and travel times within a territory. Reductions in these two indicators also represent benefits for the companies in terms of operating costs (Lespay & Suchan, 2022). Among the different applications, the design of territories, especially in last-mile logistics, is one of the most relevant ones (Kalcsics & Ríos-Mercado, 2019). It is a common practice among logistic operators to divide urban areas into delivery zones, which comprise households and commercial and institutional customers, and to assign these zones to one or more distribution centers that will deliver the parcels to the corresponding clients (Sandoval et al., 2022). TD allows companies to determine the best way to serve and respond quickly to customer demand, standardize service quality, and organize an efficient and equitable allocation of new customers among distribution centers. Most approaches for TD employ mathematical modeling or heuristic procedures. However, with the increase in available data, machine learning may help improve the current procedures.

The contributions of this paper are threefold. First, we present a non-supervised machine learning clustering method to implement districting design for many geographically dispersed customers. This approach is relevant to parcel delivery problems in megacities, such as Paris, France, which is the case considered in this paper. Second, we design delivery routes to optimize the total delivery time in the city. We propose a heuristic algorithm with a three-stage decomposition strategy to deal with the high computational complexity of the 2E-VRP. The heuristic algorithm contains the TD in the first stage, followed by an algorithm based on the well-known nearest-neighbor (NN) routing heuristic (Taiwo et al., 2013), which is implemented in the first and second echelons to generate the routes. Additionally, a local search operator is applied to improve the solution in the second echelon, which is the more complex one. Finally, to run the experiments, we adopted a case study with a real-world large-scale instance, involving an urban distribution system at a major French delivery company in the city of Paris, France. Performance indicators, such as carbon dioxide equivalent (CO_2e), fine particle emissions, fixed costs, land use, and energy consumption are used to assess the sustainability of the delivery system.

The remainder of this paper is organized into five sections. In the next section, we review the related literature. The third section discusses the methodology applied to our research. The fourth section presents the computational experiments using the case study of Paris, France, and the results are analyzed. The last section concludes the paper and outlines several perspectives for future research.

2. Literature review

The study of TD problems has its origins in urban modeling approaches, first studied in the 1960 s, mainly using mathematical models (Southworth, 2011). In urban planning, the TD or regional planning problem is defined as the problem of grouping small geographic areas called basic units (BU) –such as counties, zip codes, or customers– into larger geographic clusters called territories, in such a way that these territories are acceptable according to relevant planning criterion. Depending on the context, these considerations can either be economically motivated (e.g., average sales, workload, and number of customers) or have a demographic background (e.g., number of inhabitants and voting population). Moreover, some spatial constraints, like contiguity and compactness, are often required. Notably, the literature often uses the term territory alignment instead of TD.

Other names given to this problem in the literature are territory project, automatic zoning design, land allocation, (re)districting, region partitioning, and geographical deployment (Freire de Sousa et al., 2012). This is an important problem that is present in a great number of geographic projects and has potential application in various subjects, such as the establishment of political districts, location of schools, trash collection, social services (health centers, hospitals, etc.), emergency services, maintenance teams, sales, and distribution of products. This last application is relevant to supply chain management. An interesting evaluation of several application areas for TD was reported by Kalcsics et al. (2005).

The TD problem has been largely studied since the 1960 s, and several models and techniques have been proposed to solve it. Most of these approaches are based on set covering or set partitioning formulations (Lopez, 2012; Freire de Sousa et al., 2012), where the objective function minimizes the sum of the distances. In most cases, these models are solved using integer programming techniques that are often supported by column generation methods. In general, to solve large-scale problems, the allocation phase can be tackled by relaxing the integrality constraints on the assignment variables (i.e., binary variables). However, this procedure usually assigns portions of the BUs to more than one territory center, which is not desired. More recently, metaheuristics have been applied to the set covering and the set partitioning problems, with promising results. The works of Freire de Sousa et al. (2012) and Lopez (2012) provide a complete review of the basic concepts of TD problem approaches and algorithms. Some (hybrid) metaheuristics procedures have also been used. We refer the reader to the works of Freire de Sousa et al. (2012) and Kalcsics and Ríos-Mercado (2019) for comprehensive reviews.

In logistics and supply chain management, several applications of the TD problem can be found in the literature, mainly related to sales and marketing applications or product distribution. The problem is mainly approached as a vehicle routing problem (VRP). Haugland et al. (2007) studied the case of district design for a VRP with stochastic demands, in which actual demands are revealed only after the districting decisions are made. The objective was the minimization of the expected routing cost. Both tabu search and multi-start heuristics were proposed, and their experiments showed that tabu search outperforms multi-start in terms of solution quality. A case in the bottled beverage industry was studied by Ríos-Mercado and Salazar-Acosta (2011). These authors proposed a greedy randomized adaptive search procedure (GRASP) to simultaneously consider the design and routing decisions. Another case study, taken from the package shipping industry, was examined by Schneider et al. (2014), who also investigated the impact of time window constraints. Their analyses showed that incorporating time window characteristics and historical demand data does not lead to a perceptible improvement in the solution quality. The work of Lei et al. (2012) included regular and stochastic customers and proposed a large neighborhood search heuristic, which was tested on modified Solomon instances for vehicle routing. Later, Lei et al. (2015) studied the multiple traveling salesman problem and the districting problem with multiple periods and multiple depots. An adaptive large neighborhood search metaheuristic was developed. Furthermore, a multi-objective evolutionary algorithm was proposed by Lei et al. (2016) to solve a multi-objective dynamic stochastic districting and routing problem in which the customers of a territory stochastically evolve over several periods of a planning horizon. Zhou et al. (2021) addressed a case study in the dairy sector.

In VRP, Moreno et al. (2020) introduced a case study for meat distribution. The routing problem was modeled as a VRP, and candidate districts were generated using a modified *k*-means heuristic that evaluates the time required to deliver goods within the district. The districting plan is then obtained by solving an integer programming formulation. Within the scope of this research, few papers applying data science clustering methodologies, like *k*-means, were found in the literature on 2E-VRP, especially to deal with large-scale instances. Clustering approaches can be useful to reduce the computational complexity in large-scale logistics networks (Defryn & Sörensen, 2017; Expósito-Izquierdo et al., 2016). In two-echelon distribution systems and the 2E-VRP, we identified the works of Wang et al. (2018, 2020, 2021). For instance, Wang et al. (2021b) considered three-dimensional *k*-means clustering using a customer's geographic coordinates *(x,y)* and a time parameter *(z)* that denotes the value of each service time window interval to solve an initial part of a two-echelon distribution system. A summary of the related works is presented in Table 1, and a comparison with our approach is presented. The classification was performed in terms of existing solution approaches, objective functions, instance size, and if a case study was considered. Heuristic methods have been the most commonly used approaches to solve the 2E-VRP and its variants, and the most studied objective function is the minimization of costs.

As a background of our previous work, we addressed the 2E-VRP using a case study in the city of Paris, France with more than 90,000 delivery points, in which two strategies were considered for urban parcel delivery (Ramirez-Villamil et al., 2022). In strategy 1, each district of Paris has a satellite randomly located within the same arrondissement and can only serve customers belonging to the same assigned area. Strategy 2 involved the grouping of the 20 districts by geographical proximity and computing size, resulting in 10 groups. Then, a decomposition algorithm based on the NN search heuristic was applied as a solution approach for both strategies, and the best results were obtained using the clustering strategy. For future work, it was suggested that the design of other solution procedures may allow for improvement. Based on this perspective, an unsupervised machine learning method called the two-dimensional *k*-means (2D-*k*-means) clustering algorithm combined with a NN routing procedure was applied to obtain initial solutions for a problem-instance of 50 delivery points (Ramirez-Villamil et al., 2022). Then, two local search operators were introduced and compared with improve the initial solution.

In the current work, the case of Paris is also considered. Since it is a large-scale instance, the 2D-*k*-means approach was applied to cluster the delivery points more efficiently. In this approach, the centroid of each cluster will become the satellite that serves the cluster. Moreover, based on the research perspective mentioned before, the addition of an efficient local search operator can improve the results, which may be similar to those obtained with strategy 2 proposed in our previous study, improving the operations of the case study company further.

3. Methodology

Approximate algorithms, such as heuristics and metaheuristics, are needed to solve combinatorial optimization problems and find feasible solutions with a reasonable computational time. Owing to the NP-hardness of the 2E-VRP, decomposition strategies have been applied recently to deal with large-scale real-world problems (Flaberg et al., 2006). Hence, this paper proposes to solve this problem using a decomposition algorithm. In some studies, the solution is divided into two parts (the initial solution phase and the optimization phase) (Du & He, 2012), but in other cases (e.g., Muñoz-Villamizar et al., 2015; Ostertag et al., 2009; Ramirez-Villamil et al., 2022), the problem is split into subproblems that are solved separately. We followed this last approach by splitting the problem into three subproblems to reduce the computational complexity of a large-scale instance while guaranteeing the feasibility and quality of the solution by aggregating the subproblems. The three subproblems are:

1. Territory clustering (allocation of delivery points to the satellites) using a non-supervised clustering machine learning approach.
2. Route design for last-mile delivery (second echelon of the network).
3. Route design for the first echelon (from the depot to the satellites).

The routes of the second echelon are determined first because, after solving the routing of the second echelon, the corresponding demand of each satellite can be calculated as the sum of the demand of the customers clustered and served by second echelon routes departing from the same satellite. Once the demand for each satellite is known, the routes of the first link are constructed. Sluijk et al. (2023) and Belgin et al. (2018) also considered this strategy in their solution methods.

3.1. First subproblem: Territory clustering

In the 2E-VRP, the depots and customers are connected by a set of intermediate depots called satellites. Satellites can be an urban consolidation center, an urban distribution center, "a warehouse, a transshipment site or a cross-docking facility (no storage offered)" (Cattaruzza et al., 2017). These types of facilities are located within the city and are added to the conventional distribution networks to increase the efficiency of parcel delivery processes from the depot to the customers. It is important to have territorial planning strategies to locate the satellites in appropriate areas and ensure the maximum coverage of the distribution network so that each delivery point can be allocated to one of the satellites.

Data science methodologies have been extensively applied in different fields. Customer clustering is an effective strategy to reduce the computational complexity of optimization problems (Cinar et al., 2016; Ho et al., 2012; Zhu et al., 2019) and improve the calculation efficiency for large-scale logistics networks (Defryn & Sörensen, 2017; Expósito-Izquierdo et al., 2016). In practice, clustering methodologies can help in the design of urban parcel distribution networks, enabling some geographic clustering of the territory where customers are located in city areas, to effectively place satellites in the optimal locations. In the literature, *k*-means clustering can address the capacitated vehicle routing problem (CVRP) with initial solutions for vehicle routing optimization (Luo & Chen, 2014). In this paper, we built upon our previous work (Ramirez-Villamil et al., 2022).

The first subproblem involves the allocation of the delivery points (customers) to predetermined satellites. A non-supervised machine learning method called 2D-*k*-means clustering is used before route optimization to reduce the computational complexity (see Algorithm 1). We consider the two dimensions of each customer's geographic location (latitude and longitude); *k*-means clustering traditionally groups customers into different clusters based on the two-dimensional Euclidean distance (Wang et al., 2018, 2020). Let *k* denote the number of clusters to be defined, which corresponds to the number of satellites in the distribution network. The centroid for each cluster *k* is randomly selected. All the data is processed, and the distances from each customer to the centroids are calculated. Then, each element is assigned to its closest cluster centroid, and the new centroids of *k* clusters are updated. This algorithm continues until all customers are adjusted in the adequate cluster. Finally, the results of the clustering are saved and become the inputs to calculate the initial solution for the routing optimization (second and third subproblems).

Algorithm 1: K-means algorithm

K-means (data, k, ε): t = 0Randomly initialize k centroids: $\mu_1^t, \mu_2^t \cdots, \mu_k^t$**repeat**$t \leftarrow t+1$ $C_i \leftarrow \varnothing$ for all $i = 1, \cdots, k$// Cluster assignment**foreach** x_j in data **do**$i^* \leftarrow \text{argmin}_i \left\{ \|x_j - \mu_i^{t-1}\|^2 \right\}$ $C_i \leftarrow C_{i^*} \cup \{x_j\}$ // assign x_j to the closest centroid**end foreach**// Centroid update**foreach** $i = 1, \cdots, k$ **do**$\mu_i^t \leftarrow \frac{1}{|C_i|} \sum_{x_{j \in C_i}} x_j$**end foreach****until** $\sum_{i=1}^{k} \|x_j - \mu_i^{t-1}\|^2 \leq \varepsilon$**return** C_i, μ_k^t

3.2. Second subproblem: Last-mile delivery routing

The second subproblem determines the routing from satellites to serve the customers (last-mile delivery). A decomposition strategy is implemented in which each cluster is modeled as a CVRP. Considering a large number of delivery points, the initial solution is obtained by applying an algorithm based on the NN routing procedure (Taiwo et al., 2013). Although metaheuristics are more complex and sophisticated algorithms that can provide accurate solutions, they can be

Table 1
Classification of the literature related to 2E-VRP.

Reference	Objective function							Solution approach			Method	Case study	Instance size
	Fuel consumption	Service waiting times	Emissions	Distance	Cost	N° of vehicles	Travel time	Heuristic	Exact approach	Simulation			
This paper				**x**			**x**	**x**			**2D-*k*- means algorithm, NN heuristic, and RLS as the improvement phase**	**x**	**Large**
(Zuhanda et al., 2022)	x				x			x			*K*-means clustering and 2-opt algorithm		Medium
(Ramirez-Villamil et al., 2022)							x	x			2D-*k*-means algorithm, NN heuristic, and two options of local search operators		Small
(Ramirez-Villamil et al., 2022)							x	x		x	Decomposition algorithm based on the NN	x	Large
(Liu et al., 2022)			x		x			x			Clustering-based artificial immune algorithm (C-AIA) immune operator with the genetic algorithm		Small-medium
(Wang et al., 2021)		x			x	x		x			3D-*k*-means and improved reference point-based non-dominated sorting genetic algorithm-III (IR-NSGA-III)	x	Small-medium
(Wang et al., 2018)			x		x			x			*K*-means algorithm and an improved Non-dominated Sorting Genetic Algorithm-II (Im-NSGA-I)	x	Small-medium
(Marinelli et al., 2018)					x				x		Fuzzy C-Means Clustering improved with roulette selection, 2-opt, and Or-opt exchange heuristics		Small-medium
(Belgin et al., 2018)					x			x			Hybrid heuristic based on variable neighborhood descent (VND) and local search (VND_LS)	x	Medium-large
(Li et al., 2016)			x					x			Clarke & Wright Savings Algorithm (C&W) with a local search phase (relocate and λ-interchange).	x	Large
(Zeng et al., 2014)					x			x			GRASP and VND (GRASP + VND)		Small

computationally expensive, especially for large instances. Heuristic approaches achieve reliable solutions in a fraction of the computing time for a large class of optimization problems and are the only way to find solutions to an even larger number of real-world optimization problems (Sörensen, 2015). For example, the NN heuristic has been widely used for solving the VRP (Lima et al., 2018; Solomon, 1987). It has been proven that it can be efficient for solving this problem, especially for large-scale instances (Karaoğlu & Kara, 2022; Privé et al., 2006; Rosenkrantz et al., 2009). Furthermore, the NN has been used to build reasonable initial solutions that are then improved by local search strategies (Brandão, 2004; Du & He, 2012). The pseudocode of the proposed NN routing algorithm for the second and third subproblems is presented as Algorithm 2. Then, a relocate local search (RLS) phase that contains inter- and intra-route operations is applied to improve the initial solution given by the NN in the second echelon.

In the literature, different types of local search operators have been used to solve routing problems. In this case, a relocate operator is proposed as a local search for neighborhood solutions. RLS aims at shifting a node in route *n*, before or after another node in a different route, but considering that both routes belong to the same cluster. Fig. 1 presents an example of this local search. Two routes in the same cluster are selected. The first route, denoted as "S-A-B-C-D-S," is selected as the route that contains the node to be evaluated for relocation (e.g., node A). The relocation of node A in the first position in the route denoted as "S-E-F-G-H-S" is evaluated. The criteria to accept the insertion of the node in a specific route is twofold: (i) if the demand of node A does not exceed the maximum capacity of the vehicle in the destination route and (ii) if the insertion of that node into the route gives the greatest improvement of all feasible combinations (between all nodes and all possible positions) in terms of distance, the improvement in travel time can also be observed because travel time is calculated based on the distance and average speed in the city. If node A meets both criteria, the node is finally relocated, and the new routes "S-B-C-D-S" and "S-A-E-F-G-H-S" are constructed. It should be noted that the insertion does not yield infeasible solutions because verification of the feasible elements is made before the insertion, for instance, checking that the capacity of the vehicle is not exceeded and only adding the node to the route if the optimal improvement is obtained. If an infeasible insertion is detected, the movement is ignored.

Algorithm 2: NN search procedure

Nearest neighbor (*Dm*, demand, maxCap):visited ←∅route ←∅routes ←∅ **for** all $i =$ len (*Dm*)distance $=$ 0capacity $=$ 0vehicles $=$ 1**repeat**// Nearest-neighbor minimum distance assignmentminDistance ← argmin (*Dm*) where node in *Dm* not in visited and > 0node ← node of minDistance// Check vehicle capacity**if** capacity < maxCap **then**route append nodevisited append nodecapacity ← capacity + demand in node positiondistance ← distance + minDistance**else if** capacity ≥ maxCapacity **then**vehicles ← vehicles + 1routes append route // Add route to the routes arrayroute ←∅capacity = 0**end if****until** len (visited)≤ len (*Dm*)**if** route is not ∅ **then**routes append route**end if****return** routes, distance, vehicles

(*continued on next column*)

(*continued*)

3.3. Third subproblem: Routing from depots to satellites

The third subproblem involves the first echelon routing. The aim is to find a set of routes starting from the depots to serve the corresponding satellites. The quantity of parcels (expressed in kilograms) required to be delivered to each satellite is obtained from the total demand of the customers of cluster *k*. The distance traveled, the total travel time, and the routes in the first echelon are computed using the NN routing procedure, as presented in Algorithm 2. In the first echelon there are usually few satellites and depots for routing, so the problem is typically solved using exact methods. Nevertheless, in the review of 2E-VRP presented by Sluijk et al. (2023), they highlight that algorithms such as NN, C&W savings, cheapest insertion, and random insertion have also been used. Given that NN was used in the second echelon, it was also chosen as the solution method in this subproblem.

4. Experimental setting and case study results

4.1. Test with benchmark instances from the literature

In the first part of this section, the performance of our solution approach is tested in some deterministic benchmark instances from the literature. For this purpose, we used Set 2 of the datasets available from the ORLibrary (https://people.brunel.ac.uk/~mastjjb/jeb/orlib/files/), which was proposed by Perboli et al. (2011). Set 2 includes different instances, all with 1 depot, 2 or 4 satellites, and 21, 32, or 50 customers. These instances are heuristically solved by Perboli et al. (2011). A comparison was made between our previous approach (Ramirez-Villamil et al., 2022) and the one proposed in the current study. Both procedures were implemented in Python. Experiments were run on a PC with an Intel® Core™ i7-10510U processor, 2.3 GHz CPU, and 16 GB RAM.

Numerical results are presented in Table 2. Both heuristic approaches were tested, and the comparison was made between the best lower bound and the final solution from the literature. Results show that

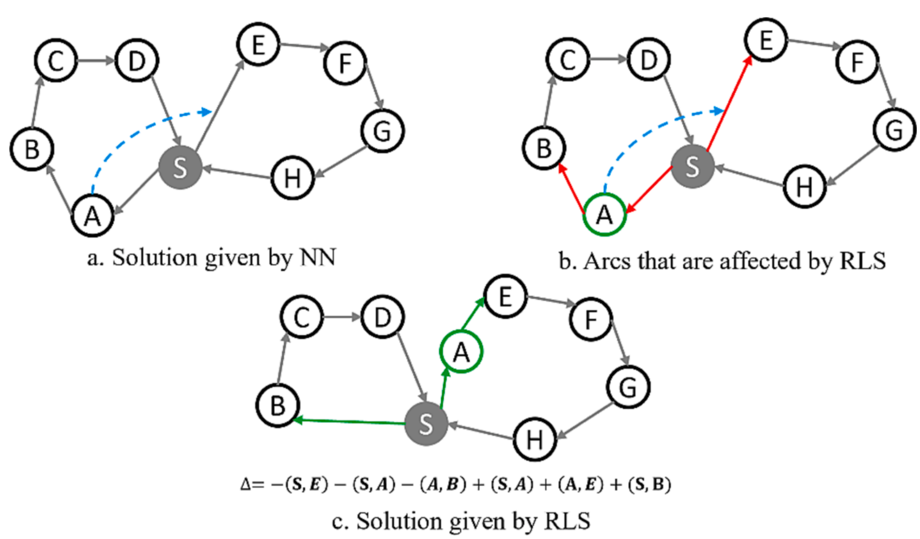

Fig. 1. Explanation of RLS operator in an example.

Table 2
Comparison between solution approaches for obtaining the lower bound and final solution using Set 2, solved and proposed by Perboli et al. (2011).

Instance	Nodes	Heuristic by (Perboli et al., 2011)		NN decomposition algorithm (Ramirez-Villamil et al., 2022)				K-means + NN + RLS algorithm				
		Best LB	Final sol.	Sol.	Gap (%) Versus LB	Versus Final sol.	T (sec)	Sol.	Gap (%) Versus NN.	Versus LB	Versus Final sol.	T (sec)
E-n22-k4-s6-17	21	417.07	417.07	600	43.9	25.2	0.4	548	−8.7	31.4	31.4	0.1
E-n22-k4-s8-14	21	384.96	384.96	598	55.3	55.3	0.3	508	−15.1	32.0	32.0	0.1
E-n22-k4-s9-19	21	470.6	470.6	782	66.2	66.2	0.4	658	−15.9	39.8	39.8	0.1
E-n22-k4-s10-14	21	371.5	371.5	548	47.5	47.5	0.3	534	−2.6	43.7	43.7	0.1
E-n22-k4-s11-12	21	427.22	427.22	742	73.7	73.7	0.3	622	−16.2	45.6	45.6	0.1
E-n22-k4-s12-16	21	392.78	392.78	712	81.3	81.3	0.3	532	−25.3	35.4	35.4	0.2
E-n33-k4-s1-9	32	730.16	730.16	1004	37.5	37.5	0.8	862	−14.1	18.1	18.1	0.2
E-n33-k4-s2-13	32	709.76	714.64	994	40.0	39.1	0.5	822	−17.3	15.8	15.0	0.2
E-n33-k4-s3-17	32	698.81	707.49	1076	54.0	52.1	0.5	808	−24.9	15.6	14.2	0.2
E-n33-k4-s4-5	32	757.39	787.29	1181	55.9	50.0	0.8	1076	−8.9	42.1	36.7	0.2
E-n33-k4-s7-25	32	745.71	760.36	1018	36.5	33.9	0.7	816	−19.8	9.4	7.3	0.2
E-n33-k4-s14-22	32	764.49	780.6	980	28.2	25.5	0.6	916	−6.5	19.8	17.3	0.2
E-n51-k5-s2-4–17-46	50	512.18	609.56	910	77.7	49.3	0.7	826	−9.2	61.3	35.5	0.3
E-n51-k5-s2-17	50	579.74	597.74	704	21.4	17.8	0.7	688	−2.3	18.7	15.1	0.3
E-n51-k5-s4-46	50	515.24	561.8	834	61.9	48.5	0.7	832	−0.2	61.5	48.1	0.3
E-n51-k5-s6-12	50	528.84	560.22	720	36.1	28.5	0.6	734	1.9	38.8	31.0	0.3
E-n51-k5-s6-12–32-37	50	507.49	571.8	842	65.9	47.3	0.6	768	−8.8	51.3	34.3	0.3
E-n51-k5-s11-19	50	559.59	588.01	810	44.7	37.8	0.8	734	−9.4	31.2	24.8	0.3
E-n51-k5-s11-19–27-47	50	507.64	724.09	876	72.6	21.0	0.8	902	3.0	77.7	24.6	0.3
E-n51-k5-s27-47	50	526.34	538.2	744	41.4	38.2	0.8	738	−0.8	40.2	37.1	0.3
E-n51-k5-s32-37	50	542.83	552.49	950	73.4	71.9	0.8	940	−1.1	71.6	70.1	0.3
Average		554.8	583.3	655.6	53.1	46.0	0.6	755.4	−9.6	38.1	31.3	0.2

the average approximation of the NN procedure (Ramirez-Villamil et al., 2022) is 53.1% compared with the best lower bound obtained by Perboli et al. (2011), with a minimum of 21.4% and a maximum difference of 81.3%. The average versus the final solution is 46%, ranging from 17.8% to 81.3%. Computational times range between 0.3 and 0.8 s. Furthermore, the results obtained using the algorithm that combines 2D-k-means with NN and the RLS improvement heuristic show that they differ on average by 38.1% compared with the best lower bound from the literature, with a maximum gap of 77.7% and a minimum of 9.4%. Compared with the final solution, it has a gap of 31.3%, with a maximum of 70.1% and a minimum difference of 7.3%. The computational times are acceptable because they fluctuate between 0.1 and 0.3 s. Moreover, the difference between the NN procedure versus the 2D-k-means with NN and the RLS improvement heuristic is on average − 9.6%, ranging from − 25.3% to 3%. These findings show that the solution method presented in this paper generates more efficient solutions than the method proposed in the previous study. In the next subsection, experiments are described using a real-world case study in the city of Paris.

As shown by the results, the solution approach presented in this article does not beat Perboli et al. (2011) matheuristics. It is to note that the study of Perboli et al. (2011) was carried out only on small data sets, and its performance on very large real-life sized instances is not currently reported in the literature. It is important to note that few papers have aimed to solve large datasets not only in the 2E-VRP but also in the VRP (Haripriya & Ganesan, 2022). The only algorithm tested on such large datasets (more than 90.000 nodes) is the one proposed by Ramirez-Villamil et al. (2022), so our experiments shows that the proposed K-means + NN + RLS algorithm outperforms this last work. In addition, it has been reported in the literature that common-sense heuristics (such as NN) are very useful and performant to solve complex realistic routing problems in large size instances (Du & He, 2012).

4.2. Case study: The case of Paris, France

Experiments were performed using real data from a French delivery company in the city of Paris, France, to test the behavior of the proposed heuristic approach with large-scale instances. Our experiments aim to determine 1) if the application of 2D-k-means in the case study is an improvement in terms of geographical clustering and 2) if the RLS can improve the solution obtained with the NN routing procedure.

The company under study is a key player in the last-mile supply chain and a leading brand in delivery. Each year, this company distributes more than 63 million parcels. It offers home deliveries and is the only private carrier with a postal license. Its services are used by major business-to-customer (B2C) clients recognized in e-commerce of fashion, equipment, publishing, and other sectors, as well as by business-to-business (B2B) clients. The company provided the data of 90,627 deliveries in Paris from four depots located in the region of Île-de-France (See Appendix A1). Fig. 2 presents the location of the four depots. In addition, Paris is administratively divided into 20 districts and the Travel Observatory of the city reports an average travel speed of 14 km/h. Fig. 3 illustrates the distribution system under study as a 2E-VRP.

The purpose of the 2D-k-means clustering is to minimize the sum of distances between each delivery point and the centroid of its cluster (satellite). The instance considered in this article contains more than 90,000 customers and was first proposed by Ramirez-Villamil et al. (2022). In that paper, two strategies were proposed. The first clustering was defined by the administrative division of the city into 20 districts, while the second strategy was based on the clustering of certain districts in the city by their geographical proximity. This selection was performed to obtain 10 clusters without objectively explaining the rationale. To make a comparison between the strategy explained before and this study, we decided to set $k = 10$ clusters. Fig. 4 shows the output of applying the proposed 2D-k-means (with $k = 10$) and how the delivery points geographically dispersed in the city are clustered. The centroid of each group becomes the satellite of the cluster (black triangles). With this clustering, it can be guaranteed that the vehicles associated with the satellite (i.e., cluster k) will travel shorter distances, and therefore, shorten their travel times since travel times are directly related to the distance traveled. Additionally, this clustering methodology strives to minimize the sum of the distances between the delivery points and the centroid to which they belong, which is the satellite in this case. Thus, vehicles associated with the satellite in cluster k may only serve the delivery points allocated to it.

As previously mentioned, the distribution network consists of a set of four depots located outside the city of Paris. Hence, 10 incapacitated satellites (the centroids of the clusters) are geographically located inside

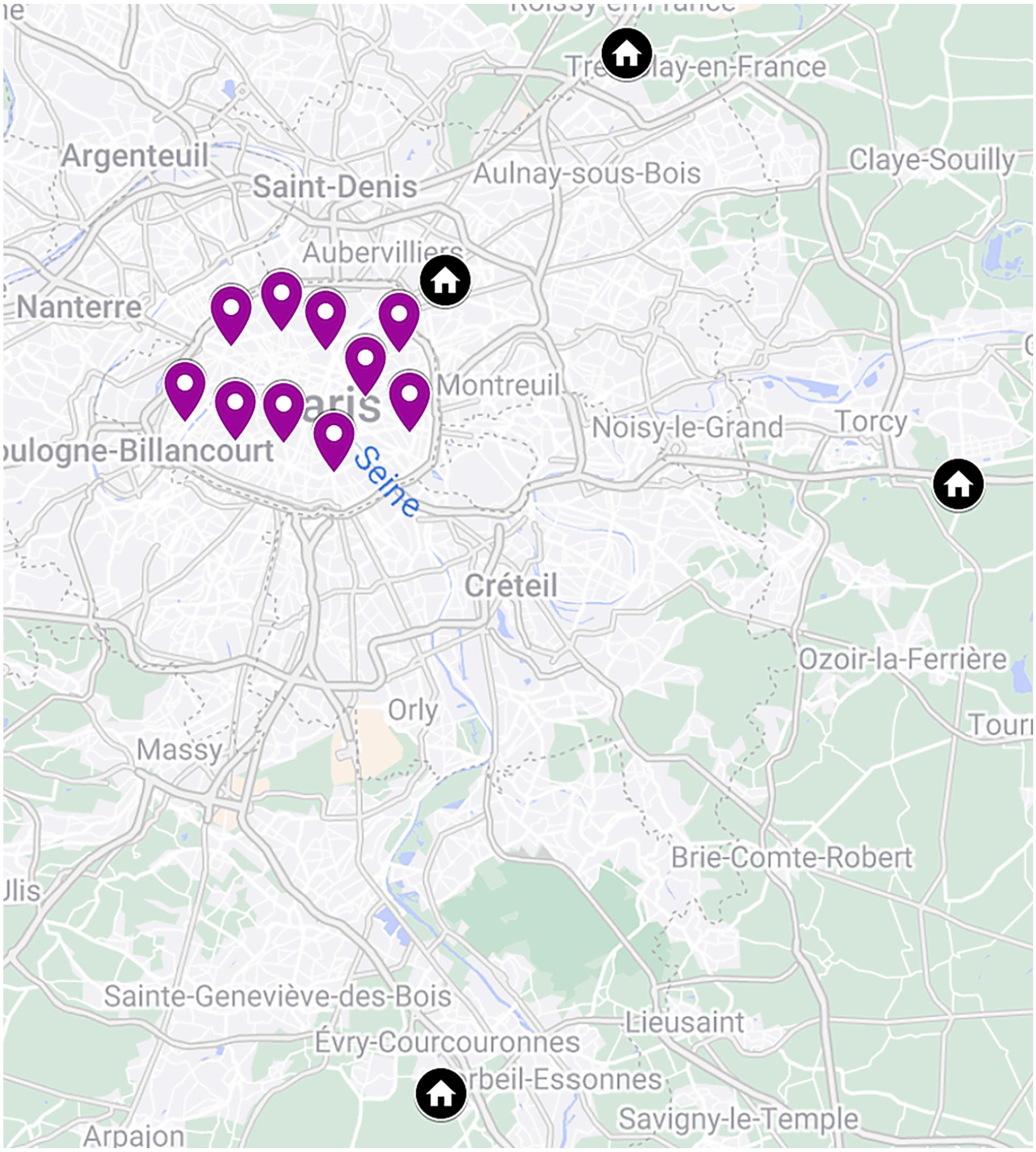

Fig. 2. Four depots and locations of satellites around Paris.

the city of Paris. From these satellites, a delivery vehicle can perform the last-mile distribution to successfully serve the customers (second echelon). In this study, there is a homogeneous fleet between echelons, so in the first and second echelons, the fleet is composed of delivery vans with 800 kg of payload. The fleet was considered in this way because the company owns vehicles with this capacity to perform delivery activities in both the first and second echelons. Furthermore, for comparative purposes, the type of vehicle is consistent with the previous study.

Performance indicators, such as the number of vehicles, CO_2e emissions, fine particle emissions, fixed cost, energy consumption, and land use, were compared for the different solution approaches to determine how efficient and sustainable the results for the last-mile delivery can be. CO_2e is a universal measurement used to indicate the equivalent of the GHG with respect to its global warming potential (EPA, 2019). Land use is used primarily to ensure that the distribution network does not invade public space in large proportions. In addition, fixed costs allow decision-makers to analyze whether the costs associated with operating the scenario are sufficiently low and decide which scenario suits their needs. Regarding energy consumption, it is necessary to quantify the cost (euros, in this case) of the energy (diesel or electricity) that each transportation mode requires to perform delivery activities.

Regarding the first echelon, Table 3 shows the results obtained for the routing, starting at the depots, to serve all satellites located around the city. The black triangles in Fig. 4 are the satellites of the distribution network. It is important to note that we compare the results obtained in this study with those obtained previously (Ramirez-Villamil et al., 2022). Notably, the solution obtained by k-means + NN requires 12 additional vehicles for depot 4 to satisfy the demand of the satellites clustered to that depot. As more vehicles are needed, the total distance and average travel time per vehicle are also increased. In addition, satellites grouped to depot 2 require that the vehicles travel longer distances, even if the fleet requires one less vehicle. Although the distances for depots 2 and 4 have increased, an improvement of 0.2% in terms of the distance traveled can be obtained when the routing of the first echelon is conducted with the satellites obtained by the 2D-k-means clustering. This improvement was calculated using Equation (1). The number of vehicles, total distance, and travel time change between scenarios because of the new clustering strategy adopted. However, the demand remains the same, and the total number of clients to be served in the second echelon does not change.

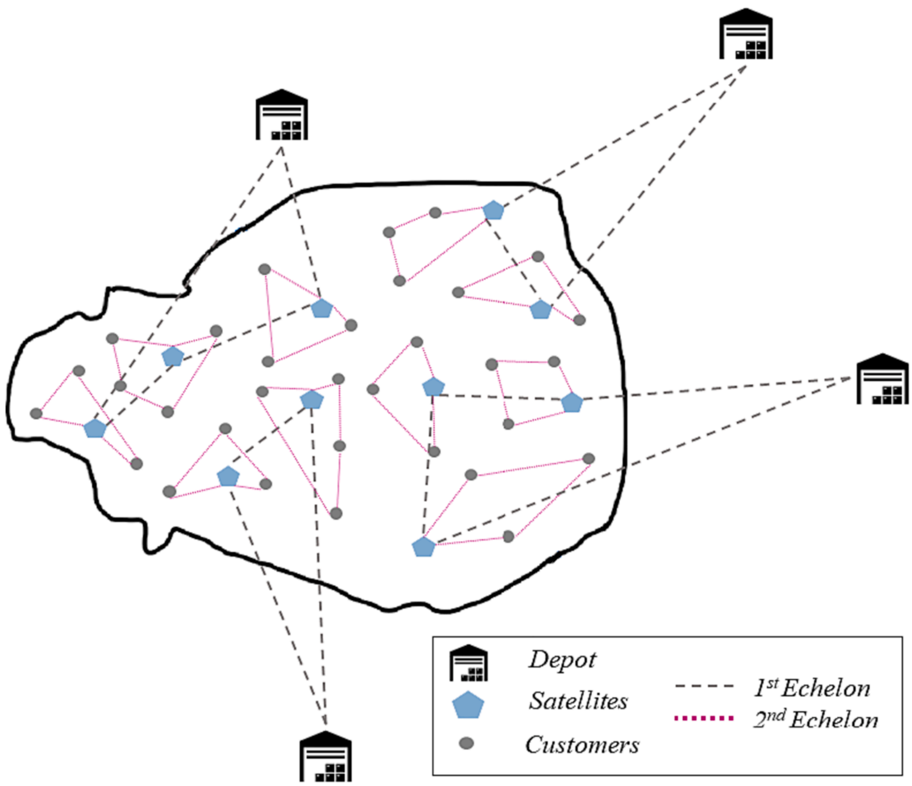

Fig. 3. Two-echelon distribution network under study.

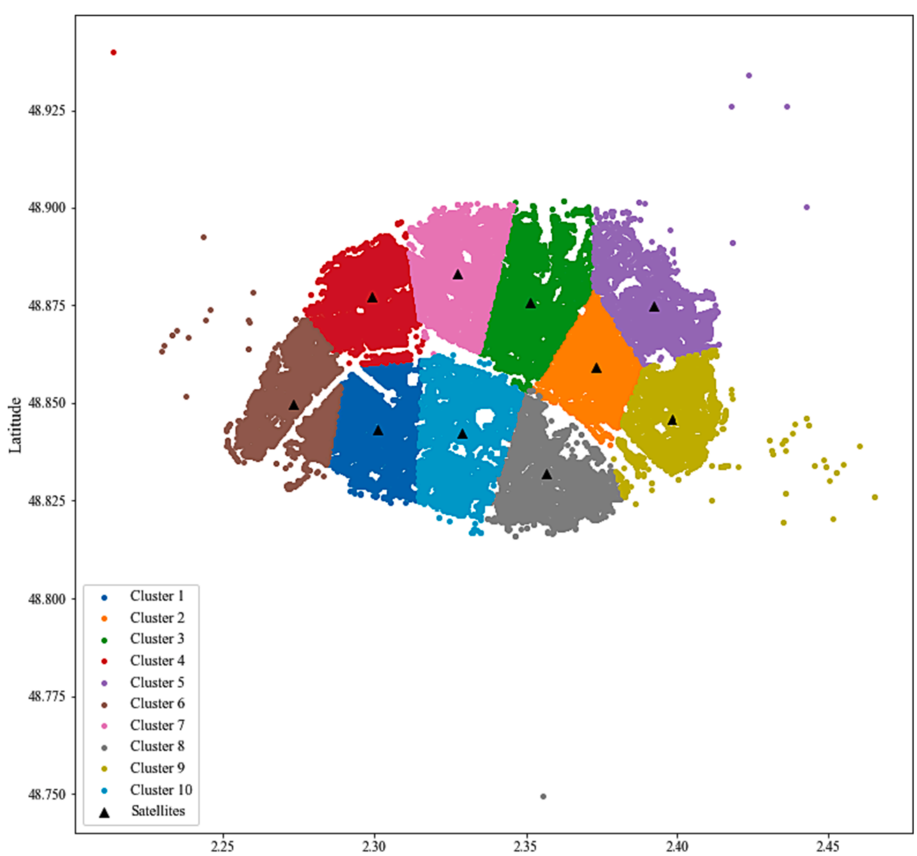

Fig. 4. Results of the 2D k-means clustering for last-mile delivery.

Table 3
First echelon results, comparison between our previous approach versus k-means + NN.

Depot number	Indicators	Ramirez-Villamil et al. (2022)	*k*-means + NN
1	Number of vehicles	24	16
	Total distance	1473.4	940.5
	Avg. distance per vehicle	61.4	58.8
	Avg. travel time	4.4	4.2
2	Number of vehicles	21	20
	Total distance	1419.6	1629.8
	Avg. distance per vehicle	67.6	81.5
	Avg. travel time	4.8	5.8
3	Number of vehicles	37	33
	Total distance	3578.1	2923.2
	Avg. distance per vehicle	96.7	88.6
	Avg. travel time	6.9	6.3
4	Number of vehicles	19	31
	Total distance	448.9	1414.5
	Avg. distance per vehicle	23.6	45.6
	Avg. travel time	1.7	3.3

$$Improvement = \left|\frac{\sum_{k=1}^{k}(currentSol_k - prevSol_k)}{\sum_{k=1}^{k}prevSol_k}\right| \times 100 \tag{1}$$

In terms of the second-echelon results (see Table 4), a comparison is made between the proposed approach and the results obtained by applying the RLS as an improvement heuristic. This procedure is only applied in the second echelon because this echelon contains the large-scale instance (more than 90,000 delivery points). In this tier, delivery points are clustered in 10 groups ($k = 10$), which is the number of satellites. This clustering was performed to reduce the distance between the delivery points and the satellite (centroid of the cluster). The column called "% of improvement" refers to the improvement in the distance traveled for all vehicles of each cluster. On average, an improvement of 22.5% in the distance is obtained when the RLS is applied to enhance the initial solution.

Table 4
Second echelon results, comparison between the initial solution (k-means + NN) versus RLS.

Cluster number	Indicator	*k*-means + NN	RLS	% of improvement
1	Number of vehicles	12	12	22.4%
	Distance	421.1	326.9	
	Travel time	28.1	21.8	
2	Number of vehicles	9	9	21.4%
	Distance	367.1	288.7	
	Travel time	24.5	19.2	
3	Number of vehicles	12	12	21.5%
	Distance	513.6	403.2	
	Travel time	34.2	26.9	
4	Number of vehicles	10	10	24.3%
	Distance	443.8	336.1	
	Travel time	29.6	22.4	
5	Number of vehicles	7	7	21.5%
	Distance	357.8	280.9	
	Travel time	23.9	18.7	
6	Number of vehicles	9	9	23.7%
	Distance	381.9	291.6	
	Travel time	25.5	19.4	
7	Number of vehicles	12	12	26.4%
	Distance	470.6	346.5	
	Travel time	31.4	23.1	
8	Number of vehicles	11	11	22.9%
	Distance	419.6	323.3	
	Travel time	28.0	21.6	
9	Number of vehicles	9	9	20.5%
	Distance	408.5	324.9	
	Travel time	27.2	21.7	
10	Number of vehicles	10	10	20.9%
	Distance	428.2	338.8	
	Travel time	28.5	22.6	

Moreover, Table 5 shows a comparison of the performance indicators among the following approaches: (i) Strategy 2 from the previous study (Ramirez-Villamil et al., 2022), which organized the 20 districts of Paris into 10 groups based on proximity and computing size criteria and applied a decomposition algorithm based on the NN heuristic; (ii) the solution approach presented in this study that combines the 2D-*k*-means clustering and the NN routing procedure; (iii) the RLS proposed as an improvement heuristic for the proposed solution approach. These three approaches are comparable because all of them involved a clustering method for the same number of customers with the same demand in 10 groups. It is important to note that the comparison was made only in the second echelon, where the results reported in Table 5 are the sum of the results obtained for the 10 clusters in each solution method. Equations (2) and (3) are used to compute the CO_2e and fine particle emissions, respectively. Concerning the appropriate emission factor for the fine particle emissions, the fleet vehicles are Euro-6 (European emission standards) compatible.

$$CO2e = \sum_{k=1}^{k} distance_k {*} f_{CO2e} \tag{2}$$

$$Fine\,particles = \sum_{k=1}^{k} distance_k {*} f_{fp} \tag{3}$$

The method previously proposed by Ramirez-Villamil et al. (2022) provided results that eventually improved the company's operations in some scenarios; however, there were more opportunities to improve parcel distribution within different areas of the city and enhance the routes through the implementation of improvement heuristics. The present study attempts to improve these results by applying additional non-supervised machine learning and optimization techniques. As a result, the gap in terms of the total distance, between the clustering strategy presented in Ramírez-Villamil et al. (2022) and our approach is 15.2%, the RLS is improved by 10.9% compared with the previous strategy, and the initial solution obtained in this study is improved by 22.6% using RLS.

This reduction in the distance traveled indicates that non-supervised machine learning methods, like 2D-*k*-means to make a TD, combined with a local search heuristic, such as the RLS, to improve the routing obtained using NN, and thereby, achieve more efficient last-mile delivery. This is also supported by improvements in terms of travel time, land use, fixed costs, CO_2e, fine particle emissions, and energy consumption. Thus, our solution method for an urban parcel delivery network can be more sustainable for last-mile delivery, allowing decision-makers to determine the most suitable delivery operations.

5. Conclusions and perspectives

This paper addresses the 2E-VRP with TD and satellite location

Table 5
Comparison of performance indicators between the three solutions.

	Ramirez-Villamil et al. (2022)	*k*-means + NN	RLS
Total vehicles	105	101	101
Total distance (*km*)	3657.7	4212.2	3260.9
Total travel time (*h*)	261.3	300.9	232.9
CO_2e emissions (*kg*)	1016.8	1171.0	906.6
Fine particles (*g/km*)	36.6	42.1	32.6
Fixed cost (€)	4828.2	5560.1	4304.5
Land use (m^2)	960.8	924.2	924.2
Energy consumption (€)	570.3	656.8	508.5
Avg. travel time per vehicle (*h*)	2.5	2.9	2.3

decisions. Under the scope of this research, there are no studies that previously considered two-echelon routing problems with these features. We present a non-supervised machine learning clustering method for the districting design of many geographically dispersed customers in the city of Paris, France, in which the satellites of the distribution network are the centroid of the cluster. This work aims to minimize the distance between the satellites and delivery points. TD strategies are used to determine the most efficient way to serve and respond quickly to customer demands and reduce distances and travel times within a territory.

In this study, the delivery routes for the first and second echelons were designed to optimize the total delivery time in the city. A three-stage decomposition algorithm was proposed to generate initial solutions for the 2E-VRP. In the second subproblem, a local search operator was applied to improve the initial solution. We compared the results obtained from a previous study (Ramirez-Villamil et al., 2022) with the initial solution of this study and the improvement heuristic RLS. The initial solution of this paper provides an improvement of 15.2% compared with our previous study (Ramirez-Villamil et al., 2022). RLS shows an additional improvement of 10.8% compared with the previous approach. On average, an improvement of 22.6% in both the distance traveled and the travel time is observed when the RLS is applied to improve the initial solution in this paper. This indicates that the application of non-supervised machine learning methods, like 2D-*k*-means, combined with a local search strategy, such as the RLS, can improve the routing obtained using NN and improve last-mile delivery in large cities with many data points by reducing the distance traveled and travel time. This is supported by additional improvements in terms of land use, fixed costs, CO_2e, and fine particle emissions.

Due to the different disruptions that can occur in a supply chain such as the one described in this study, it is necessary that the supply chain can be able to adapt and overcome in an agile and innovative way to efficiently respond to disruptions. Clustering customers for urban distribution in large cities using data science and machine learning techniques enables better route planning and improved algorithm execution by reducing computational times, which allows agile solutions to large quantities of nodes. In addition, serving customers from the satellite distribution centers located inside each cluster not only allows that if an adverse event occurs in any area of the city, other clusters remain in operation without affecting the entire system, but also the distances that vehicles must travel between satellites and clustered customers are shorter, allowing savings in energy consumption and costs, a lower CO2e and fine particle emissions, and finally a reduction in the number of vehicles, which generates less public space invasion and traffic congestion. Thus, achieving a supply chain that is sustainable in social, economic, and environmental terms.

Several avenues of future work stem from this research. First, it is necessary to apply metaheuristic algorithms that allow us to avoid the local optima and find more general solutions. Second, service times and other parameters can be considered. In practice, the service time is stochastic because the driver does not spend the same time at every delivery point, so the consideration of this parameter may impact the global performance of the distribution system. Moreover, new attributes can be added to the problem, including multimodal transportation, mobile satellites, or heterogeneous fleets in the same echelon (e.g., electric vehicles and cargo bikes with different capacities). Finally, the analysis of new performance indicators to assess the dimensions of sustainability in the proposed distribution networks may complement the findings of this study.

CRediT authorship contribution statement

Angie Ramírez-Villamil: Methodology, Validation, Formal analysis, Investigation, Writing – original draft, Visualization. **Jairo R. Montoya-Torres:** Conceptualization, Methodology, Validation, Formal analysis, Resources, Writing – original draft, Writing – review & editing, Supervision, Project administration, Funding acquisition. **Anicia Jaegler:** Conceptualization, Validation, Formal analysis, Resources, Writing – review & editing, Visualization, Supervision, Project administration. **Juan M. Cuevas-Torres:** Validation, Data curation, Visualization.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

The data that has been used is confidential.

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Appendix A1. Overview of the case study data: Sample of the delivery points

Delivery point	District	Demand	Coord_X	Coord_Y	Delivery point	District	Demand	Coord_X	Coord_Y
1	75,001	8610	48.8564734	2.3418286	51	75,001	150	48.8632406	2.3487635
2	75,001	190	48.8562387	2.3420848	52	75,001	100	48.8621959	2.3490076
3	75,001	170	48.8558578	2.3425260	53	75,001	220	48.8627578	2.3465614
4	75,001	150	48.8591918	2.3449735	54	75,001	1280	48.8627592	2.3465507
5	75,001	690	48.8588096	2.3461027	55	75,001	945	48.8615160	2.3487139
6	75,001	130	48.8581605	2.3462248	56	75,001	280	48.8622348	2.3484148
7	75,001	650	48.8595499	2.3470978	57	75,001	140	48.8618875	2.3492959
8	75,001	230	48.8607556	2.3463187	58	75,001	470	48.8603720	2.3484282
9	75,001	1760	48.8597766	2.3465990	59	75,001	580	48.8632701	2.3353659
10	75,001	580	48.8608669	2.3438953	60	75,001	420	48.8611324	2.3447227
11	75,001	240	48.8614382	2.3421425	61	75,001	930	48.8611324	2.3447227
12	75,001	260	48.8607475	2.3412265	62	75,001	361	48.8632701	2.3353659
13	75,001	200	48.8650471	2.3359868	63	75,001	361	48.8632701	2.3353659
14	75,001	410	48.8674209	2.3264395	64	75,001	2500	48.8593233	2.3472226
15	75,001	125	48.8667583	2.3281038	65	75,001	180	48.8597471	2.3467840
16	75,001	3580	48.8654239	2.3297882	66	75,001	2257	48.8589840	2.3438537
17	75,001	190	48.8647038	2.3302656	67	75,001	340	48.8593595	2.3445162
18	75,001	80	48.8657163	2.3310274	68	75,001	530	48.8617802	2.3413579
19	75,001	1160	48.8660744	2.3316523	69	75,001	50	48.8618137	2.3412305

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(*continued*)

Delivery point	District	Demand	Coord_X	Coord_Y	Delivery point	District	Demand	Coord_X	Coord_Y
20	75,001	230	48.8660610	2.3313399	70	75,001	390	48.8627551	2.3418635
21	75,001	3248	48.8670936	2.3323376	71	75,001	605	48.8641834	2.3438658
22	75,001	2610	48.8652764	2.3318039	72	75,001	80	48.8650565	2.3417039
23	75,001	300	48.8657002	2.3319501	73	75,001	2260	48.8657002	2.3367834
24	75,001	1145	48.8650310	2.3315813	74	75,001	1200	48.8656506	2.3344351
25	75,001	2972	48.8650310	2.3315813	75	75,001	55	48.8642116	2.3351204
26	75,001	230	48.8650632	2.3317476	76	75,001	816	48.8660784	2.3343332
27	75,001	350	48.8685648	2.3254015	77	75,001	2300	48.8659202	2.3360485
28	75,001	615	48.8682362	2.3256603	78	75,001	835	48.8662018	2.3356663
29	75,001	1090	48.8671915	2.3269397	79	75,001	490	48.8671888	2.3347932
30	75,001	190	48.8650028	2.3331302	80	75,001	1950	48.8667986	2.3311307
31	75,001	60	48.8641539	2.3333582	81	75,001	1555	48.8674839	2.3318441
32	75,001	770	48.8632701	2.3353659	82	75,001	4325	48.8669863	2.3322773
33	75,001	330	48.8663480	2.3352478	83	75,001	3990	48.8668844	2.3328178
34	75,001	6080	48.8661911	2.3384571	84	75,001	430	48.8659376	2.3310193
35	75,001	350	48.8660878	2.3375130	85	75,001	80	48.8674463	2.3284243
36	75,001	220	48.8663520	2.3375089	86	75,001	100	48.8674463	2.3284243
37	75,001	170	48.8629845	2.3419091	87	75,001	1140	48.8659671	2.3297346
38	75,001	1020	48.8638964	2.3400356	88	75,001	1430	48.8632701	2.3353659
39	75,001	545	48.8643363	2.3402730	89	75,001	410	48.8646743	2.3327185
40	75,001	3300	48.8639796	2.3421036	90	75,001	1295	48.8644449	2.3329975
41	75,001	50	48.8641901	2.3415095	91	75,001	220	48.8634029	2.3333569
42	75,001	1030	48.8646206	2.3456937	92	75,001	100	48.8639796	2.3421036
43	75,001	160	48.8638696	2.3422350	93	75,001	2868	48.8640560	2.3312742
44	75,001	260	48.8643014	2.3440924	94	75,001	771	48.8646998	2.3304105
45	75,001	230	48.8638937	2.3448689	95	75,001	220	48.8646461	2.3294704
46	75,001	450	48.8634016	2.3462744	96	75,001	190	48.8650042	2.3294878
47	75,001	1680	48.8637114	2.3481426	97	75,001	100	48.8657002	2.3284230
48	75,001	520	48.8637114	2.3481426	98	75,001	475	48.8649572	2.3285168
49	75,001	500	48.8649572	2.3285168	99	75,001	270	48.8697115	2.3271570
50	75,001	835	48.8650189	2.3283277	100	75,001	2940	48.8698429	2.3278289
Delivery point	District	Demand	Coord_X	Coord_Y	Delivery point	District	Demand	Coord_X	Coord_Y
101	75,001	130	48.8658035	2.3259084	153	75,001	3250	48.8695854	2.3262209
102	75,001	150	48.8686346	2.3255154	154	75,001	1000	48.8690785	2.3290130
103	75,001	1060	48.8695854	2.3262209	155	75,001	1340	48.8694459	2.3279469
104	75,001	730	48.8673699	2.3261096	156	75,001	550	48.8667583	2.3343627
105	75,001	4900	48.8663681	2.3263067	157	75,001	120	48.8678406	2.3264475
106	75,001	325	48.8664298	2.3264220	158	75,001	110	48.8673042	2.3265132
107	75,001	100	48.8626586	2.3406887	159	75,001	250	48.8660502	2.3278905
108	75,001	1460	48.8626586	2.3406887	160	75,001	140	48.8660502	2.3278905
109	75,001	420	48.8593219	2.3406605	161	75,001	60	48.8672130	2.3301543
110	75,001	620	48.8637449	2.3454215	162	75,001	170	48.8674638	2.3304038
111	75,001	189	48.8599509	2.3471770	163	75,001	370	48.8676032	2.3304521
112	75,001	220	48.8602017	2.3477563	164	75,001	2400	48.8679895	2.3296943
113	75,001	270	48.8595700	2.3471300	165	75,001	1575	48.8840398	2.2825599
114	75,001	140	48.8598020	2.3471367	166	75,001	330	48.8681062	2.3292759
115	75,001	1857	48.8597766	2.3465990	167	75,001	1410	48.8659671	2.3297346
116	75,001	250	48.8592629	2.3471193	168	75,001	110	48.8654695	2.3299706
117	75,001	300	48.8624507	2.3361692	169	75,001	440	48.8653059	2.3310515
118	75,001	520	48.8589115	2.3458815	170	75,001	500	48.8652308	2.3311937
119	75,001	1100	48.8589625	2.3457500	171	75,001	640	48.8660248	2.3312218
120	75,001	240	48.8588995	2.3439369	172	75,001	170	48.8667986	2.3311307
121	75,001	70	48.8589142	2.3448367	173	75,001	260	48.8680002	2.3312728
122	75,001	1000	48.8585816	2.3438698	174	75,001	170	48.8664231	2.3324785
123	75,001	160	48.8589840	2.3438537	175	75,001	650	48.8656439	2.3324959
124	75,001	260	48.8585240	2.3428144	176	75,001	550	48.8641834	2.3315531
125	75,001	490	48.8585240	2.3428144	177	75,001	390	48.8639702	2.3339590
126	75,001	110	48.8595164	2.3449869	178	75,001	9990	48.8654816	2.3334602
127	75,001	90	48.8605450	2.3459364	179	75,001	60	48.8653502	2.3337673
128	75,001	380	48.8605450	2.3459364	180	75,001	190	48.8654816	2.3334602
129	75,001	2050	48.8611324	2.3447227	181	75,001	270	48.8654816	2.3334602
130	75,001	130	48.8613510	2.3449789	182	75,001	1440	48.8646233	2.3328325
131	75,001	850	48.8604417	2.3406941	183	75,001	120	48.8646233	2.3328325
132	75,001	700	48.8609487	2.3418877	184	75,001	835	48.8641553	2.3323484
133	75,001	900	48.8609487	2.3418877	185	75,001	250	48.8634123	2.3349273
134	75,001	680	48.8610667	2.3414437	186	75,001	615	48.8648969	2.3346671
135	75,001	390	48.8616528	2.3416181	187	75,001	100	48.8650900	2.3345894
136	75,001	290	48.8591798	2.3429391	188	75,001	960	48.8655715	2.3345371
137	75,001	340	48.8606898	2.3436566	189	75,001	110	48.8669220	2.3339899
138	75,001	90	48.8606898	2.3436566	190	75,001	2830	48.8656506	2.3344351
139	75,001	370	48.8603264	2.3434621	191	75,001	620	48.8670118	2.3355335
140	75,001	540	48.8616353	2.3432797	192	75,001	70	48.8664378	2.3360606
141	75,001	1160	48.8610131	2.3407209	193	75,001	220	48.8667302	2.3369484
142	75,001	650	48.8610131	2.3407209	194	75,001	870	48.8661951	2.3382305
143	75,001	890	48.8627686	2.3349836	195	75,001	1200	48.8672720	2.3344284
144	75,001	280	48.8624507	2.3361692	196	75,001	220	48.8660409	2.3369591

(*continued on next page*)

(*continued*)

Delivery point	District	Demand	Coord_X	Coord_Y	Delivery point	District	Demand	Coord_X	Coord_Y
145	75,001	140	48.8667691	2.3243849	197	75,001	550	48.8660650	2.3371173
146	75,001	370	48.8667905	2.3238015	198	75,001	2280	48.8652456	2.3360686
147	75,001	670	48.8671459	2.3239759	199	75,001	100	48.8646930	2.3363891
148	75,001	320	48.8685648	2.3254015	200	75,001	350	48.8650994	2.3386931
149	75,001	140	48.8686346	2.3255154	201	75,001	1640	48.8632742	2.3381607
150	75,001	9760	48.8683677	2.3256120	202	75,001	440	48.8632742	2.3381607
151	75,001	340	48.8697557	2.3273809	203	75,001	300	48.8623287	2.3385885
152	75,001	3000	48.8697557	2.3273809	204	75,001	1000	48.8618097	2.3393007

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