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Sustainable local pickup and delivery: The case of Paris

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ABSTRACT

The two-echelon distribution networks are very common in last-mile supply chains and urban logistics systems. The problem consists of delivering goods from one depot to a set of satellites and from there to a group of customers. The most common problem is known as the two-echelon vehicle routing problem (2E-VRP), which is known to be computationally difficult to solve. In real-life, uncertainty in travel times increases this complexity to actually define a delivery schedule. To deal with this stochastic behavior, this paper proposes a solution approach based on a combination of simulation and optimization, named simheuristic, to solve the 2E-VRP with stochastic travel times. The model also considers the CO_2 equivalent and fine particles emissions. Experiments are run using real data of a French delivery company for the city of Paris. The performance of two scenarios for freight delivering is evaluated, and the results show that a global optimum gives better results than local optima. Policy makers need to take this into account when defining city policy on freight transport.

1. Introduction

To satisfy the demand of the population in cities, efficient urban logistics must be done, especially with respect to freight distribution. Urban freight distribution and logistics operations in cities are concerned with the delivery and collection activities of freight in urban centers and areas. These activities are often referred to as “city logistics” and include transportation, handling and storage of freight, inventory management, reverse logistics, as well as home delivery services, the facilities used for consolidation of products, the cost of these activities, and the policies about freight transport (Cardenas et al., 2017). Urban goods distribution is essential for the economic development of cities, it interferes with the rest of the urban activities in terms of the use of public space (Antún, 2013). The rise of e-commerce emphasizes the phenomenon (Ducret, 2014). Moreover, due to the fact that urban areas have increased their population, the number of vehicles circulating in the cities has grown. Everyday hundreds of trucks have to enter the cities to deliver the demanded products. The amount of CO_2 equivalent (CO_2e) emissions that these trucks emit to the environment is very high and affects the quality of the air. Likewise, traffic jams also increase. This generates higher fuel consumption and CO_2e emissions (Benjelloun & Crainic, 2010; Muñuzuri, Larrañeta, Onieva, & Cortés, 2005; Russo & Comi, 2010).

Over the years, governments have identified the need to implement and develop new policies, not only to regulate supply chains and delivery activities of companies that supply their products to stores and customers located in different city areas, so that congestion levels can improve at certain times; but also to reduce CO_2e emissions. Some regulations are delivery restrictions during peak hours, access for freight vehicles in certain areas due to city infrastructure, tolls and special rates for trucks, and restrictions on parking for unloading goods (Crainic, Ricciardi, & Storchi, 2004). Due to the importance of solving these issues and for the interest of satisfying the customer needs despite the restrictions imposed by the cities, city logistics was created to design strategies that allow to improve the efficiency, relieving traffic constraints and CO_2e emissions, always with innovative responses to satisfy customer demand and to mitigate the negative impact of urban freight transportation without affecting the city’s activities. (Benjelloun & Crainic, 2010). One of such efforts is the redesign of urban distribution networks by adding intermediate nodes (called satellites, hubs or urban logistics spaces) (Gonzalez-Feliu, 2011, Perboli, Tadei, & Vigo, 2011, Crainic & Sgalambro, 2014, Cuda, Guastaroba, & Speranza, 2015, Meza-Peralta, Gonzalez-Feliu, Montoya-Torres, & Khodadad-Saryazdi, 2020). Logistics operations and companies are forced to use this intermediate links despite the cost of real estate and its scarcity within cities. Hence,

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considerable efforts of the scientific community have aimed at designing efficient optimization models and algorithms capable of providing support to logistics decision-makers (Handoko, Lau, & Cheng, 2016; Muñuzuri et al., 2005; Patier & Browne, 2010).

To face the issues of urban freight distribution and looking for the improvement of its efficiency, logistics centers were created (Antún, 2013). One kind of logistics center is the Urban Consolidation Center (UCC), which is a facility that is located in the proximity of an urban area, enabling the consolidation of freight flows. When the shipments are consolidated, a UCC can perform the last-mile delivery more efficiently than individual carriers (Browne, Sweet, Woodburn, & Allen, 2005). UCCs have a central position in the logistics network connecting the logistic centers with the customers.

When designing the last-mile supply network, the two-echelon vehicle routing problem (2E-VRP) is one of the most commonly modeling approaches to solve thousands of problems encountered in urban logistics (Gonzalez-Feliu, Perboli, Tadei, & Vigo, 2008). This model aims at handling the distribution of goods firstly from a depot to a satellite or consolidation (UCC) or urban distribution center (UDC), and then from there to customers. The problem consists of determining a set of routes in the first and second levels for a fleet of vehicles associated with each level. The demand of customers is geographically dispersed within an urban area. Our problem includes both the transport from the depot to satellites (first echelon) and from these satellites to each one of the customers (second echelon). The fleet of vehicles is composed of light utility vehicles. This contributes to the reduction of the travel distance, and of the number of big trucks in cities, which at the same time would minimize the invasion of the public space during freight unloading and consequently, it could decrease the congestion in cities.

Some literature reviews (e.g., Cuda et al., 2015; Mancini, 2013) analyze the multi-echelon routing problems and its special case the 2E-VRP, and classified its basic variants according to their dependence on time or the solution approach applied. Among the variants with time dependence are the 2E-VRP with time windows (2E-VRPTW) (Dellaert, Saridarq, Van Woensel, & Crainic, 2019), and 2E-VRP with satellite synchronization (2E-VRP-SS) (Grangier, Gendreau, Lehuédé, & Rousseau, 2016). Other variants are the two-echelon multi-depot problem where the satellites are served by more than one depot and the 2E-VRP with pickup and deliveries (2E-VRPPD) (Belgin, Karaoglan, & Altiparmak, 2018).

Real-life problems have stochastic features and have been studied as a variant of the 2E-VRP. However, according to Savelsbergh and Van Woensel (2016), one of the emerging research opportunities in this topic is concerned with more real-life issues, because there are few papers that applied stochasticity for the 2E-VRP. For instance, Anderluh, Larsen, Hemmelmayr, and Nolz (2019) applied a methodology to calculate the impact of stochastic travel times on the cost of a deterministic solution using a two-stage greedy randomized adaptive search procedure (GRASP) with path relinking and Monte Carlo simulation. This method is known as simheuristic and is very useful to deal with real-life uncertainty in a natural way integrating simulation methods into a metaheuristic-driven framework.

Simheuristics facilitate the introduction of reliability during the evaluation of alternative high-quality solutions to stochastic combinatorial optimization problems (Juan, Faulin, Grasman, & Rabe, 2015). The method can be applied in different fields. In routing problems, it was applied in the study by Guimarans, Dominguez, Panadero, and Juan (2018) where they used a hybrid simheuristic that combines Monte Carlo simulation with an iterated local search, a biased-randomized routing and packing heuristics to solve the two-dimensional VRP (2 L-VRP) with stochastic travel times.

This paper proposes a solution approach based on simheuristics to solve the 2E-VRP with stochastic travel times. As objective function, we consider the minimization of travel times. The CO_2e and fine particles emissions are also considered. The efficiency of the solution approach is analyzed against the solution of the deterministic counterpart solved using a decomposition heuristic based on the nearest neighbor procedure. The impact on the objective function of adding stochastic travel speeds is afterwards evaluated through Monte Carlo simulation. Such experiments are run using real data of a French delivery company for the city of Paris.

The rest of this paper is organized as follows. Section 2 reviews the literature related to 2E-VRP, stochasticity in routing problems, and simheuristics for routing problems. Section 3 details the solution approach based on a combination of simulation and optimization. In Section 4 computational experiments for the case study of Paris are described and their results analyzed. Section 5 presents business and managerial implications. Finally, business and management implications, and conclusions are presented in Section 6.

2. Literature review

The deterministic version of the 2E-VRP has been extensively studied in academic literature. Indeed, a search for scientific papers on Scopus database using the key words “Two-echelon vehicle routing problem”, “Two-echelon capacitated vehicle routing problem” and “2E-VRP” gave a total of 87 research documents, as shown in Fig. 1. It is important to highlight that in our concern the first study about 2E-VRP was presented in 2004 by Crainic et al. (2004). They promoted the use of satellite platforms to redistribute goods where large trucks could not circulate due to the physical limitations of the streets, as is often the case in city centers. As a result of this study, the use of satellites reduced the use of large vehicles by up to 72%. Since the formalization of this article, this VRP variant has been extensively studied by researchers, but from 2014 the number of documents about this topic has been increasing. Recently, the number of investigations reached the highest point which indicates that it is an important topic to discuss and due to its variants and complexity has a great scope to be explored. The literature review was conducted in the fall of 2020. Thus 2020 and 2021 are specific years and the number of papers is not definitive. Moreover, two main literature reviews about 2E-VRP have been published. The first one by Mancini (2013), while the second by Cuda et al. (2015), both focusing on two-echelon distribution systems, not only the 2E-VRP, including the two-echelon location routing problem (2E-LRP) and the truck and trailer routing problem. Also, in these studies, authors classified the two-echelon problems regarding the types of decisions: strategic decisions dealing with the location of facilities, tactical planning decisions including the routing of goods and the allocation of clients to the satellites (Cuda et al., 2015).

In 2008, one of the first mixed-integer programming (MIP) formulations for 2E-CVRP was proposed and valid inequalities were evaluated; The model was tested using benchmarks datasets from the literature (Gonzalez-Feliu et al., 2008). In 2010, researchers analyzed the impact on the total cost of distribution with different parameters like “customer distribution, satellites-location rules, depot location, number of satellites and mean transportation cost between the satellites and the customers” (Crainic, Perboli, Mancini, & Tadei, 2010), to find the best satellite location. To solve the 2E-CVRP with valid inequalities, two math-heuristics are introduced in (Perboli et al., 2011), and an adaptive large neighborhood search heuristic is proposed with new neighborhood search operators (Hemmelmayr, Cordeau, & Crainic, 2012). A hybrid heuristic called GRASP+VND (greedy randomized adaptive search procedure with variable neighborhood descent) is proposed in (Zeng, Xu, Xu, & Shao, 2014) to solve the 2E-CVRP. A hybrid metaheuristic that combines enumerative local searches with destroy-and-repair principle and some tailored operators are used to optimize the selections of intermediate facilities is presented in (Breunig, Schmid, Hartl, & Vidal, 2016). In (Amarouche, Guibadj, & Moukrim, 2018), a hybrid heuristic is proposed, generating a group of routes that are recombined through an integer programming model. A graph-based fuzzy evolutionary algorithm hybridized with an iterative evolutionary learning process is presented in (Yan, Huang, Hao, & Wang, 2019).

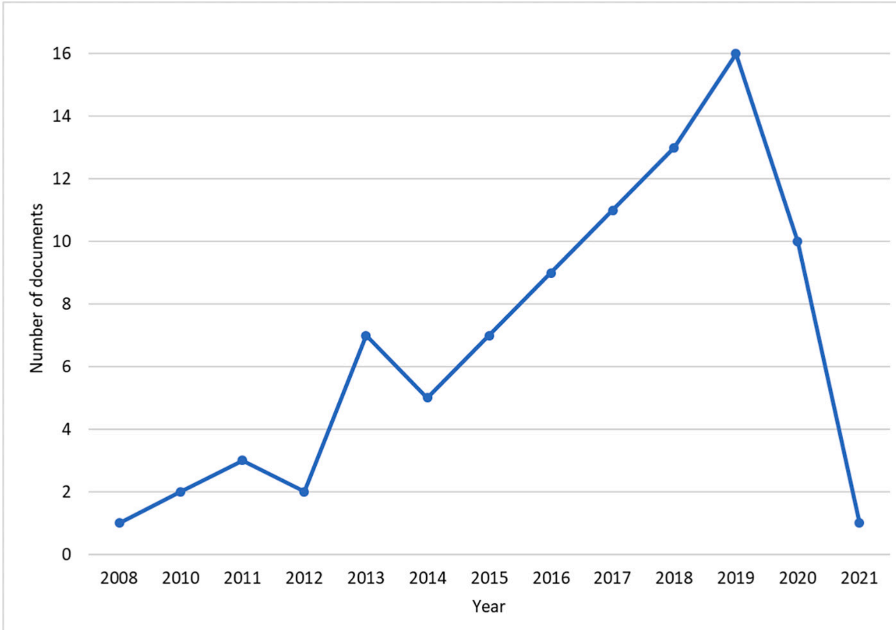

Fig. 1. Articles per year about 2E-VRP.

In the same way, a lot of methods are used by researchers to find an exact or approximate solution when the basic 2E-VRP is combined with different variants of the problem. For example, in 2015 a MILP formulation was introduced to solve the two-echelon capacitated vehicle routing problem with environmental considerations and time-dependent travel times in a case study in a supermarket chain in Netherlands (Soysal, Bloemhof-Ruwaard, & Bektaş, 2015). When the problem has the need to solve more than two objective functions, the model must be adapted, such as the case of the M2-2E-VRP model. The case was designed for adapt a multi-objective, multi-level distribution plan involving companies and city authorities to reduce traffic congestion and pollution in an urban framework. The authors of this problem used a Multi-Objective Evolutionary Algorithm (MOEA) to solve it (Eitzen, Lopez-Pires, Baran, Sandoya, & Chicaiza, 2017). Moreover, there are studies about the 2E-VRP with simultaneous pickup and delivery (2E-VRPSPD). One option to find good results, is a node-based mathematical model. Especially, considering the "NP-hardness of the model, a hybrid heuristic algorithm based on a variable neighborhood descent and local search was developed to solve medium - large size instances" (Belgin et al., 2018). Regarding the e-commerce field, a multi-depot two-echelon vehicle routing problem with delivery options for the last-mile distribution model (MD-TEVRP-DO) was analyzed in (Zhou, Baldacci, Vigo, & Wang, 2018). An important feature of the problem is that customers have different delivery options allowing them to pick up packages at intermediate pick-up facilities. To reach the best way to deliver parcels, a multi-population genetic algorithm to find the minimum handling cost was generated. Results show that the distribution system can be greatly optimized by offering both options (distribution and pickup) as this allows a final cost reduction of approximately 16% with respect to the scenario with separate distribution system and no delivery options.

Moreover, in (Kitjacharoenchai, Min, & Lee, 2020) a new routing model that provides a synchronized operation by allowing several drones to fly from a truck (mobile satellites), to serve one or more customers, and return to the same truck to change the battery and pick up the parcels (2EVRPD) is presented. It was proposed a MIP formulation, a Drone Route Construction (DTRC) and a metaheuristic based on Large Neighborhood Search (LNS) that are to handle small-size problems. Also, motivated by the distribution of drugs with drones in disaster situations, where the affected areas are no longer accessible to conventional vehicles, this is a very frequent case in rescue operations in humanitarian logistics, where every second is essential to save lives, so it is important to act quickly. Therefore, (do Martins, Hirsch, & Juan, 2021) introduced the concept of agile optimization, it allows to find good solutions for large-scale and NP-hard optimization problems in real time. In addition, it is very useful in dynamic systems where conditions are continuously changing. The problem was modeled as the real-time 2E-VRP with pickup and delivery, and it was solved with a constructive heuristic extended into a biased-randomized algorithm that is able to provide a good solution in just milliseconds.

Otherwise, the use of time windows to schedule the part of a day in which freight can be delivered and additionally the purpose of analyzing CO_2e emissions in order to seek a reduction of these emissions to minimize pollution levels is very interesting in terms of green logistics. In the case of the following study, another heuristic is used to solve the 2E-TVRP in linehaul-delivery systems considering the CO_2e emissions is the Clarke & Wright Savings Algorithm but with an additional local search phase (Li, Yuan, Lv, & Chang, 2016). The electric two-echelon vehicle routing problem (E2EVRP) is presented in (Breunig, Baldacci, Hartl, & Vidal, 2019). The authors proposed a large neighborhood search metaheuristic and a mathematical program, followed by a simulation which is applied to recreate metropolitan areas and analyze the possible results of applying the problem in real-case instances (Breunig et al., 2019).

On the other hand, since this study will also address the stochastic version of the 2E-CVRP, it is important to review the literature about stochastic issues in this problem. Within the scope of this research only four papers were found that considered real-case instances as stochastic issues in the 2E-VRP variants. Two of them studied stochastic demands (2E-CVRPSD). The first one applied a Genetic Algorithm (GA) with a simple coding and decoding scheme to minimize the travel cost and the expected cost of recourse actions resulting from potential route failures (Wang, Lan, & Zhao, 2017). In the second one, a Simulation-based Tabu Search algorithm (STS) was developed, in which each movement is analyzed in a neighborhood search based on Monte Carlo method with the aim of solving real-world large-scale 2E-VRPSD instances (Liu, Tao, Hu, & Xie, 2017). The Two-Echelon Fixed Fleet Heterogeneous VRP (2E-HVRP) on Brazilian wholesale companies was studied using a Parallel

Table 1
Classification of 2E-VRP Reviewed Papers.

Reference	1. Solution Methods						2. Variants					
	Heuristics	Metaheuristics	Math. model	Simulation	Other	Time windows	Homogeneous fleet	Heterogeneous fleet	Stochastic demand	Stochastic travel times	Synchronization constraints	Multiple trips
Gonzalez-Feliu et al. (2008)			x									
Crainic et al. (2010)					x							
(Perboli et al., 2011)	x		x									
Hemmelmayr et al. (2012)		x										
Zeng et al. (2014)	x											
Grangier et al. (2016)		x				x					x	x
Butty et al. (2016)	x											
Li et al. (2016)	x					x						
Breunig et al. (2016)		x										
Eitzen et al. (2017)		x										
Wang et al. (2017)		x							x			
Liu et al. (2017)		x		x					x			
Esmaili & Sahraeian (2017)			x				x					
Eitzen et al. (2017)		x						x				
Belgin et al. (2018)		x	x									
Zhou et al. (2018)	x											
Huang et al. (2018)	x											
Amarouche et al. (2018)		x	x					x				
Marinelli et al. (2018)	x		x		x		x					
Yan et al. (2019)	x							x				
Breunig et al. (2019)		x	x	x								
Bevilaqua et al. (2019)	x			x				x	x			
Anderluh et al. (2019)	x		x							x	x	
Su et al. (2019)		x					x					
Anderluh et al. (2019)	x	x									x	
Agárdi et al. (2019)	x							x				
Li et al. (2019)	x					x		x			x	
Wang et al. (2019)			x			x						
Li et al. (2020)	x		x			x		x			x	
Wang & Wen (2020)		x				x		x				
Kitjacharoenchai et al. (2020)	x	x	x				x					
do Martins et al. (2021)	x		x		x		x			x		

2. Variants								3 Objectives						
Multiple depots	Electric	Muti-objective	Pick up and delivery	Capacitated	Battery swapping stations	Drones	Capacity-matching constraints	Distance	Costs	Travel times	Environmental impact	Fleet size	Customer satisfaction	Other
				x					x					
				x					x					
				x					x					
				x					x					
				x					x					
		x		x					x			x		
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	x			x					x					
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x	x			x	x				x					
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				x		x				x				
			x							x				

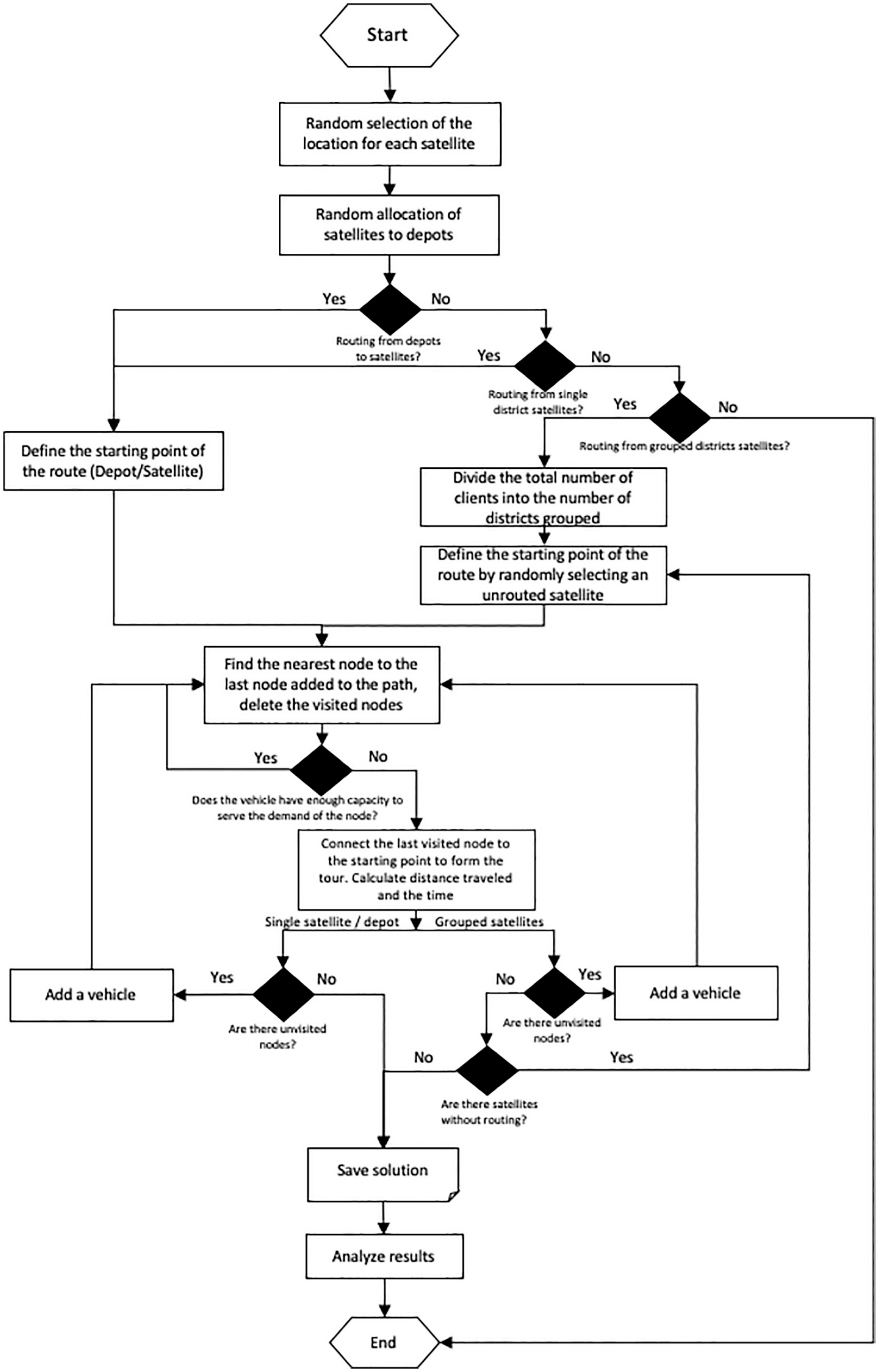

Fig. 2. Flowchart of the solution algorithm.

Fig. 3. Four depots around Paris (source: google maps).

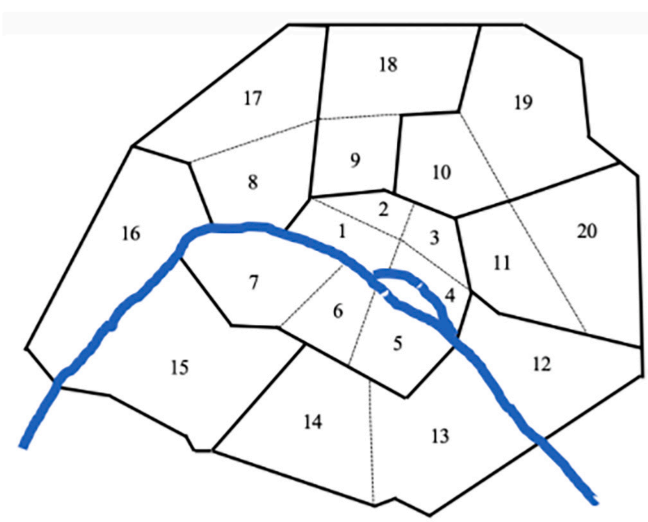

Fig. 4. The 20 districts of Paris and their grouping (source: the authors).

island based memetic algorithm with a local search procedure based on Lin–Kernighan heuristic (IBMA-LK). The stochastic part consists of picking tour size individuals from the population using a uniform probability distribution with replacement (Bevilaqua, Bevilaqua, & Yamanaka, 2019). The most recent paper had the purpose of calculating the impact of stochastic travel times on the cost of a deterministic solution of a 2E-VRP. A two-stage GRASP algorithm with path relinking was used to the deterministic part and then Monte Carlo simulation is applied to generate travel time scenarios based on a lognormal distribution (Anderluh et al., 2019).

The summary of solution approaches, variants and objective functions of reviewed works is presented in Table 1. Metaheuristics have been the most used methods to solve the 2E-VRP and its variants. The most studied objective function is the minimization of costs.

3. Solution approach: algorithm and parameters

3.1. Solution algorithm

Due to the fact that the 2E-CVRP is known for its NP-hardness (Gonzalez-Feliu et al., 2008), approximate algorithms, such as heuristics and metaheuristics, are good approaches able to find good solutions. It allows us to find feasible solutions for medium- to large-sized instances. Exact methods based on mathematical programming allow to optimally solve small-sized instances, as well as some parts of the problem. Real-life problems are very complex and modeling them as combinatorial optimization problems (COPs) with uncertain conditions makes it more difficult. Approximate algorithms allow the generation of high-quality solutions for this type of problems in relatively short computation times. But these are usually applied in scenarios where real-life uncertainty as the stochastic behavior of certain variables is simplified or is not considered (Juan et al., 2015). Simheuristics emerged as an optimization-simulation methodology that integrates simulation with some heuristics or metaheuristics so that complex stochastic COP's scenarios can be solved (Juan, Kelton, Currie, & Faulin, 2018). In addition, as Fu (2002) mentioned, the combination of simulation techniques with approximation algorithms allows the consideration of stochastic issues in the optimization problem.

A flow diagram of the proposed solution approach is shown in Fig. 2. The 2E-CVRP is solved using a decomposition algorithm based on the Nearest Neighbor Procedure (Taiwo, Josiah, Taiwo, Dkhrullahi, & Sade, 2013). The proposed algorithm splits the problem into four subproblems to reduce its complexity but aggregates them and their corresponding results to guarantee the quality and feasibility of the solutions. In addition, since this solution approach will be applied to a case study of a French company in Paris, France, with a very large amount of delivery points, as explained in Section 3.2 (more than 90,000 delivery points), splitting the problem into subproblems will make it computationally tractable.

The first subproblem is the random selection of the location point for one satellite for each district of Paris; the second one is to cluster the satellites to the depots randomly, twenty satellites divided in four depots; the third sub-problem is to find a set of routes starting from the depot to serve the corresponding satellites (first echelon) by the Nearest Neighbor Procedure, and the last sub-problem determines the routing from satellites to serve the clients (second echelon) using again the Nearest Neighbor Procedure as for the third subproblem.

3.2. Context of the case study

To go further in the explanation of the solution approach, the case study is presented. Experiments are run using real data of a major French delivery company for the city of Paris. This company distributes 44 million packages each year. It offers home deliveries in 1 or 2 days or relay deliveries in 2 to 5 days. It is the only private carrier with a postal license. 92% of deliveries are made on the first pass and 65% of passes are delivered directly to mailboxes. Its services are used by major B2C clients in the fashion, equipment, publishing and other sectors, as well as B2B. It provided the data of 90,627 deliveries in Paris from four depots around Paris . Fig. 3 presents the location of the four depots (black warehouses) and the location of the 90,627 clients in Paris (black points).

Paris is administratively divided into 20 districts. All these districts receive deliveries. In our study, we first split the data according to these 20 districts. Guided by the study of a global optimum versus local optima, we grouped some districts. Two constraints are considered: geography, and computing size. Both constraints lead to the same ten grouping (see Fig. 4). We decided to group them by proximity and number of customers within each district. Furthermore, due to the number of deliveries in the districts 12, 15 and 16, we decided to keep them as individual districts due to computational constraints. Each

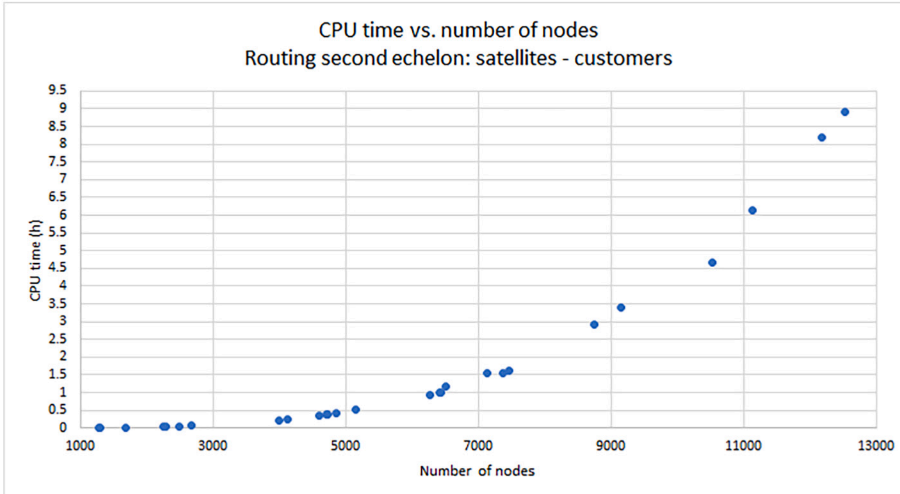

Fig. 5. CPU time versus number of nodes. Second echelon routing.

Table 2
Deterministic results for the first echelon.

		Strategy 1	Strategy 2
Depot 1	Number of vehicles	24	24
	Total distance traveled (km)	1489.6	1473.4
	Avg. distance per truck	62.1	61.4
	Avg. Travel time (h)	4.4	4.4
	Avg. Utilization rate	47.5%	47.3%
Depot 2	Number of vehicles	20	21
	Total distance traveled (km)	1374.8	1419.6
	Avg. distance per truck	68.7	67.6
	Avg. Travel time (h)	4.9	4.8
	Avg. Utilization rate	46.3%	45.1%
Depot 3	Number of vehicles	37	37
	Total distance traveled (km)	3577.8	3578.1
	Avg. distance per truck	96.7	96.7
	Avg. Travel time (h)	6.9	6.9
	Avg. Utilization rate	48.2%	47.7%
Depot 4	Number of vehicles	18	19
	Total distance traveled (km)	418.5	448.9
	Avg. distance per truck	23.2	23.6
	Avg. Travel time (h)	1.7	1.7
	Avg. Utilization rate	46.4%	46.2%

group is composed of around one tenth of the data. The travel observatory of Paris (www.paris.fr) gives an average travel speed of 14 km/h.

3.3. Travel time

Travel times are not hence deterministic, instead they are modeled using a statistical distribution dependent on the vehicle travel speed. In the literature, Vareias, Repoussis, and Tarantilis (2017) presented some mathematical models and solution methods for assigning time windows to customers in vehicle routing problems (VRP) with stochastic travel times. In that study a literature overview was done about VRP with stochastic travel times and we want to highlight two important works that considered a triangular distribution probability to model the travel times. The first one presents the stochastic vehicle routing problem with deadlines (SVRP-D) under travel time uncertainty in which the instances are described by a range and a mean value, so the probability distribution is assumed to be triangular (Adulyasak & Jaillet, 2015). Binart, Dejax, Gendreau, and Semet (2016) addressed a variant of the vehicle routing problem with time windows (VRPTW) with multiple depots, priority within customers and stochastic travel and service times; they choose to model that stochastic times with discrete triangular distributions. So, for the purpose of this paper, a triangular distribution was chosen to model this behavior. Since the average speed in Paris is 14 km/h, the parameters of the triangular distribution are defined as

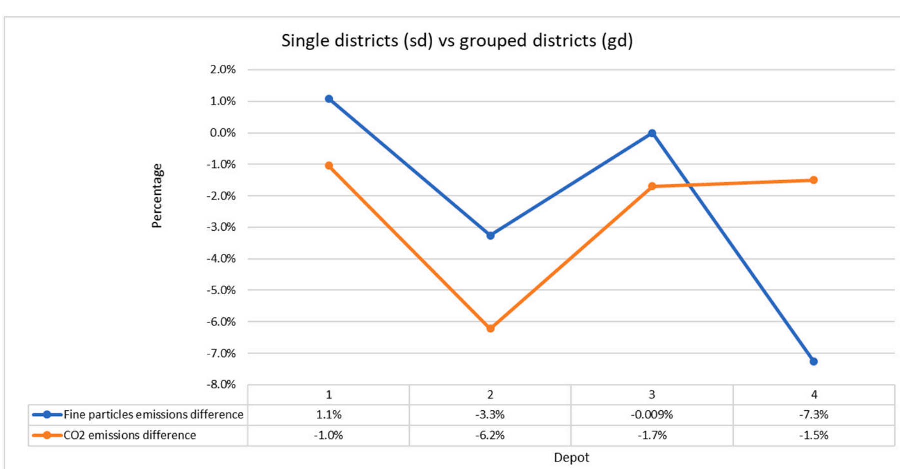

Fig. 6. Difference between strategy 1 and 2 in terms of CO_2e and fine particles emissions per depot.

minimum of 5 km/h, maximum of 30 km/h and most likely of 7 km/h, such that the mean value of this distribution is 14 km/h.

3.4. Routing from depots to satellites

This subsection explains in more detail the heuristic algorithm used to solve the first three sub-problems:

i) In the first sub-problem, given a set of points located in each of the twenty districts of Paris (Fig. 4), one point is randomly selected to be the satellite that will serve the entire district. This point will not be modified in the experiments; therefore, the satellites are fixed from this random selection.
ii) The second sub-problem consists of a random allocation of the previously selected satellites to the four depots that the company has (Fig. 3). It was decided that 5 satellites would be assigned to each one of the depots.
iii) The third sub-problem is the first-echelon routing by an algorithm based on Nearest Neighbor Procedure. To solve the routing, we use the following steps:
   (1) Define the starting point of the route (Depot);
   (2) Find the nearest node to the last node added to the path. If the nearest node is already in the path, then choose the next closest;
   (3) Repeat step 2 until the vehicle reaches its maximum capacity;
   (4) Connect the last visited node to the depot to form the tour. Calculate the distance traveled by the vehicle and the total route time;
   (5) If there are unvisited nodes, add one more vehicle and return to step 2.

Table 3
Results for second echelon.

		Strategy 1 (single districts)	Strategy 2 (grouped districts)
Districts 1-2-3-4	Number of vehicles	9	6
	Total distance traveled (km)	365.6	272.7
	Avg. distance per truck	40.6	45.5
	Avg. Travel time (h)	2.9	3.3
	Avg. Utilization rate	36.1%	40.6%
Districts 5-6-7	Number of vehicles	11	12
	Total distance traveled (km)	368.5	363.3
	Avg. distance per truck	33.5	30.3
	Avg. Travel time (h)	2.4	2.2
	Avg. Utilization rate	42.9%	39.3%
Districts 8–17	Number of vehicles	14	14
	Total distance traveled (km)	526.2	470.1
	Avg. distance per truck	37.6	33.6
	Avg. Travel time (h)	2.7	2.4
	Avg. Utilization rate	46.6%	46.6%
Districts 9–18	Number of vehicles	10	10
	Total distance traveled (km)	387.2	345.1
	Avg. distance per truck	38.7	34.5
	Avg. Travel time (h)	2.8	2.5
	Avg. Utilization rate	45.9%	45.9%
Districts 10–19	Number of vehicles	9	8
	Total distance traveled (km)	370.6	369.7
	Avg. distance per truck	41.2	46.2
	Avg. Travel time (h)	2.9	3.3
	Avg. Utilization rate	41.7%	46.9%
Districts 11–20	Number of vehicles	13	13
	Total distance traveled (km)	437.7	411.1
	Avg. distance per truck	33.7	31.6
	Avg. Travel time (h)	2.4	2.3
	Avg. Utilization rate	45.9%	45.9%
Districts 13–14	Number of vehicles	14	14
	Total distance traveled (km)	553.0	479.5
	Avg. distance per truck	39.5	34.3
	Avg. Travel time (h)	2.8	2.5
	Avg. Utilization rate	46.0%	46.0%

3.5. Routing from satellites to clients

The last sub-problem is the second-echelon routing. In this case study, we consider two different strategy:

- **Strategy 1** is that the satellite of a certain district can only serve the points located in that district (named "sd"). For this, the applied algorithm works in the same way as the algorithm based on the Nearest Neighbor Procedure presented in section 3.4.
- **Strategy 2** is based on the clustering of certain districts in the city of Paris by their proximity (named "gd"). This means that although each district has its own satellite located, satellites located inside the grouped districts can serve the nearest points not only within their district but also within the districts grouped with it. For the routing in this second strategy we use the following steps:
  - Divide the total number of clients in the grouped districts into the number of districts that were grouped i.e. if there are 4250 clients and 3 grouped districts (satellites), the number of nodes that each of the first two satellites have to serve is 1416 and the third satellite has to serve 1418 clients;
  - Define the starting point of the route (Satellite i);
  - Find the nearest node to the last node added to the path. If the nearest node is already in the path, then choose the next closest;
  - Repeat step 3 until the vehicle n reaches its maximum capacity;
  - Connect the last visited node to the satellite to form the tour. Calculate the distance traveled by the vehicle and the total route time;
  - If there are unvisited nodes, add one more vehicle and return to step 3
  - If the total number of nodes for the satellite i were already visited, the procedure for the satellite $i + 1$ is started (step 2);
  - Execute this procedure until all nodes are visited.

4. Results of the case study of Paris

4.1. Experiments

The proposed solution procedure was coded in Python, and experiments were run on a personal computer with processor Intel® Core™ i5-8250U, CPU at 1.8 GHz and 8GB RAM. A first important output concerns the computational time required to obtain a solution of the big number of nodes in the distribution network. Fig. 5 shows that computational times for the second echelon have an exponential growth, despite the tractability of the Nearest Neighbor Procedure, due to the number of nodes of the instances. Observed computational time for a single run was between 0.47 min and 8.92 h. For first echelon routing, the mean of computational times was 0.07 s.

According to the literature, the statistical precision of simulation outputs is usually given by the number of replications needed to run the experiment in a rigorous manner (Banks, Carson II, Nelson, & Nicol, 2000; Law & Kelton, 2000). However, because of the complexity of solving the two-echelon routing problem due to such a high number of

Fig. 7. Results of strategies 1 and 2 in CO_2e and fine particles emissions.

Table 4
Hypothesis test for strategies 1 and 2, first echelon.

	Hypothesis test		
	P-value	Alpha	Decision
sd-dep1	0.0604	0.05	not reject HO
sd-dep2	0.138	0.05	not reject HO
sd-dep3	0.5655	0.05	not reject HO
sd-dep4	0.09427	0.05	not reject HO
gd-dep1	0.193	0.05	not reject HO
gd-dep2	0.3223	0.05	not reject HO
gd-dep3	0.3365	0.05	not reject HO
gd-dep4	0.153	0.05	not reject HO

delivery points, carrying out an extensive number of replications is computationally unrealistic. So, following recommendations from the simulation literature, a number of replications between 5 and 10 is usually taken (Ahmed, 1999; Bourrel, 2003; Toledo et al., 2003), mainly because of the computational complexity of running simulation models (Jacobson & Yücesan, 2001). Hence, for the case of the present study, a total of 20 replications were evaluated, in order to balance computational time with a reasonable statistical precision of outputs.

4.2. Analysis of the study comparing 20-district vs clustering

For the deterministic results of the first echelon, the two proposed strategies are evaluated (single districts vs. grouped districts). The main difference between the strategies is that in strategy 2 (see 3.5) the demand for satellites could be greater or less than strategy 1 because when we have single districts, the demand of the satellite will be the sum of the demand of all the nodes to be served in the corresponding district. When the districts are grouped, the demand of the satellite will be the sum of the demand of all nodes served by that satellite, either in the corresponding district or in the districts grouped together.

The satellites randomly allocated to depot 1 are district 1, 9, 11, 13 and 19; those allocated to depot 2 are district 2, 3, 7, 12 and 14; for depot 3 were assigned districts 8, 10, 15, 16 and 17. Finally for depot 4 were assigned districts 4, 5, 6, 18 and 20. Table 2 shows that the main difference in terms of the number of vehicles is found in depots 2 and 4, where strategy 2 requires an additional vehicle as the demand is greater. This is directly related to the average travel time per vehicle, where there are differences between strategy 1 and 2, of 1.1% in depot 1, 1.7% in depot 2, −0.01% in depot 3 and − 1.6% in depot 4.

The proposed solution approach also calculates the CO_2e and fine particles emissions for each vehicle involved in the system. For the first echelon, the routing from depot 3 represents the highest level of CO_2e and fine particles emissions, because as is presented in Table 2, the average distance traveled by each vehicle is greater. Fig. 6 shows the differences between the strategies (single districts vs. grouped districts) in terms of fine particles and carbon emissions, the orange line explains the difference in terms of CO_2e and the blue one explains the difference but in terms of fine particles. In the four depots the CO_2e emissions are higher in strategy 2 because these depend on the average utilization rate of the vehicles and the distance traveled. However, depot 2 has the higher CO_2e emissions values not only in strategy 1 but also in strategy 2. For the calculation of fine particle emissions, it was considered that the vehicles used in this case study are Euro-6 (European emission standards) for the use of the appropriate emission factor. Finally, we can find the minimum values of both types of emissions in depot 4 in strategy 1 and 2.

For the deterministic results obtained in the second echelon, it is important to note that when the districts 1–2–3-4 are clustered, the number of vehicles with strategy 2 is 33.3% less and although the total distance traveled by all vehicles 25.4% shorter, the average travel time per vehicle is greater since there are fewer vehicles serving. The same happens with districts 10–19, when they are clustered, the number of

Table 5
Final deterministic and stochastic results for strategy 1 scenarios.

Scenario	Deterministic value (h)	Stochastic value (h)				Confidence interval (95%)		Gap
		min.	max.	mean	st. dev.	LL	UL	
sd-d1	6.9	3.8	11.1	7.4	2.5	6.3	8.4	−6.3%
sd-d2	7.1	4.2	17.8	7.5	3.4	6.0	8.9	−4.4%
sd-d3	4.6	2.5	8.6	4.7	1.9	3.8	5.5	−2.2%
sd-d4	7.5	4.0	16.4	8.4	3.5	6.9	10.0	−12.3%
sd-d5	7.7	4.7	15.7	9.0	2.8	7.7	10.2	−16.3%
sd-d6	7.2	3.9	14.8	9.1	3.4	7.6	10.6	−25.6%
sd-d7	11.4	6.4	27.3	14.0	6.9	11.0	17.0	−22.9%
sd-d8	17.0	10.3	42.8	21.4	9.6	17.1	25.6	−25.6%
sd-d9	12.9	7.3	33.4	13.8	6.5	11.0	16.7	−7.0%
sd-d10	14.7	7.6	26.1	16.2	5.8	13.7	18.8	−10.0%
sd-d11	16.2	8.9	30.9	17.7	7.1	14.6	20.8	−9.1%
sd-d12	19.2	11.4	45.1	22.7	8.7	18.9	26.5	−18.7%
sd-d13	22.2	14.3	46.9	27.1	10.2	22.6	31.6	−21.9%
sd-d14	17.3	10.5	36.4	19.1	7.0	16.0	22.2	−10.4%
sd-d15	24.3	14.4	42.0	27.2	8.1	23.6	30.7	−11.6%
sd-d16	24.1	12.1	57.5	28.1	11.8	23.0	33.3	−16.7%
sd-d17	20.6	12.5	48.5	25.8	11.3	20.9	30.7	−25.3%
sd-d18	14.7	7.1	40.4	17.1	8.8	13.3	21.0	−16.2%
sd-d19	11.7	6.2	22.3	13.1	5.5	10.7	15.5	−11.7%
sd-d20	15.0	7.7	28.3	14.8	5.9	12.2	17.4	1.9%

Table 6
Final deterministic and stochastic results for strategy 2 scenarios.

Scenario	Deterministic value (h)	Stochastic value (h)				Confidence interval (95%)		Gap
		min.	max.	mean	st. dev.	LL	UL	
gd-d1234	19.5	11.3	41.8	22.0	9.4	17.9	26.1	−13.1%
gd-d567	26.0	13.9	51.5	29.9	11.3	24.9	34.8	−15.0%
gd-d817	33.6	17.2	61.9	38.9	14.1	32.7	45.0	−15.8%
gd-d918	24.7	12.3	48.8	24.7	10.8	20.0	29.5	−0.4%
gd-d1019	26.4	13.2	64.0	32.4	14.6	26.0	38.9	−22.9%
gd-d1120	29.4	17.8	71.8	30.9	14.1	24.7	37.0	−5.1%
gd-d1314	34.3	20.6	78.3	40.5	15.2	33.8	47.2	−18.2%
gd-d12	19.2	11.4	45.1	22.7	8.7	18.9	26.5	−18.7%
gd-d15	24.3	14.4	42.0	27.2	8.1	23.6	30.7	−11.6%
gd-d16	24.1	12.1	57.5	28.1	11.8	23.0	33.3	−16.7%

Table 7
Hypothesis test for strategy 1, second echelon.

	Hypothesis test		
	P-value	Alpha	Decision
sd-d1	0.4292	0.05	Not reject Ho
sd-d2	0.6744	0.05	Not reject Ho
sd-d3	0.8087	0.05	Not reject Ho
sd-d4	0.2374	0.05	Not reject Ho
sd-d5	0.04851	0.05	Reject Ho
sd-d6	0.01434	0.05	Reject Ho
sd-d7	0.08977	0.05	Not reject Ho
sd-d8	0.04319	0.05	Reject Ho
sd-d9	0.5354	0.05	Not reject Ho
sd-d10	0.2598	0.05	Not reject Ho
sd-d11	0.3557	0.05	Not reject Ho
sd-d12	0.06442	0.05	Not reject Ho
sd-d13	0.03293	0.05	Reject Ho
sd-d14	0.2552	0.05	Not reject Ho
sd-d15	0.1191	0.05	Not reject Ho
sd-d16	0.1251	0.05	Not reject Ho
sd-d17	0.03862	0.05	Reject Ho
sd-d18	0.2259	0.05	Not reject Ho
sd-d19	0.2649	0.05	Not reject Ho

Table 8
Hypothesis test for strategy 2, second echelon.

	Hypothesis test		
	P-value	Alpha	Decision
gd-d1234	0.2227	0.05	Not reject Ho
gd-d567	0.123	0.05	Not reject Ho
gd-d817	0.09328	0.05	Not reject Ho
gd-d918	0.9685	0.05	Not reject Ho
gd-d1019	0.06514	0.05	Not reject Ho
gd-d1120	0.6363	0.05	Not reject Ho
gd-d1314	0.06762	0.05	Not reject Ho
gd-d12	0.06442	0.05	Not reject Ho
gd-d15	0.1191	0.05	Not reject Ho
gd-d16	0.1251	0.05	Not reject Ho

vehicles used is 11.1% fewer with a total distance traveled 0.3% shorter with strategy 2. Regarding the other districts, except districts 12, 15 and 16 it can be observed in Table 3 that the average travel time per vehicle is always lower when strategy 2 is applied.

Regarding CO_2e emissions and fine particles (Fig. 7), it is important to note that when districts are grouped together, the reduction of emissions per district is evident. However, given the logic used in the algorithm, in strategy 2, the emissions in the last district belonging to a group of districts (district 4, 7, 14, 17, 18, 19 and 20) are higher because that district may have more nodes to attend to or the distances traveled may be longer. However, when we analyze it in a global way, Fig. 7 shows the total value of the emissions in the clustered districts, where the levels of fine particles and CO_2e emissions are lower.

In order to analyze which strategy is better in terms of reducing the emission levels of both CO_2e and fine particles, an estimation of the confidence interval was made for the difference between the sum of the emissions generated using strategy 1 and strategy 2. It was obtained that the difference between strategies 1 and 2 for CO_2e emissions is 213.19 kg, it has a confidence interval of (165.32, 261.07) with a significance of 5% and 37 degrees of freedom. Moreover, for fine particle emissions, the difference is 2.97 g, in which the confidence interval is (2.37, 3.57) with a confidence level of 95% and 37 degrees of freedom. Based on these results, it can be concluded that clustering the Paris districts contributes to the reduction of both CO_2e and fine particle emissions.

4.3. Analysis of the impact of uncertainty in travel speed

One of the most important issues in urban logistics is the uncertainty in travel times mainly due to congestion within cities. The aim of this section is to evaluate the impact of such uncertainty on the performance of the proposed delivery approaches. Results of the implementation of these stochastic inputs are presented next. As for the first echelon, it is important to note that in both strategies, the stochastic mean is higher than the value obtained in a deterministic way with differences between strategies 1 and 2 that vary between −7.7% and − 19.4%. A hypothesis test was performed to validate if the mean of the stochastic values obtained for each depot scenario is equal to the value of the deterministic scenario. The results (Table 4) show that in scenarios that have single and grouped districts the mean of the stochastic values is equal to the deterministic value with a confidence level of 95%.

For the second echelon the same procedure was applied, in Table 5 and Table 6, the deterministic value for each district or group of districts, the mean, standard deviation, minimum and maximum value for stochastic results can be observed. Moreover, the confidence interval for each scenario was calculated to validate if the deterministic result fits the reality of the problem. In this case, as in the first echelon, in most scenarios the stochastic mean is higher than the value obtained in a deterministic way. However, in Table 5 the scenario that considers district 20 separately (sd-d20) is the exception having a shorter travel time in the stochastic mean than in the deterministic value with a difference of 1.9%.

Simultaneously, a hypothesis test was performed to validate if the mean of the stochastic values obtained for each scenario is equal to the value of the deterministic scenario. As shows in Table 7, the scenarios that consider district 5, 6, 8, 13 and 17 separately (sd-d5, sd-d6, sd-d8, sd-d13, sd-d17) the stochastic mean is different from the deterministic value with a significance of 5%. However, for the remaining scenarios in both separate districts (Table 7) and in clustered districts (Table 8) the mean of the stochastic values is equal to the deterministic value with a confidence level of 95%. So, in most scenarios in both strategies 1 and 2, there are not significant differences between taking an average value of the speed in Paris or doing several replications by randomizing it.

The total travel time for the global network, that is, first echelon plus second echelon travel times applying strategy 1 (single districts) is 772.55 h, as a deterministic value and 866.08 h, as the mean of the stochastic values with a difference of −12.1%. For strategy 2 (grouped districts), a travel time of 755.55 h was obtained (deterministic value) and 841.36 h as the mean of the stochastic values with a difference of −11.4%. Finally, it was decided to obtain an estimation of the confidence interval for the difference in means between strategy 1 and 2, in order to define which of the two strategies provides the greatest reduction in travel times. The total travel time in the second echelon was calculated, that is, the time that the 20 satellites takes to serve 90,627 clients, for each of the 20 replications for both strategy 1 and strategy 2, where the mean for strategy 1 (μ_1) is 323.99 h; for strategy 2 (μ_2) is 297.31 h. The difference in means ($\mu_1 - \mu_2$) is 26.68 h, and the confidence interval obtained with a significance of 5% and 37 degrees of freedom is (3.94, 49.42). Therefore, clustering the districts of Paris does contribute to reduce the travel times.

5. Business and managerial implications

Two different strategies were analyzed. The satellite of a certain district can only serve the points located in that district or some districts were clustered by their proximity. Among them, the strategy of clustering the districts of Paris does contribute to reducing the travel times, and both CO_2e and fine particle emissions. This means that the company will benefit in terms of cost per working hours by having shorter route times. Even if necessary, the company has the capacity to serve more customers or satisfy a higher demand because there is still available capacity in the vehicles. Results show that a global optimum gives better results than local optima.

It has also strong implications for city policies for example. More and more urban centers are regulated. Policy makers need to take this into account when defining city policy on freight transport. The Covid-19 crisis has increased deliveries in urban areas. It is therefore crucial to globally rethink this mode of delivery with regard to academic findings.

6. Conclusions

1. This paper studied a freight distribution problem in an urban context from a real case of a french delivery company for the City of Paris. The distribution network was composed of two Echelons, where four depots located outside the city are used to deliver the packages to a set of facilities called satellites that are located into each district of Paris, and from there to the final customers. The problem was modeled as a two-echelon vehicle routing problem (2E-VRP). Distinct features of this problem in comparison to previous works published so far in the academic literature are at least twofold. On one hand, the size of the network considered in this paper accounts for more than X delivery points geographically dispersed within the city. This represents a very big data set which is computationally intractable for the state of art routing algorithms. On another hand, this work considers stochastic travel times, while in the literature the most studied stochastic parameter is the demand. A solution approach belonging to the family of simheuristics algorithms that combines a decomposition heuristic based on the nearest neighbor procedure and Monte Carlo simulation was proposed to solve this 2E-VRP with stochastic travel times. As an objective function, we considered the minimization of travel times. We also considered the CO_2e and fine particles emissions. Although the minimization of carbon emissions has been already evaluated in the literature, the analysis of fine particles remains very less explored from the optimization standpoint.
2. For future research, several lines are still open. The research on stochastic 2E-VRP has a lot of opportunities. Other parameters, different from the travel time or demand, can be considered, such as service time, available capacity of the vehicles, or even the size of the fleet of vehicles. Considering additional constraints, like delivery time windows, load or route balancing among vehicles, heterogeneous fleet (using electric vehicles, cargo-bikes, etc.), among other challenges. Finally, another line for future research is the design of other solution procedures, especially to deal with very large amounts of delivery points.

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References

Adulyasak, Y., & Jaillet, P. (2015). Models and algorithms for stochastic and robust vehicle routing with deadlines. *Transportation Science*. https://doi.org/10.1287/trsc.2014.0581.

Agárdi, A., Kovács, L., & Bányai, T. (2019). Two-Echelon Vehicle Routing Problem with Recharge Stations. *Transport and Telecommunication, 20*(4), 305–317. https://doi.org/10.2478/ttj-2019-0025.

Ahmed, K. (1999). *Modeling Drivers' Acceleration and Land Changing Behavior, PhD Thesis*. Cambridge, MA, USA: ITS Program, Massachusetts Institute of Technology.

Amarouche, Y., Guibadj, R. N., & Moukrim, A. (2018). A neighborhood search and set cover hybrid heuristic for the two-echelon vehicle routing problem. *OpenAccess Series in Informatics., 65*(11), 1–11.

Anderluh, A., Larsen, R., Hemmelmayr, V. C., & Nolz, P. C. (2019). Impact of travel time uncertainties on the solution cost of a two-echelon vehicle routing problem with synchronization. *Flexible Services and Manufacturing Journal*. https://doi.org/10.1007/s10696-019-09351-w.

Antún, J. P. (2013). Distribución Urbana de Mercancías: Estrategias con Centros Logísticos. In *Nota Técnica IDB-TN-167*. Banco Interamericano de: Desarrollo.

Banks, J., Carson, J. S., II, Nelson, B., & Nicol, D. M. (2000). *Discrete-event system simulation* (3rd ed.). Upper Saddle River, New Jersey: Prentice-Hall, Inc.

Belgin, O., Karaoglan, I., & Altiparmak, F. (2018). Two-echelon vehicle routing problem with simultaneous pickup and delivery: Mathematical model and heuristic approach. *Computers and Industrial Engineering, 115*, 1–16.

Benjelloun, A., Crainic, T. G., Bigras., Y. 2010. Towards a taxonomy of city logistics projects. Procedia - Social and Behavioral Sciences 2(3), 6217–6228.

Bevilaqua, A., Bevilaqua, D., & Yamanaka, K. (2019). Parallel island based Memetic algorithm with Lin–Kernighan local search for a real-life two-echelon heterogeneous vehicle routing problem based on Brazilian wholesale companies. *Applied Soft Computing Journal, 76*, 697–711. https://doi.org/10.1016/j.asoc.2018.12.036.

Binart, S., Dejax, P., Gendreau, M., & Semet, F. (2016). Computers & operations research A 2-stage method for a field service routing problem with stochastic travel and service times. *Computers and Operations Research, 65*, 64–75. https://doi.org/10.1016/j.cor.2015.07.001.

Bourrel, E. (2003). *Modélisation dynamique de l'ecoulement du traffic routier: du macroscopique au microscopique, PhD thesis*. France: Institut National des Sciences Appliquées de Lyon.

Breunig, U., Baldacci, R., Hartl, R. F., & Vidal, T. (2019). The electric two-echelon vehicle routing problem. *Computers and Operations Research, 103*, 198–210.

Breunig, U., Schmid, V., Hartl, R. F., & Vidal, T. (2016). A large neighbourhood based heuristic for two-echelon routing problems. *Computers and Operations Research, 76*, 208–225. https://doi.org/10.1016/j.cor.2016.06.014.

Browne, M., Sweet, M., Woodburn, A., & Allen, J. (2005). Urban Freight Consolidation Centres Final Report. http://ukerc.rl.ac.uk/pdf/RR3_Urban_Freight_Consolidation_Centre_Report.pdf. accesed 10th April.

Butty, X., Stuber, T., Hanne, T., & Dornberger, R. (2016). A heuristic comparison framework for solving the Two-Echelon Vehicle Routing Problem. 2016 4th International Symposium on Computational and Business Intelligence, ISCBI 2016, 59–65. https://doi.org/10.1109/ISCBI.2016.7743259.

Cardenas, I., Borbon-Galvez, Y., Verlinden, T., van de Voorde, E., Vanelslander, T., & Dewulf, W. (2017). City logistics, urban goods distribution and last mile delivery and collection. *Competition and Regulation in Network Industries, 18*(1–2), 22–43.

Crainic, T. G., Perboli, G., Mancini, S., & Tadei, R. (2010). Two-echelon vehicle routing problem: A satellite location analysis. *Procedia - Social and Behavioral Sciences, 2*(3), 5944–5955.

Crainic, T. G., Ricciardi, N., & Storchi, G. (2004). Advanced freight transportation systems for congested urban areas. *Transportation Research Part C: Emerging Technologies, 12*(2), 119–137. https://doi.org/10.1016/j.trc.2004.07.002.

Crainic, T. G., & Sgalambro, A. (2014). Service network design models for two-tier city logistics. *Optimization Letters, 8*(4), 1375–1387.

Cuda, R., Guastaroba, G., & Speranza, M. G. (2015). A survey on two-echelon routing problems. *Computers and Operations Research, 55*, 185–199.

Dellaert, N., Saridarq, F. D., Van Woensel, T., & Crainic, T. G. (2019). Branch & Price Based Algorithms for the two-echelon vehicle routing problem with time windows. *Transportation Science, 53*(2), 319–622.

do Martins, C. L., Hirsch, P., & Juan, A. A. (2021). Agile optimization of a two-echelon vehicle routing problem with pickup and delivery. *International Transactions in Operational Research, 28*(1), 201–221. https://doi.org/10.1111/itor.12796.

Ducret, R. (2014). Parcel deliveries and urban logistics: Changes and challenges in the courier express and parcel sector in Europe—The French case. *Research in Transportation Business & Management, 11*, 15–22.

Eitzen, H., Lopez-Pires, F., Baran, B., Sandoya, F., & Chicaiza, J. L. (2017). A multi-objective two-echelon vehicle routing problem. An urban goods movement approach for smart city logistics. In *2017 43rd Latin American Computer Conference, CLEI 2017, 2017-Janua, 1–10*. https://doi.org/10.1109/CLEI.2017.8226454.

Esmaili, M., & Sahraeian, R. (2017). A new bi-objective model for a two-echelon capacitated vehicle routing problem for perishable products with the environmental factor. *International Journal of Engineering, Transactions A: Basics, 30*(4), 523–531. https://doi.org/10.5829/idosi.ije.2017.30.04a.10.

Fu, M. C. (2002). Optimization for simulation: Theory vs. practice. *INFORMS Journal on Computing, 14*(3), 79–84.

Gonzalez-Feliu, J. (2011). Two-echelon transportation optimisation: A meta-narrative analysis. *Working Papers on Operations Management, 2*(2), 18–30.

Gonzalez-Feliu, J., Perboli, G., Tadei, R., & Vigo, D. (2008). The two-echelon capacitated vehicle routing problem. In *Technical Report OR/02/08, Politecnico di Torino, Torino, Italy*.

Grangier, P., Gendreau, M., Lehuédé, F., & Rousseau, L. M. (2016). An adaptive large neighborhood search for the two-echelon multiple-trip vehicle routing problem with satellite synchronization. *European Journal of Operational Research, 254*(1), 80–91.

Guimarans, D., Dominguez, O., Panadero, J., & Juan, A. A. (2018). A Simheuristic approach for the two-dimensional vehicle routing problem with stochastic travel times. *Simulation Modelling Practice and Theory, 89*, 1–14.

Handoko, S. D., Lau, H. C., & Cheng, S. F. (2016). Achieving economic and environmental Sustainabilities in urban consolidation center with Bicriteria auction. *IEEE Transactions on Automation Science and Engineering, 13*(4), 1471–1479. https://doi.org/10.1109/TASE.2016.2563459.

Hemmelmayr, V. C., Cordeau, J. F., & Crainic, T. G. (2012). An adaptive large neighborhood search heuristic for two-echelon vehicle routing problems arising in City logistics. *Computers and Operations Research, 39*(12), 3215–3228.

Huang, Y., Savelsbergh, M., & Zhao, L. (2018). Designing logistics systems for home delivery in densely populated urban areas. *Transportation Research Part B: Methodological, 115*, 95–125. https://doi.org/10.1016/j.trb.2018.07.006.

Jacobson, S., & Yücesan, E. (2001). Common issues in discrete optimization and discrete-event simulation. *IEEE Transactions on Automatic Control, 47*(2), 321–345.

Juan, A., Faulin, J., Grasman, S. E., Rabe, M., Figueira., G. 2015. A review of Simheuristics: Extending Metaheuristics to Deal with stochastic combinatorial optimization problems. Operations Research Perspectives. 2, 62–72.

Juan, A. A., Kelton, W. D., Currie, C. S., & Faulin, J. (2018). Simheuristics Applications: Dealing with Uncertainty in Logistics, Transportation, and Other Supply Chain Areas. In M. Rabe, A. A. Juan, N. Mustafee, A. Skoogh, S. Jain, & B. Johansson (Eds.), *Proceedings of the 2018 Winter Simulation Conference* (pp. 3048–3059). Piscataway, New Jersey: Institute of Electrical and Electronics Engineers, Inc.

Kitjacharoenchai, P., Min, B. C., & Lee, S. (2020). Two echelon vehicle routing problem with drones in last mile delivery. *International Journal of Production Economics, 225* (December 2019), 107598. https://doi.org/10.1016/j.ijpe.2019.107598.

Law, A. M., & Kelton, W. D. (2000). *Simulation modeling and analysis*. McGraw-Hill.

Li, H., Bai, M., Wang, H., & Jian, X. (2019). The truck routing and aircraft assignment problem with time Windows. Proceedings of the 19th COTA International Conference of Transportation Professionals, 740¬–750. https://doi.org/10.1061/9780784482292.395.

Li, H., Wang, H., Chen, J., & Bai, M. (2020). Two-echelonvehicle routing problem with satellite bi-synchronization. *European Journal of Operational Research, 288*(3), 775–793. https://doi.org/10.1016/j.ejor.2020.06.019.

Li, H., Yuan, J., Lv, T., & Chang, X. (2016). The two-echelon time-constrained vehicle routing problem in linehaul-delivery systems considering carbon dioxide emissions. *Transportation Research Part D: Transport and Environment, 49*, 231–245. https://doi.org/10.1016/j.trd.2016.10.002.

Liu, R., Tao, Y., Hu, Q., & Xie, X. (2017). Simulation-based optimisation approach for the stochastic two-echelon logistics problem. *International Journal of Production Research, 55*(1), 187–201.

Mancini, S. (2013). Multi-echelon distribution Systems in City Logistics. *European Transport - Trasporti Europei., 54*, 1–24.

Marinelli, M., Colovic, A., & Dell'Orco, M. (2018). A novel Dynamic programming approach for Two-Echelon Capacitated Vehicle Routing Problem in City Logistics with Environmental considerations. *Transportation Research Procedia, 30*, 147–156. https://doi.org/10.1016/j.trpro.2018.09.017.

Meza-Peralta, K. T., Gonzalez-Feliu, J., Montoya-Torres, J. R., & Khodadad-Saryazdi, A. (2020). A unified typology of urban logistics spaces as interfaces for freight transport. *Supply Chain Forum, An International Journal, 21*(4), 274–289.

Muñuzuri, J., Larrañeta, J., Onieva, L., & Cortés, P. (2005). Solutions applicable by local administrations for urban logistics improvement. *Cities., 22*(1), 15–28.

Patier, D., & Browne, M. (2010). A methodology for the evaluation of urban logistics innovations. *Procedia - Social and Behavioral Sciences, 2*(3), 6229–6241. https://doi.org/10.1016/j.sbspro.2010.04.033.

Perboli, G., Tadei, R., & Vigo, D. (2011). The two-echelon capacitated vehicle routing problem: Models and math-based heuristics. *Transportation Science, 45*(3), 364–380.

Russo, F., & Comi, A. (2010). A classification of City logistics measures and connected impacts. *Procedia - Social and Behavioral Sciences, 2*(3), 6355–6365.

Savelsbergh, M., & Van Woensel, T. (2016). City logistics: Challenges and opportunities. *Transportation Science, 50*(2), 579–590.

Soysal, M., Bloemhof-Ruwaard, J. M., & Bektaş, T. (2015). The time-dependent two-echelon capacitated vehicle routing problem with environmental considerations. *International Journal of Production Economics, 164*(August 2013), 366–378. https://doi.org/10.1016/j.ijpe.2014.11.016.

Su, B., Zhou, J., Zhou, L., Ji, H., & Lin, G. (2019). Approximate algorithm for two-echelon vehicle routing. Proceedings - 2019. *International Conference on Economic Management and Model Engineering, ICEMME, 2019*, 425–430. https://doi.org/10.1109/ICEMME49371.2019.00092.

Taiwo, O. S., Josiah, O., Taiwo, A., Dkhrullahi, S., & Sade, O. K. (2013). Implementation of heuristics for solving travelling salesman problem using nearest neighbor insertion approaches. *International Journal of Advanced Research, 1*(3).

Toledo, T., Koutsopoulos, H., Davol, A., Ben-Akiva, M. E., Burghout, W., Andreasson, I., … Lundin, C. (2003). Calibration and validation of microscopic traffic simulation tools: Stockholm case study. *Transportation Research Record, 1831*, 65–75.

Vareias, A. D., Repoussis, P., & Tarantilis, D. (2017). *Assessing Customer Service Reliability in Route Planning with Self-Imposed Time Windows and Stochastic Travel Times*. https://doi.org/10.1287/trsc.2017.0748.

Wang, D., Zhou, H., & Feng, R. (2019). A two-echelon vehicle routing problem involving electric vehicles with time windows. *Journal of Physics: Conference Series, 1324*(1). https://doi.org/10.1088/1742-6596/1324/1/012071.

Wang, K., Lan, S., & Zhao, Y. (2017). A genetic-algorithm-based approach to the two-echelon capacitated vehicle routing problem with stochastic demands in logistics service. *The Journal of the Operational Research Society, 68*(11), 1409–1421.

Wang, Z., & Wen, P. (2020). Optimization of a low-carbon two-echelon heterogeneous-fleet vehicle routing for cold chain logistics under mixed time window. *Sustainability (Switzerland), 12*(5), 1–22. https://doi.org/10.3390/su12051967.

Yan, X., Huang, H., Hao, Z., & Wang, J. (2019). A graph-based fuzzy evolutionary algorithm for solving two-echelon vehicle routing problems. In *IEEE Transactions on Evolutionary Computation* (pp. 1–14).

Zeng, Z. Y., Xu, W. S., Xu, Z. Y., & Shao, W. H. (2014). A hybrid GRASP+VND heuristic for the two-echelon vehicle routing problem arising in city logistics. *Mathematical Problems in Engineering, 2014*. https://doi.org/10.1155/2014/517467.

Zhou, L., Baldacci, R., Vigo, D., & Wang, X. (2018). A multi-depot two-echelon vehicle routing problem with delivery options arising in the last mile distribution. *European Journal of Operational Research, 265*(2), 765–778. https://doi.org/10.1016/j.ejor.2017.08.011.

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