Proceedings of the 2020 Winter Simulation Conference
K.-H. Bae, B. Feng, S. Kim, S. Lazarova-Molnar, Z. Zheng, T. Roeder, and R. Thiesing, eds.

A SIMHEURISTIC FOR THE STOCHASTIC TWO-ECHELON CAPACITATED VEHICLE ROUTING PROBLEM

Angie Ramírez-Villamil
Jairo R. Montoya-Torres

Universidad de La Sabana
Km 7 autopista norte de Bogotá, D.C.
Chía, Cundinamarca, COLOMBIA

Anicia Jaegler

Kedge Business School
40 Avenue des Terroirs de France
Paris, 75012, FRANCE

ABSTRACT

Two-echelon distribution systems 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 usually located outside urban areas and from there to a set of geographically dispersed customers. This problem is modeled as a two-echelon vehicle routing problem (2E-VRP), which is known to be computationally difficult to solve. This paper proposes a solution approach based on optimization-simulation to solve the 2E-VRP with stochastic travel times. For the objective function, this paper considers the minimization of travel times. The efficiency of the solution approach is analyzed against the solution of the deterministic counterpart, which is solved using both exact and approximation approaches. The impact of adding stochastic travel speeds as part of the objective function is evaluated through simulation. Experiments are run using real data from several convenience stores in the city of Bogota, Colombia.

1 INTRODUCTION

The populations in cities has been growing over the years. About 3.5 billion people lives in cities today. Forecasts indicate that 5 billion people will live in cities by 2030, and about 66 % of the total population by 2050 (UN 2015). To satisfy the demand of the population in cities, an efficient supply chain management strategy must be implemented, especially with respect to freight distribution. Urban freight distribution is defined as “the transport of goods by vehicles and the activities related to this transport to or within an urban environment” (Fernandez-Barcelo and Campos-Cacheda 2012). Also, it considers the freight transportation entering the city, the facilities used for consolidation, the cost of these activities, and the policies regarding freight transport (Cardenas et al. 2017). Although the urban goods distribution is essential for the economic development of cities, it is one of the main generators of traffic congestion and interferes with the rest of the urban activities in terms of the use of public space (Antún 2013). Due to the fact that urban areas have increased their population, the number of vehicles circulating in the cities has grown. Every day, hundreds of trucks have to enter the cities to deliver the demanded products. When any means of transport has full access to cities in any area and time, traffic jams increase (Benjelloun et al. 2010; Muñuzuri et al. 2005; Russo and Comi, 2010).

To face the challenges of the 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 et al. 2005). UCCs have a central position in the logistics network connecting the logistics centers with the customers.

When designing the last-mile supply network, the most employed model is the two-echelon distribution system. The problem consists on delivering goods from one depot to a set of satellites and from there to a set of geographically dispersed customers. This problem is modeled as a two-echelon capacitated vehicle routing problem (2E-CVRP) (Gonzalez-Feliu et al. 2008). Our problem includes both the transport from the depot to satellites (first echelon) and from these satellites to each of the stores (second echelon). Each echelon or level has a specific fleet of vehicles: the first has bigger vehicles than the second. This scenario can be implemented in some companies to reduce the travel distance between the depot and the clients, so that operational cost can be reduced, too. This also contributes to the reduction 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.

The first literature review was made by Mancini (2013), focusing on routing problems arising in city logistics like the 2E-VRP, and classified the basic variants according to their dependence on time. Among the variants with time dependence are the 2E-VRP with time windows (2E-VRPTW) (Dellaert et al. 2019) and 2E-VRP with satellite synchronization (2E-VRP-SS) (Grangier et al. 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 et al. 2018). Other reviews available in the literature include some other families of two-echelon distribution problems (Cuda et al. 2015; Gonzalez-Feliu 2013; Mancini 2013).

According to Savelsbergh and Van Woensel (2016), one of the emerging research opportunities regarding the 2E-VRP is concerned with more real-life issues. Real-life problems have stochastic features and have been studied as a variant of this topic. For instance, one of the few papers that applied stochasticity to the 2E-VRP used a methodology to calculate the impact of stochastic travel times on the cost of a deterministic solution using a two-stage GRASP algorithm with path relinking and Monte Carlo simulation (Anderluh et al. 2019). This method is known as simheuristic and enables to deal with real-life uncertainty in a natural way integrating simulation 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 et al. 2015). The method can be applied in different fields like supply chain management, manufacturing, and logistics. For instance, Guimarans et al. (2018) 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 (2L-VRP) with stochastic travel times.

This paper proposes a solution approach based on simheuristic to solve the 2E-VRP with stochastic travel times. As objective function, we consider the minimization of travel times. The efficiency of the solution approach is analyzed against the solution of the deterministic counterpart solved using a decomposition heuristic using mathematical programming. The impact of adding stochastic travel speeds on the objective function is evaluated through simulation. Such experiments are run using real data for the delivery of goods to convenience stores in the city of Bogota, Colombia.

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 focuses on presenting the solution approach. In Section 4, computational experiments are described and their results analyzed. Finally, conclusions and perspectives are presented in Section 5.

2 OVERVIEW OF RELATED LITERATURE

2.1 Literature about the 2E-VRP

The first Mixed-Integer Programming (MIP) formulation for the 2E-CVRP was proposed in 2008, the model was tested using benchmarks datasets from literature (Gonzalez-Feliu et al. 2008). Crainic et al. (2010) analyzed the impact on the total cost of distribution to find the best satellite location with parameters like customer distribution, satellites-location rules, depot location, number of satellites and mean transportation cost between the satellites and the customers. Then, two math-heuristics were introduced to solve the 2E-CVRP with valid inequalities (Perboli et al. 2011). The 2E-VRP and its variants have been known due to its high computational complexity, approximate methods have been developed to find good solutions as the adaptative large neighborhood search heuristic with new neighborhood search operators that were proposed by Hemmelmayr et al. (2012). Also, a hybrid heuristic called GRASP+VND was applied by Zeng et al. (2014). For the 2E-VRP with simultaneous pickup and delivery (2E-VRPSPD), a node-based mathematical model and a hybrid heuristic algorithm based on a variable neighborhood descent and local search were developed to solve medium-large size instances (Breunig et al. 2019).

Within the scope of this research, only four papers were found that considered real-case instances as stochastic issues in the 2E-VRP. 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 et al. 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 simulation with the aim to solve real-world large-scale 2E-VRPSD instances (Liu et al. 2017). The Two-Echelon Fixed Fleet Heterogeneous VRP (2E-HVRP) on Brazilian wholesale companies was studied using a parallel island-based memetic algorithm with a local search procedure based on a 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 et al. 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. They used a two-stage GRASP algorithm with path relinking for the deterministic part, and then they applied a Monte Carlo simulation to generate travel time scenarios based on lognormally distributed travel times (Anderluh et al. 2019).

In a similar way, the VRP and the its stochastic variants have been widely studied in the last years. For this paper, we only made a brief summary of some reviews due to the fact that there are many existing articles about this subject. Berhan et al. (2014) developed a structural classification of the stochastic VRP. As final results, the authors mentioned that the most common variants are stochastic customer demands, stochastic customers, and stochastic service time. Additionally, a survey made by Braekers et al. (2016) classified the VRP literature published between 2009 and 2015 in a comprehensive taxonomy with three classes according to their characteristics: (i) customer service demand quantity, request times of new customers, and onsite service or waiting times; (ii) physical characteristics as stochastic travel times; and (iii) stochastic data in information characteristics. The authors also highlight that usually stochastic demand quantities are considered in the research (Mehrjerdi 2014; Zhang et al. 2016) or stochastic travel times (Ehmke et al. 2016; Norouzi et al. 2017; Xiao and Konak 2016), but not both.

2.2 Simheuristics for Routing Problems

A simheuristic is an optimization-simulation approach that combines metaheuristics and simulation methods like Monte Carlo, discrete-event, agent-based, to solve stochastic combinatorial optimization problems (SCOP). It has a lot of advantages due to its flexibility, accuracy, and its easy implementation (Calvet et al. 2019). Simheuristics can also be applied to deterministic problems that – due to their complexity – require the use of simulation (Juan et al. 2015). Several authors have applied this method combining an iterated local search algorithm (ILS) with a Monte Carlo simulation to solve routing problems with stochastic demands, for instance, the Multi-Depots VRP and its stochastic version (Calvet et al. 2019); the Capacitated Location Routing Problem (CLRP) (Quintero-Araujo et al. 2019); the VRP with heterogeneous fleet, site dependency, asymmetric costs, and stochastic demands (HSAVRP-SD) (Calvet et al. 2019); and the Waste Collection Problem with multiple depots (MDWCPSD) with a Horizontal Collaboration (HC) scenario (Gruler et al. 2017).

To solve cases with stochastic travel times, the application of Monte Carlo simulation method is very common, too. However, the metaheuristic may vary according to the kind of routing problem. Guimarans et al. (2018) used a hybrid simheuristic with an ILS and a biased-randomized routing and packing heuristics for the two-dimensional VRP (2L-VRP). Reyes-Rubiano et al. (2019) analyzed the Electric Vehicle Routing Problem with Stochastic Travel times (EVRPST). The simheuristic applied a multi-start metaheuristic and a biased-randomization technique.

We have derived two main observations from the literature. Firstly, there are few studies that are focused on the stochasticity in the 2E-VRP and the most studied stochastic characteristic is the demand. Secondly, simheuristics are very useful to deal with stochastic features in routing problems, but we still have not found literature that studies the 2E-VRP with this approach.

3 SOLUTION APPROACH

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 suitable approaches to find good solutions, while exact methods based on mathematical programming allow for optimally solving small-sized instances as well as parts of a real-life 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 for generating high-quality solutions for this type of problems in relatively short computation times. But, these are usually applied in scenarios where real-life uncertainty, given by the stochastic behavior of certain variables, is simplified or even not considered (Juan et al. 2015). Simheuristics emerged as an optimization-simulation methodology that integrates simulation with heuristics or metaheuristics to solve complex stochastic COP scenarios (Juan et al. 2018). In addition, as Fu (2002) mentioned, the combination of simulation techniques with approximation algorithms allows for considering stochastic issues in the optimization problem. We combine a decomposition algorithm with Monte Carlo simulation to solve the problem, and explain the components of the proposed method.

3.1 Overview of the Solution Approach

The proposed solution approach consists of two phases as shown in Figure 1. Given the stochastic version of the problem, random variables are transformed into deterministic values (expected values). Then, in the first step, we solve the deterministic 2E-VRP using a MILP-based decomposition algorithm. This decomposition algorithm splits the problem into four sub-problems to reduce its complexity, but aggregates them and their corresponding results to guarantee the quality and feasibility of the solutions. The first sub-problem is to find a set of routes starting from the depot to serve the satellites (first-echelon); the second one is the vehicle allocation to satellites; the third sub-problem is to cluster the clients to the satellites, and the last sub-problem determines the routing from satellites to serve the corresponding clients (second-echelon VRP).

The second step begins with the generation of instances from the statistical distributions. Preliminary runs with n_0 replications are solved using the MILP-based heuristic mentioned in the first step. Afterwards, the number of required replications is computed using Equation (1), where S_0 is the standard deviation of the preliminary runs, $Z_{0.05}$ is the value of the normal distribution with 95 % of confidence, and ε is the precision (Banks et al. 2000). Additional $n - n_0$ replications are run.

$$R \geq \left(\frac{Z_{0.05}S_0}{\varepsilon}\right)^2 \tag{1}$$

3.2 Routing from Depots to Satellites

A decomposition heuristic is applied to reduce the problem complexity. In this section, we explain in more detail the mathematical models employed to solve the first two sub-problems. On the first hand, we present the mathematical formulation for the VRP of the first level. Then, to determine the vehicle allocation to satellites (second sub-problem) we used the allocation model proposed in (Muñoz-Villamizar et al. 2015).

The VRP is solved using the mixed-integer linear programming (MILP) model. Given a set of n depots, m satellites, and l vehicles, binary decision variables are defined as follows: $A_i = 1$ if the depot i is opened, and 0 otherwise; $X_{ijk} = 1$ if the depot i serves the satellite j with vehicle k, and 0 otherwise; $Y_{jik} = 1$ if vehicle k goes from satellite j to depot i, and 0 otherwise; and $B_{jhk} = 1$ if vehicle k goes from satellite j to satellite h, and 0 otherwise. Auxiliary variables U_j are required for subtour elimination. The parameters of the model are: v is the speed of vehicles, De_j is the demand of satellite j, $CapT$ is the total loading capacity of a vehicle, N is the fleet size, M is the total number of satellites in the network, and, finally, D_{ij} , DR_{jh}, and DC_{jh} are the distances between depot i and satellite j and between satellites j and h. The mathematical model is presented in Equation (2).

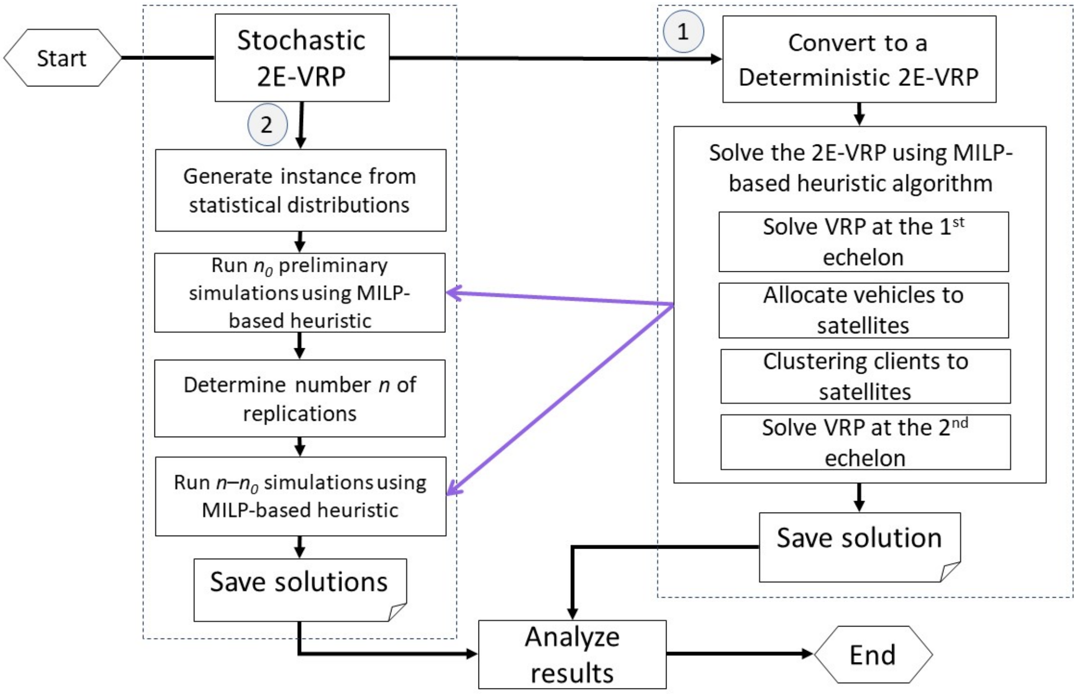

Figure 1: Flowchart of our simheuristic approach.

$$Min\ Z = \sum_{i=1}^{n}\sum_{j=1}^{m}\sum_{k=1}^{l}(D_{ij} * X_{ijk} * 1/v) + \sum_{j=1}^{m}\sum_{i=1}^{n}\sum_{k=1}^{l}(DR_{ji} * Y_{jik} * 1/v) + \sum_{j=1}^{m}\sum_{h=1}^{m}\sum_{k=1}^{l}(DC_{jh} * B_{jhk} * 1/v) \quad (2)$$

Subject to:

$$\sum_{i} A_i = 1 \quad (3)$$

$$N * A_i \geq \sum_{j}\sum_{k} X_{ijk} \qquad \forall i \quad (4)$$

$$\sum_{i}\sum_{j}\sum_{k} X_{ijk} = 1 \quad (5)$$

$$\sum_{i} X_{ijk} \leq \sum_{h} B_{jhk} \qquad \forall j,k \quad (6)$$

$$\sum_{i} X_{ijk} + \sum_{h} B_{hjk} = \sum_{i} Y_{jik} + \sum_{f} B_{jfk} \qquad \forall j,k \quad (7)$$

$$\sum_j \sum_k B_{jhk} = 1 - \sum_i \sum_k X_{ihk} \qquad \forall h \qquad (8)$$

$$\sum_h \sum_k B_{jhk} = 1 - \sum_i \sum_k Y_{jik} \qquad \forall j \qquad (9)$$

$$\sum_j X_{ijk} = \sum_j Y_{jik} \qquad \forall i, k \qquad (10)$$

$$\sum_i \sum_j X_{ijk} * De_j + \sum_h \sum_j B_{hjk} * De_j \leq CapT \qquad \forall k \qquad (11)$$

$$U_j - U_h + M * B_{jhk} \leq M - 1 \qquad \forall j, h, k \qquad (12)$$

$$\sum_i \sum_j X_{ijk} \leq 1 \qquad \forall k \qquad (13)$$

$$A_i, X_{ijk}, B_{jhk}, Y_{jik} \in \{0,1\} \qquad \forall i, j, h, k \qquad (14)$$

The objective function (2) computes the minimization of the travel times. Constraints (3) ensure that only one depot is opened. Constraints (4) ensure that if the depot is opened it is possible to send freight from it. Constraints (5) ensure that one vehicle must leave the depot to do the routing. Constraints (6) ensure that if satellite j is served from depot I, this route must be continued to another customer h with the same vehicle k. Constraints (7) define the route sequence per vehicle. Constraints (8) force all satellites to be visited exactly once. Constraints (9) define that after a satellite is visited, the vehicle goes to another satellite or returns to the depot. Constraints (10) ensure that each route must start and end at the depot. Constraints (11) ensure that the maximum capacity of vehicles is not violated. Constraints (12) correspond to sub-tour elimination. Constraints (13) ensure that each vehicle has only one route. Finally, constraints (14) ensure binary values of decision variables.

3.3 Routing from Satellites to Clients

In this section, we explain the last two sub-problems. In the third sub-problem, a clustering of the clients is made to allocate these clients to a specific satellite with a given coverage range. The model used for this clustering is the same as the one used in the first sub-problem, based on the allocation model of Muñoz-Villamizar et al. (2015).

Furthermore, to solve the VRP in the second echelon (last sub-problem), we applied the same mathematical formulation as in the previous section, but changes in both sets and binary variables were required. Thus, the VRP model of the second-level has the following sets: i corresponds to satellites, j corresponds to clients, and k remains the same for vehicles. Binary variables are defined: $A_i = 1$ if the satellite is opened, and 0 otherwise; $X_{ijk} = 1$ if the satellite i serves the client j with vehicle k, and 0 otherwise; $Y_{jik} = 1$ if vehicle k goes from client j to satellite i, and 0 otherwise; and $B_{jhk} = 1$ if vehicle k goes from client j to client h, and 0 otherwise.

4 EXPERIMENTS

4.1 Experiments with benchmark datasets

The proposed procedure was implemented in the General Algebraic Modeling System (GAMS). Experiments were run on a personal computer Intel® Core™ i3 CPU at 2.3GHz and 8GB RAM. A first experiment was carried out using datasets from the literature. We employed Set 1 proposed by Perboli et al. (2011), consisting of 1 depot, 12 customers and 2 satellites. Datasets are available at the ORLibrary (http://people.brunel.ac.uk/~mastjjb/jeb/orlib/files/). They were solved at optimality by Gonzalez-Feliu et al. (2008). Numerical results are presented in Table 1. Results show that the average approximation of the proposed approach is 18.9 % of the optimum travel time, ranging from near to 5 % to 28 %. Computational times are between 1.67 and 2.23 seconds.

4.2 Analyzing a Case Study in Bogota, Colombia

To study the performance of the procedure on real-life data, simulation experiments were made using real locations from a company with a chain of retail stores. This company has 94 stores in Bogota, D.C and 2 distribution centers (depots) outside the city. Bogota is the largest city in Colombia and also its capital. The population of Bogota is approximately 7.1 million inhabitants according to the last census (DANE 2018). We have selected Bogota as the city under study, because its configuration and size allow a complex scenario that can be an example of the behavior of cities with similar characteristics. The locations of the selected convenience stores were collected using Google Maps™. The origin-destination matrix with actual driving distances was obtained through Google Maps Distance Matrix API, the shortest path was selected for calculations as given in Muñoz-Villamizar et al. (2015) and Quintero-Araujo et al. (2016). We chose two types of vehicles: for the first-level, the JMC Carrying Plus with 3.5 tons of payload; for the second-level, the Renault Kangoo Van with 750 kg of payload. It is also assumed that availability of the necessary vehicles fleet achieves a service level of 100 %.

Table 1: Comparison using benchmark datasets.

		This paper		
Instance	OPT	Obj. func.	gap	CPU time (sec.)
E-n13-k4-2	286	300	4.9 %	2.135
E-n13-k4-3	284	320	12.7 %	1.67
E-n13-k4-4	218	280	28.4 %	2.235
E-n13-k4-5	218	278	27.5 %	1.959
E-n13-k4-6	230	292	27.0 %	1.831
Avg.	247	294	18.9 %	1.966

According to official data, the mean travel speed in Bogota is 20 km/h (Alcaldía Mayor de Bogota, 2019). However, in order to add stochasticity, we defined a triangular distribution for the travel speed with a minimum value of 10 km/h, maximum value of 35 km/h and most likely value to be 20 km/h. It must be noted that the average value of this distribution is 21.66 km/h. Hence, to run the experiments, we did use both the average of the triangular distribution (21.66 km/h) and the mean speed reported by the city of Bogota (20 km/h). Customer demands were generated from a normal distribution with $\mu = 60$ and $\sigma^2 = 6.6$ $/ De_j \sim N(\mu, \sigma^2)$. Satellites act as satellite and store at the same time. Finally, nine different scenarios that result from the combination of both depots and the use of each one separately (Gachancipa, Siberia, Gachancipa-Siberia), with 3, 5, and 7 satellites and 94 stores were generated. In order to replicate the experiments, the full origin-destination matrix and stochastic travel time sets are available upon request from the authors of this paper.

4.3 Model Validation and Verification

To verify the operation logic of the model, 30 preliminary runs were made ($n_0 = 30$). After that, the number of required replications n was obtained finding that at least 104 replications were needed to validate the model, with 95 % confidence. Finally, additional $n - n_0$ replications were run using the MILP-based heuristic and the solutions were saved for analysis by calculating the confidence interval with mean and standard deviation known for all the proposed scenarios.

4.4 Analysis of Results

A total of 105 replications were made for each of the nine scenarios. As a MILP-based decomposition algorithm was applied to solve this problem, the results were consolidated in two tables, one for the first echelon (Table 2) and another one for the second echelon (Table 3). The stochastic results presented are the mean of the results obtained in the 105 replications. However, Table 4 shows the confidence intervals for these scenarios, the minimum value that was obtained, the maximum, and the standard deviation of the stochastic travel times, and a gap that represents the difference between the deterministic (using the average value of the triangular distribution) and the stochastic values for each scenario.

Table 2: Results for the first echelon: routing from UDCs to satellites.

UDC location	Number of satellites	Number of vehicles leaving the UDC	% Vehicle utilization	Time of route (Bogota average speed: 20km/h)	Time of route (avg. value of the triangular distribution: 21.66 km/h)	Time of route (stochastic)
Gachancipa	3	2	81.2 %	331.8	306.4	328.1
	5	2	81.2 %	274.5	253.5	260.8
	7	2	81.2 %	266.7	246.3	259.3
Siberia	3	2	81.2 %	217.8	201.1	216.3
	5	2	81.2 %	361.8	334.1	349.9
	7	2	81.2 %	415.2	383.4	384.7
Gachancipa & Siberia	3	2	81.2 %	242.4	223.8	246.6
	5	2	81.2 %	250.2	231.0	239.6
	7	2	81.2 %	310.8	287.0	302.6

Table 3: Results for the second echelon: routing from satellites to clients.

Number of satellites	Satellite ID	Number of vehicles leaving the satellite	% Vehicle utilization	Number of served nodes	Served demand	Time of route (Bogota average speed: 20km/h)	Time of route (avg. value of the triangular distribution: 21.66 km/h)	Time of route (stochastic)
3	31	3	96.80	37	2238	357.6	330.2	349.4
	58	3	82.49	33	1988	363.9	336.0	362.9
	90	2	93.67	24	1459	296.4	273.7	283.8
	Total	8	90.99	94	5685	1017.9	939.9	996.1
5	31	1	88.27	12	722	228.0	210.5	219.4
	35	2	97.87	24	1469	288.9	266.8	272.6
	58	2	70.80	22	1298	267.3	246.8	259.8
	70	2	97.47	24	1472	250.8	231.6	244.5
	90	1	89.33	12	724	203.7	188.1	200.3
	Total	8	88.75	94	5685	1238.7	1143.8	1196.7
7	7	1	87.60	12	721	225.6	208.3	228.5
	11	1	75.33	12	726	153.9	142.1	149.8
	31	1	86.53	12	727	226.8	209.4	216.4
	35	1	83.33	12	726	199.8	184.5	198.0
	58	1	72.80	12	712	194.7	179.8	191.3
	70	2	85.60	22	1345	247.5	228.5	251.5
	90	1	89.87	12	728	242.7	224.1	233.8
	Total	8	83.01	94	5685	1491.0	1376.7	1469.3

In the first echelon (Table 2), for each of the proposed scenarios, two vehicles depart from the depot towards the satellites. The average vehicle utilization rate is 81.2 %. It also shows that the scenarios Siberia with three satellites, Gachancipa-Siberia with three satellites and Gachancipa-Siberia with five satellites, provide the shortest deterministic and stochastic travel times. As for the second echelon, from satellites to clients (Table 3), the distribution is not affected by the depot from which the goods are supplied. Nevertheless, it is important to mention that the total distance traveled and, therefore, the total travel time (1st echelon plus 2nd echelon) differ depending on the depot that is serving the satellites. The number of vehicles assigned to distribute the goods in the second echelon is eight in each of the scenarios, which satisfies 100 % of the demand with an average vehicle utilization rate of 90.99 % for three-satellite scenarios, 88.75 % for five-satellite scenarios, and 83.01 % for seven-satellite scenarios. In this way, if customer demand increases, the distribution network is still able to satisfy that demand without the need to incur in additional costs to include a new vehicle, human resources, or travel costs for higher fuel consumption.

The scenario that enables the total distribution of the goods to all the clients in a minimum total travel time of 1,141 minutes (deterministic), 1,212.4 minutes (stochastic) and a minimum total traveled distance of 472.6 km is the one that includes the use of the Siberia depot with three satellites and 94 clients, as shown in Table 4. This scenario has a confidence interval of (1183, 1241.8) with a significance of 5 %. The gap between the deterministic solution and the stochastic one is -6.3 %. If it is necessary, this scenario is capable to handle a bigger demand because the average utilization rate of the vehicles used is 86.1 %. Computational times for the solution of the deterministic scenarios are also presented in Table 4.

Table 4: Final deterministic and stochastic results for each scenario.

Scenario	CPU times (seconds)	Deterministic value	
		21.66 km/h	20 km/h
Gach-5-94	6.5	1397.2	1513.2
Gach-3-94	154.4	1246.3	1349.7
Gach-7-94	3.6	1623.0	1757.7
Sib-5-94	6.6	1477.8	1600.5
Sib-3-94	154.4	1141.0	1235.7
Sib-7-94	3.4	1760.1	1906.2
Gach-Sib-5-94	7.1	1374.8	1488.9
Gach-Sib-3-94	154.4	1163.7	1260.3
Gach-Sib-7-94	3.7	1663.7	1801.8

As shown in Table 5, the mean of the stochastic travel times is usually higher than the value obtained in a deterministic problem (21.66 km/h). Moreover, the confidence interval for each scenario was calculated to validate if the deterministic result fits the reality of the problem and 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. The results show that the mean of the stochastic values is different from the deterministic value of the scenarios with a confidence level of 95 %. In addition, the results obtained through the factorial design carried out over two factors allows us to verify that the use of the UDCs, the number of satellites, and the interaction of these have significant effects on the travel time, with p-values of 0.000185, $<2e-16$, and 3.8e-13, respectively.

Finally, a comparison was made between scenarios that have the same number of satellites, which was done through the analysis of box-and-whiskers plots and a hypothesis tests for equality of two means. For the scenarios with a greater number of satellites, we found that there is an equality between the mean of the stochastic travel times for Gachancipa-Siberia and Gachancipa scenarios; the difference of the stochastic travel times of these two scenarios with Siberia with the seven-satellite scenario is significant. Something similar happened in the scenarios that considered five satellites. The scenarios Gachancipa-Siberia and

Gachancipa have an equality in the means of travel times with a significance of 5 %. Regarding the scenarios that only consider three satellites, the Siberia and Gachancipa-Siberia scenarios have significantly equal means of the travel times. In contrast, the scenario that considered the Gachancipa UDC with three satellites has longer travel times and, therefore, these are not equal to those of the other two scenarios with a confidence level of 95 %.

Table 5: Final deterministic and stochastic results for each scenario.

Scenario	Stochastic value				Confidence interval (95 %)		Gap
	min.	max.	mean	st.dev.	LL	UL	
Gach-5-94	1154.4	1932.0	1457.5	161.8	1426.5	1488.4	-4.3 %
Gach-3-94	955.6	1925.1	1324.1	173.4	1291.0	1357.3	-6.2 %
Gach-7-94	1342.8	2122.9	1728.5	165.9	1696.8	1760.3	-6.5 %
Sib-5-94	1213.2	2051.9	1546.6	164.7	1515.1	1578.1	-4.7 %
Sib-3-94	894.7	1647.0	1212.4	153.8	1183.0	1241.8	-6.3 %
Sib-7-94	1515.6	2531.2	1854.0	196.7	1816.4	1891.6	-5.3 %
Gach-Sib-5-94	1146.3	1830.2	1436.2	144.4	1408.6	1463.9	-4.5 %
Gach-Sib-3-94	913.5	1632.2	1242.7	151.1	1213.8	1271.6	-6.8 %
Gach-Sib-7-94	1463.5	2194.7	1771.8	166.3	1740.0	1803.6	-6.5 %

5 CONCLUSIONS AND PERSPECTIVES

This paper presented a simheuristic approach to solve a goods distribution problem in an urban context from a real case of convenience stores in the city of Bogota, Colombia, where depots located at the periphery of the city are used to deliver goods to satellite facilities and then to final sales points where customers can buy the products. The problem was modeled as a two-echelon vehicle routing problem with limited capacity of both vehicles and satellites (2E-CVRP). This approach combines a MILP-based decomposition algorithm with Monte Carlo simulation. Numerical experiments were carried out using real data. Results were analyzed in terms of the impact of using either one or both of the urban distribution centers already available for delivery to the satellites, and the use of three, five, or seven satellites. The impact of adding stochasticity in the problem was evaluated through simulation. In future research, improvement heuristics can be designed to obtain better results in terms of routes. Also, characteristics such as delivery time windows and a heterogeneous fleet of vehicles that consider the use of both electric and gasoline-based vehicles or vehicles with different loading capacities at any of the echelon can be included.

ACKNOWLEDGMENTS

The work of the first author was carried out under a post-graduate scholarship awarded by the Faculty of Engineering at the Universidad de La Sabana, Colombia. We thank the reviewers and track coordinators for their feedback and suggestions allowing us to improve the manuscript.

REFERENCES

Alcaldía Mayor de Bogotá. 2019. “Programa de Gestión de la Velocidad para Bogotá”. Documento Base, Alcladía de Bogotá, Colombia. https://www.movilidadbogota.gov.co/web/sites/default/files/Paginas/2019-03-18/Programa de Gesti%C3%B3n de la Velocidad para Bogot%C3%A1.pdf (not available from all countries), accessed 1st April.

Anderluh, A., R. Larsen, V. C. Hemmelmayr, and P. C. Nolz. 2019. “Impact of Travel Time Uncertainties on the Solution Cost of a Two-Echelon Vehicle Routing Problem with Synchronization”. *Flexible Services and Manufacturing Journal*, in press, DOI: https://doi.org/10.1007/s10696-019-09351-w.

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

Banks, J., J. S. Carson II, B. Nelson, and D. M. Nicol. 2000. *Discrete-Event System Simulation*. 3rd ed. Upper Saddle River, New Jersey: Prentice-Hall, Inc.
Belgin, O., I. Karaoglan, and F. Altiparmak. 2018. "Two-Echelon Vehicle Routing Problem with Simultaneous Pickup and Delivery: Mathematical Model and Heuristic Approach". *Computers & Industrial Engineering* 115:1–16.
Benjelloun, A., T. G. Crainic, and Y. Bigras. 2010." Towards a Taxonomy of City Logistics Projects". *Procedia - Social and Behavioral Sciences 2(3)*:6217–6228.
Berhan, E., B. Beshah, D. Kitaw, and A. Abraham. 2014. "Stochastic Vehicle Routing Problem: A Literature Survey". *Journal of Information and Knowledge Management 13(3)*:1–12.
Bevilaqua, A., D. Bevilaqua, and K. Yamanaka. 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.
Braekers, K., K. Ramaekers, and I. Van Nieuwenhuyse. 2016. "The Vehicle Routing Problem: State of the Art Classification and Review". *Computers & Industrial Engineering 99*:300–313.
Breunig, U., R. Baldacci, R. F. Hartl, and T. Vidal. 2019. "The Electric Two-Echelon Vehicle Routing Problem". *Computers & Operations Research 103*:198–210.
Browne, M., M. Sweet, A. Woodburn, and J. Allen. 2005. "Urban Freight Consolidation Centres Final Report". http://ukerc.rl.ac.uk/pdf/RR3_Urban_Freight_Consolidation_Centre_Report.pdf accesed 10th April.
Calvet, L., A. Pages-Bernaus, O. Travesset-Baro, and A. A. Juan. 2016. "A Simheuristic for the Heterogeneous Site-Dependent Asymmetric VRP with Stochastic Demands". *Advances in Artificial Intelligence Lecture Notes in Computer Science 9868*, 408–417.
Calvet, L., D. Wang, A. Juan, and L. Bové. 2019. "Solving the Multidepot Vehicle Routing Problem with Limited Depot Capacity and Stochastic Demands". *International Transactions in Operational Research 26(2)*:458–484.
Cardenas, I., Y. Borbon-Galvez, T. Verlinden, E. Van de Voorde, T. Vanelslander, and W. Dewulf. 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., G. Perboli, S. Mancini, and R. Tadei. 2010. "Two-Echelon Vehicle Routing Problem: A Satellite Location Analysis". *Procedia - Social and Behavioral Sciences 2(3)*: 5944–5955.
Cuda, R., G. Guastaroba, and M. G. Speranza. 2015. "A Survey on Two-Echelon Routing Problems". *Computers & Operations Research 55*:185–199.
DANE. 2018. "¿Cuántos Somos?" https://www.dane.gov.co/index.php/estadisticas-por-tema/demografia-y-poblacion/censo-nacional-de-poblacion-y-vivenda-2018/cuantos-somos, accessed 1st April.
Dellaert, N., F. D. Saridarq , T. Van Woensel , and T. G. Crainic. 2019. "Branch & Price Based Algorithms for the Two-Echelon Vehicle Routing Problem with Time Windows". *Transportation Science 53(2)*: 319–622.
Ehmke, J. F., A. M. Campbell, and B. W. Thomas. 2016. "Vehicle Routing to Minimize Time-Dependent Emissions in Urban Areas". *European Journal of Operational Research 251(2)*:478–494.
Fernandez-Barcelo, I., and J. M. Campos-Cacheda. 2012. "Estimate of Social and Environmental Costs for the Urban Distribution of Goods. Practical Case for the City of Barcelona". *Procedia – Social and Behavioral Sciences 39*:818–830.
Fu, M. C. 2002. "Optimization for Simulation: Theory vs. Practice". *INFORMS Journal on Computing 14(3)*:79–84.
Gonzalez-Feliu, J. 2013. "Vehicle Routing in Multi-Echelon Distribution Systems with Cross-Docking : A Systematic Lexical-Metanarrative Analysis". *Computer and Information Science Archives 6(3)*:28–47.
Gonzalez-Feliu, J., G. Perboli, R. Tadei, and D. Vigo. 2008. "The Two-Echelon Capacitated Vehicle Routing Problem". Technical Report OR/02/08, Politecnico di Torino, Torino, Italy.
Grangier, P., M. Gendreau, F. Lehuédé, and L. M. Rousseau. 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.
Gruler, A., C. Fikar, A. A. Juan, P. Hirsch, and C. Contreras-Bolton. 2017. "Supporting Multi-Depot and Stochastic Waste Collection Management in Clustered Urban Areas via Simulation-Optimization". *Journal of Simulation 11(1)*:11–19.
Guimarans, D., O. Dominguez, J. Panadero, and A. A. Juan. 2018. "A Simheuristic Approach for the Two-Dimensional Vehicle Routing Problem with Stochastic Travel Times". *Simulation Modelling Practice and Theory 89*:1–14.
Hemmelmayr, V. C., J. F. Cordeau, and T. G. Crainic. 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.
Juan, A. A., J. Faulin, S. E. Grasman, M. Rabe, and G. Figueira. 2015. "A Review of Simheuristics: Extending Metaheuristics to Deal with Stochastic Combinatorial Optimization Problems". *Operations Research Perspectives 2*:62–72.
Juan, A. A., W. D. Kelton, C. S. Currie, and J. Faulin. 2018. "Simheuristics Applications: Dealing with Uncertainty in Logistics, Transportation , and Other Supply Chain Areas". In *Proceedings of the 2018 Winter Simulation Conference*, edited by M. Rabe, A. A. Juan, N. Mustafee, A. Skoogh, S. Jain, and B. Johansson, 3048–3059. Piscataway, New Jersey: Institute of Electrical and Electronics Engineers, Inc.
Liu, R., Y. Tao, Q. Hu, and X. Xie. 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.

Mehrjerdi, Y. Z. 2014. "A multiple Objective Stochastic Approach to Vehicle Routing Problem". *International Journal of Advanced Manufacturing Technology* 74:1149–1158.

Muñoz-Villamizar, A., J. R. Montoya-Torres, C. A. Vega-Mejía. 2015. "Non-Collaborative versus Collaborative Last-Mile Delivery in Urban Systems with Stochastic Demands". *Procedia CIRP 30*:263–268.

Muñuzuri, J., J. Larrañeta, L. Onieva, and P. Cortés. 2005. "Solutions Applicable by Local Administrations for Urban Logistics Improvement". *Cities 22(1)*:15–28.

Norouzi, N., M. Sadegh-Amalnick, and R. Tavakkoli-Moghaddam. 2017. "Modified Particle Swarm Optimization in a Time-Dependent Vehicle Routing Problem: Minimizing Fuel Consumption". *Optimization Letters 11(1)*:121–134.

Perboli, G., R. Tadei, and D. Vigo. 2011. "The Two-Echelon Capacitated Vehicle Routing Problem: Models and Math-Based Heuristics". *Transportation Science 45(3)*:364–380.

Quintero-Araujo, C. L., D. Guimarans, and A. A. Juan. 2019. "A Simheuristic Algorithm for the Capacitated Location Routing Problem with Stochastic Demands". *Journal of Simulation,* in press. DOI: https://doi.org/10.1080/17477778.2019.1680262.

Quintero-Araújo, C. L., A. A. Juan, J. R. Montoya-Torres, and A. Muñoz-Villamizar. 2016. "A Simheuristic Algorithm for Horizontal Cooperation in Urban Distribution: Application to a Case Study in Colombia". In *Proceedings of the 2016 Winter Simulation Conference*, edited by T. M. K. Roeder, P. I. Frazier, R. Szechtman, E. Zhou, T. Huschka, and S. E. Chick, 2193–2204. Piscataway, New Jersey: Institute of Electrical and Electronics Engineers, Inc.

Reyes-Rubiano, L., D. Ferone, A. A. Juan, and J. Faulin. 2019. "A Simheuristic for Routing Electric Vehicles with Limited Driving Ranges and Stochastic Travel Times". *SORT 43(1)*: 3–24.

Russo, F., and A. Comi. 2010. "A Classification of City Logistics Measures and Connected Impacts". *Procedia – Social and Behavioral Sciences 2(3)*:6355–6365.

Savelsbergh, M., and T. Van Woensel. 2016. "City Logistics: Challenges and Opportunities". *Transportation Science 50(2)*:579–590.

UN 2015. United Nations Sustainable Development Goals – Goal 11: Make Cities Inclusive, Safe, Resent and Sustainable. https://www.un.org/sustainabledevelopment/cities/, accessed 17th September 2019.

Wang, K., S. Lan, and Y. Zhao. 2017. "A Genetic-Algorithm-Based Approach to the Two-Echelon Capacitated Vehicle Routing Problem with Stochastic Demands in Logistics Service". *Journal of the Operational Research Society 68(11)*:1409–1421.

Xiao, Y., and A. Konak. 2016. "The Heterogeneous Green Vehicle Routing and Scheduling Problem with Time-Varying Traffic Congestion". *Transportation Research Part E: Logistics and Transportation Review 88*: 146–166.

Zeng, Z. Y., W. S. Xu, Z. Y. Xu, and W. H. Shao. 2014. "A Hybrid GRASP+VND Heuristic for the Two-Echelon Vehicle Routing Problem Arising in City Logistics". *Mathematical Problems in Engineering 2014,* Article ID 517467.

Zhang, J., W. H. K. Lam, and B. Y. Chen. 2016. "On-Time Delivery Probabilistic Models for the Vehicle Routing Problem with Stochastic Demands and Time Windows". *European Journal of Operational Research 249(1)*: 144–154.

AUTHOR BIOGRAPHIES

ANGIE P. RAMIREZ-VILLAMIL is a master student in design and process management at the Universidad de La Sabana, Chía, Colombia, where she earned an Industrial Engineering degree. Her research has been focused on solving vehicle routing problems in urban logistics context using simulation and optimization. Other research interests include supply chain management and optimization of logistics and transportation systems. She can be contacted by email at angieravi@unisabana.edu.co.

JAIRO R. MONTOYA-TORRES is a Full Professor and Director of the Ph.D. program in Logistics & Supply Chain Management at the Universidad de La Sabana, School of Engineering, in Chia, Colombia. He holds a Ph.D. from Mines Saint Etienne. His research focuses on quantitative modeling for the resolution of complex, realistic decision-making problems in the areas of reverse and sustainable logistics, supply chain management, urban logistics, and scheduling in manufacturing and services. His e-mail address is jairo.montoya@unisabana.edu.co.

ANICIA JAEGLER holds a degree in engineering and a Ph.D. in industrial engineering and management science from Mines Saint-Etienne, France, as well as a Habilitation to Research Direct (HDR), from the CRET-LOG at Université Aix-Marseille, France. Anicia is a Professor of supply chain management at Kedge Business School. Since 2018, she is heading the Operations Management and Information Systems department in the same institution. Her teaching and research topics focus on sustainable supply chains, supply chain management, and simulation. Her e-mail address is anicia.jaegler@kedgebs.com.