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A SIMHEURISTIC ALGORITHM FOR HORIZONTAL COOPERATION IN URBAN DISTRIBUTION: APPLICATION TO A CASE STUDY IN COLOMBIA

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ABSTRACT

The challenge in last-mile supply chains deliveries is to maintain and improve the operational cost-effectiveness by the implementation of efficient procedures while facing increased levels of congestion in cities. One competitive alternative is Horizontal Cooperation (HC). City distribution problems under HC conditions can be modeled as multi-depot vehicle routing problems, which are NP-hard problems meaning that exact methods provide optimal solutions only for small datasets. This complexity increases when considering stochastic demand. Therefore, real-life situations must be solved using heuristic algorithms. This paper proposes the implementation of a simheuristic (i.e., an algorithm combining heuristics with simulation). Experiments are carried out using realistic data from the city of Bogotá, Colombia, regarding the distribution of goods to the whole network of the three major chains of convenience stores currently operating in the city. Results show the power of the proposed simheuristic in comparison with traditional solution approaches based on mathematical programming.

1 INTRODUCTION

The complexities of current supply chains and the increased requirements from customers require logistics systems with more efficient and cost-effective delivery tours (Ehmke 2012). In supply chain management (SCM), the term last mile delivery refers to the distribution of goods to customers (either at home or via a retail store), usually located in cities. Efficient methods for transport planning have become increasingly important (Álvarez et al. 2010). However, congestion in cities is continuously rising due to increasing levels of traffic demand, and most large cities are confronted with problems regarding air and noise pollution and congestion caused by motorized road traffic (Geroliminis and Daganzo 2006). The evolution of urban logistics in the past decades worsened that situation due to an increasing use of heavier goods vehicles in city centers (Benjelloum et al. 2010). Because of the increase in mobility patterns in cities (both in the case of people and freight), new services based on resource sharing have appeared

(Muñoz-Villamizar et al. 2015). One strategy that can be followed in order to become more competitive is horizontal cooperation (HC), which allows the use of economies of scale, the increase of resource utilization, and cost reduction. The European Union (2001) has defined HC as "concerted practices among companies operating at the same level(s) in the market." Bahinipati et al. (2009) define HC as "a business agreement between two or more companies at the same level in the supply chain or network in order to allow ease of work and co-operation towards achieving a common objective". These companies can either be competing or unrelated suppliers, manufacturers, retailers, receivers, or logistic service providers that share information, facilities or resources with the goal of reducing costs and/or improving service. Although the main goals of HC are to reduce shipping costs and also to provide a faster distribution service to customers, other important benefits are related to a reduction of the environmental impact of distribution activities (Bektas and Laporte 2011, Ubeda et al. 2011, Erdogan and Miller-Hooks 2012, Lera-López et al. 2012).

A large number of real-life optimization problems in operations, logistics, and SCM are NP-hard, which means that exact solution methods can provide optimal solutions only for small datasets. Therefore, heuristics and metaheuristics methods have been developed to provide near-optimal solutions to mid- to large-sized instances or to real-life cases. Due to the fact that many of the enterprises in a horizontal cooperation schema are competitors, one key aspect when promoting these practices among firms is the consideration of the magnitude of the costs reduction associated with cooperation strategies. Unfortunately, it is not easy to quantitatively estimate those costs; this constitutes a serious obstacle for the development of this praxis. This complexity is also increased by the aforementioned NP-hardness of most problems in operations, logistics, and SCM. Accordingly, new hybrid methods are needed in order to design effective cooperation strategies as well as to analyze how routing costs might vary in different cooperation scenarios. These hybrid methods typically combine quantitative and computing techniques such as metaheuristics, computer simulation, parallel and distributed computing, etc. In particular, the use of simheuristics (Juan et al. 2015a), could be an original and efficient way to deal with some of the most difficult optimization problems that can arise in horizontal cooperation and that have to be considered in most practical applications, especially when dealing with real-life uncertainty and complexity, e.g., random demands, random traveling/processing times, etc.

This paper addresses the problem of evaluating the impact of horizontal cooperation for goods delivery in a congested city. In the Operations Research literature, the problem under study becomes a variant of the well-studied vehicle routing problem (VRP), which is a NP-hard combinatorial optimization problem (Lenstra and Rinnooy Kan 1981). To solve it, a simheuristic algorithm is proposed. Numerical experiments are carried out using real-life data from the city of Bogotá, Colombia. The performance of the simheuristic is compared with an alternative solution procedure based on mathematical programming. The remainder of this paper is organized as follows. The problem under study is introduced in Section 2. The proposed solution approach is developed in Section 3. Section 4 presents the simulation experiments and the analysis of results. Finally, Section 5 highlights the conclusions of this work and draws some opportunities for further research.

2 LITERATURE REVIEW

Freight transportation is essential for the economic development, but it is also harmful to the environment and to human health. Until recently, the planning of freight transportation activities has mainly focused on cost minimization (Demir et al. 2014). Due to the growing concern about the environment, organizations have started to realize the importance of the environmental and social impacts (e.g., air pollution, noise, and congestion) associated with transport operations (Demir et al. 2015). As pointed out previously, in order to improve the efficiency and effectiveness of urban logistics systems, decision-makers have been led to consider cooperative strategies to reduce overall cost of the supply process (Paché 2008). This phenomenon has been increased by both the new trends in retail and commerce organization and the technological innovation in supply chain and distribution planning (Gonzalez-Feliu and Salanova 2012).

Cooperation schemas are commonly used in the field of SCM (Montoya-Torres and Ortiz-Vargas 2014), but they still remain less explored in the context of urban goods delivery, especially in developing economies where the retailing is dominated by small stores and the cities' infrastructure is insufficient to deal with the increase in traffic (Montoya-Torres et al. 2016). Cooperation in urban logistics can take place at several stages and with different levels of interaction (Gonzalez-Feliu and Morana 2011): transactional, informational, and decisional. This last collaborative dimension concerns the collaboration at different planning horizons of logistics and transportation activities: (a) operational planning, related to daily operations that can be coordinated or shared (goods transportation or cross-docking); (b) tactical planning, related to middle-term planning stage regarding forecasting, shipping, inventory, production management, and quality control; and (c) strategic planning (the highest cooperation stage), related to long-term planning decisions such as network design, facility location, finance, and production planning.

Cooperation is possible when at least two actors share their efforts to reach a common objective. This also requires confidence, trust, and information sharing between the actors involved in the process. The exchange of information is often affected by complexities and risks. Even within companies, the cost of sharing information is still often an obstacle. Companies or internal departments are often reluctant to share information, for fear that could result in revenue losses, from the information itself, from the costs of sharing information or because of legal and technological constraints (Barratt 2004). Technological issues are of high relevance to ensure effective and efficient cooperative networks in urban goods transport. In addition, the diverse and (very often) conflicting interests of stakeholders have to be taken into account. Similar services/goods providers differed in the degree of importance to the collaborative attributes. This is due to the differing priorities of the various members of the supply chain. As collaborative efforts add costs and brings benefits differently to the chain members, the identification of most appropriate attributes would enable the network members to understand each other's concerns and find effective solutions that benefit all parties (Bahinipati et al. 2009). HC in urban freight delivery is hence one of the most promising areas of study in order to create mechanisms that encourages the collaborative practices to achieve a better global performance.

In summary, available literature related to HC in urban distribution is scarce. Moreover, most of published works assume unrealistic situations in which all parameters are known in advance. In order to fulfill this gap, this work propose the use of Monte Carlo simulation combined with a ILS metaheuristic to deal with urban distribution of goods subject to uncertainty in demand under cooperation scenarios.

3 PROBLEM DESCRIPTION

Goods distribution in urban and metropolitan areas concerns both pick-up and delivery in retail, parcel and courier services, waste transport, transport of equipment for the construction industry, and a broad range of other types of transport (Russo and Comi 2010). One approach to perform urban distribution of goods consists of: *(i)* storage of goods inside a logistics facility (warehouse, depot, etc.) and *(ii)* the corresponding route planning to deliver such goods to retail points (convenience stores). Traditionally, each company serves its own customers from its central depot using its own (or subcontracted) fleet of vehicles. However, HC arises as a new strategy that can be implemented between companies in order to reduce operational costs, among other benefits. Under some general circumstances, HC in urban freight delivery can be modelled as a multiple depot vehicle routing problem (MDVRP). As described in Juan et al. (2015b), in the MDVRP a set of clients much be served by a set of depots (Figure 1).

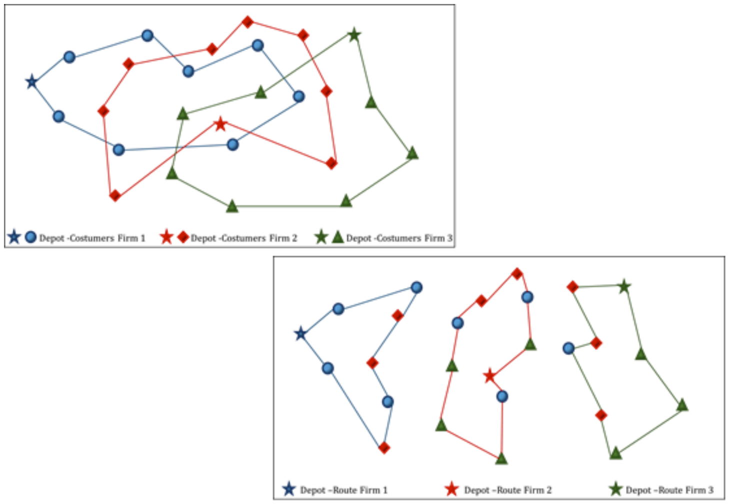

Figure 1: A simple example illustrating the impact of HC strategies on the routing plans.

This is a challenging problem because it integrates the allocation of delivery points to depots and its routing process. MDVRP hence belongs to the class of NP-hard problems, which means that it is not possible to find optimal solutions for large-sized instances in reasonable computing times. Therefore, the design of approximation algorithms to efficiently solve this problem is required. A comparison of both components in Figure 1 provides a first intuitive idea regarding the benefits, in terms of routing distances and times that can be reached throughout horizontal cooperation in relation to travel cost and distances. According to a survey carried by Cruijssen et al. (2007), the estimation of the benefits obtained by joint route planning is one of the biggest obstacles to encouraging horizontal cooperation. This is perhaps due to difficulty in isolating the effects of joint routing from the other benefits of collaborating horizontally, such as cost reduction by centralized purchase of necessary equipment, use of common warehouses, or common training of employees (Sancha et al. 2016). In the non-cooperative scenario (top-left), different companies control carriers and shippers and hence each of them must define the corresponding routing for goods delivery. Afterwards, the cooperative scenario (bottom-right) deals with the ideal routing, in which companies are incentivised to share their customers in order to improve their individual profits by reducing their transportation costs, the number of necessary vehicles and, as a direct consequence, the environmental impact of their delivery activity.

4 DESCRIPTION OF THE SOLUTION APPROACH

Taking into account the complexity of the MDVRP, which is known to be NP-Hard, approximate algorithms seem to be the right way to tackle this problem, instead of exact methods which allow to optimally solve very small instances. However, as explained by Juan et al. (2015a, p. 62) metaheuristics "...have been mostly applied to simplified scenarios where real-life uncertainty (i.e., stochastic or random behavior) is usually not taken into account." Thus, an approach combining optimization with simulation is more appropriate when dealing with stochastic components in the optimization problem. In particular, the approach used in this paper belongs to the so-called simheuristics framework. A simheuristic is a first-hand resource to deal with combinatorial optimization problems with stochastic components (SCOP). As defined by Juan et al. (2015a, p. 66), "a simheuristic algorithm is a particular simulation-optimization approach oriented to efficiently tackle a combinatorial optimization problem instance that typically contains stochastic components", these latter located either in the objective function or in the set of constraints. Taking into account that the deterministic version of a problem is an instance of the same stochastic problem with variance equal to zero, simheuristic algorithms use in a first stage the (meta-) heuristic component to solve the relaxed (deterministic) version of the problem (under the assumption that these high quality solutions for the deterministic version of the problem could be good solutions for the stochastic version). Then, in a latter phase, the solutions obtained so far go through a 'fast' simulation process in order to test their potential in the stochastic scenario. Finally, the most promising (e.g., the top-10) solutions pass through a more time-consuming simulation process (i.e., one with more iterations) in order to better estimate their expected stochastic costs and expected reliability.

As mentioned before, we use a simheuristic approach to solve the horizontal cooperation problem in urban distribution settings. In particular, we combine an iterated local search algorithm (Lourenço et al. 2010) with Monte Carlo simulation to solve the problem. Our method splits the problem into two sub-problems to reduce its complexity, but aggregates them and their corresponding costs in order to guarantee the quality of solutions. The first sub-problem is the customer allocation to depots, while the second one is to find the set of routes starting from each depot to serve the corresponding customers. We next explain the components of the proposed approach.

4.1 Assumptions

The most common way to assess the potential of a solution approach is to use benchmark instances available in the literature. However, when dealing with routing problems with stochastic demands, benchmark sets are scarce. As a consequence, the most natural way is to use deterministic benchmarks and transform them into stochastic ones by assuming that the deterministic value of the demand is the mean value of the demand in the stochastic world and generate pseudo-random values of the demand following a given probability distribution. Since real-life demands are mostly associated with non-negative values, therefore they should be modeled by using a distribution offering non-negative values or asymmetries due to long right-hand tails (e.g., log-normal, Weibull, etc.) In our case we assume that stochastic demand follows a lognormal distribution. The parameters of the distribution will be obtained using $\mu = \mathrm{E}[D_i]$ and $\mathrm{VAR}[D_i] = k \times d_i$, with $k = \{0.2, 0.5\}$.

4.2 Construction of Feasible Solutions

To determine customer allocation to depots we use a kind of distance-based saving list and apply a biased-randomized selection over this saving list to create allocation maps (Juan et al. 2013, Faulin et al. 2008). Once all customers are assigned to any depot, we use the Clarke & Wright savings (CWS) heuristic (Clarke and Wright 1964) to obtain the routes. This process is executed during a given number of iterations and the best solution obtained so far is also kept as the basis solution. It is to note that, when planning routes, we use the concept of safety stock introduced in Juan et al (2013) to face the uncertainty of the demand, i.e., we plan the routes with a reduced truck capacity W', where $W^{'} = (1 - SS) \times W$. In our case, $SS = \{0.01, 0.05\}$ and $W = 800$ is the original truck capacity.

4.3 Iterated Local Search Phase

In the iterated local search phase, we apply a perturbation procedure to the customer-allocation maps belonging to the basis solution. Then, we apply the biased-randomized version of the CWS heuristic proposed by Juan et al. (2013) and Faulin et al. (2008). If the new solution improves the best solution found, we update it; otherwise, we apply an acceptance criterion in order to update the basis solution. This process is executed during 350 iterations and the top-10 solutions are kept to go through the simulation phase.

4.4 Simulation Phase

In this phase, we test each top solution generated in the previous step in a stochastic scenario. The original capacity of vehicles, W, is used. A 'fast' simulation process (30 iterations) is executed over each solution. Demands are generated as mentioned in Subsection 3.1. In this case, a route could become infeasible due to the capacity violation generated by the uncertainty of the demand; in such a case the vehicle is allowed to return to the depot to re-load and resume the route. This will count as a route failure and will lead to an increase in the routing cost (due to the unplanned trip to the depot). After the short simulation, expected stochastic costs and reliabilities are calculated for each solution and they are sorted by increasing value of the expected total costs (deterministic cost plus expected stochastic cost). This sorted list is passed again over a simulation engine, during 5,000 iterations, in order to have better estimations of expected costs and reliabilities. Therefore, new calculations of expected stochastic costs, expected total costs and reliabilities are carried out. The solution with the lowest expected total cost is reported. The flowchart of the procedure is presented in Figure 2.

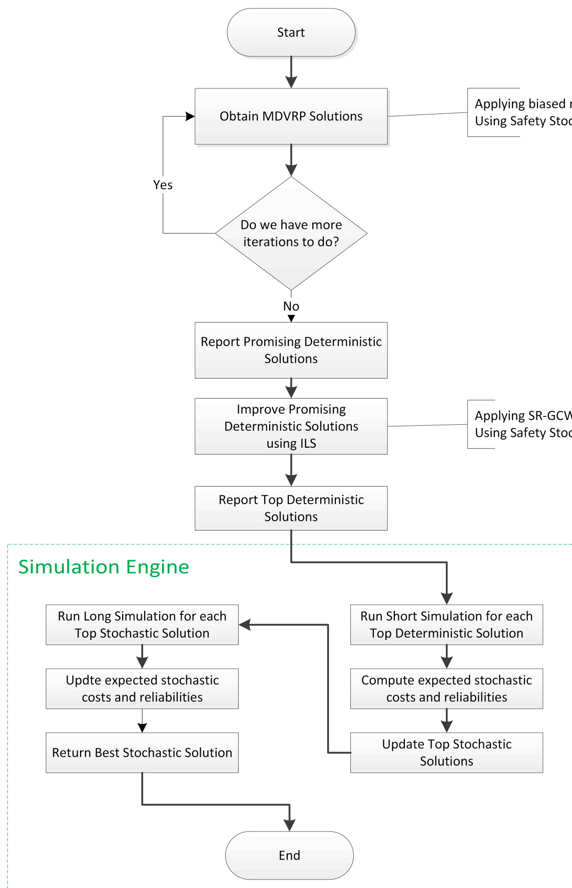

Figure 2: Flowchart of the solution approach.

5 SIMULATION EXPERIMENTS AND ANALYSIS OF RESULTS

The proposed procedure was implemented as a Java application. Simulation experiments were run on a personal computer Intel® Core™i5 CPU at 2.4 GHz and 8 GB RAM. In order to study the performance of the proposed procedure, simulation experiments were undertaken on using the same real data for the case of the three major convenience stores (proximity shops) operating in Bogotá, D.C. (Colombia), as employed in the works of Muñoz-Villamizar (2015) and Montoya-Torres et al. (2016). Bogotá is the capital of and the largest city in Colombia. It is the fifth largest city in Latin America and twenty-fifth in the world (City Majors 2015). The selection of Bogotá as the city under study is at least twofold. Size and dynamics of Bogotá allow having a complex and complete example of the behavior of cities in emerging economies. Modern convenience stores offer not only food, snacks, and drinks, but also daily services, including payment of bills (e.g., utilities), purchase of tickets (e.g., trains/buses, concerts, or sport events) and many others. As in our previous works, actual locations of proximity shops of selected companies are obtained using a geographical information system (GIS). Company E has a total of 16 stores, Company O has a total of 35 stores, and Company M has 10 stores. The origin-destination matrix was obtained using actual driving distances using Google Maps^{TM} mapping service, as given in (Muñoz-Villamizar et al. 2015, Montoya-Torres et al. 2016). The shortest path criterion was kept for calculations, among the different options provided by the software. The selected vehicle for urban freight transport was the Renault Kangoo Van, with 800 kg of payload and 119 g/km CO_2 emissions (Renault 2015). Stochastic demand was randomly generated from a uniform distribution according to the parameters explained in Section 3. It is also assumed that availability of the necessary vehicles fleet achieves a 100% of service level. Finally, ten different sets of demands (instances) for all the 61 delivery points were generated. In order to replicate the experiments, full origin-destination matrixes and stochastic demand sets are available upon request to the corresponding author of this paper.

5.1 Comparison of the Proposed Procedure with Previous Works from the Literature

This subsection presents a comparison of the proposed approach with the work of Muñoz-Villamizar et al. (2015), in which a hierarchical approach using mathematical programming was proposed to solve the same problem. Tables 1 and 2 present a comparison of results for the route length (travel distance) and load, respectively, for each of the ten tested instances. Table 1 reports the values, in kilometers, of the total length of the delivery routes for each company under study, as well as the total distance of the three companies together. The last column reports the percentage deviation (gap) between these two approaches. The last row of the table presents the average values of length routes. Table 2 presents results obtained for the values of the total load transported by vehicles in terms of the units of product demand.

Note that our simulation-based approach was able to improve the solutions for route length, provided by the hierarchical approach of Muñoz-Villamizar et al. (2015), in every instance. Route length improvements have an average of almost 7%. On the other hand, our approach re-distributes load of company O to company M by an average of 3.1%, while company A continues transporting, on average, the same load amount. This implies that our approach not only improves routing solution, but also improves the allocation of customers to depots.

Table 1: Comparison of results for route length (km) between our approach and a former one.

	Results from Muñoz-Villamizar et al. (2015)				Our best results				
Scenario	Dist. E	Dist. O	Dist. M	Total Dist.	Dist. E	Dist. O	Dist. M	Total Dist.	GAP %
1	72.60	47.74	94.79	215.13	74.60	52.49	82.92	210.01	-2.38%
2	72.10	50.99	104.42	227.51	49.12	49.84	112.87	211.83	-6.89%
3	68.00	61.34	100.47	229.81	47.50	47.54	114.94	209.98	-8.63%
4	64.50	59.39	104.12	228.01	63.85	46.44	96.77	207.06	-9.19%
5	69.80	45.89	99.32	215.01	74.85	53.59	83.57	212.01	-1.40%
6	104.00	57.64	96.79	258.43	64.60	34.64	110.07	209.31	-19.01%
7	67.30	54.24	95.02	216.56	62.30	53.84	93.72	209.86	-3.09%
8	71.30	50.59	102.04	223.93	48.10	49.84	111.47	209.41	-6.48%
9	74.30	50.09	95.69	220.08	49.00	49.84	110.32	209.16	-4.96%
10	57.05	67.24	98.47	222.76	49.12	49.84	112.37	211.33	-5.13%
Average	72.10	54.52	99.11	225.72	58.30	48.79	102.90	210.00	-6.97%

Table 2: Comparison of results for the total load between our approach and a former one.

	Results from Muñoz-Villamizar et al. (2015)				Our best results			
Scenario	Load E	Load O	Load M	Total Load	Load E	Load O	Load M	Total Load
1	720	728	1118	2566	795	797	974	2566
2	734	724	1320	2778	736	679	1363	2778
3	721	723	1144	2588	605	526	1457	2588
4	742	728	1105	2575	795	673	1107	2575
5	723	773	1131	2627	772	737	1118	2627
6	733	722	1252	2707	791	445	1471	2707
7	720	727	1262	2709	769	795	1145	2709
8	721	771	1366	2858	648	655	1555	2858
9	749	738	1356	2843	672	655	1516	2843
10	726	746	1289	2761	706	589	1466	2761
Average	728.9	738	1234.3	2701.2	728.9	655.1	1317.2	2701.2

Finally, in order to visually compare the performance of the proposed procedure, Figure 3 presents a box-and-whisker plot over the route length of the ten instances employed to test both procedures. Benefits of implementing our approach can be observed. The first insight from this comparison is the difference between both procedures regarding the value of the total distance traveled by vehicles. Furthermore, another interesting feature of the procedure proposed in this paper is the small variance. Standard deviation of Muñoz-Villamizar et al. (2015) procedure is 12.69, while our procedure's deviation is 1.47. This means a reduction of 88% in dispersion of results. We can hence state a preliminary good performance of the proposed method, at least for the case under study.

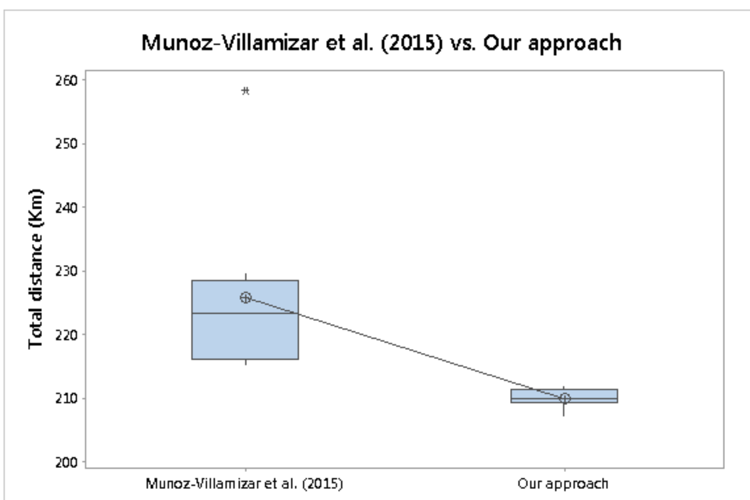

Figure 3: Comparison between procedures for total distances.

5.2 Extended Simulation Analysis of the Proposed Approach

In order to better assess the behavior of the proposed procedure, an extended simulation experiment was carried out. To this end, we compared the performance of the proposed procedure in terms of the total distribution cost under a stochastic demand behavior. High and low values of the variance of demand were considered, respectively 50% and 20%, for each of the ten instances previously tested. In addition, a safety stock is allowed with values of 1% and 5% of the vehicle capacity. Table 3 presents the average values of key performance metrics allowing the comparison of results for these scenarios. The total stochastic cost corresponds to the total distribution cost under stochastic behavior (i.e. distance cost plus failure costs). The distance cost is the deterministic cost of distribution. The failure cost is the cost associated with the corrective action executed in order to satisfy the total demand of clients. In other words, once a vehicle arrives to a delivery point (client) and it does not have all required products, the vehicle must return to the depot to be loaded (or unloaded, accordingly). This cost is computed using the distance to return to the depot and then go back to the client. Finally, an estimate for the reliability is computed as the number of times that a delivery satisfy the actual demand of a client (e.g., the delivery is not a failure) divided by the number of simulation runs.

Box-and-whisker plots are presented in Figures 4 and 5 comparing the total stochastic cost and the reliability values by the different values of variance and safety stock. After these figures, we conclude that there is a clear difference in the quality of solutions with low variance and low safety stock level versus high variance and high level of safety stock. It might not be surprising that total costs are higher for the highest variance of demand (i.e., 1.89% higher on average). Nevertheless, a higher reliability is achieved for the highest safety stock level (i.e., 3.97% higher on average). Therefore, it can be concluded that safety stock avoids failures in delivery in a greater proportion than the generated over cost. Another interesting feature is the small variance in the reliability for just 5% of safety stock.

Table 3: Comparison of best results with different safety stock and variance levels.

	Variance = 20%, Safety Stock = 1%				Variance = 50%, Safety Stock = 5%			
Instance	Total Stochastic Cost (km)	Distance Cost (km)	Failure Costs (km)	Reliability	Total Stochastic Cost (km)	Distance Cost (km)	Failure Costs (km)	Reliability
1	223.79	223.29	0.50	97.3%	228.01	227.95	0.07	99.6%
2	229.46	228.52	0.94	94.7%	238.11	238.10	0.02	99.9%
3	222.64	222.30	0.34	97.3%	230.58	230.53	0.05	99.6%
4	223.45	222.82	0.63	95.4%	230.30	230.25	0.05	99.7%
5	227.96	227.21	0.75	96.7%	230.80	230.75	0.04	99.7%
6	228.49	227.73	0.76	95.4%	229.54	229.50	0.04	99.8%
7	228.40	227.58	0.82	95.6%	230.63	230.57	0.06	99.7%
8	231.29	230.69	0.60	96.9%	233.91	233.88	0.04	99.8%
9	231.73	231.39	0.35	98.1%	234.82	234.77	0.05	99.8%
10	228.76	228.45	0.31	98.4%	230.61	230.59	0.02	99.8%

6 CONCLUSIONS

This paper presented a simulation-based approach to evaluate the impact of horizontal cooperation in urban logistics scenarios. The presented approach combines metaheuristic algorithm with Monte Carlo simulation to fully define the collaborative network's allocation and routing. Our approach has been compared against a heuristic method available in the literature for the same problem and same datasets: urban distribution of goods for the three major networks of convenience stores operating in Bogotá, Colombia. Results showed the benefits that can be achieved using this approach.

Other simulation experiments were executed to evaluate the impact of the variance of demand (stochastic behavior) in the distribution costs. To face the uncertainty of demand, the safety stock concept was used. Results showed that the safety stock and the variance of demand influence total distribution costs and process reliability. Improvements in reliability can be achieved with small safety stocks. Future research could evaluate further routing aspects, e.g. the impact of HC on environmental and social issues. Also, the stochastic component could be extended to consider stochastic travel times or other input variables under uncertainty.

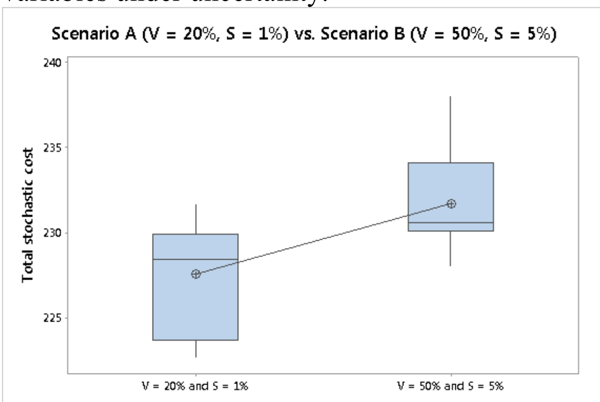

Figure 4: Comparison between scenarios for stochastic costs.

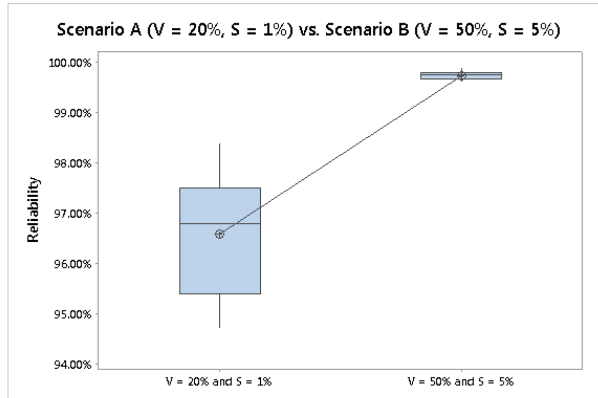

Figure 5: Comparison between scenarios for reliability.

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