A Decision Support Tool for the Location Routing Problem During the COVID-19 Outbreak in Colombia

Andres Felipe Martinez Reyes, Carlos Quintero Araujo and Elyn Lizeth Solano Charris

August 20, 2020

A decision support tool for the location routing problem during the COVID-19 outbreak in Colombia

Andrés Martínez-Reyes[1], Carlos L. Quintero-Araújo[1], and Elyn L. Solano-Charris[1]

Operations & Supply Chain Management Research Group, International School of Economic and Administrative Sciences, Universidad de La Sabana, Chía, Colombia
{andres.martinez9,carlosqa, elynsc}@unisabana.edu.co

Abstract. During the outbreak of coronavirus disease 2019 (COVID-19) in Bogotá, Colombia, some strategies for dealing with the increasing number of infected people and the level of occupation of intensive care units include the use of Personal Protective Equipment (PPE). PPE is a crucial component for patient care and a priority for protecting health-care workers. For attending this necessity, the location of distribution centers within the city and the corresponding routes to supply the intensive care units (ICU) with PPE have an important role. Formally, this problem is defined as the Location Routing Problem (LRP). The LRP is an NP-Hard problem that combines the Facility Location Problem (FLP) and the Vehicle Routing Problem with Multiple Depots (MDVRP). This work presents a decision support tool based in a hybrid method consisting of an Iterated Local Search (ILS) algorithm combined with Monte Carlo simulation to deal with the LRP with uncertain demands. Realistic data from Bogotá (Colombia) was retrieved using Google Maps to characterize the geographical distribution of both potential facilities and ICUs, while demands were generated using the uniform probability distribution. Our preliminary results suggest the competitiveness of the algorithm in both the deterministic and the stochastic versions of the LRP.

Keywords: COVID-19, Healthcare Logistics, Location-Routing, Decision support tool, ILS, Monte Carlo simulation.

1 INTRODUCTION

In December 2019, a new coronavirus disease emerged characterized as a viral infection with a high level of transmission in Wuhan, China. Coronavirus 19 (COVID-19) is caused by the virus known as Severe Acute Respiratory Syndrome coronavirus 2 (SARS- CoV-2) established by the Coronaviridae Study Group of the International Committee on Taxonomy of Viruses (ICTV) [1]. As the cumulative numbers of confirmed cases have considerably increased worldwide, academics and practitioner are mainly concerned about modeling and prediction of COVID-19 ([2], [3]).

In Colombia, according to the report of August 4th, 2020, 33.9% of the cases are located in Bogotá D.C. (capital city) with 113,548 confirmed cases, and the 89.2% of the total intensive care units are occupied [4]. As COVID-19 is predominantly caused by contact or droplet transmission attributed to relatively large respiratory particles which are subject to gravitational forces and travel only approximately one meter from the patient [5], personal protective equipment (PPE) has become crucial for protecting healthcare workers and alleviating the burden in the hospitals and controlling the epidemic [6].

Considering the city needs and that most of the studies about COVID-19 deal with prediction models and do not integrate their results to support decision making, e.g., estimating cities' implications, supplies and demand of material resources; in this paper, we study the location of distribution centers within the city and the corresponding routes to supply PPE to the Intensive Care Units (ICU) and, therefore, support decision making. The problem is formally defined as the Location Routing Problem (LRP). The LRP is one of the most complete problems in supply chain management and logistics since it involves all decision levels, i.e., strategic, tactical and operational. From an operations research perspective, it can be seen as the combination of two well-known NP-Hard problems such as the Facility Location Problem and the Vehicle Routing Problem with Multiple Depots. Thus, the LRP is also NP-Hard.

From a practical point of view, there is a recent trend to create both easy-to-implement and powerful algorithms when solving complex problems. Accordingly, in this work, we propose an ILS algorithm in which initial solutions are created using a random choice of depots combined with the biased randomized version of the nearest neighbor heuristic. Moreover, with the aim of providing an easy-to-use tool, we have implemented our algorithm as an Excel Macro, considering its advantages in data manipulation, consolidation and analysis. Our preliminary results have been compared to the ones obtained by GAMS/Cplex for the deterministic LRP, showing promising results. Besides, we have carried out a set of experiments for the LRP with Stochastic Demands by combining our Iterated Local Search (ILS) algorithm with Monte Carlo simulation (MCS). The results on the stochastic version demonstrate that using safety stocks as protective policies against uncertainty could improve not only expected costs but also the reliability of the obtained solutions.

The remainder of this paper is organized as follows: section 2 presents the literature review; section 3 introduces the description of the problem; section 4 outlines the proposed approach; in section 5 we analyze the obtained results; finally, section 6 presents some conclusions and further research perspectives.

2 LITERATURE REVIEW

This section presents a brief literature review focusing on location routing problems and also on logistics applications for pandemics such as the current one generated by Covid-19.

2.1 Location Routing Problems

The LRP was initially proposed by [7]. Due to its complexity, the first studies on the LRP proposed to tackle it by separating the two related subproblems, i.e., the facility location problem and the vehicle routing problem. However, it has been demonstrated that such approach leads to sub-optimal solutions [8]. This complex problem can be used to support decision-making processes in different fields of application such as city logistics, humanitarian logistics, horizontal cooperation, among others ([9], [10], [11], [12]).

Considering its NP-Hard nature, heuristics and metaheuristics yield better results than classical optimization approaches, specially for large sized instances [13]. We refer to [14] for an overview on LRP problems. The deterministic version of the LRP has been widely studied while its stochastic counterpart has been scarcely analyzed. In the stochastic demands version, the main assumption is that demands are not known in advance, i.e., the real value of demands is revealed once the vehicle arrives at the customer. Thus, planned routes could not function properly due to the uncertainty on this value.

Among the recent works on the LRP with stochastic demands (LRPSD), [15] proposed a simheuristic algorithm to deal with the LRPSD. The authors proposed three simulation processes to deal with: (i) the estimation of the right safety stock policy to protect against uncertainty, (ii) estimate stochastic costs and reliabilities of the proposed solution, (iii) refinement of the estimation of both stochastic costs and reliabilities. However, their work was tested using benchmark instances adapted from literature, while in this work we use realistic data from Bogotá, Colombia related to the current pandemic.

2.2 Logistic approaches for dealing with COVID-19

Mainly, most of the literature on COVID-19 is focused on prediction models (e.g., [2], [3], [16]). [2] studied the prediction of cases of COVID-19 infection in Mexico. [16] considered the logistic growth modelling of COVID-19 proliferation in China and its international implications. [3] predicted the global trend and the specific trends of Brazil, Russia, India, Peru and Indonesia.

However, just few works integrate the results of the prediction models to support decision making (e.g., [17], [18]). [17] analyzed the impact of COVID-19 on transport volume in German food retail logistics, as well as its resulting implications. The author proposed a regression analysis to validate the interdependencies of COVID-19 and transport logistics in retail logistics. [17] considered the reallocation of health care capacity, repurposing of hospitals, and close collaboration between the government and the health care committee. [19] deal with the scheduling of vehicles to transport infected people to isolated medical areas and solved it using a metaheuristic approach. [20] propose the design of a multi-objective reverse logistic network in epidemic outbreaks. More specifically, this work aims to determine the location of temporary facilities and transportation of the increased medical waste generated by a pandemic. To the best of our knowledge there are no published works on the location of depots and the consequent routing of PPEs (maks, gloves and disposable suits) for caregivers (physicians, nurses, therapyst, etc) located all long the city. Thus, the importance and novelty of this work.

3 PROBLEM DESCRIPTION

Due to the COVID-19 pandemic and its associated effects, many governments have adopted lock-down mechanisms as a strategy to diminish the speed of contagion and have more prepared health systems, especially by having a higher number of available ICUs. Particularly, in Bogotá - Colombia, lock-down started in March 2020 but currently, we are facing a high number of new cases and deaths every day. Besides, the occupancy of ICUs is becoming critical with a 90% value. Thus, logistic approaches are a must to optimize the response of the system to the current pandemic.

In particular, we aim to analyze the efficient delivery of PPE (composed by masks, gloves, and disposable suits) required by medical teams (physicians, nurses, and therapists) to take care of COVID-19 patients. In this work, we propose to study the location of distribution centers within the city and the corresponding routes to supply the different ICUs that are habilitated to receive COVID-19 patients in Bogotá. This situation could be represented by the Location Routing Problem with Stochastic Demands (LRPSD) due to the nature of the field of application.

The LRP considered in this work is adapted from [21]. As stated by [22], the LRP 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. The LRP is defined in a directed graph $G = (V, A, C)$. V is a set of nodes comprising a subset I of m possible depot locations and a subset $J = V \backslash I$ of n customers. The cost of any arc $a = (i, j)$ in the arc set A is given by C_a. A capacity W_i and an opening cost O_i are associated with each depot site $i \in I$. Each customer $j \in J$ has a demand d_j. A set K of identical vehicles of capacity Q is available. When used, each vehicle incurs a fixed cost F and performs one single route. The following constraints must be taken into account:

- Each demand d_j must be served by one single vehicle.
- All nodes are allocated to an open depot.
- The number of depots within the set must guarantee that total demand can be serviced.
- Each route must begin and end at the same depot and its total load must not exceed vehicle capacity.
- The total load of the routes assigned to a depot must respect the capacity of the selected depot.

The goal of our problem is to determine the subset of distribution centers (DCs) to open, allocate ICUs to DCs, and planning the routes from DCs to serve ICUs, in order to minimize the total expected costs. The total expected costs of a solution include the fixed cost of opening facilities F, the costs of traversed arcs, the fixed cost of using vehicles and the cost of recursive actions (in case of route failures due to the stochastic demands). The mathematical model of the stochastic version can be found in [15].

Figure 1 depicts a complete solution for our LRP. Potential distribution centers locations are represented by squares while ICUs are represented by circles. This figure illustrates how, from an initial problem setting (top-left), a complete solution could be obtained by *(i)* selecting the distribution centers to be opened (top-right), *(ii)* assigning ICUs to open DCs (bottom-left) and, *(iii)* creating routes from each DC to its allocated ICUs (bottom-right), while satisfying all constraints.

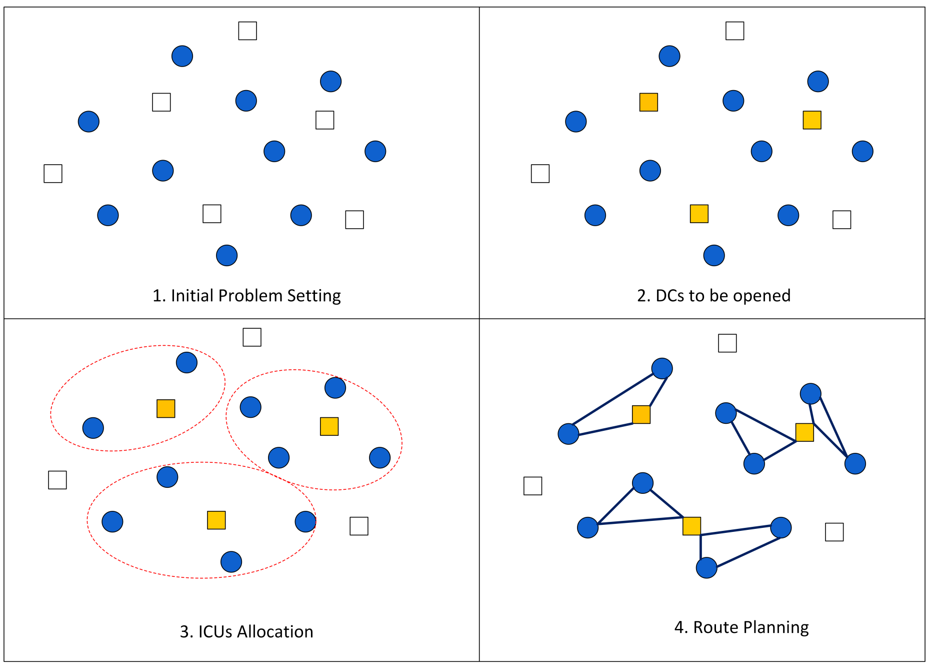

Fig. 1. A Complete Solution for our LRP

4 SOLVING APPROACH

To deal with the LRPSD, we have developed a hybrid method consisting of an Iterated Local Search (ILS) algorithm [23] combined with Monte Carlo simulation. The procedure is driven by the ILS while the simulation is used to test the quality of the solution in the stochastic setting of the problem. Considering that ILS is a powerful local search-based metaheuristic to deal with deterministic problems, we need to use a kind of protection policy (safety stocks) to face uncertainty and get better results in the stochastic setting of the problem.

Safety stock is used when planing routes to reduce the possibility of not serving some ICUs, when executing the planned routes, due to demand uncertainty. However, after a certain value (too conservative) of safety stock, expected costs tend to increase due to excessive deterministic costs. The idea, then, is to find the most convenient safety stock policy providing the best trade-off among costs and reliability.

Our proposed method is composed of three main phases: *(i)* location phase, *(ii)* customer allocation and, *(iii)* vehicle routing. To deal with the location decisions, we randomly open depots until the total available capacity is enough to serve total demands. Then, in the allocation phase, ICUs are randomly selected and assigned to the nearest open depot with the available capacity to serve it. Besides, the available capacity of the corresponding depot is updated and the ICU is marked as assigned. This process is repeated until all nodes have been allocated to an open depot. In case that a given ICU can not be assigned to any open depot due to capacity constraints, a new depot is opened and the customer is allocated to it. In the routing phase, the starting node for each route is randomly selected. Next, a modified version of the nearest neighbor heuristic is applied. A route finishes when the next customer to be added to the route can not be served due to vehicle capacity constraints, so the vehicle is sent back to the depot.

This three-phase process is executed during a given number of iterations and we keep the best solution found among them. The aforementioned solution is sent to a short simulation process to estimate stochastic costs and reliabilities. Stochastic costs are generated when a planned route can not serve a certain ICU and, as a consequence, a corrective round-trip from such ICU to the depot is executed to re-load the vehicle and resume the planned route. After the short simulation, the ILS framework is executed. To do so, we propose as a perturbation operator the interchange of an open depot with a closed depot, i.e., a previously open depot is closed and a previously closed depot is opened. The ICU is assigned to the closing depot are allocated to the opening one. A graphical representation of this operator can be seen in figure 2. Moreover, two local search operators have been designed. The first one is the exchange of two customers among different routes from the same depot (see figure 3 top) while the second one is the exchange of two customers from routes belonging to different depots (see figure 3 bottom).

Promising solutions obtained by the ILS framework are passed through the short simulation process. Next they are stored in a pool of solutions which is sorted by increasing costs. Finally, the top-10 solutions stored within the pool are passed through a more intensive simulation process to refine both stochastic costs and reliabilities. The process is depicted in figure 4.

The reliability $reliab_r$ for each route r in solution S is computed as follows:

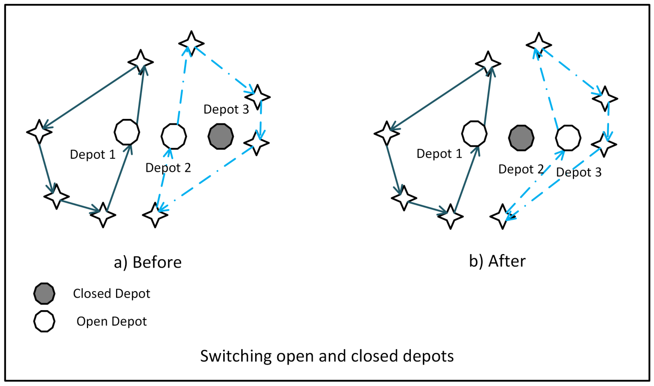

Fig. 2. Diversification Operator

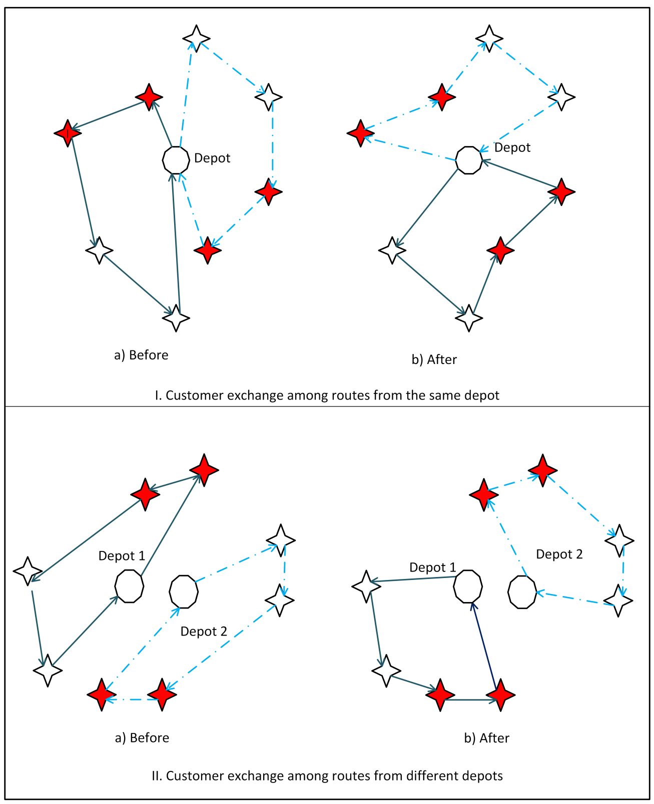

Fig. 3. Local-Search Operators

$$reliab_r = \left(1 - \frac{\sum_{n=0}^{TotalSimulationRuns} RouteFailures}{TotalSimulationRuns}\right) * 100\% \qquad (1)$$

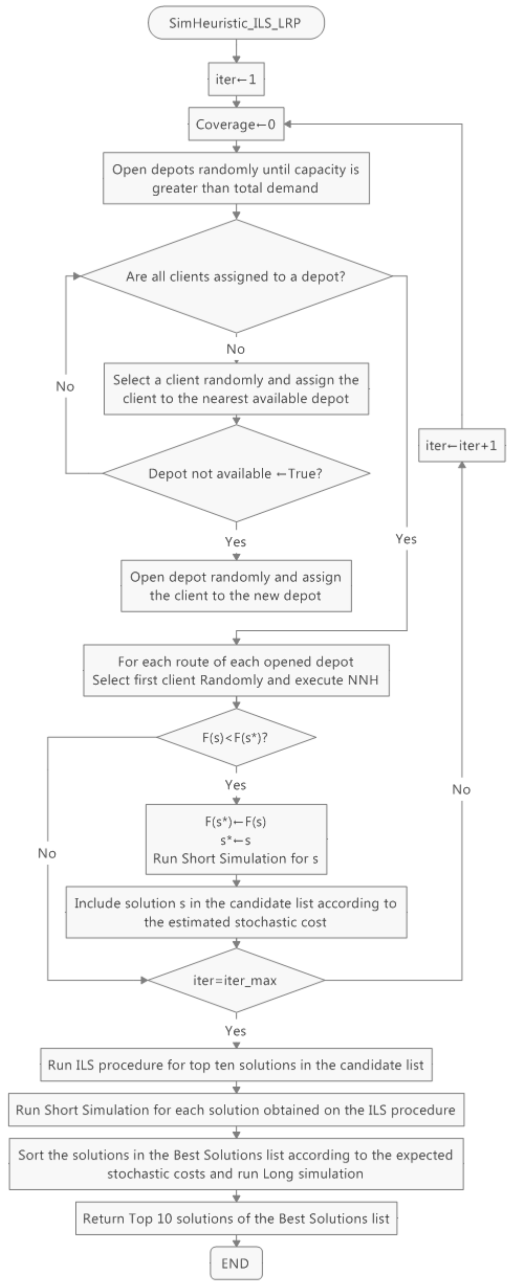

Fig. 4. Flowchart of the proposed method for the LRPSD

It is important to note that each route within a solution could be seen as an independent component of a series system, i.e., the proposed solution will fail if, and only if, a failure occurs in any of its routes. Therefore, the reliability index of a solution S with R routes can be calculated as $\prod_{r=1}^{R} reliab_R$.

5 RESULTS AND ANALYSIS

The proposed algorithm was coded as an Excel macro using the Visual Basic for Applications (VBA) language. The version used for the spreadsheet was MS Excel 2013. As stated by [24], using spreadsheet-based solutions have several advantages such as interface familiarity, ease of use, flexibility, and accessibility. Moreover, since MS Excel is largely known around the world, using it as the engine for the spreadsheet provides additional benefits, such as integration with software packages that offer built-in functionalities to obtain/send data from/to MS Excel, and the possibility of customizing code in Visual Basic for Applications ([24]). It is also important to mention that using spreadsheet-based solutions may result in low-cost solutions that may yield significant savings for enterprises, especially in non-developed countries.

We have tested our proposed method using different instances with real locations in Colombia. Instances were generated by retrieving -from Google Maps-latitude and longitude coordinates belonging to retailing and warehousing points located in Bogotá (Colombia's main city and its capital). The expected value for demands corresponds to the PPE required for each ICU assuming that each patient is served by a team consisting of one physician, one nurse, and one therapist. The team visits each patient once per hour, so 24 visits are required during a complete day. The capacity of DCs was generated to guarantee the satisfaction of total demands. Opening costs, in US Dollars, for each facility corresponds to real construction costs of warehouses in Bogotá. The vehicle capacity corresponds to the real-load capacity of the Renault Kangoo, which is a vehicle broadly used in Colombia to execute urban distribution tasks. Instances are named MQS-BOG#, where # identifies the number of the instance. All instances are available in https://cutt.ly/SpreadsheetSimheuristicILS.

All deterministic instances were modeled using the GAMS modeling language. However, due to the complexity of the problem, the Cplex solver was unable to find a solution after eight hours of execution time. Thus, we generate a set of reduced instances to have a fair comparison between the exact method and our proposed algorithm. The experiments were carried out using a standard windows PC with Intel® Core$^{\text{TM}}$ i7 – 6th generation and 8Gb RAM. Each instance was solved using five different random seeds. The obtained results are summarized in table 1. GAMS/Cplex column shows the best solution reported by this software for each instance after 27,000 secs of computational time. It is worth mentioning that none of the solutions was proven as optimal. OBDS is the best deterministic solution reported by our algorithm among all executions, while OADS is the average value of the obtained solutions. Besides, GAP shows the percentual gap of OADS concerning GAMS/Cplex. We can see that, on average, our algorithm has an average gap of 1.64% compared to the results provided by GAMS/Cplex.

Table 1. Results - Deterministic Case

INSTANCES	SUB-PROBLEM	GAMS/cplex(1)	OBDS(2)	GAP% (2)-(1)
MQS-BOG1	1	2,558,514.72	2,558,516.65	0.00008%
MQS-BOG1	2	2,389,528.66	2,389,529.89	0.00005%
MQS-BOG1	3	2,401,725.86	2,401,728.02	0.00009%
MQS-BOG1	4	2,806,031.04	2,806,034.95	0.00014%
MQS-BOG1	5	2,818,227.57	2,818,233.07	0.00020%
MQS-BOG1	6	2,649,244.88	2,649,246.32	0.00005%
MQS-BOG2	1	1,972,433.46	2,231,267.37	13.12257%
MQS-BOG2	2	2,558,516.41	2,558,519.50	0.00012%
AVERAGE				1.64041%

As this work concerns the stochastic version of the LRP, we have transformed the deterministic instances by assuming their demands as the expected value (EV) of the stochastic case. Besides, stochastic demands are revealed once the vehicle arrives at the UCIs by using the uniform probability distribution $\sim U[EV - 10\%, EV + 10\%]$. It is worth to mention that any other probability distribution according to the real demand's behavior could be used.

Our proposed method was tested using five different random seeds and different safety stock policies (0%, 1%, 3%, 5% and 7%) to handle uncertainty. The results are presented in table 2. For each safety stock policy, the best stochastic solution (OBSS), the average of stochastic solutions (OASS) and the expected reliability of the OBSS (Reliab.), are reported. Furthermore, figure 5 shows the behavior of expected stochastic costs and reliabilities for a given instance when using different safety stock policies. As expected, when no protection is considered there are many route failures due to demand uncertainty. Therefore, we can see higher costs and lower reliability. On the other hand, when the value of safety stock policy increases, costs tend to decrease while reliability increases; however, when the safety stock is greater than 5%, costs start to increase again. Similar situation occurs for the different instances, i.e., costs start to decrease when the percentage of safety stock is increased and, at a certain point (ideal safety stock policy), the costs reach its minimum value. After that value, costs become higher. This situation occurs when decision-makers for protecting against uncertainty, tend to greatly increase the % of safety stock for augmenting reliability and, therefore, costs are increased due to a higher number of planned routes.

Moreover, we have compared Our Best Deterministic Solution (OBDS) for a given instance against the solutions obtained for two different values of the stochastic setting. Besides generating lower expected stochastic costs, the stochastic solutions, even if they are not the optimal ones, show less variability than

Table 2. Results - Stochastic Case

Safety Stock Policy	0%			1%			3%			5%			7%		
Instance Name	OBSS	OASS	Reliab.	OBSS	OASS	Reliab.	OBSS	OASS	Reliab.	OBSS	OASS	Reliab.	OBSS	OASS	Reliab.
MQS-BOG1	8,602,359,004.19	9,496,356,470.59	33%	8,602,358,922.17	8,808,236,359.20	52%	8,602,358,781.84	9,178,211,302.19	75%	8,602,356,349.06	8,606,418,544.88	94%	8,602,358,584.88	8,827,993,933.44	100%
MQS-BOG2	11,888,198,383.13	12,546,632,163.50	17%	11,888,199,113.51	12,847,416,089.27	49%	11,888,197,027.05	13,111,625,922.51	75%	11,888,197,767.40	12,915,130,613.89	97%	11,888,195,544.36	12,855,036,733.53	100%
MQS-BOG3	18,747,950,727.91	19,199,220,695.54	47%	18,747,943,157.57	19,279,643,690.21	46%	18,747,947,581.35	19,343,962,198.47	82%	18,747,943,818.55	18,827,639,885.28	97%	18,747,950,202.88	19,303,038,652.53	100%

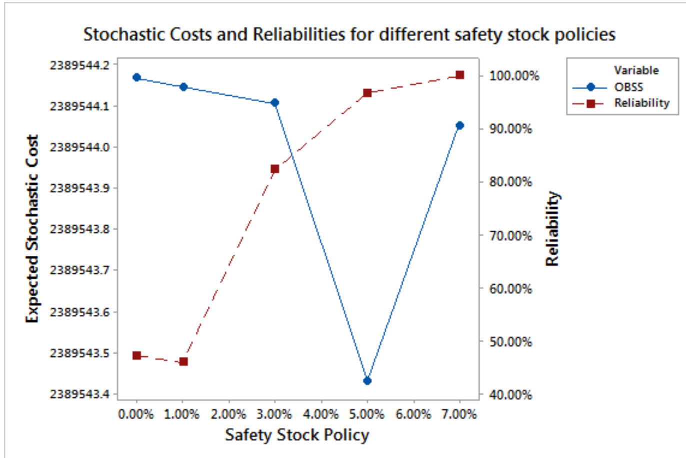

Fig. 5. Average Values of Expected Costs and Reliabilities of Our Best Stochastic Solutions for Different Safety Stock Policies

the deterministic one in the stochastic case, as can be seen in figure 6.

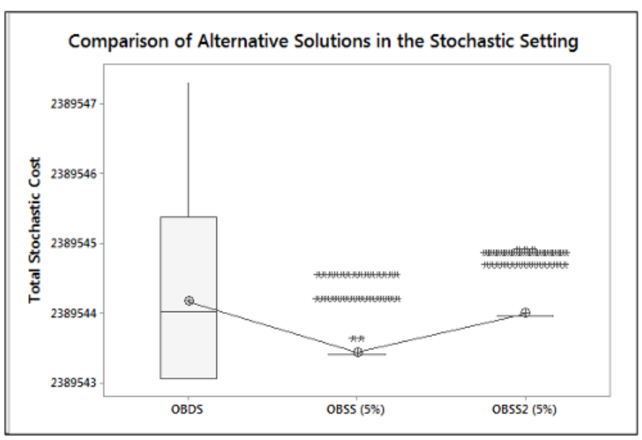

Fig. 6. Example of Behavior of Alternative Solutions in the Stochastic Setting

6 CONCLUSIONS

This article has presented a decision support tool based in a hybrid method consisting of an Iterated Local Search algorithm combined with Monte Carlo simulation to deal with the Location Routing Problem with stochastic demands. This version finds applications in humanitarian logistics and last-mile deliveries problems. Our proposed method was tested using five different instances generated with Google Maps to characterise the geographical distribution of customers. Besides, different safety stock policies are tested.

Results show the behavior of the expected stochastic costs and reliabilities when using different safety stock policies per each tested scenario. Furthermore, results also show that this version of the LRP is a hard problem and its complexity increases according to the level of uncertainty. As expected, when no protection is considered there are many route failures due to demand uncertainty and higher costs and lower reliability are obtained. On the other hand, when the value of safety stock policy reach the ideal value, costs tend to decrease while reliability increases.

Regarding future research, there is a room for including other representations for uncertainties and to design other approaches for handling them. Moreover, adaptation for large scale problems will be also considered.

ACKNOWLEDGMENTS

This work has been partially supported by the Master Program in Operations Management and the General Direction of Research from Universidad de La Sabana, grant EICEA-112-2018

References

[1] A. Gorbalenya, S. Baker, and R. Baric, "The species severe acute respiratory syndrome-related coronavirus: Classifying 2019-ncov and naming it sars-cov-2," Nature Microbiology, vol. 5, pp. 536–544, 2020.

[2] O. Torrealba-Rodriguez, R. Conde-Gutiérrez, and A. Hernández-Javier, "Modeling and prediction of covid-19 in mexico applying mathematical and computational models," Chaos, Solitons Fractals, vol. 138, pp. 582–589, 2020, ISSN: 0960-0779. DOI: https://doi.org/10.1016/j.chaos.2020.109946.

[3] P. Wang, X. Zheng, J. Li, and B. Zhu, "Prediction of epidemic trends in covid-19 with logistic model and machine learning technics," Chaos, Solitons Fractals, p. 110 058, 2020. DOI: https://doi.org/10.1016/j.chaos.2020.110058. [Online]. Available: http://www.sciencedirect.com/science/article/pii/S0960077920304550.

[4] S. Secretaria Distrital de Salud. (Aug. 2020). Casos confirmados de covid-19, [Online]. Available: http://saludata.saludcapital.gov.co/osb/index.php/datos-de-salud/enfermedades-trasmisibles/covid19/.

[5] T. Cook, "Personal protective equipment during the covid-19 pandemic – a narrative review," Anaesthesia, vol. 75, no. 75, pp. 920–927, 2020.
[6] F. Chirico, G. Nucera, and N. Magnavita, "Covid-19: Protecting healthcare workers is a priority," Infection Control & Hospital Epidemiology, vol. 2020, no. 1, pp. 1–4, 2020.
[7] F. Maranzana, "On the location of supply points to minimize transport costs," Journal of the Operational Research Society, vol. 15, no. 3, pp. 261–270, 1964.
[8] S. Salhi and G. K. Rand, "The effect of ignoring routes when locating depots," European Journal of Operational Research, vol. 39, no. 2, pp. 150–156, 1989, ISSN: 0377-2217.
[9] S. Nataraj, D. Ferone, C. Quintero-Araujo, A. Juan, and P. Festa, "Consolidation centers in city logistics: A cooperative approach based on the location routing problem," International Journal of Industrial Engineering Computations, vol. 10, no. 3, pp. 393–404, 2019.
[10] S. V. Ukkusuri and W. F. Yushimito, "Location routing approach for the humanitarian prepositioning problem," Transportation research record, vol. 2089, no. 1, pp. 18–25, 2008.
[11] C. L. Quintero-Araujo, A. Gruler, A. A. Juan, and J. Faulin, "Using horizontal cooperation concepts in integrated routing and facility-location decisions," International Transactions in Operational Research, vol. 26, no. 2, pp. 551–576, 2019.
[12] A. Almouhanna, C. L. Quintero-Araujo, J. Panadero, A. A. Juan, B. Khosravi, and D. Ouelhadj, "The location routing problem using electric vehicles with constrained distance," Computers & Operations Research, vol. 115, p. 104 864, 2020.
[13] C. L. Quintero-Araujo, J. P. Caballero-Villalobos, A. A. Juan, and J. R. Montoya-Torres, "A biased-randomized metaheuristic for the capacitated location routing problem," International Transactions in Operational Research, vol. 24, no. 5, pp. 1079–1098, 2017.
[14] C. Prodhon and C. Prins, "A survey of recent research on location-routing problems," European Journal of Operational Research, vol. 238, pp. 1–17, 2014.
[15] C. L. Quintero-Araujo, D. Guimarans, and A. A. Juan, "A simheuristic algorithm for the capacitated location routing problem with stochastic demands," Journal of Simulation, pp. 1–18, 2019.
[16] C. Y. Shen, "Logistic growth modelling of covid-19 proliferation in china and its international implications," International Journal of Infectious Diseases, vol. 96, pp. 582–589, 2020.
[17] D. Loske, "The impact of covid-19 on transport volume and freight capacity dynamics: An empirical analysis in german food retail logistics," Transportation Research Interdisciplinary Perspectives, vol. 6, p. 100 165,

2020, ISSN: 2590-1982. DOI: https://doi.org/10.1016/j.trip.2020.100165. [Online]. Available: http://www.sciencedirect.com/science/article/pii/S2590198220300762.
[18] M. Her, "Repurposing and reshaping of hospitals during the covid-19 outbreak in south korea," One Health, vol. 10, p. 100 137, 2020, ISSN: 2352-7714. DOI: https://doi.org/10.1016/j.onehlt.2020.100137.
[19] M.-X. Zhang, H.-F. Yan, J.-Y. Wu, and Y.-J. Zheng, "Quarantine vehicle scheduling for transferring high-risk individuals in epidemic areas," International Journal of Environmental Research and Public Health, vol. 17, no. 7, p. 2275, 2020.
[20] H. Yu, X. Sun, W. D. Solvang, and X. Zhao, "Reverse logistics network design for effective management of medical waste in epidemic outbreaks: Insights from the coronavirus disease 2019 (covid-19) outbreak in wuhan (china)," International Journal of Environmental Research and Public Health, vol. 17, no. 5, p. 1770, 2020.
[21] C. Prins, C. Prodhon, and R. Calvo, "Solving the capacitated location-routing problem by a grasp complemented by a learning process and a path relinking," 4OR, vol. 4, pp. 221–238, 2006.
[22] C. Quintero-Araújo, A. Juan, J. Montoya-Torres, and A. Muñoz-Villamizar, "A simheuristic algorithm for horizontal cooperation in urban distribution: Application to a case study in colombia," in 2016 Winter Simulation Conference (WSC), 2016, pp. 2193–2204.
[23] H. R. Lourenço, O. C. Martin, and T. Stützle, "Iterated local search: Framework and applications," in Handbook of Metaheuristics, M. Gendreau and J.-Y. Potvin, Eds. Boston, MA: Springer US, 2010, pp. 363–397, ISBN: 978-1-4419-1665-5. DOI: 10.1007/978-1-4419-1665-5_12. [Online]. Available: https://doi.org/10.1007/978-1-4419-1665-5_12.
[24] G. Erdoğan, "An open source spreadsheet solver for vehicle routing problems," Computers & operations research, vol. 84, pp. 62–72, 2017.