sustainability

MDPI

Article

Supplying Personal Protective Equipment to Intensive Care Units during the COVID-19 Outbreak in Colombia. A Simheuristic Approach Based on the Location-Routing Problem

Andrés Martínez-Reyes, Carlos L. Quintero-Araújo * and Elyn L. Solano-Charris

Operations and Supply Chain Management Research Group, Escuela Internacional de Ciencias Económicas y Administrativas, Universidad de La Sabana Km 7 Autopista Norte de Bogotá, D.C., Chía 250001, Colombia; andres.martinez9@unisabana.edu.co (A.M.-R.); elynsc@unisabana.edu.co (E.L.S.-C.)
* Correspondence: carlosqa@unisabana.edu.co

Abstract: The coronavirus disease 2019, known as COVID-19, has generated an imminent necessity for personal protective equipment (PPE) that became essential for all populations and much more for health centers, clinics, hospitals, and intensive care units (ICUs). Considering this fact, one of the main issues for cities' governments is the distribution of PPE to ICUs to ensure the protection of medical personnel and, therefore, the sustainability of the health system. Aware of this challenge, in this paper, we propose a simheuristic approach for supplying personal protective equipment to intensive care units which is based on the location-routing problem (LRP). The objective is to provide decision makers with a decision support tool that considers uncertain demands, distribution cost, and reliability in the solutions. To validate our approach, a case study in Bogotá, Colombia was analyzed. Computational results show the efficiency of the usage of alternative safety stock policies to face demand uncertainty in terms of both expected stochastic costs and reliabilities.

Keywords: COVID-19; location-routing; uncertain demands; simheuristic

Citation: Martínez-Reyes, A.; Quintero-Araújo, C.L.; Solano-Charris, E.L. Supplying Personal Protective Equipment to Intensive Care Units during the COVID-19 Outbreak in Colombia. A Simheuristic Approach Based on the Location-Routing Problem. *Sustainability* **2021**, *13*, 7822. https://doi.org/10.3390/su13147822

Academic Editor: Ferry Jie

Received: 20 May 2021
Accepted: 6 July 2021
Published: 13 July 2021
Corrected: 14 September 2022

1. Introduction

COVID-19 has generated many challenges for governments and all economic activities. For the health sector and logistics industries, the challenge is undeniable considering variations of demands (i.e., people infected), needs of supplies, hospital capacities, among others. Therefore, the efficiency of all logistics and supply chain management activities, especially during pandemics and risk events, has a crucial role to play [1].

Considering the growing rate of confirmed cases of COVID-19, in certain countries, the occupancy of intensive care units (ICUs) has augmented. In Colombia, according to the 21 June 2021 report, the city with the highest number of confirmed cases was Bogotá, representing 29% of confirmed cases of the country and 97.43% of the occupation of the ICUs [2]. In addition, Bogotá is Colombia's biggest city with a surface of 685 mi^2, and a population of around 11.2 million inhabitants [3]. The health system is composed of both public and private institutions from which 53 have ICUs allocated to serve COVID-19 patients. Currently, the number of habilitated ICU beds is 2261 while the number of COVID-19 confirmed cases is up to 1.29 million [2].

Due to the high exposure of health care workers at ICUs, personal protective equipment (PPE) such as masks, face shields, and gloves are essential for preventing the spread of COVID-19 [4]. Considering this fact, the Bogotá local government is concerned with the distribution of PPE to ICUs. Therefore, in this paper, we propose an approach for the location of potential facilities to distribute PPE to ICUs and the subsequent route planning. This problem could be represented by the location-routing problem (LRP) which is an NP-hard problem [5].

The decision-making of the LRP considers two types of problems, i.e., the facility location problem (strategic decision term) and the vehicle routing problem (tactical/operational decision term). Generally, due to the complexity of the facility location and the vehicle routing problem, most works in the literature tend to deal with each problem separately; however, this approach can provide infeasible or suboptimal solutions. Thus, dealing with these problems in an integrated way can provide better results considering the interdependency of the two problems [6]. As stated by Akpunar and Akpinar [7], the LRP has become a relevant and active research area in the last years that has considered different applications, for example, waste management collection, humanitarian context, urban delivery, multimodal transportation network, among others.

Regarding logistic challenges of the COVID-19, some works can be found, principally for preventing the spreading of the virus, for example, Pachecho and Laguna [8] addressed the vehicle routing for the urgent delivery of face shields. The work done by Zhang et al. [9] considered vehicle scheduling for transferring high-risk individuals in epidemic areas. The contribution provided by Yu et al. [10] introduced the reverse logistics network design for the effective management of medical waste in epidemic outbreaks and works from Valizadeh and Mozafari [11] and Sukseea and Sindhuchao [12] deal with waste management problems.

However, despite the importance of supplying personal protective equipment to intensive care units during the COVID-19 outbreak, few works have studied this problem [13]. In particular, this work is based on the LRP with uncertain demands. To handle the uncertain version of the LRP, different approaches are available to model uncertainty, e.g., probability and fuzzy variables [14], and to solve this type of problem, e.g., simheuristics [15,16] and robust optimization [17].

In our study, we handle the location and routing decisions with uncertain demands through a simheuristic approach as an alternative to deal with the supply of PPE to ICUs. Therefore, the main contributions of our paper are:

(i) We attend an emerging real-life problem for supplying PPE to ICUs.
(ii) We consider one of the cities in a country (i.e., Bogotá, Colombia) with more infected people and deaths due to the pandemic.
(iii) Real data of facilities and ICUs are considered.
(iv) Demand uncertainty due to daily variation of COVID-19 patients was estimated using historical data of ICUs occupancy in Bogotá.
(v) A simheuristic approach is proposed to facilitate the reliability analysis during the assessment of alternative high-quality solutions integrating an iterated local search with a Monte Carlo simulation.
(vi) Different safety stock policies were evaluated for dealing with uncertain demand.
(vii) Assessment of solutions considering distribution cost and reliability are provided.

The remaining sections of this paper are organized as follows: Section 2 gives the literature review; the problem is specified in Section 3; Section 4 presents the simheuristic approach; in Section 5 computational experiments are conducted; finally, Section 6 presents the concluding remarks, conclusions, and future research.

2. Literature Review

The LRP integrates the following decision-making problems: the number of facilities and their location, the allocation of the customers to the opened facilities, and the corresponding vehicle routing to serve customers [7,18]. As stated by Nagy and Salhi [19], the LRP is defined as an NP-hard problem.

Considering the practical impact on industries, the LRP became relevant. Thus, different variations and applications are found in the literature. Broadly, variations of the problem consider characteristics of depots, vehicles, or the consideration of uncertainty [20]. Readers are referred to Drexl and Schneider [21], Prodhon and Prins [6], and Nagy and Salhi [19], as key surveys of the LRP.

Generally, contributions about LRPs consider deterministic parameters [20]. However, in real case applications, uncertain parameters are an issue, regarding data availability. In the literature, uncertainty in the LRP is commonly associated with demands, travel times, time windows, among others, and modeled as single or multiple uncertain parameters. In terms of the LRP with uncertain demands, the type of uncertainty is mainly considered as fuzzy and stochastic.

Regarding fuzzy uncertainty, Ghaffari-Nasab et al. [22] tackle the LRP with fuzzy demands. The authors proposed a fuzzy chance-constrained and a hybrid simulated annealing with stochastic simulation. Nadizadeh and Nasab [23] studied the dynamic capacitated location-routing problem with fuzzy demands. To solve the problem, fuzzy chance-constrained programming is designed with a hybrid heuristic algorithm that contemplates stochastic simulation and local search. Mehrjerdi and Nadizadeh [24] studied the capacitated LRP with fuzzy demands. The authors proposed a fuzzy chance-constrained programming model with a greedy clustering method which includes the stochastic simulation.

Another study of the LRP with uncertain demand is presented in Fazayeli et al. [25]. The authors considered a multimodal transportation network with time windows and fuzzy demands and developed a genetic algorithm. Nadizadeh and Kafash [26] addressed the fuzzy capacitated LRP with demand uncertainty in pickup and delivery. To model the problem, a fuzzy chance-constrained programming model and a greedy clustering method were developed. In the same way, Zhang et al. [27] tackled the LRP with fuzzy demands. A fuzzy chance-constrained programming approach and a hybrid PSO algorithm, including stochastic simulation and local search based on variable neighborhood search (VNS), were introduced.

Concerning stochastic uncertainty, Albareda-Sambola et al. [28] cope with the stochastic location-routing problem. The authors modeled uncertainty as a vector of independent random variables following the Bernoulli distribution. Then, a two-phase heuristic is developed with an iteratively local search procedure. Zhang et al. [29] addressed the electric vehicle battery swap station location-routing problem with stochastic demands. A hybrid VNS algorithm was proposed and integrated with the binary PSO.

Additionally, Rabbani et al. [30] tackled the stochastic multi-period industrial hazardous waste location-routing problem with uncertain demands. The authors formulated a multi-objective stochastic mixed-integer nonlinear programming model, a non-dominated sorting genetic algorithm-II, and a Monte Carlo simulation. Quintero et al. [16] investigated the capacitated LRP with stochastic demands. They proposed four versions of a VNS metaheuristic hybridized with Monte Carlo simulations. Tordecilla et al. [20] studied the flexible-size LRP considering both stochastic and fuzzy approaches to model uncertain demands. The authors proposed a simheuristic combining an iterated local search (ILS) metaheuristic with a Monte Carlo simulation for the stochastic version.

Recently, an LRP with stochastic demand is found in Martínez-Reyes et al. [13]. The authors developed a preliminary version of a simheuristic in which an iterated local search (ILS) algorithm was enhanced through a Monte Carlo simulation to face demand uncertainty in supplying the intensive care units with personal protective equipment. Tirkolaee et al. [31] formulated multi-trip location-routing for medical waste management in the COVID-19 pandemic.

Similarly, Valizadeh et al. [32] studied waste collection management during the pandemic. To solve the problem the authors proposed a Benders decomposition method and generated stochastic scenarios of the outbreak for evaluating decision-making. Moreover, they introduced a cooperative game theory method for solving the problem. Pasha et al. [33] proposed the "Factory-in-a-box" concept which has applications to the delivery of products with urgent demands, such as PPE. In addition, the authors proposed a mixed-integer linear programming model and four metaheuristics to solve the associated routing problem. Chen et al. [34] proposed a hybrid metaheuristic to solve the contactless joint distribution of food for closed gated communities.

Other approaches for dealing with uncertainty are through robust optimization, for example, Kahfi et al. [35] presented a mathematical modeling approach to tackle the location-arc routing problem with time windows and uncertain demand in a bank case study. Even though the LRP with uncertain demand is broadly studied, few works consider real applications and just one considers the LRP for providing personal protective equipment to intensive care units during the COVID-19 pandemic [13]. Thus, the relevance of this work can provide a real impact in society.

3. Problem Definition

In this section, we introduce a model for supplying PPE to ICUs in Bogotá. The idea is to find a set of locations for warehouses to provide PPE to the different ICUs belonging to the health system in Colombia's capital. It is clear that many sources of uncertainty can appear in this situation (travel times, arc disruptions, among others). However, as we are facing the COVID-19 pandemic, we decided to focus on demand uncertainty because in the current situation it is critical to guarantee that the amount of PPE delivered to the different ICUs will satisfy the expected demands. Taking into consideration the above-mentioned, the problem is formally defined as a location-routing problem with stochastic demands (LRP-SD), considering the behavior of patients with COVID-19 at ICUs.

The LRP-SD is defined in a directed graph $\mathrm{G} = (\mathrm{V}, \mathrm{A})$. V denotes the set of nodes comprising m possible depot locations (W is the subset of potential locations and S is a subset of nodes) and n ICUs (I is the subset of ICUs), while A is the set of arcs $a = (i, j)$ with a cost C_a. $\delta^-(S)$ and $\delta^+(S)$ denote the set of arcs entering and leaving S, respectively, and $L(S)$ the set of arcs ending in S. Each depot is associated to a fixed capacity Q_w and an opening cost O_w. The ICUs have a stochastic demand $D_i > 0$ and its variation is defined in a probability distribution. To deal with the uncertain demand, a safety stock $\%SS$ is considered. A fleet of K of homogeneous vehicles with capacity h is available for supplying the PPE to ICUs. A variable cost related to fuel consumption is considered per vehicle considering the traversed distance performed in a single route. The following binary decision variables are used: Y_w is used to represent the opening of depot w, f_{ak} represents if vehicle k traverses arc a, or not and, finally, X_{iw} is to represent if ICU i is assigned to depot w or not.

A solution of the LRP-SD is a set of open depot locations with allocated ICUs and vehicle routes for supplying the PPE to ICUs from the assigned depot. The LRP-SD aims at minimizing the total expected cost while ensuring the reliability of the solution. The total expected cost includes: (i) the opening facility cost, (ii) the cost of visiting all ICUs, (iii) the cost of vehicles **-U-**, and (iv) the corrective **-ρ-** cost of a solution when the demand surpasses the vehicle capacity due to the stochastic nature of the ICUs' demand. Additionally, the reliability considers when a route failure occurs because of the demand uncertainty. As part of the constraints, the demand D_i must be attended by a vehicle. The total demand of the ICUs must be respected. Each route starts and ends at the opened depot. Depots and routes must respect the depot and vehicle capacity, respectively.

The proposed model for the LRP-SD is based on previous works done by Martínez-Reyes et al. [13], Prins et al. [36], and Quintero et al. [16], and is formulated as follows:

$$\min \boldsymbol{z} = \sum_{\boldsymbol{w} \in \boldsymbol{W}} \boldsymbol{O_w Y_w} + \sum_{\boldsymbol{k} \in \boldsymbol{K}} \sum_{\boldsymbol{a} \in \delta^+(\boldsymbol{M})} \boldsymbol{U f_{ak}} + \sum_{\boldsymbol{k} \in \boldsymbol{K}} \boldsymbol{E}[\boldsymbol{R_k}] \tag{1}$$

$$\boldsymbol{R_k} = \begin{cases} \sum_{\boldsymbol{a} \in \boldsymbol{A}} \boldsymbol{C_a f_{ak}} & \text{If } \sum_{\boldsymbol{i} \in \boldsymbol{I}} \sum_{\boldsymbol{a} \in \delta^-(\boldsymbol{i})} \boldsymbol{E}[\boldsymbol{D_i}] \boldsymbol{f_{ak}} \leq (1 - \%\boldsymbol{SS})\boldsymbol{h} \\ \sum_{\boldsymbol{a} \in \boldsymbol{A}} \boldsymbol{C_a f_{ak}} + \boldsymbol{\rho} & \text{otherwise} \end{cases} \tag{2}$$

$$\sum_{k \in K} \sum_{a \in \delta^-(i)} f_{ak} = 1 \qquad \forall i \in I \tag{3}$$

$$\sum_{i \in I} \sum_{a \in \delta^-(i)} E[D_i] f_{ak} \leq (1 - \%SS)h \qquad \forall k \in K \tag{4}$$

$$\sum_{\boldsymbol{a} \in \delta^{\mp}(\boldsymbol{j})} \boldsymbol{f_{ak}} - \sum_{\boldsymbol{a} \in \delta^-(\boldsymbol{j})} \boldsymbol{f_{ak}} = \boldsymbol{0} \qquad \forall \boldsymbol{k} \in \boldsymbol{K}, \forall \boldsymbol{j} \in \boldsymbol{V} \tag{5}$$

$$\sum_{a \in \delta^{\mp}(j)} f_{ak} \leq 1 \qquad \forall k \in K, \forall i \in I \tag{6}$$

$$\sum_{a \in L(s)} f_{ak} \leq |S| - 1 \qquad \forall S \subseteq I, \forall k \in K \tag{7}$$

$$\sum_{a \in \delta^{+}(\boldsymbol{w}) \cap \delta^{-}(\boldsymbol{I})} \boldsymbol{f_{ak}} - \sum_{a \in \delta^{-}(\boldsymbol{i})} \boldsymbol{f_{ak}} \leq \mathbf{1} + \boldsymbol{x_{iw}} \qquad \forall \boldsymbol{i} \in \boldsymbol{I}, \forall \boldsymbol{w} \in \boldsymbol{W}, \forall \boldsymbol{k} \in \boldsymbol{K} \tag{8}$$

$$\sum_{a \in L(s)} E[D_i] x_{iw} \leq Q_w \, y_w \qquad \forall w \in W \tag{9}$$

$$f_{ak},\ x_{iw},\ y_w \in \{0,\ 1\} \qquad \forall a \in A, \forall k \in K, \forall i \in I,\ \forall w \in W \tag{10}$$

Equation (1) is the objective function consisting in the minimization of the opening, routing, and failure costs. Equation (2) computes the failure costs. Constraints (3) ensure that each arc is traversed once. Constraints (4) guarantee that expected demands served by each route respect the reduced capacity of each vehicle (i.e., the capacity once the safety stock policy is applied). Constraints (5) ensure the continuity of each route and combined with Constraints (6) force the vehicle to return to its departure warehouse. Inequalities (7) avoid sub-tours. Constraints (8) ensure that ICUs are assigned to a facility only if there are routes starting at that facility. Constraints (9) respect depot capacity. Finally, expressions (10) define our decision variables.

The LRP-SD is illustrated in Figure 1. The problem considers potential distribution center locations (circles) and the ICUs (squares). Figure 1 shows an initial solution setting (top-left), the selection of the depots to be opened (top-right), the allocation of ICUs to the opened depots (bottom-left), and the routing from the opened depot to its allocated ICUs (bottom-right) while satisfying the set of constraints.

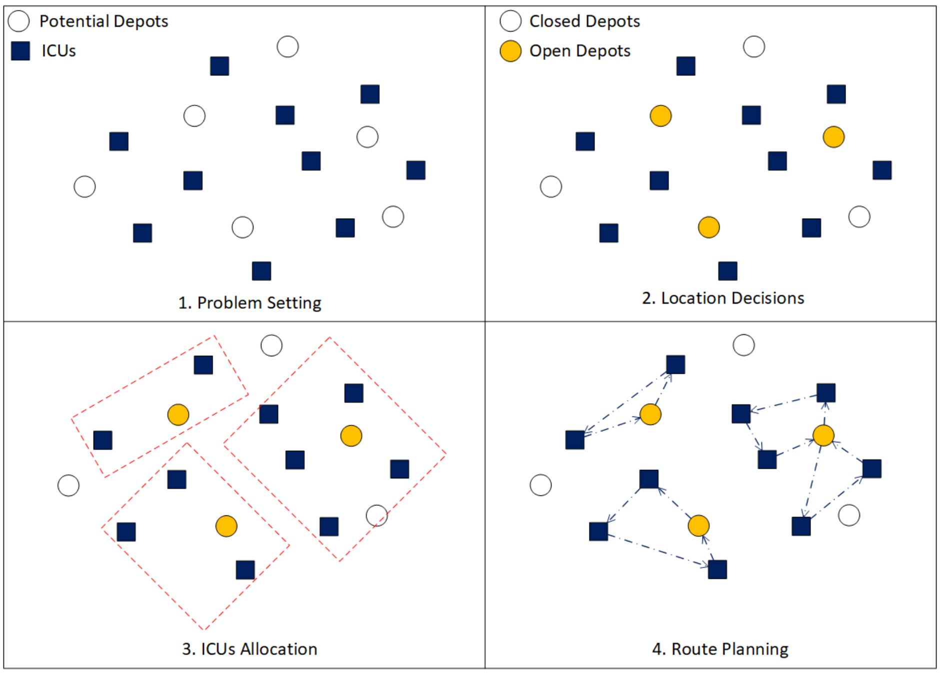

Figure 1. Graphical representation of a complete LRP solution. Source: the authors.

It is well known that location decisions have a huge impact on routing plans. Thus, the problem of supplying PPE to the ICUs must be addressed through the LRP with stochastic demands. However, daily, the situation could derive into a multi-depot vehicle routing problem with stochastic demands. Therefore, our algorithm is flexible to handle both situations with minor adjustments.

4. Solving Approach

To deal with the LRP-SD, we have developed a hybrid method belonging to the so-called simheuristics paradigm. It consists of an ILS algorithm [37] combined with a Monte Carlo simulation (MCS). The optimization part of the procedure is carried out by the ILS framework while the simulation is used to assess the quality of the provided solutions under the stochastic setting of the problem. ILS is a well-known and powerful local search-based approach to cope with deterministic problems. Thus, we need to use a protection strategy (safety stock policy) to face demand uncertainty and, therefore, to obtain better results in the stochastic scenario.

Our simheuristic algorithm comprises a multi-start procedure to obtain a set of initial solutions. Next, these solutions are passed through an MCS engine to estimate their quality in stochastic settings. Then, the top-ranked promising solutions are improved within an iterated local search framework. Finally, we carry out two MCS processes to refine the estimations on the quality of the obtained solutions in the stochastic scenario setting. Once the complete algorithm is finished, we report the top 10 obtained solutions (see Algorithm 1).

Algorithm 1. Pseudocode of our approach. Source: the authors.

```
Procedure Sim-Heuristic (LS_op, Div_op)
    For iter ← 1 to max_iter    do
        Multi_Start_LRP (MS_pool)    // Construct MS_pool of random initial solutions.

    Next
    Simulation (Short_iter, MS_pool)
    Simulation (Long_iter, Top10_MS_pool)

    ILS (ILS_Pool, Top10_MS_pool, LS_op, Div_op)    //ILS algorithm for every solution in
                                                      Top10_MS_pool.
    Simulation (Short_iter, ILS_pool)
    Simulation (Long_iter, Top10_ILS_pool)

    Report Top10_ILS_Pool solutions
End Procedure
```

In the following, we will give a detailed explanation of each component of our solving approach. The multi-start procedure is divided into three stages:

(i) Opening of depots—depots to be opened are randomly selected until there is enough available capacity to serve the total expected demands.

(ii) ICUs' allocation to open depots—a non-allocated ICU is randomly chosen, and it is allocated to its nearest open depot with available capacity to serve the demand of the selected ICU; this process is executed until all ICUs have been allocated. In the case that a subset of ICUs could not be assigned because of capacity constraints, a closed depot is randomly selected, set as open, and the non-allocated ICUs are assigned to it.

(iii) Route planning—to create routes, from each open depot, the first ICU to be visited is randomly selected, while the next ICUs are added using the nearest neighbor heuristic until capacity is satisfied, then the vehicle is sent back to the depot and new routes are added using the same logic until all ICUs are visited.

The aforementioned stages are executed during a certain number of iterations while keeping the top solutions found so far. An outline of the multi-start procedure can be seen in Algorithm 2.

Algorithm 2. Pseudocode of the multi-start algorithm to obtain feasible solutions. Source: the authors.

```
Procedure Multi_Start_LRP (MS_Pool)
        MS_Pool← ∅

        Location ()       //  Open depots randomly.
        Clustering ()     //  Random choice of ICU to be allocated to the nearest
                              depot with available capacity.
        Routing ()        //  Construct routes for each opened depot using NNH
                              modified algorithm.
        Include s and F(s) in MS_pool
End Procedure
```

Once the multi-start procedure is executed, two simulation stages are carried out. The first one is a short simulation to have a first approximation of the expected stochastic costs and reliabilities for each solution. Next, a more intensive simulation (i.e., with more simulation runs) is performed to refine the previous estimations for the top 10 solutions according to their estimated stochastic costs. It is important to note that stochastic costs are computed as the required cost to serve a given ICU when its demand cannot be fully served, i.e., the cost of a round-trip from the corresponding ICU to the depot to fully reload the vehicle and going back to serve the ICU. Every time that a route cannot serve all customers, the number of route failures is increased by one. Then, the estimated reliability of each route can be computed as one minus the quotient among route failures and the total simulation runs, as shown in Equation (11).

$$reliab_r = \left(1 - \frac{\sum_{n=0}^{TotalSimulationRuns} RouteFailures}{TotalSimulationRuns}\right) \times 100\% \tag{11}$$

Accordingly, the reliability for a given solution s conformed by R routes is computed as $\prod_{r=1}^{R} reliab_R$.

After the second simulation process, the top 10 solutions are improved using an ILS framework (see Algorithm 3) in which we first apply a local search on each solution, then we apply perturbation to the solution and again apply local search. To do so, two different perturbation operators and four different local search operators were implemented. The perturbation operators are: (i) switching of open and closed depots—one depot is randomly selected among the opened ones and is interchanged with one randomly selected closed depot with equal or higher capacity to satisfy the demand of the corresponding ICUs, i.e., the ICUs previously allocated to the closed depot next the ICUs are allocated to the recently opened depot and routes are planned using the routing heuristic explained within the multi-start procedure (see Figure 2, top). (ii) Customer reallocation among different depots—a given percentage of nodes, ranging from 20 to 50%, is randomly selected and exchanged among the opened depots (breaking of ICUs' allocation) and, the next routes are created with the already mentioned routing heuristic (see Figure 2, bottom). Regarding the four local search operators, they are: (i) exchange of two-node chains among routes from the same depot, (ii) exchange of two-node chains among routes from different depots, (iii) exchange of two non-consecutive nodes among routes from the same depot, and (iv) exchange of two non-consecutive nodes among routes from different depots.

Algorithm 3. ILS framework. Source: the authors.

```
Procedure ILS (ILS_Pool, Top10_MS_pool, LS_op, Div_op)
    ILS_Pool← ∅
    S^Best← ∅
      For i ← 1 to Top10_MS_pool size do
        S_0 ← Top10_MS_pool_i
            S* ← Local_Search (S_0, LS_op)
            Include S* and F(S*) in ILS_pool
            if ILS_pool is full then
                    delete the worst solution in pool (S″) if F(S*) < F(S″)
        end if
            if F(S*) < F(S^Best) or S^Best = ∅ then
                    S^Best ← S*
                    F(S^Best) ← F(S*)
            end if
        For j ← 1 to LS_iter size do
            S* ← Local_Search (S^Best, LS_op)

                    Include S* and F(S*) in ILS_pool

                    if ILS_pool is full then
                            delete the worst solution in pool (S″) if F(S*) <
                    F(S″)
            end if
                    if F(S*) < F(S^Best) or S^Best = ∅ then
                        S^Best ← S*
                        F(S^Best) ← F(S*)
                    end if
            Next
            For iter to max_iter_Div do
              S′ ← Diversification (S*, Div_op)

                            Include S′ and F(S′) in ILS_pool
                            if ILS_pool is full then
                                  delete the worst solution in pool (S″) if F(S′) <
                    F(S″)
                    end if
                    For j ← 1 to LS_iter size do
                            S* ← Local_Search (S′, LS_op)
                            Include S* and F(S*) in ILS_pool
                            if ILS_pool is full then
                                    delete the worst solution in pool (S″) if
                                    F(S*) < F(S″)
                            end if
                            if F(S*) < F(S′) then
                                    S′ ← S*
                                    F(S′) ← F(S*)
                            end if
                    Next
            Next
    Next
End Procedure
```

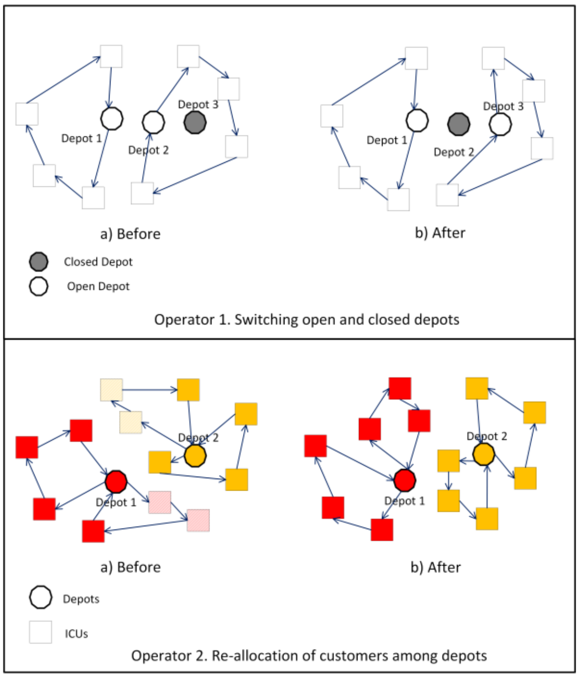

Figure 2. Diversification operators. Source: the authors.

A graphical representation of the four local search operators is presented in Figure 3.

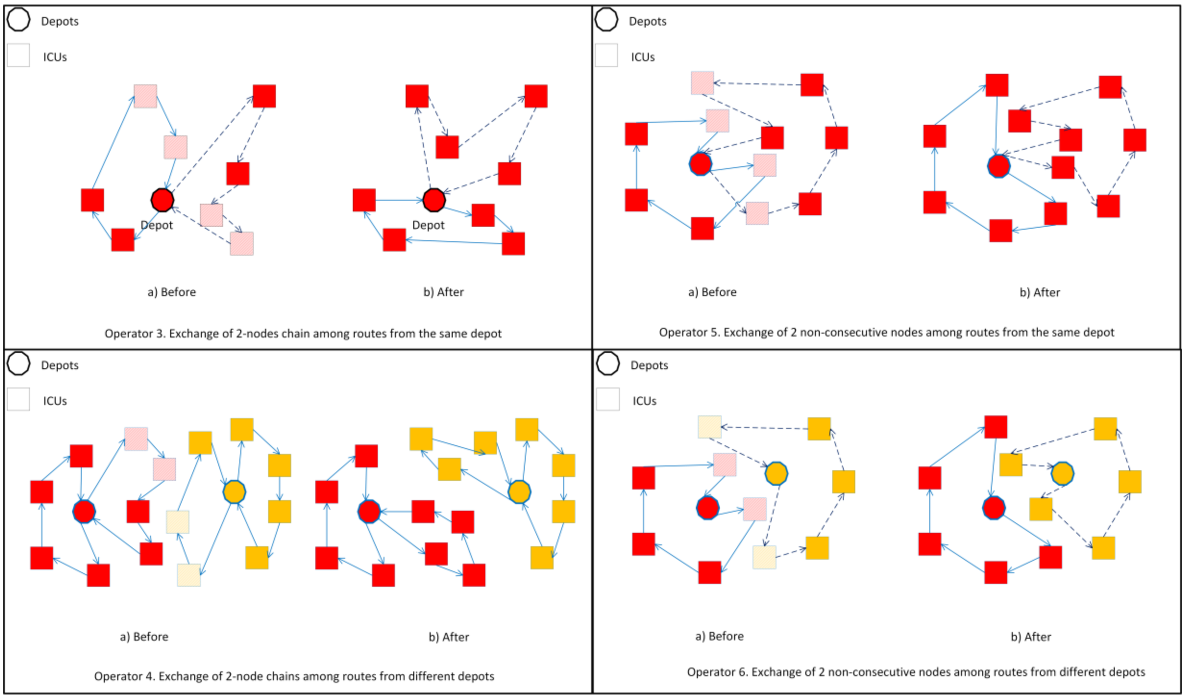

Figure 3. Local search operators. Source: the authors.

Promising solutions obtained so far are then passed through a short simulation process, after which they are sorted by their expected stochastic costs. Next, the top 10 stochastic solutions go through an intensive (long) simulation process to refine the estimates on both expected stochastic costs and reliabilities. It is worth mentioning that safety stocks (%SS) are used when planning routes to reduce the possibility of not serving some ICUs, when performing the routing tasks, due to demand uncertainty. However, after a certain value (too conservative) of safety stock, expected costs could be increased due to excessive deterministic (fixed) costs. The idea, then, is to find the most convenient safety stock policy, i.e., the value that provides the best trade-off between expected costs and reliability.

5. Computational Settings

The experiments were performed on a personal windows PC with Intel® CoreTM i7 6th generation and 8Gb RAM. The LRP was modeled and solved using modeling language, with Cplex 12.8.0.0 as solver and a time limit of 8 h (28,800 s). To do so, we have adapted the LRP-SD formulation proposed by Quintero et al. [16], to represent the deterministic version, by eliminating the failure costs, assuming deterministic demands, and using $\%SS$ = 0. The proposed simheuristic for the LRP-SD was coded in Visual Basic for Applications (VBA) language in MS Excel 2013. Spreadsheet-based solutions are considered due to their interface familiarity, ease of use, flexibility, accessibility, and low cost, which may generate important savings for enterprises, especially in non-developed countries [13,38].

The set of instances was generated considering the location of ICUs and possible locations of DCs in Bogotá, Colombia. Locations were retrieved from Google Maps with their corresponding latitude and longitude coordinates. The distance for each arc (i, j) was retrieved using the Google Distances API. The expected value for demands (ED) corresponds to the PPE kit, i.e., mask, gloves, and impermeable coveralls, 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 [13].

For the LRP-SD, uncertain demand related to the PPE is modeled with a probability distribution according to the August 31, 2020 report of confirmed cases of COVID-19 in Bogotá and the occupation of the total ICUs [2]. Distribution fitting is done using IBM SPSS Statistics version 26 to select the statistical distribution that best fits the demand. As a result, the Weibull distribution with parameters a = 13.8 and = 1.4 was obtained, where a is scale and b is shape. Thus, variation of demands D_i are generated with the following equation:

$$D_i = b \times (-LN(RAND()) \text{\^{}} (1/a) \tag{12}$$

The capacity of DCs guarantee the total demand satisfaction. The O_i for each DC corresponds to the real month rent costs in Bogotá in USD (USD 4.7/m^2 per month). The fleet capacity $Q = 2218$ K, and fuel consumption (11.4 Km/gallon) correspond to the real-load information of the Chevrolet NHR [39]. Each PPE kit weighs 1 Kg, and the fuel cost is USD 2.1/gallon. All instances are available in https://cutt.ly/obASjVa (accessed on 2 June 2021). The file names are defined as MQS-BOG#, where # identifies the number of the instance.

6. Results and Analysis

For the set of instances, two scenarios are evaluated, i.e., the deterministic version of the LRP and the LRP-SD. The detailed results for the deterministic case are provided in Table 1. The table shows, per each instance, the number of possible depots, the number of ICUs, the GAMS results, the best deterministic solution reported by our algorithm (OBDS), and the GAP between the OBDS and the GAMS results. We have compared the results provided with GAMS against our proposed method. It is worth mentioning that none of the solutions provided by GAMS was proven to be optimal in the defined time limit (i.e., 28,800 s).

Table 1. Results—deterministic case. Source: the authors.

Instance Name	Available Depots	Opened Depots	ICUs	GAMS/cplex (1)	OBDS (2)	Time to Find Best Solution	Total Computational Time	GAP% (2)−(1)
MQS-BOG1	5	2	30	44,889.30	44,873.22	1.2	23.6	−0.04%
MQS-BOG2	5	2	35	53,853.77	53,819.30	0.9	26.0	−0.06%
MQS-BOG3	5	3	40	59,881.04	59,837.62	29.1	30.0	−0.07%
MQS-BOG4	5	4	45	82,393.23	79,592.58	7.8	32.1	−3.40%
MQS-BOG5	5	3	50	101,602.15	79,978.69	1.4	39.2	−21.28%
MQS-BOG6	5	3	53	92,227.30	91,243.88	22.4	37.4	−1.07%
MQS-BOG7	7	2	30	53,829.25	53,818.07	13.0	22.5	−0.02%
MQS-BOG8	7	2	35	62,773.60	57,566.13	5.3	26.6	−8.30%
MQS-BOG9	7	3	40	62,753.39	58,956.63	6.9	30.5	−6.05%
MQS-BOG10	7	2	45	92,202.79	69,725.26	21.5	32.5	−24.38%
MQS-BOG11	7	3	50	97,794.08	76,236.93	23.7	36.9	−22.04%
MQS-BOG12	7	3	53	110,441.48	87,012.70	23.3	38.0	−21.21%
MQS-BOG13	9	2	30	49,635.79	49,597.50	23.2	25.2	−0.08%
MQS-BOG14	9	2	35	69,746.49	53,822.32	20.5	25.5	−22.83%
MQS-BOG15	9	3	40	75,367.08	69,288.43	0.7	30.4	−8.07%
MQS-BOG16	9	3	45	75,372.46	69,293.43	1.0	33.7	−8.07%
MQS-BOG17	9	3	50	95,046.09	75,377.60	24.5	37.5	−20.69%
MQS-BOG18	9	4	53	N/A	79,549.95	1.0	45.8	-
				AVERAGE				−9.862%

As can be seen, our approach outperforms GAMS for all instances, with percentual gaps ranging from −24.38% to −0.02%. On average, our gap represents a reduction of 9.86% compared with GAMS results. In addition, it is important to mention that our algorithm requires short computational times to be executed (around 46 s on average per instance in the worst-case scenario). This is a key factor of our method since the available time for the associated decision-making is scarce (2–3 h in real life).

Results for the stochastic case are presented in Tables 2 and 3. The behavior of expected stochastic costs and reliabilities for each instance when using six different safety stock policies (0, 3, 6, 9, 12, and 15%) is analyzed. For each safety stock policy, the best stochastic solution (OBS), the average of our top 10 stochastic solutions (OTTAS,) and the expected reliability of the OBS (Avg. Reliability) and the gaps between OTTAS and OBS, are reported. According to these gaps, we can see that our algorithm provides consistent results independently of the instance size, i.e., the OTTAS is quite near the OBS for each instance.

Moreover, a graphic example based on a representative instance is presented in Figure 4 for analyzing the behavior of the expected stochastic costs and reliabilities using the different safety stock policies. As expected, in the case of not considering any type of protection (i.e., 0% of safety stock), the associated reliability is the lowest among all policies. Once the protective policy is increased, the corresponding value of expected reliability tends to increase as well. Regarding stochastic costs, we can see their augmentation when considering the lowest values of protective policies (below 9%) because of the increase in fixed vehicle costs that do not compensate the diminution in corrective costs (those associated with the round-trip from ICU to the corresponding depot to reload the vehicle, serve the ICU and resume the original planned route). After the 9% policy, the costs due to route failures become too small in such a way that total stochastic cost tends to fall when increasing the percentage of safety stock.

Table 2. Results for 0 to 6% safety stock policies—stochastic case. Source: the authors.

Safety Stock Policy	0%				3%				6%			
Instance Name	OBS	OTTAS	Reliability	Gap	OBS	OTTAS	Reliability	Gap	OBS	OTTAS	Reliability	Gap
MQS-BOG1	44,872.79	44,872.93	96.52%	0.0003%	44,875.11	44,875.23	98.03%	0.0003%	44,875.17	44,875.20	98.19%	0.0001%
MQS-BOG2	53,820.53	53,821.06	97.38%	0.0010%	53,817.14	53,820.59	99.06%	0.0064%	53,820.03	53,820.92	94.50%	0.0017%
MQS-BOG3	59,837.75	59,837.83	88.04%	0.0001%	59,837.56	59,837.81	87.78%	0.0004%	59,835.35	59,835.80	92.76%	0.0007%
MQS-BOG4	79,593.46	79,593.71	70.14%	0.0003%	79,592.76	79,593.87	70.56%	0.0014%	79,593.01	79,593.47	81.78%	0.0006%
MQS-BOG5	79,983.40	79,984.18	90.64%	0.0010%	79,983.02	79,983.69	68.65%	0.0008%	79,982.34	79,984.14	57.85%	0.0023%
MQS-BOG6	91,245.51	91,246.39	79.12%	0.0010%	91,245.49	91,246.72	79.67%	0.0014%	91,245.48	91,246.05	88.75%	0.0006%
MQS-BOG7	53,817.45	53,817.90	94.55%	0.0008%	53,817.79	53,818.27	97.36%	0.0009%	53,817.62	53,818.32	98.80%	0.0013%
MQS-BOG8	57,565.79	57,566.55	94.31%	0.0013%	57,565.66	57,566.16	94.18%	0.0009%	57,566.95	57,567.26	97.01%	0.0005%
MQS-BOG9	58,955.90	58,956.26	93.00%	0.0006%	58,956.34	58,957.03	98.56%	0.0012%	58,955.30	58,955.94	92.98%	0.0011%
MQS-BOG10	69,722.11	69,725.33	71.96%	0.0046%	69,725.74	69,727.42	69.63%	0.0024%	69,727.60	69,728.15	78.75%	0.0008%
MQS-BOG11	76,236.10	76,238.09	35.36%	0.0026%	76,236.16	76,238.06	46.27%	0.0025%	76,235.71	76,238.49	59.07%	0.0036%
MQS-BOG12	87,009.98	87,011.58	87.24%	0.0018%	87,010.16	87,010.99	88.16%	0.0010%	87,010.42	87,010.93	93.10%	0.0006%
MQS-BOG13	49,599.43	49,599.75	80.94%	0.0006%	49,599.03	49,600.61	89.06%	0.0032%	49,600.36	49,600.77	81.00%	0.0008%
MQS-BOG14	53,822.45	53,822.87	95.80%	0.0008%	53,822.77	53,822.79	82.06%	0.0000%	53,823.42	53,824.62	80.84%	0.0022%
MQS-BOG15	69,288.51	69,288.79	80.45%	0.0004%	69,288.27	69,289.02	80.76%	0.0011%	69,289.07	69,289.41	87.86%	0.0005%
MQS-BOG16	69,290.82	69,292.28	80.82%	0.0021%	69,289.65	69,290.62	80.09%	0.0014%	69,293.84	69,294.27	87.84%	0.0006%
MQS-BOG17	76,237.71	76,238.75	88.55%	0.0014%	76,235.55	76,238.16	81.38%	0.0034%	76,237.68	76,238.92	81.16%	0.0016%
MQS-BOG18	79,548.20	79,549.12	72.47%	0.0011%	79,548.64	79,549.59	76.48%	0.0012%	78,688.90	79,033.96	69.78%	0.4385%

Table 3. Results for 9% to 15% safety stock policies—stochastic case. Source: the authors.

Safety Stock Policy	9%				12%				15%			
Instance Name	OBS	OTTAS	Reliability	Gap	OBS	OTTAS	Reliability	Gap	OBS	OTTAS	Reliability	Gap
MQS-BOG1	44,874.96	44,875.22	96.60%	0.0006%	44,875.12	44,875.18	98.64%	0.0001%	44,872.86	44,873.44	99.44%	0.0013%
MQS-BOG2	53,820.79	53,821.16	94.26%	0.0007%	53,819.79	53,821.89	97.40%	0.0039%	53,821.40	53,822.23	94.60%	0.0015%
MQS-BOG3	59,839.85	59,840.09	93.12%	0.0004%	59,844.47	59,844.56	97.35%	0.0002%	59,842.27	59,842.28	99.60%	0.0000%
MQS-BOG4	79,595.61	79,596.43	80.90%	0.0010%	79,596.84	79,597.16	89.26%	0.0004%	79,596.19	79,596.40	89.24%	0.0003%
MQS-BOG5	79,982.87	79,983.72	93.73%	0.0011%	79,983.61	79,983.62	71.77%	0.0000%	79,983.43	79,983.44	81.97%	0.0000%
MQS-BOG6	91,246.63	91,247.28	70.44%	0.0007%	91,247.72	91,248.67	87.21%	0.0010%	91,250.07	91,251.34	92.61%	0.0014%
MQS-BOG7	53,817.73	53,818.83	98.90%	0.0020%	53,818.35	53,818.65	98.84%	0.0006%	53,818.76	53,819.47	99.02%	0.0013%
MQS-BOG8	57,564.59	57,565.12	97.10%	0.0009%	57,566.10	57,567.73	97.20%	0.0028%	57,566.79	57,567.29	98.80%	0.0009%
MQS-BOG9	58,957.83	58,957.85	93.97%	0.0000%	58,955.86	58,956.90	98.66%	0.0018%	58,958.16	58,958.58	99.88%	0.0007%
MQS-BOG10	69,727.41	69,728.70	87.21%	0.0019%	69,730.17	69,731.13	84.29%	0.0014%	69,728.18	69,729.13	83.71%	0.0014%
MQS-BOG11	76,235.07	76,238.45	57.81%	0.0044%	76,239.91	76,241.62	71.14%	0.0022%	76,237.24	76,239.20	81.47%	0.0026%
MQS-BOG12	87,011.12	87,011.72	92.69%	0.0007%	87,010.46	87,010.85	96.52%	0.0004%	87,008.45	87,009.53	97.09%	0.0012%
MQS-BOG13	49,599.69	49,600.27	88.60%	0.0012%	49,600.33	49,600.35	90.34%	0.0000%	49,600.78	49,601.10	93.98%	0.0006%
MQS-BOG14	53,822.53	53,823.02	89.22%	0.0009%	53,823.61	53,824.25	81.14%	0.0012%	53,824.00	53,824.29	97.46%	0.0005%
MQS-BOG15	69,287.80	69,288.74	88.47%	0.0013%	69,286.15	69,287.49	93.74%	0.0019%	69,286.10	69,287.13	94.17%	0.0015%
MQS-BOG16	69,293.35	69,293.96	81.46%	0.0009%	69,290.80	69,293.15	87.98%	0.0034%	69,293.23	69,293.23	94.56%	0.0000%
MQS-BOG17	76,235.91	76,237.80	81.56%	0.0025%	76,237.32	76,238.86	81.68%	0.0020%	76,238.08	76,239.45	80.87%	0.0018%
MQS-BOG18	78,687.33	79,036.47	70.08%	0.4437%	78,687.14	78,692.49	93.02%	0.0068%	79,549.12	79,550.91	88.83%	0.0022%

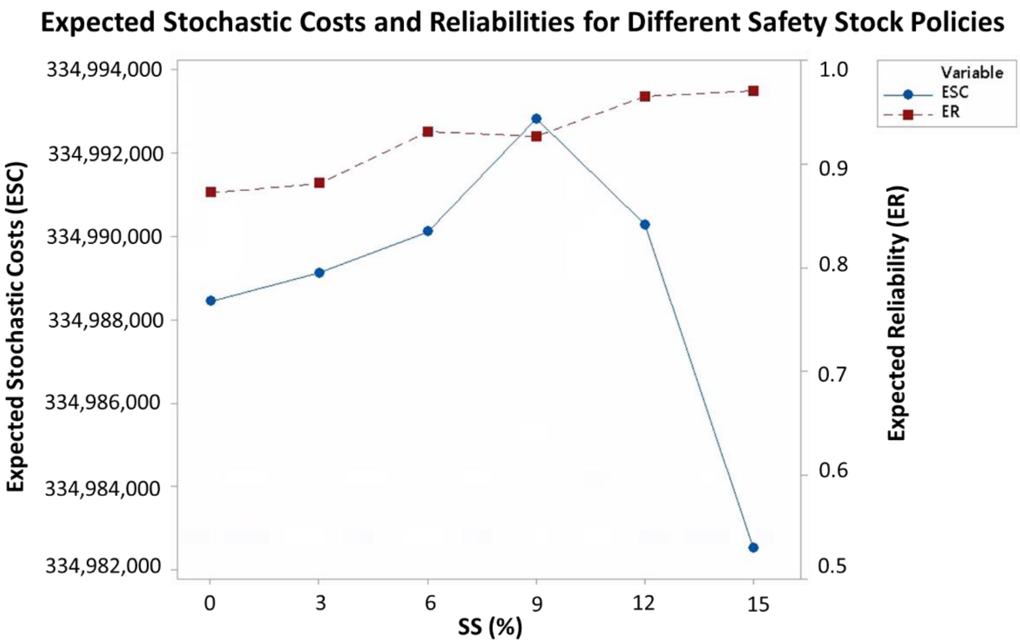

Figure 4. Average values of expected costs and reliabilities of our best stochastic solutions for different safety stock policies. Source: the authors.

Moreover, we have compared the best deterministic solution for a given instance against the top two solutions obtained in the stochastic scenario. As can be seen in Figure 5, both stochastic solutions, i.e., the ones with protective (safety stock) policies, outperform the deterministic one in the stochastic case, in terms of expected stochastic costs. There is also a slightly lower variability of the results obtained during the 5000 simulation runs.

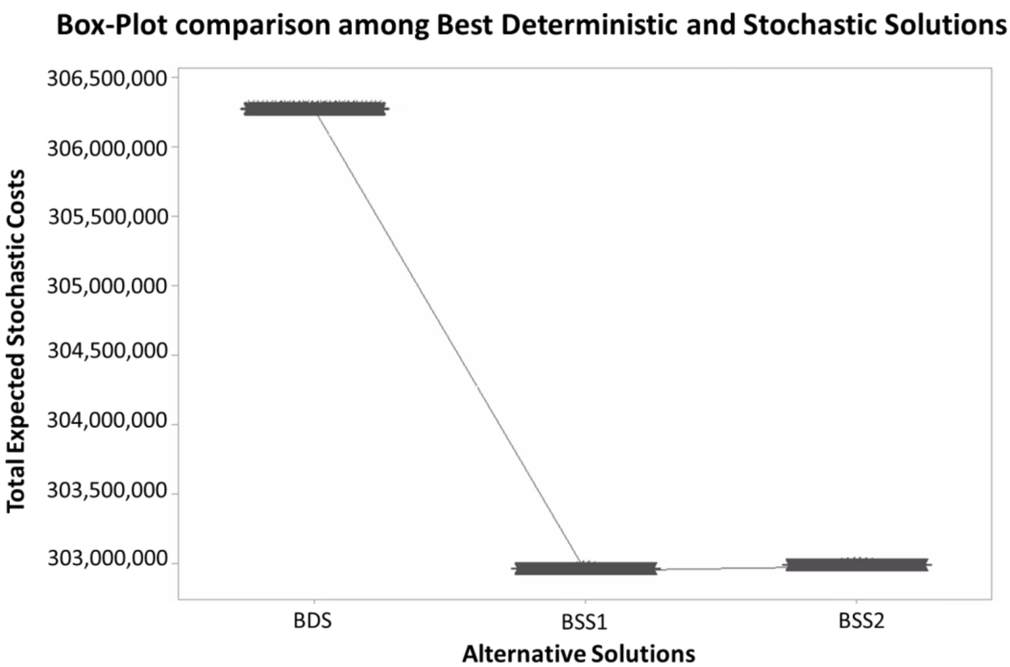

Figure 5. Example of behavior of alternative solutions in the stochastic setting. Source: the authors.

Results show the robustness of our method for supplying PPE to ICUs during the COVID-19 outbreak, which face uncertain and variable demands. Moreover, this method can be adapted to other cities or zones dealing with the same problem or even in other types of applications handling the LRP-SD. To do so, historical cases of infected people need to be analyzed to define the demand probability distribution, as well as the number of ICUs to be attended, the number of available facilities, the fleet size, the vehicle capacity, the safety stock policies, distances between arc connections of nodes, i.e., facilities and ICUs, the opening facility cost, the cost of visiting all ICUs, the cost of vehicles, and the corrective cost of a solution when the demand exceeds the vehicle capacity due to the uncertain nature of the ICUs' demand.

7. Conclusions

This article has studied an imminent necessity of supplying personal protective equipment to intensive care units during the COVID-19 outbreak in Bogotá, Colombia, defined as a location-routing problem with stochastic demands. As the number of infected people may vary from day to day, and consequently the number of ICU patients, we have gathered real data from ICUs in the city to estimate the associated stochastic distribution and, consequently, estimate the needs for PPEs at each ICU. To cope with this complex problem, we proposed a simheuristic approach that considers uncertain demands, distribution cost, and reliabilities in the solutions. Our simheuristic algorithm combines a Monte Carlo simulation with iterated local search. The proposed method was coded in VBA and tested using eighteen different instances generated with data retrieved from Google Maps to characterize the geographical distribution of both warehouses and ICUs in Colombia's biggest city.

In terms of results, different safety stock policies are considered as protection against demand uncertainty. Our results were compared to the ones obtained by GAMS in the deterministic version of the problem, showing promising results. In the stochastic setting of the problem, our method provides an estimation of the expected stochastic costs and reliabilities when using different safety stock policies for each instance. 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, once the value of the safety stock policy reaches the ideal value, costs tend to decrease while reliability increases. These results on a realistic application can be used to ensure the sustainability of the health system of the city in terms of guaranteeing the supply of a critical product to protect physicians, nurses, and therapists of the front line, who are struggling with the current pandemic.

Regarding future directions of this work, there is an opportunity to evaluate sustainable criteria for dealing with emergency decision-making. In addition, since our model considered the Weibull distribution for representing the demand's behavior, other distributions could be adapted for evaluating the robustness of our proposed method. Considering that uncertainty may affect the decision-making in humanitarian crisis, other methods (e.g., robust optimization), and sources of uncertainties (e.g., uncertain travel times, uncertain time windows, imperative pickup, and delivery loads) could be implemented. Finally, equity and cost deprivation are also criteria to be considered for attending the total demand in a crisis context.

Author Contributions: Conceptualization, C.L.Q.-A. and E.L.S.-C.; methodology, A.M.-R., C.L.Q.-A. and E.L.S.-C.; software, A.M.-R. and C.L.Q.-A.; validation, A.M.-R., C.L.Q.-A. and E.L.S.-C.; formal analysis, A.M.-R., C.L.Q.-A. and E.L.S.-C.; writing—original draft preparation, C.L.Q.-A. and E.L.S.-C.; writing—review and editing, C.L.Q.-A. and E.L.S.-C. All authors have read and agreed to the published version of the manuscript.

Funding: This research was funded by the Master Program in Operations Management and the General Direction of Research from Universidad de La Sabana, grant number EICEA-112-2018.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: Not applicable.

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.

Conflicts of Interest: The authors declare no conflict of interest.

References

1. Illahi, U.; Mir, M.S. Maintaining efficient logistics and supply chain management operations during and after coronavirus (COVID-19) pandemic: Learning from the past experiences. *Environ. Dev. Sustain.* **2021**, *23*, 11157–11178. [CrossRef]
2. Secretaría Distrital de Salud. Casos Confirmados de COVID-19 | SALUDATA. Available online: https://saludata.saludcapital.gov.co/osb/index.php/datos-de-salud/enfermedades-trasmisibles/covid19/ (accessed on 5 July 2021).
3. Population Stat. Bogota, Colombia Population (2021)—Population Stat. Available online: https://populationstat.com/colombia/bogota (accessed on 5 July 2021).
4. Das, S.; Rajalingham, S. Personal Protective Equipment (PPE) and Its Use in COVID-19: Important Facts. *Indian J. Surg.* **2020**, *82*, 282–283. [CrossRef]
5. Salhi, S.; Rand, G.K. The effect of ignoring routes when locating depots. *Eur. J. Oper. Res.* **1989**, *39*, 150–156. [CrossRef]
6. Prodhon, C.; Prins, C. A survey of recent research on location-routing problems. *Eur. J. Oper. Res.* **2014**, *238*, 1–17. [CrossRef]
7. Akpunar, Ö.Ş.; Akpinar, Ş. A hybrid adaptive large neighbourhood search algorithm for the capacitated location routing problem. *Expert Syst. Appl.* **2021**, *168*, 114304. [CrossRef]
8. Pachecho, J.; Laguna, M. Vehicle routing for the urgent delivery of face shields during the COVID-19 pandemic. *J. Heuristics* **2020**, *26*, 619–635. [CrossRef]
9. Zhang, M.-X.; Yan, H.-F.; Wu, J.-Y.; Zheng, Y.-J. Quarantine vehicle scheduling for transferring high-risk individuals in epidemic areas. *Int. J. Environ. Res. Public Health* **2020**, *17*, 2275. [CrossRef]
10. Yu, H.; Sun, X.; Solvang, W.D.; Zhao, X. 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). *Int. J. Environ. Res. Public Health* **2020**, *17*, 1770. [CrossRef]
11. Valizadeh, J.; Hafezalkotob, A.; Alizadeh, S.M.S.; Mozafari, P. Hazardous infectious waste collection and government aid distribution during COVID-19: A robust mathematical leader-follower model approach. *Sustain. Cities Soc.* **2021**, *69*, 102814. [CrossRef]
12. Suksee, S.; Sindhuchao, S. GRASP with ALNS for solving the location routing problem of infectious waste collection in the Northeast of Thailand. *Int. J. Ind. Eng. Comput.* **2021**, *12*, 305–320.
13. Martínez-Reyes, A.; Quintero-Araújo, C.L.; Solano-Charris, E.L. A Decision Support Tool for the Location Routing Problem During the COVID-19 Outbreak in Colombia. In *Production Research. ICPR-Americas 2020*; Rossit, D.A., Tohmé, F., Mejía Delgadillo, G., Eds.; the Communications in Computer and Information Science Book Series; Springer: Cham, Switzerland, 2021; Volume 1408. [CrossRef]
14. Erbao, C.; Mingyong, L. A hybrid differential evolution algorithm to vehicle routing problem with fuzzy demands. *J. Comput. Appl. Math.* **2009**, *231*, 302–310. [CrossRef]
15. Juan, A.A.; Faulin, J.; Grasman, S.E.; Rabe, M.; Figueira, G. A review of simheuristics: Extending metaheuristics to deal with stochastic combinatorial optimization problems. *Oper. Res. Perspect.* **2015**, *2*, 62–72. [CrossRef]
16. Quintero-Araujo, C.L.; Guimarans, D.; Juan, A.A. A simheuristic algorithm for the capacitated location routing problem with stochastic demands. *J. Simul.* **2019**. [CrossRef]
17. Solano-Charris, E.L.; Prins, C.; Santos, A.C. Solving the bi-objective Robust Vehicle Routing Problem with uncertain costs and demands. *RAIRO Oper. Res.* **2015**, *50*, 689–714. [CrossRef]
18. Lopes, R.B.; Ferreira, C.; Santos, B.S.; Barreto, S. A taxonomical analysis, current methods and objectives on location-routing problems. *Int. Trans. Oper. Res.* **2013**, *20*, 795–822. [CrossRef]
19. Nagy, G.; Salhi, S. Location-routing: Issues, models and methods. *Eur. J. Oper. Res.* **2007**, *177*, 649–672. [CrossRef]
20. Tordecilla, R.D.; Copado-Méndez, P.J.; Panadero, J.; Quintero-Araujo, C.L.; Montoya-Torres, J.R.; Juan, A.A. Combining heuristics with simulation and fuzzy logic to solve a flexible-size location routing problem under uncertainty. *Algorithms* **2021**, *14*, 45. [CrossRef]
21. Drexl, M.; Schneider, M. A survey of variants and extensions of the location routing problem. *Eur. J. Oper. Res.* **2015**, *241*, 283–308. [CrossRef]
22. Ghaffari-Nasab, N.; Ahari, S.G.; Ghazanfari, M.A. A hybrid simulated annealing based heuristic for solving the location-routing problem with fuzzy demands. *Sci. Iran.* **2013**, *20*, 919–930. [CrossRef]
23. Nadizadeh, A.; Nasab, H.H. Solving the dynamic capacitated location-routing problem with fuzzy demands by hybrid heuristic algorithm. *Eur. J. Oper. Res.* **2014**, *238*, 458–470. [CrossRef]
24. Mehrjerdi, Y.Z.; Nadizadeh, A. Using greedy clustering method to solve capacitated location-routing problem with fuzzy demands. *Eur. J. Oper. Res.* **2013**, *229*, 75–84. [CrossRef]
25. Fazayeli, S.; Eydi, A.; Kamalabadi, I.N. Location-routing problem in multimodal transportation network with time windows and fuzzy demands: Presenting a two-part genetic algorithm. *Comput. Ind. Eng.* **2018**, *119*, 233–246.
26. Nadizadeh, A.; Kafash, B. Fuzzy capacitated location-routing problem with simultaneous pickup and delivery demands. *Transp. Lett.* **2019**, *11*, 1–19. [CrossRef]

27. Zhang, H.; Liu, F.; Ma, L.; Zhang, Z. A hybrid heuristic based on a particle swarm algorithm to solve the capacitated location routing problem with fuzzy demands. *IEEE Access* **2020**, *8*, 153671–153691. [CrossRef]
28. Albareda-Sambola, M.; Fernández, E.; Laporte, G. Heuristic and lower bound for a stochastic location-routing problem. *Eur. J. Oper. Res.* **2007**, *179*, 940–955. [CrossRef]
29. Zhang, S.; Chen, M.; Zhang, W. A novel location-routing problem in electric vehicle transportation with stochastic demands. *J. Clean. Prod.* **2019**, *221*, 567–581.
30. Rabbani, M.; Heidari, R.; Yazdanparast, R. A stochastic multi-period industrial hazardous waste location-routing problem: Integrating NSGA-II and Monte Carlo simulation. *Eur. J. Oper. Res.* **2019**, *272*, 945–961. [CrossRef]
31. Tirkolaee, E.B.; Abbasian, P.; Weber, G.W. Sustainable fuzzy multi-trip location-routing problem for medical waste management during the COVID-19 outbreak. *Sci. Total Environ.* **2021**, *756*, 143607. [CrossRef]
32. Valizadeh, J.; Mozafari, P. A novel cooperative model in the collection of infectious waste in COVID-19 pandemic. *J. Model. Manag.* **2021**. [CrossRef]
33. Pasha, J.; Dulebenets, M.A.; Kavoosi, M.; Abioye, O.F.; Wang, H.; Guo, W. An Optimization Model and Solution Algorithms for the Vehicle Routing Problem with a "Factory-in-a-Box". *IEEE Access* **2020**, *8*, 134743–134763. [CrossRef]
34. Chen, D.; Pan, S.; Chen, Q.; Liu, J. Vehicle routing problem of contactless joint distribution service during COVID-19 pandemic. Transp. *Res. Interdiscip. Perspect.* **2020**, *8*, 100233. [CrossRef]
35. Kahfi, A.; Seyed Hosseini, S.M.; Tavakkoli-Moghaddam, R. A robust optimization approach for a multi-period location-arc routing problem with time windows: A case study of a bank. *Int. J. Nonlinear Anal. Appl.* **2021**, *12*, 157–173.
36. Prins, C.; Prodhon, C.; Calvo, R.W. Solving the capacitated location-routing problem by a GRASP complemented by a learning process and a path relinking. *4OR* **2006**, *4*, 221–238. [CrossRef]
37. Lourenço, H.R.; Martin, O.C.; Stützle, T. Iterated local search: Framework and applications. In *Handbook of Metaheuristics*; Gendreau, M., Potvin, J.-Y., Eds.; Springer: Boston, MA, USA, 2010; pp. 363–397. [CrossRef]
38. Erdoğan, G. An open source spreadsheet solver for vehicle routing problems. *Comput. Oper. Res.* **2017**, *84*, 62–72. [CrossRef]
39. Chevrolet. NHR Reward Euro IV. Available online: https://www.camionescolombia.com.co/comprar-vehiculo-chevrolet-colombia-nhr-reward-euro-iv.html?m=&m=adwords&ad=457630024942&kw=%2Bnhr%20%2Breward&mt=b&nw=g&dev=c&pm=&tg=&ap=&gclid=Cj0KCQjw-LOEBhDCARIsABrC0TlZIXYNXQ44bWxJd5wbFL1S7SxpCuPEGlXWF5F1jcLME7kBSWlGMcsaAsE_EALw_wcB (accessed on 18 November 2020).