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ARTICLES

REVERSE LOGISTICS BASED ON GREEN OPEN VEHICLE ROUTING FOR WASTE COLLECTION IN THE URBAN CONTEXT

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ABSTRACT. Research related to vehicle routing and its applications reveals the interest in supporting the authorities in solving society's problems. In this way, a bi-objective model of mixed integer linear programming and metaheuristics based on genetic algorithm and local search, applied to reverse logistics by green open vehicle routing, is presented. The process consists of collecting solid urban waste at collection points, contributing to urban sustainability through the route plan determined by the proposal, optimizing distances and costs as well; it also measures the fuel consumption of the vehicles from their departure from the depot to the last collection point, as well as the CO2 emissions during routing. The proposals, implemented in GLPK and Python, obtain results in various scenarios. The model generates solutions quickly in scenarios between 5 and 25 collection points. For larger scenarios it does not find solutions within the time limit of 7200 seconds. The metaheuristics have greater potential as for 31 collection points, the processing time was 2.3 seconds which is a good indication for larger scenarios. Three Sectors of Trujillo city are tested to evaluate our proposal.

Keywords: reverse logistics, open vehicle routing, urban sustainability.

1 INTRODUCTION

Every city has diverse daily activities such as food supply, waste disposal, building works, route maintenance, etc., all of these are essential for a productive and buoyant economic system.

Economic growth is essential for a city to thrive, however, this growth also produces a huge quantity of waste material that has an adverse environmental impact, it causes preoccupation in terms of environmental consequences. Intense consumption activities result in the generation of large quantities of waste, which the authorities have often been unable to address because their collection plans are not effective.

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A successful solid waste collection plan whose objective is to optimize in harmony the economic and environmental aspects is extremely convoluted. Perhaps for that reason the Municipal Institutions or Central Government authorities which are responsible for the protection of the environment have not been able to obtain the expected success. In this situation, location of collection points and routing of vehicles are an alternative to be applied in urban logistics (Stopka et al., 2020). In Feng et al. (2017), it is stated that vehicle routing has attracted attention in the management of logistics processes. A paper related to localization-routing integration is discussed in Drexl & Schneider (2015).

In this paper we present a mixed integer linear programming model and two metaheuristics (genetic algorithm and local search) in the urban context, based on open vehicle routing to establish an efficient and sustainable reverse logistic system. The proposal optimizes the distance traveled during the solid waste collection process, which begins when the collection vehicle leaves a depot and ends after having served all the collection points located in strategic locations in urban areas. In addition, it avoids excess of fuel consumption and as a consequence, it also reduces the amount of CO2 in kg/ton-km generated. This integration of the proposal is a great contribution to the sustainability of cities and the protection of the environment. See Figure 1.

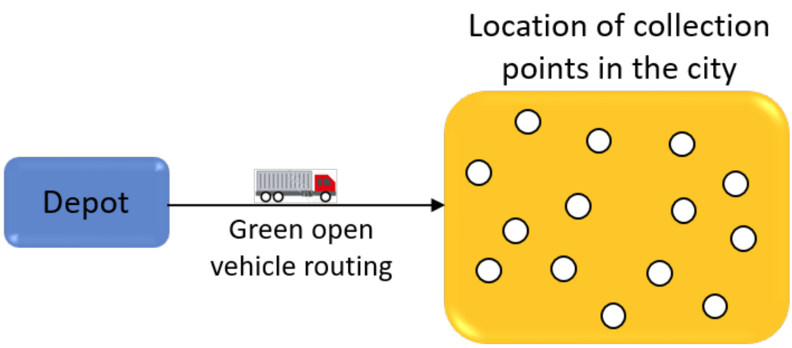

Figure 1 – Green open vehicle routing scheme for solid waste collection.

The article is structured in the following sections: Section 2 shows the research method used to reach the proposed objective of the article. Section 3 consists of a review of the literature related to the research conducted. In section 4, the problem is discussed through the description and formulation of a mixed integer linear programming model with two objective functions and two metaheuristics based on a genetic algorithm and a local search algorithm. The section number 5 shows the results and discussions. Section 6 presents the conclusions of the research conducted.

2 RESEARCH METHOD

Investigation of current logistics prompted a review of the specialized literature through the database Scopus. Investigations from the years 2018 to 2023 were considered, with the search keywords being the terms ”reverse”, ”logistics”, ”green”, ”vehicle”, ”routing”, ”open vehicle” and "genetic algorithm". The filter used was to consider only research and review articles published in journals.

The result was 167 articles with which the existing relationships between them were verified through keywords, that is, co-occurrence networks were built using VOSviewer Prianes-Rodríguez et al. (2016) and Donthu et al. (2021). In addition, the complete count of all keywords with a minimum number of one occurrence was considered. Figure 2 shows the importance of vehicle routing in general and a variant called open vehicle routing, which can be solved through computational strategies such as branch-and-cut, branch-price-and-cut, lagrangian relaxation and approximation strategies such as simulated annealing, iterated local search, genetic algorithm applied in contexts city logistics, green logistics, and reverse logistics.

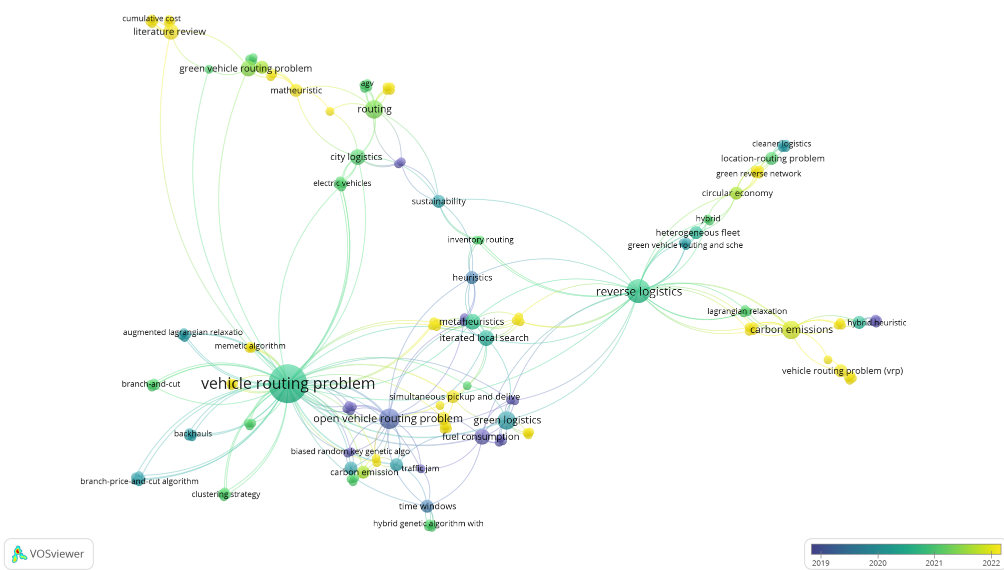

Figure 2 – Co-occurrence of keywords.

The investigation of the proposals based on the Design of logistics networks in various contexts; Quantitative Integer Linear Optimization Models and Quantitative Methods for Solving Network Design Problems, show the existence of a few proposals for green vehicle routing, as can be deduced from Figure 2. In addition, some articles were found to have a certain relationship with our proposal, since they propose modified genetic algorithms for open vehicle routing, with the variables and restrictions of the problem focused on optimizing routes, distance, and economic costs, but do not consider environmental sustainability. Other articles in the literature are loosely related to the article being proposed. See Table 1.

According to a thorough analysis in Table 1, there are several proposals for forward logistics and supply chains based on green vehicle routing in its traditional form (the process starts and ends in the same warehouse), where the goal is always to optimize economic costs and CO_2 emissions

Table 1 – A comparative between the proposal paper and reviewed papers.

	VRP	Distance	Fuel used	GHP	CO2	Model	Alg
Proposal paper	Green open	x	x		x	x	x
Abdoli et al. (2017)	x	x	x	x	x	x	x
Afshar et al. (2016)	Green	x	x		x	x	
Amiri et al. (2022)	Green	x		x		x	x
Defalque et al. (2021a)	x	x				x	
Ferreira et al. (2021)	Green	x	x		x	x	x
Feng et al. (2017)	x	x	x			x	x
Foroutan et al. (2020)	Green	x			x	x	x
Hasheme (2021)	x		x			x	x
Moghdani et al. (2021)	Green						
Mojtahedi et al. (2021)	x					x	x
Niu et al. (2018)	Green open	x	x		x	x	x
Niu et al. (2022)	Green open	x	x		x	x	x
Normasari et al. (2019)	Green	x	x			x	x
Olgun et al. (2021)	Green	x	x			x	x
Peng et al. (2020)	Green				x	x	x
Rezaei et al. (2019)	Green	x			x	x	x
Ruiz et al. (2019)	Open	x					x
Wang et al. (2019)	Green	x			x	x	x
Wen et al. (2022)	Green	x			x	x	x
Wu & Wu (2022)	Green		x		x	x	x
Xu et al. (2019)	Green		x			x	x

applying optimization models and algorithms. In Afshar et al. (2016) the authors reach their goal in a generic approach by using a mixed integer linear programming model to optimize routes that will increase customer satisfaction while also taking into account environmental costs; similarly to this, Wu & Wu (2022) increases customer satisfaction while reaches to deliver agricultural products on time by reducing costs and consumption of fuel, through a multi-objective optimization model and a variable neighborhood search combined with the non-dominated sorting genetic algorithm. In Amiri et al. (2022), they suggest a model and an Adaptive Large Neighborhood Search (ALNS) algorithm to reduce transportation costs and greenhouse gas emissions when distributing goods from distribution centers. They consider a fleet of conventional and electric vehicles. Similar proposals to reduce costs and CO2 emissions are given in the paper by Wang et al. (2019) y Wen et al. (2022) when they apply them to situations involving multi-dept. Other proposals were made by Rezaei et al. (2019), Peng et al. (2020), and Ferreira et al. (2021). In Normasari et al. (2019), by means of capacitated vehicle routing, in a generic approach it shows how to minimize the distance traveled by a vehicle that uses alternative fuel through a mixed integer linear programming model and a simulated annealing algorithm. Olgun et al. (2021) successfully reaches the goal of minimizing fuel consumption while simultaneously collecting and distributing a product.

The goal of this article is to minimize transportation costs as much as possible, which requires to put into practice the process of collecting waste stored at collection points and measuring the amount of CO2 generated by the vehicles, while also taking into account the distance traveled by the vehicles to be used. This differs from the proposal presented by Niu et al. (2018) and Niu et al. (2022), who have an interest to minimize the costs of fuel emissions and the expenses of payment driver wages. As a result of this, although both proposals make use of green open vehicle routing, our investigation has a specific objective that is focused on reverse logistics in urban areas, while Niu et al. (2018) and Niu et al. (2022) applies it to third-party logistics without indicating specifically what use their proposal will be put to. Foroutan et al. (2020) show a reverse logistics application based on green vehicle routing that is used to collect returned products (such as damaged, expired, or defective goods), but not urban solid waste, and does not utilize green open routing.

As was already mentioned in the previous paragraphs, this article offers a significant contribution that can be used in the urban context because, in addition to have a specific objective, it is also focused to aid maintain sustainability in cities by using green open vehicle routing that is not specifically discussed in the literature.

In conclusion, the bibliographical research carried out motivated the realization of other comprehensive proposal whose optimization model presents a bi-objective function to collect waste through reverse logistics based on open green vehicular routing in the urban context.

3 REVIEW OF SPECIALIZED LITERATURE

As a basis for the proposal in this article of green logistics related to sustainability, a review of the results of the researched literature is discussed.

3.1 Combinatorial optimization and routing of vehicles

Combinatorial optimization discussed in Korte & Vygen (2018) mentions that many realities can be formulated as abstract optimization problems, that is: problems that can be formulated in terms of networks and as optimization models; for some applications these are the result of the process of abstraction of cases found in reality and that when trying to solve them one is confronted with complex cases

Applications of network-based problems can be found in the traveling agent and the particular case of vehicle routing and its different variants Marinakis et al. (2018) and Tan & Yeh (2021), where the objective is to serve a set of customers, to optimize distance, cost or time, starting and ending at a depot. A variant to be applied in the context of urban logistics is open vehicle routing, in other words, the vehicle does not return to the depot after having fulfilled its job of providing a service. The problem is solved with optimization models; however, for large scenarios the development of metaheuristics is necessary (Maleki & Yousefikhoshbakht, 2019). See Figure 3.

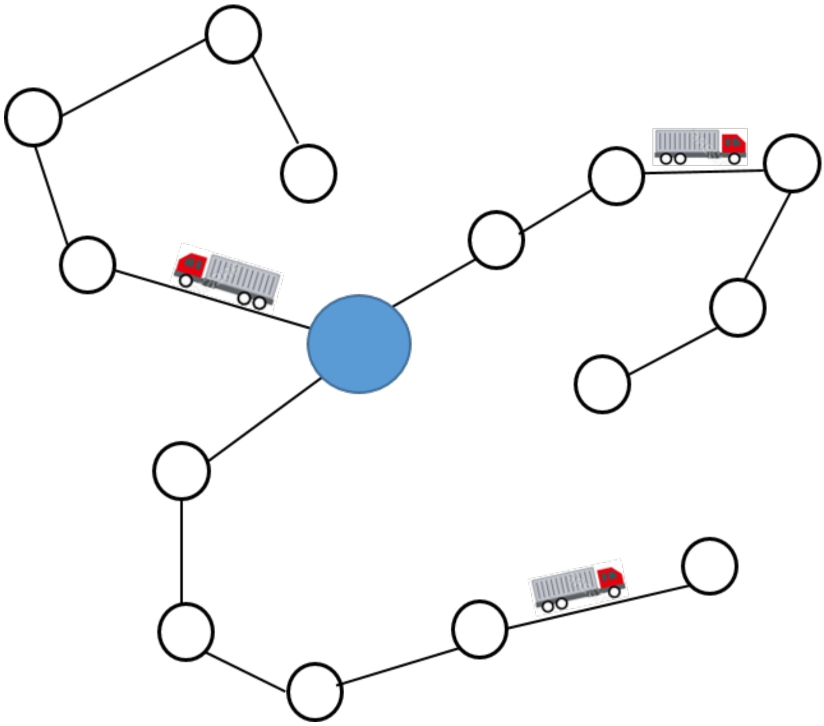

Figure 3 – Open vehicle routing with three routes.

A tendency in the globalized world is the mitigation of environmental and social externalities, which poses new issues for which profit maximization is not the only factor to consider. As a result, traditional vehicle routing and urban vehicle routing varies depending on objectives of interest. In a recent review that had three objectives that were successfully reached, it was found that the environmental and social issues had received less attention. Consequently, the results of the study will help future research to learn more about sustainability models and methods (Dündar et al., 2021).

3.2 Logistics and sustainability

Optimal service of delivering products or providing a service in the right place at the right time is due to adequate planning by the responsible companies or institutions, with the aim of maintaining market hegemony. This is called logistics. Certainly success would be possible if a set of constraints or conditions are met, such as having a fleet of vehicles.

Transportation is the support of logistics; however, it also generates high social costs such as vehicle congestion and consequently the generation of toxic gases such as CO2 and others, polluting the environment which cannot be avoided with fossil fuel burning vehicles. This reality has led to the development of the concept of the logistics city, whose goals are related to the reduction of congestion and pollution, without compromising commercial activities in cities. In other words, a new concept of logistics has emerged, called green or ecological logistics, for which it is possible to use vehicle routing.

Urban development has determined new ways of doing logistics to be beneficial. It must act in harmony with other activities, such as the supply chain, which partners with companies supplying products, warehouses, carriers, customers, etc. Thus, thanks to its application, sustainable development emerges, which is very important for countries. Currently, supply chains are sustainable (Bouchery et al., 2017).

It is concluded that it is imperative to consider the environmental impact when considering new logistical solutions (Kauf, 2016). Therefore, in the urban context, reverse logistics is indispensable to maintain the sustainability of cities, through the use of green vehicle routing Afshar et al. (2016), to meet the different types of demands that citizens require, such as the collection of solid waste generated in homes in order to avoid dumping it in undesirable places so that it can be recycled, reused and transported to specialized places (landfills), depending on the state of the waste collected.

Abdoli et al. (2017) made a suggestion with a future vision for the use of green fuels like biodiesel and compressed natural gas as an unavoidable substitute in vehicles. They provide an optimization model and simulated annealing metaheuristics applied to vehicle routing, where the fleet vehicles run on green fuels to lessen the impact of greenhouse gas produced by the transport sector. The authors promise a decrease in environmental contamination through tests with random instances. Recently Peng et al. (2020) presented an evolutionary algorithm to solve green vehicle routing and thus control carbon dioxide emissions in the areas where it is applied.

The globalization experienced by the world today has been decisive for the development of logistics. Given this situation, recently Asghari & Mirzapour Al-e hashem (2021) conducted a study of the state-of-the-art contributions made with green vehicle routing, with the aim of identifying situations not considered to bring future research closer to the reality under study. To do this, they present a scheme to classify the existing variants, as well as the types of vehicles that are proposed. Additionally, an analysis of existing formulations and solution strategies for green vehicle routing is also discussed. A review by Moghdani et al. (2021), based on the systematic analysis of 309 articles published between 2006 and 2019 from various perspectives, proposes an extensive structure for green vehicle routing, where it has been possible to develop new variants in order to protect the environment. The authors even assume that some new research areas can be traced as a result of the study that was investigated, which has the potential to future research.

The quantity of waste generated in cities has made it necessary to apply reverse logistics because, despite the difficulty of the process, it must be collected and transported to specialized centers for recycling or reuse or taken to landfills. Therefore, for municipal management, a new framework for a practical and efficient vehicle routing problem has recently been introduced based upon the triple bottom line of sustainability through a logistics network for waste elimination, for which a new multi-objective optimization model and meta-heuristic was proposed (Mojtahedi et al., 2021). In Kermanshah, Iran, a case study for municipal solid waste management was proposed using a sustainable network and a mathematical model (Eghbali et al., 2022). The sustainable reverse logistics to collect urban solid waste with the objective of reducing emissions was possible through the development of an optimization model, bee colony and genetic algorithms with goods results (Hasheme, 2021).

To plan the recycling of collected paper waste, Defalque et al. (2021b) present a bibliographical review of proposals that present quantitative models and their solutions. The analysis of the five research categories conducted as part of the review is particularly significant because it will be used to guide future research on environmental sustainability. In a recent study, Defalque et al. (2021a) emphasized the importance of organizing and planning reverse logistics on a network. As a consequence, they developed and implemented a new model of mixed integer linear programming of multiple objectives, which allows improving the sustainability and efficiency of the logistics process of waste paper, including collection through vehicle routing, for its subsequent recycling in a specialized center. The computational results obtained with real data provide competitive solutions.

In summary, the proposals found in the researched publications show the importance of logistics and its variant called green logistics, since considering the development of today's world, the notion of sustainability is an important concept that allied with vehicle routing contributes to the reduction of the impacts of the greenhouse gas effect, pollution, economic and social sustainability. In this context, new contributions are required.

4 GREEN VEHICLE ROUTING APPLIED IN REVERSE LOGISTICS IN AN URBAN CONTEXT

Based on the insights discussed in Sections 2 and 3, as well as in Rezaei et al. (2019) and Hasheme (2021), a bi-objective open vehicle routing model and two metaheuristics are investigated. The proposals in this research not only optimize the distance traveled, but also the amount of CO2 generated in the travel process of the waste collection vehicles, through the use of the formula to measure CO2 given in Corporation (2020), which was adapted to the model and metaheuristics; in addition to the amount of fuel consumption. Therefore, it is a case of green open vehicle routing applied to reverse logistics, where it is assumed that the term demand has been determined by the collection points.

In addition, the collected waste transported to specialized centers, speed and acceleration of the collector vehicle, as well as traffic in the area, are not considered in this proposal.

4.1 Optimization model

Sets:

a) N : Collection points, where $d1$ is the depot from which the vehicles depart.

b) K : Collector vehicles.

Parameters:

a) $dist_{ij}$: Distance between collection points $i, j \in N$.

b) d_i: Demand of the collection points $i \in N$.

c) Q: Number of available collector vehicles.

d) q_k: Capacity of collector vehicles $k \in K$.

e) cf_k: Fixed cost for operation of the collector vehicle $k \in K$.

f) T_k: Maximum fuel tank capacity of the collector vehicle $k \in K$.

g) CC: Fuel consumption in liters per kilometer.

h) EM_k: CO2 emission of the collector vehicle $k \in K$.

Decision variables:

a) X_{ijk}: Binary variable denoting attention to collection points $i, j \in N$.

b) u_i: Accumulation of remains collected after visiting a collection point $i \in N$.

c) M_k: Binary variable indicating vehicle assigned to collection point $i \in N$.

d) Y_{ik}: Fuel in the vehicle tank when it reaches the collection point $i \in N$.

The mixed integer linear programming model with two objective functions is given as follows:

$$Min: \sum_{i,j \in N, k \in K} dist_{ij} X_{ijk} + \sum_{k \in K} cf_k M_k \tag{1}$$

$$Min: \sum_{i,j \in N, k \in K} CC \left(\frac{EM_k}{q_k} \right) dist_{ij} X_{ijk} \tag{2}$$

subject to

$$\sum_{i \in N, k \in K} X_{ijk} = 1, \forall j \in N, j \neq d1 \tag{3}$$

$$\sum_{j \in N, k \in K} X_{ijk} \leq 1, \forall i \in N, i \neq d1 \tag{4}$$

$$\sum_{i,j \in N: i \neq d1, j = d1} X_{ijk} \leq Q, \forall k \in K \tag{5}$$

$$u_j - u_i + q_k \left(1 - X_{ijk}\right) \geq d_j, \forall i, j \in N, k \in K : i, j \neq d1 \tag{6}$$

$$d_i \leq u_i \leq q_k, \forall i \in N, k \in K : i \neq d1 \tag{7}$$

$$X_{ijk} \leq M_k, \forall i,j \in N, k \in K \tag{8}$$

$$\sum_{i,j\in N} X_{ijk} - \sum_{i,j\in N} X_{jik} = 0, \forall k \in K \tag{9}$$

$$Y_{jk} \leq Y_{ik} - CC\left(\frac{EM_k}{q_k}\right) dist_{ij} X_{ijk} + T_k\left(1 - X_{ijk}\right), \forall i,j \in N, k \in K \tag{10}$$

$$Y_{jk} \leq T_k - CC\left(\frac{EM_k}{q_k}\right) dist_{ij} X_{ijk}, \forall i,j \in N, k \in K \tag{11}$$

The objective function (1) optimizes waste transportation costs between collection points, in addition to the fixed cost of operating the collection vehicles. The CO2 generated is measured during the travel process generated by the objective function (2) to attend the collection points.

Equation (3) indicates that each collection point is served exactly once by a vehicle. Condition (4) models the output of at least one collector vehicle leaving the depot. Condition (5) models the collection vehicles available to serve the collection points. Equation (6) indicates the capacity of viable routes to serve the collection points. In (7), it is established that the amount collected should not exceed the capacity of the collecting vehicle.

The guarantee that the collection points will be served by the collecting vehicles is modeled in (8). Constraint (9) indicates that the collecting vehicle arrives at a collection point, provides the service and continues its work to serve the next collection point thus providing the required service, in other words, called the equilibrium condition.

Equation (10) models the fuel level in the tank of the collector vehicle when it reaches the collection point. Finally, the restriction (11) ensures that the fuel tank will be charged for the operation of the collector vehicle.

4.2 Metaheuristics

Due to the combinatorial nature of vehicle routing problems and the substantial amount of processing required to find a solution, exact solution methods are typically not feasible for utilization in large scenarios. For this reason, it is recommended to use the metaheuristics genetic algorithm and local search to find an approximate solution of the open vehicle routing.

In this section, the results of applying these two metaheuristics are compared with the aim of optimizing the distance traveled and thus producing a route plan using the least amount of collector vehicles to reduce CO2 kg/ton-km emission as well as fuel consumption.

4.2.1 Genetic Algorithm

Considering the amount of waste, collection points and collection vehicles, the initial population is generated (line 4 of Algorithm 1). The collection vehicles make up the homogeneous fleet parked at the depot, which, according to demand at the collection points, will collect the solid waste until they reach their maximum available capacity or consume all the fuel in their tank.

Subsequently, another vehicle will leave the depot to perform the same task at the remaining collection points until all demands have been met. In this phase different routes are formed for each collector vehicle; as well as the measurement of the amount of CO2 generated in the routing process. All the resulting information obtained by the proposed algorithm is stored in a list of routes of the collector vehicles that is part of an individual in the population.

Algorithm 1 Metaheuristics based on Genetic Algorithm

Require: TamIndividuals, NumGenerations, ProbCrossing, FileTxT.

Ensure: Minimum number of vehicles and minimum distance traveled to collect solid waste from collection points.

1: Initialize CollectPoints, depot and trucks when reading the FileTxt.
2: Initialize TamIndividuals, NumGenerations, ProbCrossing, Individuals.
3: t = time.time()
4: Individuals := GeneratePopulationInitialIndividuals()
5: **for** Generation = 1: Generation $<$ NumGenerations : Generation ++ **do**
6:     kContestants = int(TamIndividuals * 0.2)
7:     parents = selectionTournament(Individuals,kContestants)
8:     randon = random.uniform(0.0, 1.0)
9:     **if** randon $\geq$ ProbCrossing **then**
10:         Individuals = Croosover(parents, Individuals, trucks, CollectionPoints)
11:     **else**
12:         Individuals = Mutation(parents, Individuals, trucks, CollectionPoints)
13:     **end if**
14: **end for**
15: BestIndividual = BestSolution(Individuals) ▷ Find best solution based on minimum number of vehicles and minimum total distance traveled.
16: elapsed = time.time() - t ▷ Total algorithm time.
17: **return** Optimal Solution

Additionally, in each generation, individuals mutate or crossover (lines 5- 14 of Algorithm 1). If the random value is greater than or equal to the ProbCrossover of 0.6, the individuals crossover; otherwise the individuals mutate. The selection of the best individuals to cross or mutate is through the tournament, in other words, 20% of the population is selected and the two best individuals are chosen to be the future parents. In the mutation operator, two collection points are chosen from the list of routes and exchanged to form a new Individual child with new routes validating the vehicle constraints. The final validation is that the generated child is not repeated with any individual in the population.

In the case of the crossover operator, the HGreX operator discussed in Puljić & Manger (2013) was modified for use in this proposal. Since you already have the list of routes of both parents chosen, find the collection point close to the depot to form the first arc of the route of the vehicle1 of the child, then locate in both parents who is the other collection point that forms an arc with the chosen one. Choose the one whose distance is the minimum with such a collection point and thus form the second arc of the son.

On the other hand, if in both parents the collection points that form an arc with the chosen one are already in the list of routes of the child, choose another collection point from the list of missing points. Repeat the previous steps. Otherwise, if there are no more missing collection points in the list of both parents, then the process is terminated by obtaining the optimal route.

Finally, in order to find the best individual in the population, consider the number of vehicles and the distance of travel, so the individual is chosen at the end of the number of generations of Genetic Algorithm 1. Subsequently calculate the total time spent.

4.2.2 Local Search

The following is a different proposal for the creation of routes for collecting vehicles, according to the minimum distance between neighboring collection points. In Algorithm 2, the collecting vehicles leave the depot to the collection points, creating routes whose initial vertex will be the depot and the next vertex will be the nearest collection point to it; then, the next chosen collection point will be the neighbor of the current one, and so on (lines 4 – 18 of Algorithm 2).

The constraints for creating the routes of a new collector vehicle leaving the depot are given by the amount of fuel in the tank and the capacity of the collector vehicle (line 5), in other words the current collector vehicle must not exceed its capacity or run out of fuel; when this happens, a new collector vehicle will leave the depot (lines 6 - 11). The idea is to find a minimum distance between the last collection point of the route network with the rest of the collection points (line 16); in this way, the collection vehicle collects waste from those collection points that are close to it, until the vehicle's capacity is full or its fuel tank is empty (lines 4-15). Finally, the routes for each collector vehicle are formed (line 19) and the total processing time used by the algorithm is calculated (line 20).

5 RESULTS AND DISCUSSION

A laptop with Core (TM) i7-855ou CPU 1.8 Ghz with 8.00 Gb RAM was used to evaluate the proposal. The optimization software GLPK (GNU Linear Programming Kit) was used to implement the optimization model; and for the metaheuristics the Python programming language in Google Colaboratory was used to solve the various scenarios considered, where the instances obtained from the Networking and Emerging Optimization - NEO benchmark were adapted to the context of this article (www.neo.lcc.uma.es/vrp/vrp-instances/). The computational complexity of vehicle routing problems, determines that the time required to obtain optimal solutions in large scenarios is large (Archetti et al., 2015); for this reason, in the present proposal it was decided that the experiments performed by the optimization model should be executed within the time limit of 7200 seconds.

Algorithm 2 Local Search Based Metaheuristics

Require: Collection points, vehicles.

Ensure: Minimum number of vehicles and minimum distance traveled to collect solid waste from collection points.

```
Initialize CollectPoints, CollectPointsCoordinates, depot and trucks when reading the FileTxt.
Initialize variables IndividualRoutes, truckId, TotalTank, QtyDistancy, QtyCO2, QtyLoad, routes, routeIndex, CollectionPointInitialPosition, CollectionPointListRoutes, CollectionPointsNumber
t = time.time()
for pointcollect = 1: pointcollect < NumCollectPoints : pointcollect ++ do
    if QtyLoad + CollectionPoint[CollectionPointInitialPosition].getCantWastes() >= trucks[truckId].getCapacity() or TankTotal <= 0 then
                                                        ▷ Creates a new route list with a new vehicle.
        truckId += 1
        TankTotal = trucks[truckId].getTank()
        pathIndex = 0
        QtyLoad = 0
        PointCollectInitialPosition = 0                 ▷ Start with the deposit.
    else                                                ▷ Continues to create arcs on the route of the current vehicle.
        route = Route()
        pathIndex += 1
    end if
    TankTotal, route, InitialCollectionPointPosition, routeIndex, QtyDistancy, QtyCO2, QtyLoad, ListCollectionPointRoutes = CreateMinimumDistancy(CollectionPointCoordinates, NumCollectionPoints, TotalTank, RouteCollectionPointList, CollectionPoints, routes, InitialPositionCollectionPoint, truckId, routeIndex, DistanceQty, QtyCO2, QtyLoad)
    routes.append(route)
end for
IndividualRoutes.append([routes, QtyDistancy, QtyCO2, ListCollectionPointRoutes])
elapsed = time.time() - t                               ▷ Total algorithm time.
return IndividualPaths
```

Based on the documentation review of the specialized literature and modeling experience with combinatorial problems, it was possible to develop the optimization model and the metaheuristics whose computational results, in various scenarios, allowed the proposal to be validated thanks to the criteria of expert judges who judged the applicability of the formulations based on the simulation carried out, with the data used to collect residues through simulation.

5.1 Results using the optimization model

5.1.1 Case 1:

A deposit located in $d1$:(10,15) and twelve collection points with their respective geographic locations and demands were considered as a case study. See Table 2. In addition, three collection vehicles with a capacity of 50 tons each will be considered to serve the collection points.

Table 2 – Location of twelve collection points and their demands.

Collection points	Location	Demand to pick up
pc1	(3,25)	2
pc2	(20,61)	1
pc3	(31, 81)	4
pc4	(40, 90)	2
pc5	(80, 50)	2
pc6	(150, 30)	1
pc7	(40,25)	4
pc8	(45,35)	2
pc9	(20,5)	3
pc10	(19, 24)	3
pc11	(15, 40)	3
pc12	(35, 57)	5

Table 3 – Results obtained with the optimization model.

Collection point	Collection point	Pickup	Distance	Fuel consumption	CO2
d1	pc1	0	12.2	30	0.23
pc1	pc6	2	13	29.76	0.24
pc6	pc11	3	10	29.52	0.18
pc11	pc2	6	21.58	29.33	0.4
pc2	pc12	7	15.52	28.92	0.29
pc12	pc3	12	24.33	28.63	0.45
pc3	pc4	16	12.72	28.17	0.24
d1	pc9	0	14.14	30	0.26
d1	pc10	0	12.72	30	0.24
pc10	pc7	3	21.02	29.75	0.39
pc7	pc8	7	11.18	29.36	0.21
pc8	pc5	9	38.07	29.15	0.71

Table 3 shows as a computational result the route plan obtained through the green open vehicle routing, where any of the three vehicles, which form the fleet, can meet the waste collection demand generated by the collection points. In this way, three possible routes are formed, all of which start at the depot and end at the last collection point served. In addition, the amount of waste collected is shown; the distances traveled by the collection vehicle expressed in km. and the amount of fuel, in liters L, used during the travel process; which is going gradually decreasing in the tank as the vehicle makes attenuating demand. Each vehicle starts its day with 30 L. of fuel in the tank. Finally, the optimal routing plan built by the model determines that fuel consumption is not in excess, which in turn influences the reduction of CO_2 generation in kg/ton-km.

5.1.2 Case 2:

The proposed model was also tested in other scenarios; for this purpose, the number of collection points, their locations and demands were increased as shown in Table 4; where the demand of deposit $d0$ is 0 and its geographical location has the coordinates (82, 76). Additionally, the type of vehicles as established in Case 1 are the same, but the capacities were increased due to the fact that there are more collection points to be served.

With such data from Table 4, the collection points were grouped to form a total of six scenarios, whose computational results are shown in Table 5; where it is observed that the time in seconds taken to find the solution increases according to the number of collection points that form the scenarios. Consequently, the distance traveled and CO_2, in kg/ton-km, generation also vary, since more fuel is being used, in other words, for each of the scenarios the model estimates the amount of fuel used during the formation of the route as presented in Table 3.

For scenarios with a number greater than or equal to 25 collection points, it was not possible to obtain results within the established time limit of 7200 seconds, in other words, for larger scenarios the time to obtain solutions is large. Thus, it is confirmed that vehicle routing is a case of network problems considered of high computational complexity, and therefore more difficult to obtain answers in acceptable computational time, as indicated in the investigated literature.

5.2 Results using metaheuristics

Next, a case called base is presented to represent the initial configuration of the parameters that will be the input for the genetic algorithm.

5.2.1 Base case:

A fixed scenario of 100 collection points is considered, where the number of individuals in the initial population and the number of generations vary from 100 to 500. See Table 6 for the average results of the various experiments performed. It is important to note that when the code was run five times, the results were generally the same for the same initial population, causing the result to remain at a minimum level and not to vary no matter how many generations change when the code is run again. In almost all experiments the number of vehicles considered was 12, except in the last two experiments where it was 11; however, the difference is in the distance traveled by the collector vehicles, which vary from 1809.41 km to 2846.43 km.

Table 4 – Location of thirty-one collection points and their demands.

Collection points	Location	Demand to pick up
pc1	(96,44)	19
pc2	(50,5)	21
pc3	(49,8)	6
pc4	(13,7)	19
pc5	(29,89)	7
pc6	(48,30)	12
pc7	(84,39)	16
pc8	(14,24)	6
pc9	(2,39)	16
pc10	(3,82)	8
pc11	(5,10)	14
pc12	(98,52)	21
pc13	(84,25)	16
pc14	(61,59)	3
pc15	(1,65)	22
pc16	(88,51)	18
pc17	(91,2)	19
pc18	(19,32)	1
pc19	(93,3)	24
pc20	(50,93)	8
pc21	(98,14)	12
pc22	(5,42)	4
pc23	(42,9)	8
pc24	(61,62)	24
pc25	(9,97)	24
pc26	(80,55)	2
pc27	(57,69)	20
pc28	(23,15)	15
pc29	(20,70)	2
pc30	(85,60)	14
pc31	(98,5)	9

Table 5 – Results of the optimization model in six scenarios.

Scenarios	Collection points	Time	Tour	Distance	CO2
1	5	0.1	1	134.33	1.26
2	10	3.8	2	249.96	2.36
3	15	108.5	3	310.08	2.93
4	18	927.9	3	361.9	3.41
5	20	4256.5	3	372.21	3.51
6	25	9912	-	-	-

Table 6 – Experiments obtained in the initial configuration with 100 collection points.

Scenario	Number of Individuals	Number of Generations	Time of Processing	Distance total traveled	Emissions of CO2	Qty. from vehicles
100	100	100	7.17	2240.18	21.17	12
		200	**13.46**	**1951.97**	**18.445**	**12**
		300	20.41	2059.43	19.46	12
		400	24.18	2721.63	25.71	12
		500	31.56	2186.37	20.66	12
	200	100	7.16	2033.59	19.21	12
		200	11.79	2628.99	24.84	12
		300	**19.13**	**1879.96**	**17.77**	**12**
		400	**22.96**	**1879.96**	**17.76**	**12**
		500	**34.01**	**1921.53**	**18.16**	**12**
	300	100	5.36	2002.45	18.92	12
		200	**15.27**	**1960.49**	**18.52**	**12**
		300	**21.48**	**1974.26**	**18.40**	**12**
		400	**25.43**	**1918.40**	**18.12**	**12**
		500	**31.66**	**1809.41**	**17.09**	**12**
	400	100	6.01	2279.6	21.54	12
		200	12.35	2103.46	19.88	12
		300	18.75	2232.79	21.09	12
		400	22.99	2503.81	23.66	12
		500	32.13	2072.41	19.58	12
	500	100	**6.1736**	**1954.78**	**18.47**	**12**
		200	9.82	2237.45	21.14	12
		300	16.58	2550.79	24.10	12
		400	**24.79**	**2846.43**	**26.89**	**11**
		500	**30.14**	**2680.10**	**23.14**	**11**

Proceeding in a similar way to that found in Table 6, ten experiments were run in the genetic algorithm considering a scenario of 31 collection points with the same initial population of 100 individuals and 100 generations. Table 7 shows a consolidation of the results obtained for the input parameters with their respective sample standard deviation, mean and variance. The processing time was similar in all runs with a small variance of 0.004 and sample standard deviation of 0.064. In all cases, the results indicated that 4 vehicles are necessary. The distances to be traveled by the vehicles varied between 573.26; 580.99 and 593.48, so there is a variation of 37.28 with a standard deviation of 6.11. These results show that the data are somewhat dispersed from the mean of 580.18, due to the distances between collection points.

Two other case studies are presented below, whose results were obtained through the implementation of the genetic algorithm and local search.

Table 7 – Experiments with 31 collection points using the Genetic Algorithm.

Scenario	Quantity of Individuals	Number of Generations	Time of Processing	Total distance Tour	Number of vehicles
31	100	100	0.46	593.48	4
			0.28	583.60	4
			0.30	580.99	4
			0.45	580.99	4
			0.37	580.99	4
			0.35	580.99	4
			0.33	580.99	4
			0.34	573.26	4
			0.28	573.26	4
			0.40	573.26	4
Sample standard deviation			**0.064**	**6.11**	**0**
Media			**0.36**	**580.18**	**4**
Variance			**0.004**	**37.28**	**0**

5.2.2 Case 3:

Thirty-one collection points obtained from Table 4 were considered as input information, the results of which are discussed below.

(a) **Results with genetic algorithm:**
The Figure 4 and Table 8 shows the solutions obtained with the given proposal, where each of the four vehicles in the process of meeting the demand of the collection points (pc), start their journey from the depot ($d0$). In addition, the distance (kms) between collection points is shown, as well as the fuel used by the collector vehicle and the CO2 emissions (kg/ton-km) generated by them in each section of the constructed route.

In this simulation, an initial population and a number of generations composed of 300 individuals were considered. Finally, the processing time was 1.99 seconds and the total distance traveled was 533.45 km, with total CO2 emissions of 5.04 kg/ton-km.

(b) **Results with local search algorithm:**
The Table 9 shows the solutions found with the implementation of the proposed local search process, where the processing time to find the best path was 0.004 seconds, the number of collector vehicles needed 4 and the distance traveled was 576.18 km., which generate a total of 5.44 kg/ton-km of CO2 emissions. The Figure 5 shows the route taken by the vehicles.

Comparing this result with case (a), it can be seen that there is not much difference in the answers found; this is because both algorithms found a good solution, varying slightly the distance traveled and the processing time, but without significant changes.

Table 8 – Collection at 31 collection points using the Genetic Algorithm.

Origin	Destination	Pickup	Distance	Fuel consumption	CO2
d0	pc30	0	16.28	29.85	0.15
pc30	pc1	14	19.42	29.66	0.18
pc1	pc16	33	10.63	29.56	0.10
pc16	pc14	51	28.16	29.30	0.27
pc14	pc24	54	3.0	29.27	0.03
pc24	pc27	78	8.06	29.19	0.08
pc27	pc20	98	25.0	28.96	0.24
d0	pc26	0	21.10	29.80	0.20
pc26	pc12	2	18.23	29.63	0.17
pc12	pc7	23	19.10	29.45	0.18
pc7	pc13	39	14.0	29.32	0.13
pc13	pc21	55	17.8	29.15	0.17
pc21	pc31	67	9.0	29.06	0.09
pc31	pc19	76	5.39	29.01	0.05
pc19	pc17	100	2.24	28.99	0.02
d0	pc6	0	51.88	29.51	0.49
pc6	pc2	12	26.25	29.26	0.25
pc2	pc3	33	3.16	29.23	0.03
pc3	pc23	39	7.07	29.16	0.07
pc23	pc28	47	19.92	28.98	0.19
pc28	pc4	62	12.81	28.86	0.12
pc4	pc11	81	8.54	28.77	0.08
pc11	pc8	95	16.64	28.62	0.16
pc8	pc18	101	9.43	28.53	0.09
d0	pc5	0	54.57	29.48	0.52
pc5	pc25	7	21.54	29.28	0.20
pc25	pc10	31	16.16	29.13	0.15
pc10	pc29	39	20.81	28.93	0.20
pc29	pc15	41	19.65	28.75	0.19
pc15	pc22	63	23.35	28.53	0.22
pc22	pc9	67	4.24	28.49	0.04

Table 9 – Collection at 31 collection points using Local Search.

Origin	Destination	Pickup	Distance	Fuel consumption	CO2
d0	pc30	0	16.28	29.85	0.15
pc30	pc26	14	7.07	29.78	0.07
pc26	pc16	16	8.94	29.69	0.08
pc16	pc12	34	10.05	29.60	0.09
pc12	pc1	55	8.25	29.52	0.08
pc1	pc7	74	13.00	29.40	0.12
pc7	pc13	90	14.00	29.27	0.13
d0	pc24	0	25.24	29.76	0.24
pc24	pc14	24	3.00	29.73	0.03
pc14	pc27	27	10.77	29.63	0.10
pc27	pc20	47	25.00	29.40	0.24
pc20	pc5	55	21.38	29.19	0.20
pc5	pc29	62	21.02	28.99	0.20
pc29	pc15	64	19.65	28.81	0.19
pc15	pc10	86	17.12	28.65	0.16
pc10	pc25	94	16.16	28.49	0.15
d0	pc6	0	51.88	29.51	0.49
pc6	pc3	12	23.77	29.29	0.22
pc3	pc2	18	3.16	29.25	0.03
pc2	pc23	39	8.94	29.17	0.08
pc23	pc28	47	19.92	28.98	0.19
pc28	pc8	62	12.73	28.86	0.12
pc8	pc18	68	9.43	28.77	0.09
pc18	pc22	69	17.20	28.61	0.16
pc22	pc9	73	4.24	28.57	0.04
pc9	pc11	89	29.15	28.29	0.28
d0	pc21	0	64.03	29.39	0.60
pc21	pc31	12	9.0	29.31	0.09
pc31	pc19	21	5.39	29.26	0.05
pc19	pc17	45	2.24	29.24	0.02
pc17	pc4	64	78.16	28.50	0.74

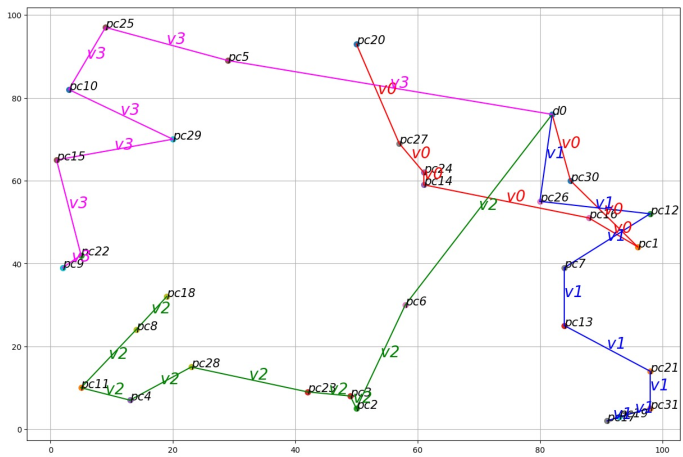

Figure 4 – Traversal of 31 collection points using the Genetic Algorithm.

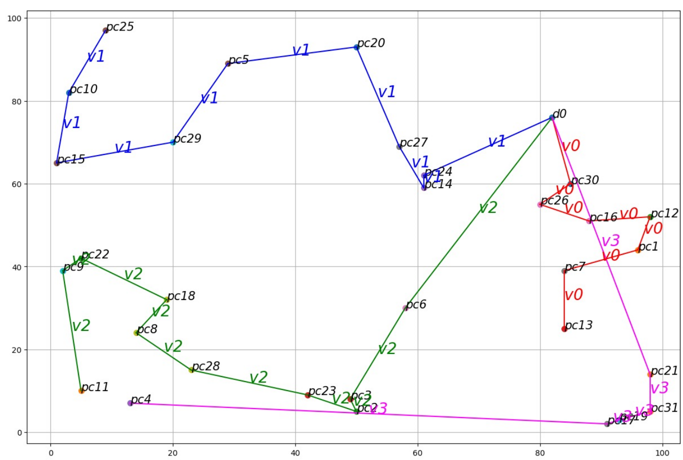

Figure 5 – Traversal of 31 collection points using Local Search.

5.2.3 Case 4:

In this new situation, results obtained according to the proposed implementations of the genetic algorithm and local search are presented, for which 15 scenarios with a number of collection points ranging from 4 to 100 will be considered, as shown in Table 10.

Starting with the Genetic Algorithm, the code runs five times in each scenario, considering the number of individuals in the initial population and the number of generations from 100 to 500, respectively. As the number of collection points with their respective demands increases, the processing time for a good answer in terms of the number of vehicles required, the distance traveled, and the amount of CO_2 emissions also increases. On the other hand, in the Local Search, the code was executed only once to find the desired answer.

Table 10 – Results with the proposed metaheuristics for 15 scenarios.

Scenario	Collection points	Genetic Algorithm						Local Search			
		Individuals	Generations	Time (secs)	Trucks	Distance (km)	CO2 (kg/ton-km)	Time (secs)	Trucks	Distance (km)	CO2 (kg/ton-km)
1	4	100	100	0.06	1	134.35	1.27	0.0006	1	134.35	1.27
2	9	100	100	0.09	2	230.24	2.18	0.0008	2	230.24	2.18
3	14	100	100	0.46	2	326.7	3.09	0.0017	2	494.39	3.36
4	19	100	100	0.32	3	432.61	4.09	0.0020	3	456.34	4.67
5	24	100	100	1.36	4	600.93	5.68	0.0020	4	587.13	4.31
6	29	100	100	2.0	4	587.13	5.54	0.0030	4	576.18	5.54
7	31	300	300	1.99	4	533.45	5.04	0.0300	4	578.29	5.45
8	36	300	300	1.66	4	598.08	5.65	0.004	4	765.85	5.46
9	42	300	300	6.27	6	965.86	9.12	0.004	6	824.77	7.24
10	52	300	300	2.05	7	965.10	9.12	0.004	6	888.62	7.79
11	59	500	500	3.48	8	990.78	9.36	0.005	8	813.20	8.40
12	64	300	300	3.48	8	1082.90	10.23	0.007	8	916.38	7.68
13	68	300	300	3.33	8	1613.90	15.25	0.008	8	916.38	8.65
14	79	400	400	5.76	9	1586.60	14.99	0.013	9	1117.62	10.56
15	100	500	500	6.17	12	1954.78	18.47	0.016	12	1438.10	13.59

In all scenarios Table 10 shows that the processing time employed by the Local Search was faster than the Genetic Algorithm. However, the number of collector vehicles was almost similar in both metaheuristics, except in scenario 10 the Genetic Algorithm returned 1 more vehicle than the other metaheuristic. In both proposals, the difference is in the distance traveled by vehicles and CO2 emissions. As can be seen, there are cases where the Genetic Algorithm returns a smaller distance in the scenarios whose collection points are less than 31 collection points, for scenarios where the distance traveled by vehicles is relatively lower in the Local Search.

In conclusion, both proposals show good results, the difference being in the distance traveled, CO2 emissions and processing time.

5.2.4 Case 5: Actual situation in District Trujillo.

One of the most important regions of Peru is the La Libertad region, which includes the capital city of Trujillo. Due to the region size and population density, waste generation is considerable, and inefficient collection of waste is expensive. According to studies carried out in the District of Trujillo, each residence produces 2.66 kg of waste each day on average. This article offers a different approach in which the District is divided into sectors and waste is collected from the collection points instead of house by house as it is now done. Three areas are illustrated in Figure 6 that have been taken into account to test and validate the idea in real-world scenarios.

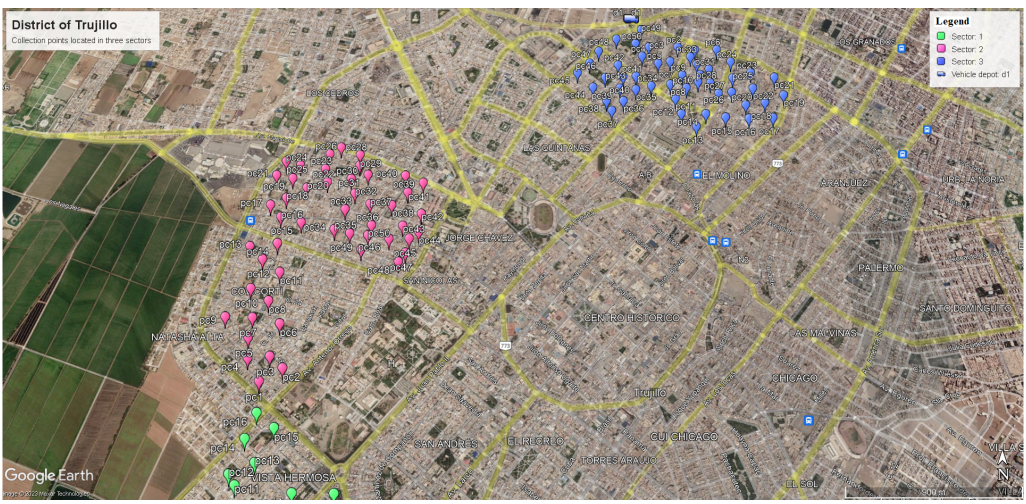

Figure 6 – Sectors of the District of Trujillo with 142 collection points and one deposit.

Table 11 provides details on the three sectors that have been selected as a sample for testing the proposal in actual contexts. For every sector, the table specifies the collection points and collector vehicles that can be utilized for the solid waste collecting process as depicted in Figure 6. The first three sectors are merged to form Sector 4.

Table 11 – Collection points in four sectors of Trujillo.

Información/Sectors	Sector 1	Sector 2	Sector 3	Sector 4
Collection point	42	50	50	142
Collector vehicles	5	5	5	5
Capacity collector vehicles (kgs)	13600	13600	13600	13600
Tank fuel (Gallon)	20	20	20	20

The data in Table 11 was processed using the algorithmic strategies of genetic and local search, and the results were reported in terms of processing time, distance traveled, CO2 emissions, and the required number of collector vehicles. When applied to the sectors under consideration, these sectors will minimize economic costs and also have an ecological impact thanks to the route plan that was created using the research proposals, contributing to decision-making. The local search performed better computationally in terms of the time required to obtain results, route plan generated and the total distance traveled, which caused fewer CO2 emissions and helped protect the environment. To see Tables 12 and 13.

Table 12 – Results obtained using the genetic algorithm.

Results/ Sector	Sector 1	Sector 2	Sector 3	Sector 4
Process time (secs)	1.40043	2.81397	2.08197	31.32175
Distance traveled (kms)	14.43415	13.84597	9.69341	56.24246
Emissions of CO2 (kg/ton-km)	0.00100	0.00096	0.00067	0.00390
Number of used vehicles	1	2	2	4

Table 13 – Results obtained using the local search algorithm.

Results/ Sector	Sector 1	Sector 2	Sector 3	Sector 4
Process time (secs)	0.00628	0.00475	0.00425	0.01678
Distance traveled(kms)	11.35138	11.01886	8.33513	32.10290
Emissions of CO2 (kg/ton-km)	0.00078	0.00076	0.00057	0.00223
Number of used vehicles	1	2	2	4

Route plan generated by the genetic algorithm in sectors 1, 2, 3, and 4.

a) **Sector 1:**
Vehicle 1: d1, pc16, pc15, pc2, pc40, pc39, pc18, pc19, pc5, pc17, pc20, pc22, pc24, pc23, pc25, pc27, pc28, pc37, pc26, pc30, pc38, pc36, pc29, pc33, pc32, pc35, pc34, pc21, pc6, pc8, pc9, pc10, pc14, pc13, pc12, pc11, pc7, pc4, pc1, pc3, pc42, pc41, pc31

b) **Sector 2:**
Vehicle 1: d1, pc41, pc42, pc43, pc48, pc38, pc37, pc32, pc33, pc36, pc45, pc44, pc46, pc34, pc16, pc13, pc18, pc31, pc29, pc27, pc26, pc23, pc22, pc24, pc25, pc17, pc21, pc28, pc30, pc20, pc19, pc9, pc8, pc7, pc5, pc4, pc1, pc3, pc2, pc6, pc10, pc11, pc12, pc14, pc15

Vehicle 2: d1, pc40, pc39, pc47, pc49, pc50, pc35

c) **Sector 3:**
Vehicle 1: d1, pc49, pc3, pc48, pc47, pc45, pc38, pc5, pc7, pc2, pc33, pc31, pc28, pc26, pc10, pc29, pc30, pc9, pc27, pc25, pc24, pc32, pc6, pc1, pc8, pc34, pc41, pc40, pc39, pc46, pc50, pc4, pc11, pc12, pc13, pc14, pc19, pc22, pc18, pc15, pc17, pc16, pc20, pc21, pc23

Vehicle 2: d1, pc42, pc43, pc44, pc37, pc36, pc35

d) **Sector 4:**
Vehicle 1: d1, pc141, pc95, pc142, pc97, pc125, pc83, pc70, pc63, pc59, pc58, pc56, pc54, pc77, pc61, pc65, pc60, pc75, pc71, pc68, pc69, pc91, pc62, pc82, pc81, pc84, pc88, pc78, pc90, pc74, pc72, pc66, pc85, pc87, pc57, pc73, pc79, pc92, pc80, pc86, pc89, pc55, pc53, pc48, pc47

Vehicle 2: d1, pc140, pc133, pc76, pc64, pc67, pc50, pc52, pc42, pc41, pc8, pc9, pc10, pc14, pc13, pc6, pc21, pc26, pc24, pc23, pc27, pc30, pc36, pc37, pc28, pc35, pc29, pc32, pc38, pc25, pc2, pc45, pc46, pc51, pc43, pc11, pc5, pc17, pc39, pc40, pc19, pc18, pc3, pc49, pc44

Vehicle 3: d1, pc96, pc119, pc118, pc111, pc110, pc114, pc112, pc113, pc116, pc122, pc102, pc129, pc130, pc138, pc134, pc106, pc105, pc121, pc107, pc120, pc123, pc117, pc108, pc109, pc115, pc103, pc100, pc101, pc124, pc98, pc93, pc99, pc132, pc131, pc127, pc139, pc135, pc126, pc94, pc128, pc136, pc137, pc104, pc15

Vehicle 4: d1, pc16, pc1, pc12, pc7, pc4, pc20, pc22, pc33, pc34, pc31

In a similar way to the routes generated by the genetic algorithm, the routes obtained by the local search algorithm in the considered sectors are presented below.

a) **Sector 1:**

Vehicle 1: d1, pc16, pc15, pc14, pc13, pc12, pc11, pc10, pc9, pc8, pc6, pc5, pc3, pc2, pc39, pc40, pc17, pc18, pc41, pc42, pc19, pc25, pc20, pc21, pc26, pc22, pc23, pc27, pc24, pc38, pc30, pc36, pc28, pc33, pc37, pc29, pc35, pc34, pc32, pc4, pc1, pc7, pc31

b) **Sector 2:**
Vehicle 1: d1, pc41, pc40, pc39, pc38, pc37, pc32, pc30, pc29, pc28, pc27, pc26, pc23, pc22, pc20, pc19, pc24, pc25, pc21, pc18, pc17, pc16, pc15, pc14, pc12, pc13, pc11, pc8, pc7, pc5, pc4, pc3, pc2, pc1, pc6, pc10, pc9, pc34, pc35, pc50, pc36, pc46, pc43, pc45, pc44

Vehicle 2: d1, pc42, pc47, pc48, pc49, pc33, pc31

c) **Sector 3:**
Vehicle 1: d1, pc49, pc50, pc3, pc4, pc5, pc7, pc9, pc10, pc29, pc30, pc31, pc32, pc33, pc1,

pc2, pc6, pc24, pc25, pc26, pc27, pc28, pc8, pc11, pc12, pc13, pc14, pc15, pc16, pc19, pc18, pc17, pc20, pc21, pc22, pc34, pc35, pc39, pc40, pc41, pc42, pc43, pc44, pc38, pc37

Vehicle 2: d1, pc48, pc47, pc46, pc45, pc36, pc23

d) **Sector 4:**

Vehicle 1: d1, pc141, pc142, pc95, pc96, pc97, pc99, pc101, pc102, pc121, pc122, pc123, pc124, pc125, pc93, pc94, pc98, pc116, pc117, pc118, pc119, pc120, pc100, pc103, pc104, pc105, pc106, pc107, pc108, pc111, pc110, pc109, pc112, pc113, pc114, pc126, pc127, pc131, pc132, pc133, pc134, pc135, pc136, pc130, pc129

Vehicle 2: d1, pc140, pc139, pc138, pc137, pc128, pc83, pc82, pc81, pc80, pc79, pc74, pc72, pc71, pc70, pc60, pc68, pc65, pc64, pc62, pc61, pc66, pc67, pc63, pc60, pc59, pc58, pc57, pc56, pc54, pc55, pc53, pc50, pc49, pc47, pc46, pc45, pc44, pc43, pc16, pc15, pc14, pc13, pc12, pc11

Vehicle 3: d1, pc115, pc84, pc86, pc87, pc89, pc90, pc88, pc85, pc78, pc92, pc91, pc77, pc76, pc75, pc73, pc52, pc51, pc48, pc7, pc1, pc4, pc3, pc2, pc5, pc6, pc8, pc9, pc10, pc42, pc41, pc18, pc17, pc39, pc40, pc19, pc25, pc20, pc21, pc26, pc22, pc23, pc27, pc24, pc38

Vehicle 4: d1, pc30, pc36, pc28, pc33, pc37, pc29, pc35, pc34, pc32, pc31

Figures 7 and 8 show the routing plans developed for the waste collection process in Sector 2 of the City of Trujillo through genetic algorithms and local search. It has been noted that the local search-generated route has shown to be less expensive and, thus, more sustainable, which minimizes the environmental impact of CO2. Sectors 1, 3, and 4 showed similar results, where local search presents better results based on the direction of traffic in the city's streets.

5.3 Use of the proposed meta-heuristics, the difference between these and other approximate strategies

To use optimization methods such as Single-Solution Based Metaheuristics, Population-Based Metaheuristics, Metaheuristics for Multiobjective Optimization, Hybrid Metaheuristics, or Parallel Metaheuristics (Talbi, 2009) is essential to solving NP-Hard problems. These algorithms are effective at exploring the solution space, finding solutions that are close to the optimum while satisfying the constraints of the problem. As a result, they are well-suited for solving complex problems. Population-Based Meta-heuristics such as Genetic Algorithms and Single-Solution Based Metaheuristics such as Local Search have been frequently utilized in the literature to solve complex problems which include the green vehicle routing problem. Both strategies were used in this proposal to enable a comparison of their performance when processing time, distance traveled, CO2 emissions, and the number of vehicles used associated with the route plan generated.

Compared to the Genetic Algorithm, the Local Search produced better results while planning the solid waste collection routes in the city of Trujillo. This result can be attributed to the fact that the Genetic Algorithm improved the solutions with each evolutionary cycle through processes

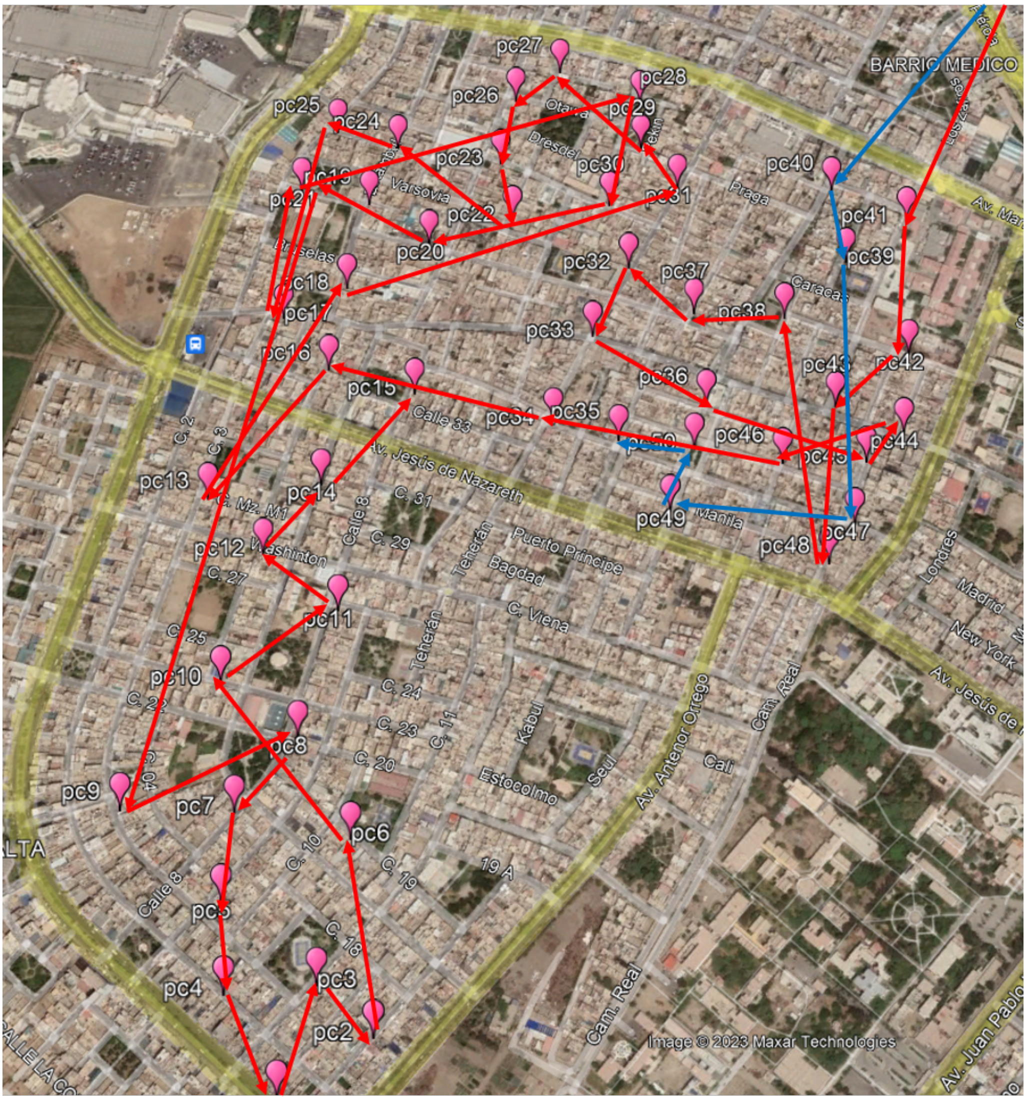

Figure 7 – Green open vehicle routing by Genetic Algorithm for the Sector 2.

including crossover, mutation, and selection, but it was unable to outperform the performance attained by the Local Search.

The difference between the two is that Genetic Algorithms begin the process with a randomly generated initial population of individuals, then subject it to an evolutionary process that is evaluated based on a fitness function, until a set of stopping criteria is satisfied. The best individuals among the population are chosen at the culmination of this process. Local Search, on the other hand, starts with a basic solution and concentrates on refining it iteratively through local improvements until a local optimum is reached, where further improvements are no longer possible. Both

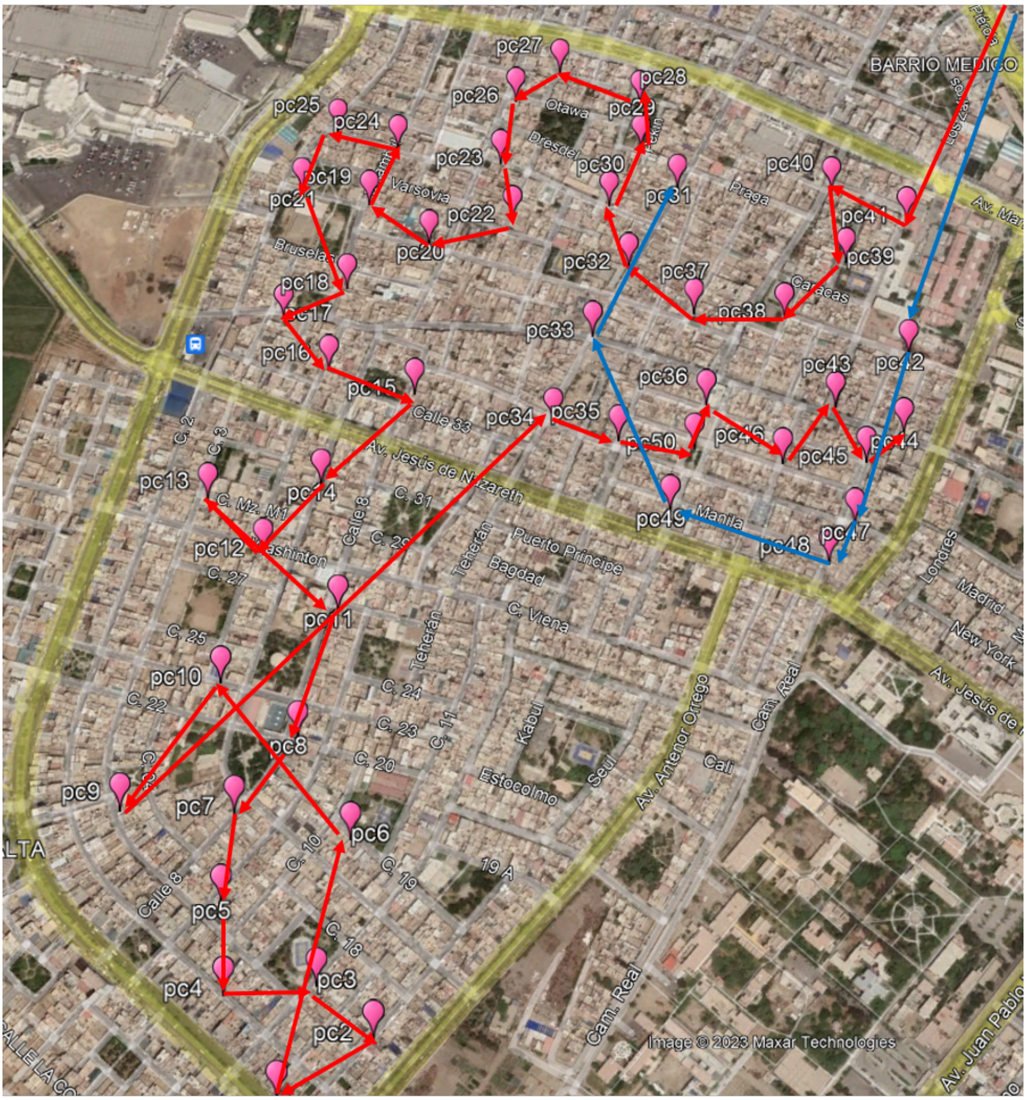

Figure 8 – Green open vehicle routing by Local Search Algorithm for the Sector 2.

approaches were modified and used to address the problem of open green vehicles routing for solid waste collection in urban context.

In general vehicle routing problems, various proposals have emerged in the state of the art. These solutions aim to address the specific constraints and challenges of the problem, with the goal of finding solutions that approach the optimal outcome. Due to the popularity of Genetic Algorithms, there are different variants such as Genetic Algorithm and a Population-based Simulated Annealing (Rezaei et al., 2019), Optimized crossover genetic algorithm (Nazif & Lee, 2012), A Modified Kruskal's Algorithm to Improve Genetic Search (Dutta et al., 2019), Membrane-

Inspired Hybrid Algorithm (Niu et al., 2022). On the other hand, single-solution based metaheuristics such as Simulated annealing that begins with an initial solution and iteratively modifies the current solution within the search space by evaluating the objective function (Vincent et al., 2017); the Tabu search that uses a Tabu list to keep track of visited solutions to avoid revisiting previously explored solutions and encourages the exploration of new solutions (Goeke, 2019); Large neighborhood search (Schiffer & Walther, 2018) that starts with an initial solution, it then iteratively modifies a portion of the solution, expanding the search space to explore new solutions and avoid staying in a nearby neighboring space to escape from local optima. Finally, there are other strategies based on swarm intelligence that are based on the collective behavior of individuals or particles that share information following rules in the search of solutions close to the optimum, for example, the Bee Colony Optimization (Zarzycki & Skubisz, 2022), the Ant colony optimization (Li et al., 2019; Jabir et al., 2017).

6 CONCLUSIONS

The article shows a new model of bi-objective mixed integer linear programming and metaheuristics based on green open vehicle routing in the urban context. The operational activity of routing applied to reverse logistics consisted of collecting solid waste from the collection points through the proposed optimized distances, which contribute to the non-generation of excess CO2 in the routing process, since the fuel consumption of the vehicle would not be in excess, in other words, its implementation contributes to the protection of the environment in the urban areas.

The proposals are based on the estimated premise of a certain amount of solid waste generated at home and stored in collection points by individuals. This premise reduces costs, so the proposals when executed determine a route plan as shown in the tests performed. Therefore, the use of a fleet of collector vehicles traveling on the best routes generated is also reduced.

The results in the cases presented show the potential aspect of the proposals. The model finds optimal results quickly for scenarios between 5 and 25 collection points, but not in scenarios with a lot of data within the time limit of 7200 seconds. This limitation is solved through the use of the genetic algorithm and local search, which find good solutions, since for example for cases with 31 collection points the processing time was 0.06 (Genetic Algorithm) and 0.006 (Local Search) seconds, respectively. This indication is favorable for testing larger scenarios, as 100 collection points, since the time limit is far from being reached with the metaheuristics, as shown in an application for the City of Trujillo, Peru.

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