Bi-objective routing model with speed variation and consideration of emissions: Case study of solid waste collection in Coveñas, Sucre

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Abstract. Models for routing vehicles have been applied to solve a variety of transport route design problems. Also, it has taken an important trend on environmental care in consideration of the negative environmental impact generated by the emissions resulting from transportation. Another relevant aspect of environment care is the collection of solid wastes due to the high quantities generated by human activities. In this paper, we developed a bi-objective model for routing vehicles for solid waste collection that considers the minimization of costs associated with both vehicles and CO₂ emissions. The model considers heterogeneous fleet, capacity, hard time windows, and speed variation in an urban center. A case study in the Caribbean region of Colombia is studied, with a total of 50 nodes in the network. Because of the computational hardness, nodes are clustered in five sets of 10 nodes to obtain optimal solutions. The sum of costs showed a reduction of 9.447% compared to current costs (50 nodes without clustering). Subsequently, we reviewed and restructured some constraints that allowed to soften the complexity of the model and obtain improved solutions with reduced current costs by 16.55%.

1. Introduction
Nowadays, organizations need to make their processes more efficient to generate competitive advantages and improve their organizational logistics. For this purpose, the process of transportation is considered one of the most important in the supply chains in terms of reducing costs, distances, times, among other factors, when delivering goods [1].

The vehicle routing problem (VRP) is a well-known optimization problem dealing with decision-making at the operational level of the supply chain, usually employed for goods pick-up and delivery [2],[3]. This routing process may consider one or more stages of the transportation system, however, this type of operational planning generally includes only one level and must be carried out on a daily schedule [5], for which VRP has been highly efficient since its introduction by [6]. In this way, VRP translates into a model for organizations to minimize transportation costs, which can be between 20% and 55% of total logistics costs [7], [8].

The routing problem consists of assigning routes to satisfy customer demand in a given area starting from a depot and returning to it at the end of the route [9]. This model allows simulating real contexts [10], [11] presenting a large number of variants and restrictions, making it computationally complex. Indeed, the simplest version of the VRP is known to be NP-complete [12]. Among the variants addressed
in the VRP are simultaneous pickups and deliveries [13], [14], time window [15], [16], multiple depots [17], capacity constraints [18], as well as variants considering the car of the environment [19]–[21].

In addition, the inclusion of vehicle speeds on the routing process is paramount since travel times depend on this magnitude. This is directly linked to fuel consumption and carbon emissions [22]. Also, speed is one of the main variables that specify the amount of energy a vehicle consumes while performing a job, in addition to load and distance traveled [23],[21],[24].

On another note, one of the relevant practical variants of the VRP is the solid waste collection problem [4]. Indeed, this type of problem has taken on greater relevance in response to the gradual increase in the generation of solid waste in terms of volume and composition, and which is linked to the growth in population. Hence, managing solid wastes is a problem that demands the attention of all countries and regions of the world, because it generates a direct impact that influences both public health and the environment [25]. To approach this problem, the academic community has formalized the so-called Waste Collection Vehicle Routing Problem (WCVRP). One of the first works is presented in [26], where the objective is the efficient collection of waste [27].

Several works associated with the solid waste collection have been developed by applying theoretical instances. In [28] develop a modified particle swarm optimization (PSO) algorithm to solve a capacitated vehicle routing problem. The routing is programmed for a week of collection. In [29] an improved non-dominated sorting genetic algorithm with direct local search (NSGA-dLS) is applied to solve a two-echelon multi-objective location routing problem (2E-MOLRP). Theoretical instances were developed due to the lack of publication of solid waste collection data that present the developed variants.

However, this type of problem presents more practice in real situations. In [30] a model of solid waste collection that considers container selection is developed as an inventory routing problem. The model is solved through a heuristic method for real instances of a company located in the Netherlands, generating cost savings of up to 40%. In [31] apply a two-stage method for solving a solid waste collection problem based on an assembly coverage problem and a VRP with split deliveries. The model is applied to the waste collection process in Kaohsiung City in Taiwan. In [32] apply an improvement approach to solve a problem that presents the combination of shift scheduling and generation of routes for waste collection. Moreover, in [33] a greedy randomized adaptive search procedure (GRASP) is applied to solve an eco-efficient routing model for waste collection on the island of La Palma, Spain.

In [34] the ORD software and dynamic programming are used for the construction of selective routes for the collection of recyclable elements in Río de Janeiro with reductions of 27.72% in costs. Regarding scenarios under uncertainty, in [35] propose a model for the waste collection under uncertainty in a logistic network of three steps. The uncertain parameter corresponds to recyclable, biodegradable, and hazardous waste in southern Tehran, Iran, and is solved by the CPLEX solver. Finally, in [36] apply artificial intelligence in the development of an application that allows the identification of points and the construction of routes for the waste collection of electronic equipment in a city of Poland.

In this paper, we intend to show a bi-objective vehicle routing model with a heterogeneous fleet, capacity, hard time windows, and speed interval variation. The case of solid waste collection in the municipality of Coveñas, Colombia, is taken as a case study. In particular, the objectives presented by the model are: (i) minimization of the costs linked with the use of the vehicle in terms of distance traveled, and (ii) minimization of CO$_2$ emissions in terms of the fuel consumed during the collection process.

In addition to the above works, our model is also applied to a real case study. Likewise, CO$_2$ emissions are considered, which are less studied in this type of problem. On the other hand, our model applies the speed calculation for urban spaces considering that the processes of solid waste collection are carried out in this type of area worldwide. Finally, because this problem is NP-complete [37], we demonstrate the sensitivity in the constraint construction, which can make the model more complex or softer in terms of the number of nodes to be solved with exact methods.

The remainder of this document is organized as follows. Section 2 corresponds to the conceptual and mathematical development of the model. The computational results are summarized in Section 3. Finally, the conclusions are shown in Section 4.
2. Mathematical model

Formally speaking, the problem is modeled on a directed graph \( G = (N, A, D, T, O, S) \), where \( N \) represents the set of nodes, being \( N_o = \{n_1, n_2, n_3, \ldots, n_n\} \) customers and \( N_a = \{0\} \) is the depot \( N = N_o \cup N_a \). \( A \) is the set of arcs, the matrices of distance between nodes and time between nodes travelled at speed \( r \) are represented by \( D = [d_{ij}] \) and finally, \( T = [T_{ij}] \). Also, \( O \) corresponds to the collection vector in each \( i \) node \( [d_i] \) and finally, \( S \) is the service time vector \( [S_r] \). The fleet of vehicles \( k \) is heterogeneous \( K = \{1, 2, 3, \ldots, k\} \), with limited capacity \( Q_k \), which must perform service in a hard time window \( [a_i, b_i] \). Each edge \((i, j) \in A\) where \( i, j \in N \) and \( i \neq j \), and is linked to a travel time \( T_{ij} \) that is calculated through the Equation (1):

\[
T_{ij} = \frac{d_{ij}}{V_{ij}} 
\]  

(1)

Each vehicle can travel the arc \((i, j)\) at a speed \( V_{ij} \) which is calculated according to the speed equation for urban spaces adapted by [23], as shown in Equation (2):  

\[
V_{ij} = l_r + \frac{dc_i + dc_j}{2R}(u_r - l_r)
\]  

(2)

A set of speeds \( r \) is considered, in addition to the speed limitation on each arc \((i, j)\), where \( l_r \) is the minimum speed, and \( u_r \) is the maximum speed the vehicle can travel. We also have that \( dc_i \) is the distance from the node \( i \) to the center of the city and finally, \( R \) is considered the radius of the city.

Considering the environmental implications generated by land transport activities, we decided to work with an objective-based on minimizing fuel consumption by referencing works such as [20]. An objective function of fuel consumption based on mechanistic consumption models is proposed [38]. This model is based on the use of Equation (3):

\[
W = F \ast C
\]  

(3)

Where \( C \) represents the distance, and \( F \) is the set of the four forces acting on the vehicle (the aerodynamic force \( f_{z1} \), the rolling force \( f_{z2} \), the slope force \( f_{z3} \), and the inertia force \( f_{z4} \)) [39]; these forces are calculated as expressed in [40] and [41] obtaining a general equation for the calculation of the work, as shown in Equation (4):

\[
W = \left[ jCaRAeV_{ij}^2 + m \left( C \cos \theta + \sin \theta \right) g + a \left( u + \frac{n}{r_t^2} \right) \right] C
\]  

(4)

Forces \( f_{z2}, f_{z3} \), and \( f_{z4} \), according to [20], are calculated from the distance traveled and the weight of the vehicle in the arc \((i, j)\) (full and empty), so two equations are obtained. Equation (5) considers the weight of the empty vehicle, called "tare"[19], while Equation (6) calculates from the vehicle’s load.

\[
\left( \sin \theta_j + Cr \cos \theta_j \right) g + a_k \left( u + \frac{n}{r_t^2} \right) d_{ij} tare_k
\]  

(5)

\[
\left( \sin \theta_j + Cr \cos \theta_j \right) g + a_k \left( u + \frac{n}{rpt_k^2} \right) d_{ij} \text{Load}_k
\]  

(6)
For the inertia force \( f_{z_i} \), which specifically considers vehicle parameters, it can be calculated by the travel speed \( V_{ijr} \), the drag coefficient \( C_{a} \), the frontal area of the vehicle \( A_{k} \), and the air density \( R \), as presented in Equation (7).

\[
  f_{z_i} = jC_{a}Rd_{ij}V_{ijr}^{2}
\]

The cost of fuel \( cf \) is considered in liters, so the Equation (8) used to calculate the cost of emissions is applied according to \([42]\).

\[
  e = \sum_{j=1}^{n}(\text{Spent fuel} * \text{Emission factor} * \text{Oxidized fraction} * \frac{44}{12})
\]

Therefore, the cost of emissions \( ce \), considering an oxidized fraction of 0.99 \([43]\), takes a value of 8.28 \([41]\). Then we have that the costs of CO\(_2\) emissions are obtained by the sum of \((cf + ce)\).

**Index and sets:**

- \( i = j = h \): Index of clients or companies
- \( k \): Vehicle index
- \( r \): Speed index
- \( N_{n} \): Set of customers \( \{1, 2, 3, \ldots, n\} \)
- \( N_{0} \): Deposit \( \{0\} \)
- \( N \): Set of customers and the deposit \( N = N_{0} \cup N_{n} \)
- \( K \): Vehicle fleet \( \{1, 2, 3 \ldots k\} \)
- \( R \): Speeds \( \{1, 2, 3 \ldots r\} \)

**Parameters:**

- \( Q_{k} \): Vehicle capacity \( k \in K \)
- \( C_{f_{k}} \): Fixed cost per use of the vehicle \( k \in K \)
- \( C_{v_{k}} \): Variable cost per use of the vehicle \( k \in K \)
- \( d_{ij} \): Distance between nodes \( i \in N, j \in N \)
- \( d_{i} \): Offer to collect from customers \( i \in N_{n} \)
- \( a_{i} \): Earliest time of arrival to the customer \( i \in N_{n} \)
- \( b_{i} \): Late arrival time at the customer \( i \in N_{n} \)
- \( S_{i} \): Time of collection \( i \in N_{n} \)
- \( M \): Very large number to avoid negativity and customer-to-customer point selection
- \( d_{c_{i}} \): Distance from point \( i \) to city center \( i \in N \)
- \( l_{r} \): Minimum speed \( r \in R \)
- \( u_{r} \): Maximum speed \( r \in R \)
- \( V_{ijr} \): Speed \( r \) in arc \((i, j)\) \( i \in N, j \in N_{n}, r \in R \)
- \( T_{ijr} \): Travel time in the arc \((i, j)\) at speed \( r i \in N, j \in N_{n}, r \in R \)
- \( R \): Radius of region or area

**Variables:**
2.1. Formulation of the mixed integer linear programming model

The bi-objective model considers the minimization of costs by vehicle allocation and variable costs in terms of distance traveled, in addition to the costs of fuel consumption.

**Bi-objective function:**

$$
\text{Min } Z = \alpha \left( \sum_{i \in N_0} \sum_{j \in N_n} \sum_{k \in K} C_f X_{ijk} + \sum_{i,j \in N \setminus k} \sum_{j \in N} \sum_{k \in K} (C_v d_{ij}) X_{ijk} \right) + \beta \left( \sum_{i,j \in N \setminus k} \sum_{j \in N} \sum_{k \in K} (c_f + c_e) \delta_{ijk} d_{ij} \text{tare}_k X_{ijk} + \sum_{i,j \in N \setminus k} \sum_{j \in N} \sum_{k \in K} (c_f + c_e) \delta_{ijk} d_{ij} \text{Load}_k + \sum_{i,j \in N \setminus k} \sum_{j \in N} \sum_{k \in K} (c_f + c_e) \text{CaRA}_k V_{ijr}^2 d_{ij} X_{ijk} \right)
$$

**Constraints:**

$$
\sum_{j \in N \setminus k} \sum_{k \in K} X_{ijk} = 1; \quad \forall i \in N_n
$$

(10)

$$
\sum_{j \in N \setminus k} X_{ijk} \leq 1; \quad \forall k \in K
$$

(11)

$$
\sum_{i \in N \setminus h} X_{ihk} = \sum_{j \in N \setminus h} X_{hjk}; \quad \forall k \in K, \forall h \in N
$$

(12)

$$
T_j \geq \sum_{r \in R} T_{0jr}^* Z_{jr} + S(j) - M \ast \left( 1 - X_{0jk} \right); \quad \forall i \in N, \forall j \in N_n, \forall k \in K
$$

(13)

$$
T_j \geq T_i + \sum_{r \in R} T_{ijr}^* Z_{jr} + S(i) - M \ast \left( 1 - X_{ijk} \right); \quad \forall i \in N, \forall j \in N_n, \forall k \in K
$$

(14)

$$
a_i \leq T_i \leq b_i; \quad \forall i \in N_n
$$

(15)

$$
\text{Load}_d + d_j - \text{Load}_j \leq M \ast \left( 1 - X_{ijk} \right); \quad \forall i \in N, \forall j \in N_n, i \neq j, \forall k \in K
$$

(16)

$$
\text{Load}_d + d_j - \text{Load}_j \geq -M \ast \left( 1 - X_{ijk} \right); \quad \forall i \in N, \forall j \in N_n, i \neq j, \forall k \in K
$$

(17)

$$
\text{Load}_d \leq Q_k X_{ijk}; \quad \forall j \in N_n, \forall k \in K
$$

(18)

$$
\text{Load}_d \leq 0; \quad \forall i \in N_0, \forall k \in K
$$

(19)

$$
\sum_{r \in R} Z_{ijr} = f_{ij}; \quad \forall i, j \in N
$$

(20)
The bi-objective function (9) minimizes vehicle usage and fuel consumption costs. Constraints (10) ensure that each customer is visited exactly once by a vehicle. Constraints (11) ensure that vehicles must leave the deposit. Constraints (12) ensure the flow of the network. Constraints (13) and (14) establish the time of arrival at each customer. Constraints (15) corresponds to the hard time windows. Constraints (16) and (17) ensure that pick-ups are met at each node. Vehicle capacity is restricted by Constraints (18). Constraints (19) ensure that, upon return to the depot, the vehicle must unload everything. These Constraints (16) and (17) are derived from the non-linear equation worked by [44], as shown in Equation (25), which ensures that a load is made on each node giving values to the variable, and also avoids the subtours in the routing:

\[
\sum_{i \in N} \sum_{j \in k} X_{ijk} (\text{Load}_{ik} + d_j - \text{Load}_{jk}) = 0; \quad \forall j \in N
\]  

Constraints (20) and (21) are equality artifices that assign the range of speeds and vehicle usage to the arcs made on the route. Constraints (22), (23), and (24) establish the nature of the decision variables.

### 3. Computational results

#### 3.1. Data collection

The model was coded in GAMS (General Algebraic Model System) software and run on a computer with the following features: Windows 64-bit operating system, 4 GB RAM with 1 TB HDD, and processor Intel Core i7-5500 CPU@ 2.40 GHz. The model was evaluated with the data obtained in the characterization of the solid waste collection process in the municipality of Coveñas, Colombia. The data collection was done through the on-site monitoring of the current waste collection route by the company responsible for this process. Details of the coordinates of the points were recorded using a Garmin GPSMAP 64s; also, the service time and arrival and departure times at each point were registered. The average amount of waste was identified through data reported in the Plan for the Integral Management of Solid Wastes - (by its Spanish acronym PGIRS) of the municipality of the Coveñas - Department of Sucre [45].

A total of 49 waste collection points was identified along the current route. The vehicle starts the route from the landfill located in the municipality of Sincelejo, Sucre, and returns to it at the end of the tour. This process begins at 5:00 a.m., ends at approximately 12:00 a.m., and is performed by a vehicle with a capacity of 13 tons. The route presents 176.5 kilometers characterized by restrictions on vehicle speeds according to the tourist or urban area. These points are depicted in Figure 1.

Due to the computational complexity of the problem, it was not possible to work initially with the set of 50 nodes (49 collection points and the landfill). Therefore, a zoning is made based on the geographic conditions of the municipality. The total set of nodes was clustered into five zones, each one containing ten nodes; the initial node of a zone routing was the final node of the precedent zone, as shown in Figure 1. Additionally, we divide and allocate the fixed routing costs for each zone considering the cost of toll and of transporters.
3.2. Results by zones

The zones include a total of 10 nodes each. In the first zone, the landfill is included, and three-speed ranges are established considering that the landfill is in a different city. For zones 2, 3, 4, and 5, two ranges of speeds were enabled according to those allowed in the urban center. Variable costs were calculated in terms of tire wear and oil consumption per kilometer traveled. In the third and fifth zones, the additional fixed cost is increased because these contain the location of tolls. The results of the zone are shown in Table 1.

Table 1. Results obtained by zones.

| Zone | Fixed costs (COP) | Variable costs (COP/km) | Speeds (km/hr) | Total route costs (COP) | Fuel consumption (Lt) |
|------|------------------|-------------------------|----------------|------------------------|----------------------|
| 1    | 28.333,4         | 109,18                  | $r_1 : [u_1 = 40, \ t_1 = 80]$ | 125.608,5             | 38,97                |
|      |                  |                         | $r_2 : [u_2 = 10, \ t_2 = 30]$ |                       |                      |
|      |                  |                         | $r_3 : [u_3 = 20, \ t_3 = 40]$ |                       |                      |
| 2    | 28.333,4         | 109,18                  | 125.608,5             | 38,97                |
| 3    | 64.533,4         | 109,18                  | $r_1 : [u_1 = 40, \ t_1 = 80]$ | 84.094,4             | 8,8                  |
| 4    | 28.333,4         | 109,18                  | $r_2 : [u_2 = 10, \ t_2 = 30]$ | 48.976,4             | 9,37                |
| 5    | 64.533,4         | 109,18                  | $r_3 : [u_3 = 20, \ t_3 = 40]$ | 89.289              | 11,34               |

As a cumulative result, we added all the costs to obtain the total cost of routing in the municipality (COP 401.333,3). We note that, despite the division of routes, the cost is still 9.45 % lower than the current total cost of COP 443.206,5. The total fuel consumption calculated by the model is 79.22 Lt or
20.92 gallons. This, compared to the current consumption of 22 gallons, shows a difference of 1.08 gallons saved.

3.3. Constrains Analysis
Additionally, we performed an analysis of the constraints of the model due to the complexity of working with larger instances. We review other ways to build constraints to obtain the same functionality. We verified the constraints (16), (17), (18), and (19) that ensure the collection scheme and proposed the construction of the following constraints that fulfill the same function.

\[ \sum_{i \in N_n} \sum_{j \in N_n} \sum_{k \in K} Load_{jk} - \sum_{i \in N_n} \sum_{j \in N_n} \sum_{k \in K} Load_{jk} = d_j; \forall j \in N_n \]  \hspace{1cm} (26)

\[ Load_{jk} \leq Q_{ik} \cdot X_{ij}; \forall i \in N_0, \forall j \in N_n, \forall k \in K \]  \hspace{1cm} (27)

\[ Load_{jk} \leq MX_{ik}; \forall i \in N_n, \forall j \in N_n, \forall k \in K \]  \hspace{1cm} (28)

\[ Load_{jk} = 0; \forall i \in N_n, \forall j \in N_0, \forall k \in K \]  \hspace{1cm} (29)

For this proposition, the variable \( Load_{jk} \) changes to \( Load_{jk} \) assuming the amount of waste collected in the arc \( ij \) with vehicle \( k \). Constraint (26) ensures the collection of the amounts offered by each customer. Constrains (27) ensure that the capacity of the vehicle is not exceeded. Constrains (28) state that if a node is visited, a quantity must be loaded. Finally, Constrains (29) ensure that not everything is discharged into the depot.

3.4. Comparing results
For the new model, Constrains (26), (27), (28), and (29) replace Constrains (16), (17), (18), and (19), and the variable \( Load_{jk} \) replaces \( Load_{jk} \). With this new building, it is possible to obtain model solutions for the 50 nodes corresponding to the solid waste collection in Coveñas, Sucre, without the need to make zoning. We obtained four solutions with a gap below 10%, of which \( \alpha = 0.6 \) and \( \beta = 0.4 \) correspond to the lowest cost ($\text{COP} \ 369.860$ with a gap of 9.98%). The total consumption was 18.7 gallons of fuel. This shows a 16.55% reduction in the current cost and a 15% reduction in the fuel consumed. Likewise, the percentage of reduction concerning the first model solution is 8.09% and 10.61% of the cost and fuel consumption, respectively.

4. Conclusions
In this paper, a bi-objective mixed-integer programming model was designed to provide decision-making for vehicle routing in the process of solid waste collection in urban centers. The model considers the variants of the heterogeneous fleet, capacity limits, hard time windows, and the implementation of speed ranges that allow calculating the optimal speed of travel within the city. The model aims at minimizing fixed and variable costs by vehicle assignment and distance traveled, as well as the costs for fuel consumption and equivalent CO\(_2\) emissions, thus generating an environmentally friendly. Tests were carried out with real data on the solid waste collection in the municipality of Coveñas, Colombia, a coastal area dedicated to the sun and beach tourism.

Due to the complexity of the problem, it was initially not possible to generate solutions for the municipality’s data set, so zoning was carried out based on the geography of the site. A total of five zones was constituted with 10 nodes each. The costs associated with the routing of each zone were obtained. The accumulated sum of the costs per zone determined the total cost of waste collection.

Total routing costs were $\text{COP} \ 401.333.3$, representing savings of 9.447% compared to the current cost. This daily savings of $\text{COP} \ 41.873.2$ can be translated into an annual savings of $\text{COP} \ 12.059.481.6$. Additionally, fuel savings were estimated at 1,077 gallons. After modifying some constraints in the model to reduce the computational complexity, numerical results generated lower routing costs ($\text{COP} \ 369.860$), which means a decrease of 16.55% over the current operational cost. That is, a reduction of 8.09% over the solution of the first model. Likewise, fuel consumption was reduced by 15% of the current value. This represents a daily saving of $\text{COP} \ 73.346.5$. 

\[ \text{doi:10.1088/1757-899X/1154/1/012007} \]
In regards of future research opportunities, it is necessary to develop heuristic or metaheuristic algorithms that allow obtaining good solutions in low computational times. On the modeling approach, the waste collection problem can also be approached as an Open Vehicle Routing Problem (OVRP), where collecting vehicles do not leave from or finish the route at the same landfill.

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