

Article

A Mathematical Model for Scheduling and Assignment of Customers in Hospital Waste Collection Routes

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Abstract: The collection, transport, and final disposal of hospital waste may cause contamination and disease if improperly handled. Therefore, such residues are hazardous to the health of waste collectors. These wastes are generated by public agencies, such as hospitals, family health centers, dialysis centers, and private healthcare providers. In this study, a mixed-integer linear programming model is proposed for monthly customer scheduling and route assignment. The proposed approach was fulfilled according to customers' collection frequency, truck capacity, and customer geographical location. The proposed mathematical model successfully balanced the number of customers and the workload during each day. The effectiveness of the proposed model was tested on data obtained from a waste collection company. The model has been implemented in AMPL language, and the performance of commercial solvers, GUROBI and CPLEX, to obtain an optimal solution were tested. The results show the efficiency of the proposed approach to balance the workload concerning previous scheduling is done ad hoc at the company. The use of the formulated model provides an automatic procedure that was previously performed manually. The methodology can be adapted to other companies with similar requirements.

Keywords: mixed-integer linear programming model; hospital waste collection; geographic clustering; customers scheduling; customers frequency



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1. Introduction

Because of difficulties or limitations in assigning resources, including machines, facilities, staff, or inputs, one of the leading problems facing any company's operations management, whether in manufacturing or services, is customer-proposed scheduling work activities. Such problems are difficult to solve and have been the subject of several research studies. Many experts have proposed solutions, ranging from heuristics and meta-heuristics approaches to the application of precisely defined rules. Both manual techniques and specialized software programs have been employed by Ballesteros Silva and Duque Vanegas [1].

The problem of Hospital Waste Collection (HWC) includes dividing customers into specific groups (clusters), scheduling visits within a particular time frame, and searching for efficient routes for visiting customers. From a theoretical standpoint, the HWC problem involves interdependent vehicle clustering, planning, and routing sub-problems with specific complexities imposed by constraints. The classical models in the literature overlook such issues as described by De la Peña et al. [2].

The HWC problem involves a set of customers to whom a waste collection service is provided. The problem consists of a subset of Hospital Waste (corresponding to special waste), which requires scheduling of customers and vehicle assignment, with a predefined frequency of visit. In particular, for the HWC problem, not visiting customers at the given frequency and time implies economic losses for the service provider. The suppliers has

publicly awarded contracts through tenders, and non-compliance is punishable by waste management laws. As a variant of the vehicle routing problem (VRP), the HWC problem is considered a non-deterministic polynomial-time hard (NP-Hard) problem. No exact algorithms with short solution times that can solve real-life instances with a large number of customers are known.

In this study, a mixed-integer linear programming (MILP) model is proposed that solves the scheduling of customers and collection vehicle assignment for HWC. The model was programmed in A Mathematical Programming Language (AMPL) and solved using the GUROBI 9.0 and CPLEX 12.10 solvers. To validate the effectiveness of the method, data from a Chilean company that provides these services and a subsidiary of an international holding company was used. The results show the proposed method's efficiency in support of decision making. The company's business collects and temporarily stores pollution and disease-causing Hospital Waste generated by hospitals, family health centers, dialysis centers, first-aid rooms, and private healthcare providers in Chile. Most of its customers are public bodies. Thus, their Hospital Waste removal and final disposal operations are regulated by the Chilean Ministry of Health.

The main contribution of this paper is the mathematical structure of the proposed model. This structure allows balancing the number of customers and the workload during each day. The model has been tested in a real case of a waste collection company. Under this context, this strategy is expected to bring the theory closer to the current reality by analyzing a productive system sector capturing this environment's aspects. The proposed model is generic and could be adapted to other companies with similar requirements.

State of the art concerning problems related to collecting hazardous materials and solid waste is presented in Section 2. The method proposed to address the problem is performed in Section 3, whereas the computational results are shown in Section 4. Lastly, Section 5 includes conclusions and future perspectives.

2. State of the Art

Because of its potential environmental and public health risks, Hospital Waste Management is a significant problem. Operators must collect medical waste and control its recovery or disposal. The recovery of medical waste includes the reuse, remanufacturing, and recycling of materials and requires a specially structured reverse logistics network to collect such products efficiently. In Shi [3], a mixed-integer linear programming model is proposed for recoverable Hospital Waste Management. The efficiency of the model is validated in a real-life case study involving medical waste returned by hospitals to the manufacturer of the products.

Shih [4] analyzes the infectious medical waste collection problem. The problem is expressed as the well-known periodic vehicle routing problem. The problem is solved with a two-phase matheuristic algorithm. In the first phase, the standard vehicle routing problem is solved. Conversely, in the second phase, a mixed-integer linear programming model assigns routes to particular days of each week. A stochastic version of the problem is analyzed by Nolz et al. [5]. In this study, the problem is modeled as a particular case of the routing and inventory problem with waste management. In the process of optimization and planning for a defined time frame, identification by radio-frequency technology is considered. Two similar solution strategies are proposed. Horvat et al. [6] present a binary programming model to support the decision-making process, addressing workforce programming in health care organizations. Therefore, the irrational allocation of resources can have various negative impacts on the financial outcome, the quality of medical services, and both patients' and employees' satisfaction.

The Hospital Waste Collection problem is included in the general Routing of Waste Collection (RWC) problem. Several articles have analyzed the RWC problem. Several articles have analyzed the RWC problem. In Ghose et al. [7], a mathematical model is proposed to determine the minimum distance when transporting solid waste to landfills. The model uses data on population density, solid-waste generation capacity, vehicle types,

and container and collection vehicle types. In Dotoli et al. [8], an algorithm is proposed to solve the vehicle routing problem and to program the collection of hazardous waste. The proposed method enables us to limit the distance traveled by trucks and their emissions. Additionally, the proposed approach allows us to assess the possibility of future investment in fleet acquisition. In Zhao et al., [9], the network design problem of hazardous waste management is analyzed. The problem is solved using a mathematical model of multi-objective mixed-integer linear programming.

Algorithms considering multiple objectives for the waste collection problem have been proposed by several authors. In Nolz et al. [10], the authors consider the design of a collection system for infectious medical waste. A multi-objective stochastic waste collection problem is formulated considering two conflicting objective functions. Social objectives, specifically the satisfaction of pharmacists and local authorities involved in the collection process and the minimization of public health risks, need to be traded off against distribution costs comprising routing costs and fixed costs incurred each time a tour is planned. Heuristic approaches have been proposed to solve the considered problem.

Rabbani et al. [11] address a new industrial hazardous waste location-routing problem by emphasizing some new aspects in its formulation, such as considering constraints about the incompatibility between some kinds of wastes and incorporating routing decisions into the model. Simultaneous minimization of three significant criterion takes place, including total cost, total transportation risk of hazardous waste related to population exposure, and site risk.

A multi-objective location-routing model is developed by Samanlioglu [12]. The proposed approach has been tested in the Marmara region of Turkey. The model aims to help decision-makers decide on treatment centers' locations utilizing different technologies, routing different types of industrial hazardous wastes to compatible treatment centers, locations of recycling centers and routing hazardous waste and waste residues to those centers, and locations of disposal centers and routing waste residues there. Three criteria are considered: minimizing the total cost, minimizing total transportation risk related to the population exposure, and minimizing total risk for the population around treatment and disposal centers. A similar approach is introduced by Alumur and Kara [13]. The proposed model aims to open treatment centers and their technologies, open disposal centers and the different route types of hazardous waste to which of the compatible treatment technologies, and route waste residues to disposal centers. Large-scale implementation of the model in the Central Anatolian region of Turkey is presented.

In Yilmaz et al. [14], a multi-objective mixed integer location/routing model aiming to minimize transportation costs and risks for large-scale hazardous waste management systems is proposed. A Pareto optimal curve for two conflicting objectives is proposed as a solution scheme. The suggested model was used in a case study targeting HWMS in Turkey. A bi-objective obnoxious facility location problem that deals with the existing tradeoff between a low-cost operating network and the negative effect on the population living near the waste management facilities are introduced by Medaglia et al. [15]—a hybrid approach combining a multi-objective evolutionary algorithm (NSGA II) with a mixed-integer program.

A new mathematical model to solve the vehicle routing problem with backhauls and time windows (VRPBTW) is proposed by Quila et al. [16]. In this problem, customers are divided into two subsets, for delivery and collection. The objective is to minimize the total distance and the number of vehicles to make the route is minimized. In Wichapa and Khokhajaikiat [17], a new multi-objective facility location problem model which hybridizes fuzzy AHP and goal programming (GP) has been introduced. Finally, the vehicle routing problem (VRP) for a case study was formulated, and it was tested using a hybrid genetic algorithm (HGA) which hybridizes the push forward insertion heuristic (PFIH), genetic algorithm (GA), and three local searches, including 2-opt, insertion-move, and interexchange-move.

In Samanlioglu [12], a mathematical model is proposed for collecting, transport, treatment, recycling, and disposal of hazardous industrial materials. The model has three objectives: minimization of total costs, including hazardous material transport costs and fixed costs from establishing waste treatment centers; minimization of total transport risks related to population exposure to the developed routes; and minimization of overall risks for populations near waste treatment centers.

Alumur et al. [13] propose a model for the location and routing problem of hazardous waste management. The model makes decisions related to the opening and location of treatment centers and the routes developed for waste collection. The model considers total cost and transport risk minimization. In Yilmaz et al. [14], a multi-objective mixed-integer linear programming model is presented to minimize transport costs and risk for hazardous waste management systems. The model is tested in a case study in Turkey. Medaglia et al. [15] propose a bi-objective hybrid algorithm for the location of final Hospital Waste disposal centers. The paper analyzes the conflict of objectives between the network operating costs and the adverse effect on the population living near the potential waste disposal centers by applying the algorithm to a real-life case in the Boyaca Department, Colombia.

In Abdi et al. [18], a new stochastic optimization model using two-stage stochastic programming for solving a closed-loop supply chain network design problem is proposed. A nature-inspired algorithm, namely Whale Optimisation Algorithm (WOA) and Particle Swarm Optimisation (PSO) algorithms, are utilized to solve the considered problem. Besides, Genetic Algorithm (GA) and Simulated Annealing (SA) as the well-known meta-heuristics are employed to have a comprehensive comparison. Lorenc and Kužnar [19] propose research and a method enabling the engineers to create a tool/program that facilitates making decisions about additional cargo insurance or the use of monitoring systems for the location and parameters of the cargo.

Osaba et al. [20] focused their research on the solution of a real-world drug distribution problem with pharmacological waste collection. The authors modeled it as a multi-attribute-rich vehicle routing problem (RVRP). A Discrete and Improved Bat Algorithm (DaIBA) has been proposed to solve the considered problem. The main feature of this adaptation is using the well-known Hamming Distance to calculate the differences between the bats. An effective improvement has also been contemplated for the proposed DaIBA, which consists of two different neighborhood structures, which are explored depending on the bat's distance regarding the best individual of the swarm.

Wang et al. [21] conduct a two-stage reverse logistics network design for urban healthcare waste. The first stage involves the prediction of the amount of medical waste. Based on the Grey GM(1,1) prediction model, the amount of medical waste in a multi-period of the target hospitals is predicted. In the second stage, a multi-objective model aimed at minimizing operating costs and minimizing environmental impact is developed for facilities allocation decisions, which include the configuration of critical facilities such as hospitals, collection centers, transshipment centers, processing centers, and disposal sites, as well as medical waste flow control among facilities.

A Periodic Load-dependent Capacitated Vehicle Routing Problem (PLCVRP) encountered by healthcare centers and medical waste collection companies to design a weekly inventory routing schedule to transport medical wastes to treatment sites is considered by Taslimi et al. [22]. The authors propose a decomposition-based heuristic algorithm to solve this problem. Homayouni and Pishvae [23] propose a multi-objective robust optimization model to design a collection and disposal network of Hazardous Hospital Waste under uncertain conditions. The objectives minimize the total cost, including transportation and operations costs, and the real risk of transportation and operation. An augmented epsilon-constraint method was employed to solve the proposed model.

A study of the Real-life Healthcare Waste Collection vehicle routing problem (HWCVRP) in Iran has been published by Ghannadpour et al. [24]. This work considers social, environmental, and economic objective functions, aiming to achieve sustainable development. A self-adaptive multi-objective evolutionary algorithm is generated with numerous effective op-

erators to solve the proposed model. Specific metrics are employed to compare the proposed meta-heuristic algorithm's performance with those of multiple other evolutionary algorithms.

Valizadeh et al. [25] consider infectious, hazardous waste generated by individuals and hospitals during the COVID-19 pandemic. This paper proposes a mathematical model for hazardous infectious waste collection and government aid distribution to control COVID-19. The model is related to the operational decisions of contractors with limited capacities. In a stochastic programming approach, four possible scenarios are examined, depending on the outbreak's severity. In addition, as a solution approach, the Benders decomposition method is combined with Karush–Kuhn–Tucker conditions.

A Biomedical Waste (BMW) problem is solved using route optimization by Agrawal et al. [26]. This work addresses finding the shortest path using the Cohort Intelligence algorithm for BMW management with the consideration of human risk. Finally, the readers are encouraged to study a recent review related to the Waste Collection Routing Problem (WCRP) (Liang et al. [27]). This paper provides a mini-review of the latest approaches and their application in collecting and routing waste. A performance comparison of a real-world benchmark and future research opportunities in the WCRP field are presented.

Recently, Wichapa and Khokhajaikiat [17] proposed a hybrid scheme that combines multi-objective programming with a genetic algorithm to solve a location and routing problem involving infectious medical waste. The location problem is solved using a hybrid fuzzy Analytic Hierarchy Process (AHP) and multi-objective programming. In turn, the corresponding routing problem is solved through a genetic hybrid algorithm. Lastly, Rabbani et al. [11] analyze a multi-objective case involving the location and routing problem of industrial hazardous waste, with incompatibility between material types. Three objectives are considered: total cost, total transport risk for the exposed population, and potential risk in the location of waste treatment centers. Two multi-objective population algorithms are proposed to solve the problem: the nondominated sorting genetic algorithm (NSGA-II) and multi-objective particle swarm optimization (MOPSO).

Lorenc et al. [19] developed a prediction method to prevent disruption related to temperature anomaly in the cold chain supply. Automatic Big Data analysis and mathematical modeling were used to identify the disruption. Artificial Neural Network (ANN) was used to predict possible temperature-related disruption in transport. The literature review confirms that there is no similar method to prevent disruption in the transport chain. The Internet of Things (IoT) sensors for collecting data connected with Big Data analysis and ANN enables chain resilience provision. Ienca et al. [28] review the existing scientific literature on big data approaches to dementia and commercially available mobile-based applications in this domain. Our analysis suggests that big data approaches in dementia research and care hold promise for improving current preventive and predictive models, casting light on the etiology of the disease, enabling earlier diagnosis, optimizing resource allocation, and delivering more tailored treatments to patients with specific diseases trajectories. Jagadeeswari et al. [29] propose a detailed study on the recently emerging technologies in personalized healthcare systems focusing on cloud computing, fog computing, Big Data analytics, IoT, and mobile-based applications. The paper highlights the rapidly growing need for better healthcare systems in real-time and provides possible future work guidelines.

Alotaibi et al. [30] propose Sehaa, a big data analytics tool for healthcare in Saudi Arabia (KSA) using Twitter data in Arabic. Sehaa uses Naive Bayes, Logistic Regression, and multiple feature extraction methods to detect various diseases in the KSA. Sehaa found that the top five diseases in Saudi Arabia in terms of the actual addicted cases are dermal, heart diseases, hypertension, cancer, and diabetes. The dataset used comprises 18.9 million tweets collected from November 2018 to September 2019. Finally, Addo-Tenkorang et al. [31] attempt to thoroughly investigate "big data", its application and analysis in operations or supply-chain management, and the trends and perspectives in this research area.

Lastly, state-of-the-art reviews related to waste collection planning are found by Beliën et al. [32] and Han and Ponce Cueto [33]. Similarly, case studies in which quantitative methods for infectious and hazardous waste management were successfully applied by Hachicha et al. [34], Yong et al. [35], Alagöz et al. [36], Kergosien et al. [37], Nuortio et al. [38], Zhao and Ke [39], and Ogwuleka and Agunwamba [40].

We have introduced the problem of scheduling and assignment of customers in Hospital Waste Collection Routes. The considered problem has numerous real applications. The proposed mathematical formulation is unique concerning similar related problems. However, we could highlight as main novelties the consideration of a combination of hours scheduling and location of nodes. In addition, we have considered polar coordinates instead of the distance between two nodes to obtain a good approximation of the distance between two points of the Earth's surface. Finally, the mathematical structure of the model is flexible and could be adapted or scaled for similar problems.

3. Materials and Methods

A mixed-integer linear programming model is proposed to support decision-making in a Hospital Waste Collection company where it must be decided: (a) which day each customer should be visited and (b) which vehicle should be used to visit each customer. These customers are characterized according to three aspects. The first is the frequency of visit, which can be daily, weekly, monthly, or other. The second is the quantity and type of waste to be collected. Finally, there is the geographic location, expressed in polar coordinates, to obtain the angle θ , associated with its sector in the city. In addition, a four-week month, with a Monday through Friday workday, and a fleet of vehicles with capacity must be considered. A block chart of the proposed solution method is presented in Figure 1.

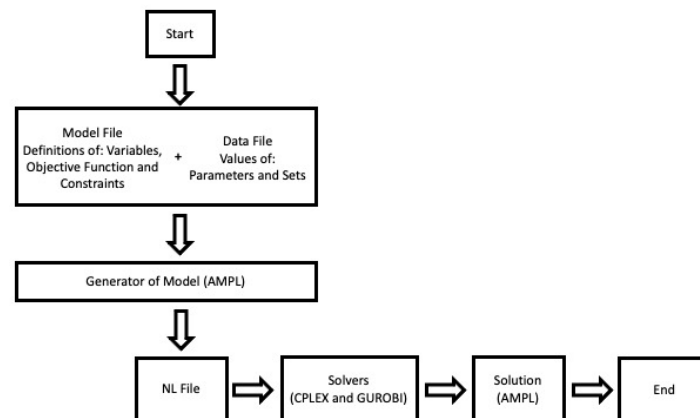


Figure 1. Block chart of the proposed solution method. Source: By the authors.

The proposed mathematical model schedules visits satisfying the frequency associated with each customer, without exceeding the capacity of the vehicle associated with each route and the maximum number of customers that can be visited in a day. The customers of each route belong to a limited sector of the city through polar coordinates. Among all the possible combinations, the one that minimizes the maximum demand of a route should be selected as a key performance indicator (KPI) to balance each day's work.

Input datasets

D: Customers with daily frequency without considering non-business (civil or religious) days fixed by the country's authorities.

TW: Customers with thrice-weekly frequency (visited on Monday, Wednesday and Friday).

SW: Customers with semi-weekly frequency (visited on Monday and Wednesday, or on Tuesday and Thursday).

W: Customers with weekly frequency (visited once a week, always on the same day of the week).

B: Customers with biweekly frequency (visited every two weeks).

M: Customers with monthly frequency (visited once a month).

I: All Customers ($D \cup TW \cup SW \cup W \cup B \cup M$).

J: Days of the month.

V: Trucks available daily for Hospital Waste Collection.

Model parameters:

F_i : Number of visits in a month to customer *i*.

K_i : Demand of customer *i* (containers).

C_k : Capacity of truck *k* (containers per day).

θ_i : Angle in radian associated with customer *i* in relation to the depot.

θ_{max} : Maximum angle of each sector of customer.

$CusMax$: Maximum number of customers assigned to a truck daily.

M : Angle in radian of a full circle, $2 * \pi$, used as Big-M.

Decision variables:

$x_{ij} = 1$ if the customers *i* is assigned to day *j*, and 0 otherwise.

$y_{ijk} = 1$ if the customers *i* is assigned to day *j* and to truck *k*, and 0 otherwise.

$capmax$ = Maximum demand collected on one day (containers).

$\theta_{m_{jk}}$ = Minimum angle of the customers on day *j* to truck *k*.

$\theta_{p_{jk}}$ = Maximum angle of the customers on day *j* to truck *k*.

The proposed mathematical model of integer linear programming seeks to solve customers' scheduling and assignment in a monthly calendar, scheduled according to their visit frequency (daily, weekly, three-weekly, weekly, biweekly, and monthly). In addition, customers' assignment to the different collection trucks is performed according to their location concerning the located warehouse. The main goal is to balance loads of the trucks daily and cluster by geographical areas.

The model only considers customers having a particular infectious waste product for transportation. The proposed model uses homogeneous resources for the hazardous waste collection service that have a daily truck assigned, and also, the visit to these customers is coordinated in advance and at their request. The proposed model's formulation corresponds to (1)–(14):

$$\text{Minimize } z = capmax \quad (1)$$

subject to:

$$\sum_{j \in J} x_{ij} = F_i \quad \forall i \in I \quad (2)$$

$$x_{ij} = 0 \quad \forall i \in TW, \forall j \in \{2, 4, 7, 9, 12, 14, 17, 19\} \quad (3)$$

$$x_{ij} = x_{i(j+\alpha)} \quad \forall i \in SW, \forall j \in 1, 2, \forall \alpha \in \{2, 5, 7, 10, 12, 15, 17\} \quad (4)$$

$$x_{i\alpha} = 0 \quad \forall i \in SW, \forall \alpha \in \{5, 10, 15, 20\} \quad (5)$$

$$x_{ij} = x_{i(j+\alpha)} \quad \forall i \in W, \forall j \in \{1..5\}, \forall \alpha \in \{5, 10, 15\} \quad (6)$$

$$x_{ij} = x_{i(j+10)} \quad \forall i \in B, \forall j \in \{1..10\} \quad (7)$$

$$\sum_{i \in I} K_i * x_{ij} \leq capmax \quad \forall j \in J \quad (8)$$

$$x_{ij} = \sum_{k \in V} y_{ijk} \quad \forall i \in I, \forall j \in J \quad (9)$$

$$-M * (1 - y_{ijk}) + \theta m_{jk} \leq \theta_i \leq \theta p_{jk} + M * (1 - y_{ijk}) \quad \forall i \in I, \forall j \in J, \forall k \in V \quad (10)$$

$$\theta p_{jk} - \theta m_{jk} \leq \theta_{max} \quad \forall j \in J, \forall k \in V \quad (11)$$

$$\sum_i y_{ijk} \leq CusMax \quad \forall j \in J, \forall k \in V \quad (12)$$

$$x_{ij}, y_{ijk} \in \{0, 1\} \quad \forall i \in I, \forall j \in J, \forall k \in V \quad (13)$$

$$\theta m_{jk}, \theta p_{jk} \geq 0 \quad \forall j \in J, \forall k \in V \quad (14)$$

The objective function (1) of the model seeks to minimize the maximum daily truck-loads (Min-Max), achieving no days with an excess of work for the main problem company.

According to their associated frequency, the set of constraints (2) assign several visits on the month to reach customers. For example, for monthly customers, F_i takes the value of 1, that is, they are assigned only one visit in a month, on the other hand, for weekly customers, F_i takes the value of 4, and they are assigned four visits in a month. Note that F_i considers the number of visits each month. Therefore, the model's maximum planning period is a month considering each day's visits (F_i takes the value of 30). In addition, (2) ensures the monthly customers and diary customers must be assigned at least once a month and every day, respectively.

The set of constraints (3)–(7) ensures that the frequency is respected according to a pre-established pattern. The customers on a daily basis only need the constraints (2) because they are visited every day of the month. The customers with frequency thrice-weekly need the constraints (2) and (3) to ensure not being allocated on Tuesday and Thursday. The customers with frequency semi-weekly need the constraints (2), (4), and (5) to ensure to be allocated on Monday and Wednesday, or Tuesday and Thursday, but not on Friday. The customers with frequency weekly need the constraints (2) and (6) to be always allocated on the same day of the week. The customers with frequency biweekly need the constraints (2) and (7) to ensure that they are visited every two weeks. The customers with frequency monthly need the constraints (2) to ensure that they are visited once a month.

The set of constraints (8) contains the maximal demand of customers for every day. In particular, the demand for each route must be less than the maximal capacity of each truck. Note that the $capmax$ is used at the objective function to be minimized in a min-max strategy. Therefore, the main goal is to decrease the load of the trucks avoiding their full load. Note that the meaning of the variables on the left-hand side indicates that the value of $capmax$ must be greater or equal to 0.

The set of constraints (9) links the variables x_{ij} with variables y_{ijk} . These constraints (9) ensure that the one customer is assigned to a day only if an available truck performs the scheduled route.

The set of constraints (10)–(12) perform the balance of workload. The set of constraints (10) and (11) are used to obtain scheduled customers' geographic clusters. Each cluster corresponds to a truck; therefore, the customer i is assigned to day j , and the vehicle k represents a customer's cluster. The set of constraints (10) determines the lowest and highest angle theta for the set of customers assigned to the day j and a truck k . Note that the difference must be less than equal to each sector of the customer's maximum angle. These equations restrict the space of each cluster of customers. The set of constraints (11) bounds the maximum dispersion of customers for the tour performed on the day j by truck k . Indeed, these equations seek to control the number of maximum customers for each cluster. Indeed, the cluster must have a similar load represented by the number of visited customers avoiding an unequal dispersion. The set of constraints (12) bounds the maximum number of customer visits for the tour performed on the day j by truck k . The set of constraints (13) and (14) are the domain of variables. The binary variable is set on (13) and the non-negative on the (14).

One of the approaches to measure the traveling distance for Vehicle Routing Problems is using Haversine Distance. The Haversine (or great circle) distance is the angular distance

between two points on the surface of a sphere. The first distance of each point is assumed to be the latitude, and the second is the longitude, given in radians. As the Earth is nearly spherical, the Haversine formula provides a good approximation of the distance between two points of the Earth's surface, with a less than 1% error on average (Hakim et al. [41]). Some examples dealing with polar coordinates for routing problems are considered by Hakim et al. [41], Arnold & Sørensen [42], and Danandeh et al. [43].

In our work, the use of polar coordinates based on radians angle is essential due to the consideration of the cities sector (north, south, east, west) and the neighborhoods with unique and special characteristics (sectors with people with high income, sectors with people low income, business sector, among others). Besides, the polar coordinates facilitate the work of the drivers due to the location of sectors.

The model's efficiency was tested with real-life data collected from a world leader company in medical and biological infectious waste collection, treatment, and disposal services. The company serves clinics, hospitals, laboratories, medical and dental offices, surgical centers, funeral homes, veterinary clinics, and any establishment that generates needles and potentially infectious waste.

The company has been operating in Chile since 2008, with branches in the main cities. The company provides collection, transportation, storage, and disposal services for marine, mining, urban, hazardous, and special waste. The company has a fleet of eight trucks, six for special waste collection and one for hazardous waste collection. The last truck transports the waste to the various final disposal points.

4. Results

The transitional cost of the proposed approach is related to the training of the decision-makers in its use. The company's data must be ported over and validated to complete the manual planning transition to use the proposed approach. If it is significant enough, the company may have some downtime during the transition as well. However, free commercial solvers to solve the problem make it so that the costs of transitioning are trivial compared to the expensive commercial licenses commonplace for solutions. Indeed, it is essential to mention that the implementation and transitional costs must be compared to using a manual solution of the problem which often uses suboptimal considerations. Implementation and transitional costs are significant to calculate because they require upfront capital. Training and software need to be purchased, which means the company needs to have the liquidity to afford the project. Implementation and transitional costs are also a one-time expenditure, however, which means that long-term, they are not as important as the ongoing and total cost of obtained solutions.

To measure the angle θ_i of each customer about the depot, each of them was georeferenced using the Google Maps tool. Subsequently, the Coticchia-Surace equations were used to transform UTM coordinates into Euclidian coordinates (x,y) . Lastly, the angle was calculated using the function atan2 . Thus, θ_i is the angle in degrees between the positive x -axis of a plane and the point given by the coordinates (x,y) . In this case, θ_i ranges from 0 to $2 * \pi$, thus enabling us to divide the region into sectors to cluster customers based on their polar coordinate in the plane. The values of θ_{max} and $CusMax$ are obtained from the company; the suggested value was near the minimal value to obtain a feasible solution and have a solution with a good work balance.

In particular, we considered a month with four weeks and each week with five days, with the following waste collection frequencies:

- Daily: Customers visited every day of the month.
- Thrice-weekly: Customers visited on Monday, Wednesday, and Friday, every week.
- Semi-weekly: Customers visited two times, every week of the month.
- Weekly: Customers visited the same days of the week, every week.
- Biweekly: Customers visited 2 times, two weeks apart.
- Monthly: Customers only visited once a month.

Table 1 outlines the number of customers distributed by customer frequency.

Table 1. Customer visit frequency.

Frequency	Special Waste Customers	Percentage	Cumulative Percentage
Monthly	444	54.41%	54.41%
Weekly	214	26.23%	80.64%
Biweekly	99	12.13%	92.77%
Semi-weekly	30	3.68%	96.45%
Thrice-weekly	23	2.82%	99.27%
Daily	6	0.73%	100.00%
Total	816	100.00%	

Source: By the authors based on data obtained from company.

Demand was estimated based on the mean monthly kilograms of waste removed by the trucks during 2019. The capacity of the vehicles was determined based on the maximal number of containers per truck. Medium trucks have a capacity of 12 containers with a capacity of 40 kg each. Large trucks have a capacity of 16 containers.

The customers to whom the particular waste transport service is provided were selected for the computational experiments because they account for more than 80 percent of all the company customers (Table 1). The categories that correspond to the mean monthly kilograms generated by the customers to whom the special waste collection service is provided are shown in Table 2. We use the customers with ten or more kilograms per month of demand, 85 customers from the Maule region, and 214 from the Bio-bio region.

Table 2. Customer classification.

Range in Kilograms (X)	No. Customers	% Customers
$X \leq 10$	517	63.36%
$10 \leq X \leq 100$	215	26.35%
$100 \leq X \leq 1000$	76	9.31%
$1000 \leq X$	8	0.98%
Total	816	100.00%

Source: By the authors based on data obtained from company.

4.1. Computational Experiments and Findings

The proposed model was programmed using AMPL and solved with GUROBI 9.0 and CPLEX 12.10 solvers. The computer has an Intel Core i3-3217U processor with 4 GB RAM Windows 10 64-bit operating system. In the tables, CPU time is the time the solver requires to obtain the solution. The gap is the percentage between the best bound obtained and the model's best integer solution. In addition, all instances were executed with a time limit of 35,000 s (9.7 h). The proposed approach was applied twice, with GUROBI and CPLEX, to each region independently to compare both solvers' performance.

The algorithm for solving the proposed mixed-integer linear programming model is called branch-and-bound. Initially, this procedure considers the original model by removing all integrality constraints (13). The resulting linear programming model (LP) is called the relaxation of the original model. The LP model is solved, and if the obtained result satisfies all of the integrality constraints, the approach has obtained the optimal solution for the original problem. If not, as is usually the case, then the standard procedure is to pick some variable that must be constrained to be an integer whose value in the LP relaxation is fractional. This variable is then called a branching variable, and the algorithm must branch on it, producing the two new sub-MIP problems P1 and P2. If we can compute optimal solutions for each of P1 and P2, the algorithm takes the better of these two solutions and will be optimal to the original model. The algorithm now applies the same idea to these two MIPs, solving the corresponding LP relaxations and, if necessary, selecting branching variables. Therefore, a search tree is generated. The MIPs generated by the search procedure is called the tree's nodes, with the original model designated as the root

node. In general, the algorithm has solved the original MIP if it reaches a point at which it can solve or otherwise dispose of all leaf nodes.

4.1.1. Scheduling and Assignment of Customers—Maule Instance

The proposed mixed-integer linear programming model was applied to 85 customers from the Maule region. Two trucks with a 16-container capacity each were used. Because of the geographic location of customers, the θ_{max} in the Maule instance was $\pi/9$. The maximum number of customers serviced daily by truck (*CusMax*) was seven. The performance of each solver with the described parameters are presented below.

The GUROBI solver explored 2070 nodes and iterated 422,658 times in 91.15 s to obtain the optimal solution (Table 3). CPLEX solved the model with a maximum time of 35,000 s (Table 4). The performance of GUROBI vs CPLEX is presented in Figure 2. Note that CPLEX could not find the optimal solution but obtain a feasible solution with a minimal gap of 0.01 percent, which is considered a very good solution.

Table 3. Performance GUROBI solver—Maule Instance.

Incumbent	Best Bound	Gap	CPU Time
6.52000	4.03950	38.0%	3.00
4.53000	4.03950	10.8%	3.00
4.09000	4.04000	1.22%	5.00
4.08000	4.04000	0.98%	8.00
4.07000	4.04000	0.74%	15.00
4.05000	4.04000	0.25%	34.00
4.04000	4.04000	0.00%	91.15

Source: By the authors.

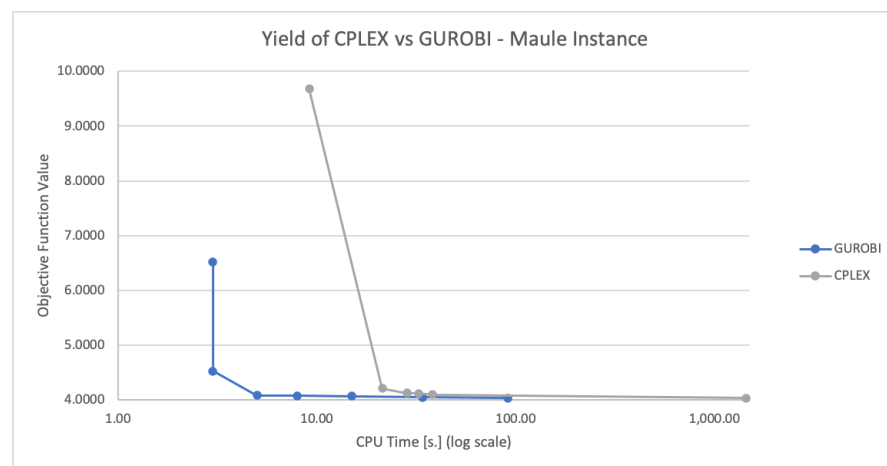


Figure 2. Performance CPLEX vs. GUROBI—Maule Instance. Source: By the authors.

Table 4. Performance CPLEX solver—Maule Instance.

Incumbent	Best Bound	Gap	CPU Time
9.68	4.0395	69.94%	9.16
4.21000	4.0395	4.05%	21.33
4.13000	4.0395	2.19%	28.41
4.12000	4.0395	1.95%	32.64
4.10000	4.0395	1.48%	38.33
4.04000	4.0395	0.01%	1443.64
4.04000	4.0395	0.01%	35,000.00

Source: By the authors.

4.1.2. Scheduling and Assignment of Customers—Biobio Instance

The solution for the Biobio Region considers 214 customers and four trucks with a capacity of 16 containers. The θ_{max} take a value of $\pi/2$ in the studied region, dividing the region into four equal sectors. The maximum number of customers served daily by a truck was 15.

The GUROBI solver explored 73,328 nodes and iterated 25,728,519 times in 19,380.86 s to find the optimal solution (Table 5). Table 6 shows the performance of the CPLEX solver. It can be observed that the optimum could not be reached within the time limit. However, a feasible solution was achieved with a very small gap of 0.06 percent.

Table 5. Performance GUROBI solver—Biobio Instance.

Incumbent	Best Bound	Gap	CPU Time
29.96000	29.3900	1.90%	291.00
29.49000	29.3900	0.34%	312.00
29.44000	29.3900	0.17%	338.00
29.43000	29.3900	0.14%	338.00
29.42000	29.3900	0.10%	682.00
29.40000	29.3900	0.03%	747.00
29.39000	29.3900	0.00%	19,380.00

Source: By the authors.

Table 6. Performance CPLEX solver—Biobio Instance.

Best integer	Best Bound	Gap	CPU Time
30.0100	29.3835	2.09%	6360.00
29.5400	29.3835	0.53%	6560.00
29.5200	29.3835	0.46%	9638.70
29.4100	29.3835	0.09%	9838.70
29.4000	29.3835	0.06%	29,040.00
29.4000	29.3835	0.06%	30,000.00

Source: By the authors.

4.1.3. Workload Balance

The results obtained from the model can generate dispatch routes since we know the day and the truck assigned to each of the customers; this can be observed in Figure 3. The work balance can be analyzed through the average number of customers and daily containers delivered, which can be seen in Table 7. We can see that the model obtains a balanced work program.

Table 8 shows the number of unattended visits to customers in the sub-optimal solution (company solution before executing the proposed model). As can be seen, the current solution is infeasible since the demand is not satisfied by stopping making 422 visits to customers. Note that the total number of visits obtained by the model is 1349 regardless of the used software. The obtained solution by the model is feasible, minimizing the maximum demand collected in one day. For the Maule instance, we have 5257 variables and 9545 constraints. For the Bio-Bio instance, we have 20,331 variables and 38,990 constraints. Indeed, a feasible solution for the company case study allows compliance with the contracts and regulations of the health area.

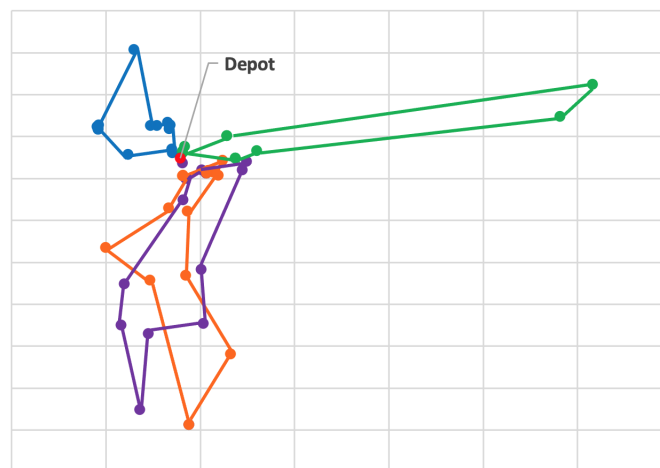


Figure 3. Example of routes for the first Thursday of the month—Instance Biobio. Source: By the authors.

Table 7. Average results of customers and containers delivered each day—Instance Biobio.

Day	Customer	Container
1	13.3	29.4
2	15.0	29.4
3	14.5	29.4
4	14.0	29.3
5	14.3	29.4
6	13.3	29.4
7	15.0	29.4
8	11.5	29.4
9	14.5	29.4
10	13.5	29.4
11	13.5	29.4
12	15.0	29.4
13	13.3	29.4
14	14.3	29.4
15	14.3	29.4
16	13.3	29.4
17	15.0	29.4
18	11.5	29.4
19	14.3	29.4
20	14.0	29.4

Source: By the authors.

Table 8. Model Results versus Current Solution.

Frequency	Proposed Solution		Current Solution		Non-Performed Visits (Current Solution)	
	Biobío	Maule	Biobío	Maule	Biobío	Maule
Daily	120	0	110	0	8.3%	0.0%
Semiweekly	208	16	191	14	8.2%	12.5%
Three times a week	264	0	232	0	12.1%	0.0%
Weekly	432	160	384	141	11.1%	11.9%
Biweekly	64	44	59	39	7.8%	11.4%
Monthly	20	21	18	18	10.0%	14.3%
Total	1108	241	994	212	9.6%	8.3%

5. Conclusions

Customer scheduling and truck assignment for Hospital Waste Collection is critical if the collection service fails to visit customers under predefined frequency and geographical location. In this article, a mixed-integer linear programming model was proposed to solve the problem. The model successfully scheduled all visits during the month while balancing the number of customers and the truckloads and optimally assigning customers according to collection frequency. The proposed model's effectiveness was tested using a local waste collection company, a subsidiary of an international holding company.

Comparing the model's solutions using two datasets (two regions, Maule and Biobio) indicated that solver CPU time used increases with the amount of data. In addition, in both cases, the GUROBI solver's performance was superior to that of the CPLEX solver.

Future research studies are related to the solution of the stochastic version of the problem by using techniques such as Sample Average Approximation (SAA) (Paz et al. [44], Rodado et al. [45] and Escobar et al. [46]), and also the use of heuristic or metaheuristic strategies based on a granular search for large instances such as similar works proposed by Bernal et al. [47], Bernal et al. [48], Bernal et al. [49], Escobar [50], Puenayan et al. [51], and Escobar et al. [52], Escobar and Linfati [53], and Linfati et al. [54].

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