

Improving the tactical planning of solid waste collection with prescriptive analytics: a case study

Angie Paola Vargas^{a,b} , Danilo Díaz^a , Santiago Jaramillo^a , Francisco Rangel^a , Daniel Villa^c ,
Juan G. Villegas^{b*} 

^aLogística, Consultoría e Integración, Medellín, Colombia

^bUniversidad de Antioquia, Departamento de Ingeniería Industrial, Medellín, Colombia

^cUniversidad EAFIT, Departamento de Ingeniería de Producción, Medellín, Colombia

*juan.villegas@udea.edu.co

Abstract

Paper aims: This study presents several business analytics tools that allow improving the tactical planning of the collection process for a Colombian solid-waste management company.

Originality: The extant literature of operations research/analytics applied to these systems focuses on facility location or vehicle routing. Tactical decisions are seldom studied in the operations research/analytics literature devoted to waste management systems. By contrast, the focus of this paper is on tactical decisions: fleet sizing, frequency assignment, route scheduling and internal resource allocation in a new waste transfer station.

Research method: We follow a multimethodology approach that uses mathematical programming, metaheuristics, and discrete event simulation. The models use historical information of the system, and the solution of a model are used as input data for the other models.

Main findings: Introducing a new waste transfer station allows an important reduction of the compactors fleet. However, to prevent a collapse in its internal operation an even operation is needed. This is achieved by rescheduling the routes to balance their arrival during the day. Additional benefits can be attained if some soft constraints are relaxed.

Implications for theory and practice: Practitioners looking for tactical planning tools on waste collection systems have here an example of their application and benefits. Improvements can be achieved by tactical planning without heavily disrupting decisions at the operational level.

Keywords

Optimization model. Metaheuristic algorithm. Discrete event simulation model. Waste management. Waste transfer station.

How to cite this article: Vargas, A. P., Díaz, D., Jaramillo, S., Rangel, F., Villa, D., & Villegas, J. G. (2022). Improving the tactical planning of solid waste collection with prescriptive analytics: a case study. *Production*, 32, e20210037. <https://doi.org/10.1590/0103-6513.20210037>

Received: Apr. 30, 2021; Accepted: Dec. 15, 2021.

1. Introduction

The world generates 2010 million tonnes of solid waste annually, its generation increases as the population growth, economic development is promoted, standard of living improves, and consumptions habits change (Kaza et al., 2018). Solid waste generates from unwanted or discarded materials at the end of its life cycle, comes from domestic, commercial, institutional, and industrial consumption (Sulemana et al., 2018). Waste comes mainly from metals, glass, plastics, papers, leather, rubbers, batteries, textiles, and construction materials (Kaza et al., 2018).



Globally, development countries generate 34% of waste (Kaza et al., 2018). Latin America generates on average, one kilogram of solid waste per inhabitant per day representing around 10% of the solid waste generation worldwide. Colombia generates approximately 6% of this waste, which equals to 12 million tonnes per year. The high generation of these waste and the low level of reusing and recycling of them leads to saturation in landfills and facilities to dispose and treat them generating a negative impact on the environment and the society (Machado & Hettiarachchi, 2020).

Solid waste management involves the process of generation, separation and onsite storage, collection, transfer and transport, processing, recovering and final disposal (Rada et al., 2013; Gonela et al., 2020). Collection and transport represent between 60%-80% of the total cost of solid waste management (Beliën et al., 2014). These processes include the activities of collecting and transporting solid waste to a destination that may be a landfill, a material processing or treatment facility or waste transfer station (WTS). Particularly, a WTS is a place within an urban area where the transfer of solid waste of compactor vehicles to other vehicles with greater load capacity is carried out, which efficiently transports the waste to the landfill usually located on the outskirts of the city (Gonela et al., 2020).

Planning decisions in waste collection systems are made at the strategic, tactical, and operational levels (Gonela et al., 2020). At the strategic level, the focus is the location of waste treatment/disposal facilities (WTS, landfills, recycling plants, etc.) and the different flows from waste generation to disposal at landfills or recovery at treatment plants. The tactical level includes districting for collection zone definition, frequency assignment, and fleet sizing. Finally, the operational level mainly focuses on detailed routing of collection vehicles and personnel scheduling. As pointed out by Van Engeland & Beliën (2021) tactical decisions are seldom studied in these systems. Most research aim at collection routing planning (Beliën et al., 2014) and studies including transfer stations mainly focus on their location (Ghiani et al., 2014). By contrast, in this paper, we present a multimethodology approach that can be used for tactical decision making in waste collection planning. The proposed approach integrates several analytical tools previously introduced in the literature (mathematical programming, metaheuristic optimization and discrete event simulation) for the tactical planning of these systems. Moreover, we apply the proposed approach in a case study related to the tactical (re)planning that must be done in a Colombian waste management company due to the entry into operation of a new WTS.

The remaining of this paper is structured as follows. Section 2 contains a literature review on applications of business analytics (operations research models) in solid waste collection planning at the tactical level. Section 3 describes the case study and Section 4 presents the multimethodology approach based on prescriptive analytics tools. Section 5 presents the results of the case study including sensitivity analysis and possible improvement that can be obtained in the operation. Finally, Section 6 present our final remarks as well as future research opportunities.

2. Literature review

Prescriptive analytics supports optimal decision making based on data from different sources. Prescriptive analytics encompasses several methods: probabilistic models, machine learning, mathematical programming, metaheuristics and evolutionary computation, simulation, and logic-based models (Lepeniotti et al., 2020). So, in this review we focus on tactical decision making in waste collection systems using business analytics methods with applications of mathematical programming and simulation models. The interested reader is referred to (Ghiani et al., 2014) for a recent review or operational research methods for strategic and tactical decisions and to (Beliën et al., 2014) for a review focused mainly on collection routing (the most studied decision in these systems).

Tactical decision making in waste collection includes several interrelated decisions: districting, fleet sizing, collection day and frequency assignment, among others (Gonela et al., 2020). In waste collection, the districting decision seeks to partition the road network into a given number of sectors to facilitate the organization of the collection operations within the region. The sectoring arc-routing problem appears when the detailed routing is considered (Mourão et al., 2009). However, some other districting applications foster some properties of the districts (contiguity, compactness, Eulerian properties of the resulting graph, among other) but do not consider explicitly the routing decisions (García-Ayala et al., 2016). There are several districting applications in waste collection planning (Gonela et al., 2020). However, in our case study, districting decisions and detailed routing cannot be changed since the company under study does not want to heavily alter its operation. Rather, they wanted to evaluate how to reschedule existing collection routes once the new WTS begins its operation and which is the impact of this new schedule on fleet size. So, in our study, we take as fixed the zones in which the city has been partitioned, their collection time windows, and the frequency, duration, and waste load of the

collection routes performed in each zone. Nevertheless, in a sensitivity analysis of our study, we evaluate the effect of allowing frequency change for a proportion of the routes of the city.

Frequency assignment decides the number of visits, specific days and amounts to collect for a given set of points/areas to minimize the total collection cost or the maximum peak of waste collected in each day. In some cases, this decision also includes fleet sizing and composition to decide the number of each size of compactors to use and the assignment of vehicles to the collection routes. Mansini & Speranza, (1998), studied this decision in Brescia (Italy) considering the effect of separate collection. Likewise, (Aguirre-Gonzalez & Villegas, 2017), applied a three-stage approach that includes districting, fleet sizing and frequency assignment for planning the animal waste collection for a rendering company operating in Medellín (Colombia).

Van Engeland & Beliën (2021) studied a frequency assignment/fleet sizing problem that is closely related to ours since after performing each collection route, the central disposal facility must be visited to weight and discharge the waste. Something that will be required once the WTS enters into operation. However, we do not include waste collection quantity as a decision variable. It is rather a parameter defined by the historical records of each collection route. Moreover, their fleet sizing and vehicle assignment models share some elements with the ones we use in the proposed methodology.

The tactical decisions addressed in our study fits within the category of truck allocation problems where the decision do not include the routing of the trucks but the timing of disposal trips (Beliën et al., 2014). For example, Li et al. (2008) studied the scheduling of waste collection routes in the city of Porto Alegre (Brazil), the aim of their study was to minimize collection costs including fleet and variable costs associated with the routes. Although this problem can be efficiently solved in some cases, the objective of balancing the waste that reaches the transfer and recycling facilities force the authors of this study to resort to heuristic methods inspired on the generalized assignment problem. In our case study, (meta)heuristic methods are also used to program the routes on a particular day. However, we considered an (alternative) objective function that has been studied previously in the truck allocation problem. This is the minimization of the number of routes that arrive at the WTS in each hour to prevent queuing and the collapse in the internal operation of the WTS.

Applications of mathematical models for fleet sizing and vehicle scheduling also appear in the broad context of reverse logistics planning and optimization. For instance, Ramos et al. (2014) presented a mixed-integer programming model for the integrated strategic, tactical, and operational planning of a recyclable waste collection system. Their model addresses simultaneously tactical and operational decisions including the collection zone districting for each depot and the definition and scheduling of collection routes for each vehicle. Likewise, fleet planning for single and multimodal planning has been also a successful field of application of operations research/business analytics models (Baykasoğlu et al., 2019). For instance, Carosi et al. (2019) proposed a matheuristic for integrated timetabling and vehicle scheduling in public transportation.

Tactical decisions also appear in studies carried out for waste management in smart and sustainable cities, which consider the optimization of the use of resources for costs minimization, carbon emissions reduction, and the segregation of waste for later use. For example, Anagnostopoulos et al. (2015) use the Internet of Things (IoT) for efficient waste management in real time. Unlike our model, using IoT allows dynamic routing for waste collection. Their models include homogeneous and heterogeneous fleet and considers multiple intermediate depots for waste transfer seeking to maximize the profitability obtained by the required fleet. As pointed out by Fadda et al. (2018), the use of IoT-enabled sensing of waste generation removes the need of fixed periodic routes that is common in this context.

Likewise, Akbarpour et al. (2021) proposes a model that involves the optimization of collection routes for the maximization of the recovery value of the waste collected in different waste processing facilities. The maximum of the value of the waste collected is related with selective collection that generates a positive impact due to the best use that can be made of the different waste. For example, Korcyl et al. (2019) present a mixed integer programming model (MIP) for the selective routing of waste collection considering time windows, the availability of vehicles and the different types of waste.

Discrete event simulation is a classical and effective tool for internal transport/material handling modelling and analysis (Banks et al., 2015). Moreover, the recent introduction of the digital twin concept as a tool for logistics operations analysis (Agalianos et al., 2020; Santos et al., 2020) give DES a new application framework, individually or in conjunction with optimization models and machine learning techniques (Kosacka-Olejnik et al., 2021). Particularly, DES has been used in the past as a tool for fleet sizing in waste collection operations (Larson et al., 1991). However, very few studies report its recent usage in tactical decision making in waste management systems. In a closely related work, Simonetto & Borenstein (2007) proposed a decision support system (DSS) for recyclable waste management planning that includes among other components a truck allocation model. An important feature of their DSS is the incorporation of a discrete event simulation (DES)

model to estimate the waste generation quantity and to define the waste processing capacity at intermediate sorting facilities. The validation of the proposed DSS was performed with data from the city of Porto Alegre (Brazil). In our case study, we also resort to a DES model to evaluate the effects of the routing scheduling in the arrival of compactors to the WTS and its internal workload. Likewise, we also use the DES model to define the processing capacities of the WTS and the size of the truck fleet needed to transport waste from the WTS to the landfill. More recently, Lima et al. (2015) integrated process mapping and DES in the design of a recycling facility in a Brazilian city. Likewise, Knapčíková et al. (2020), used a DES model for the design of a recycling plant producing new fabrics from waste tires. These two case studies illustrate how DES serve as an effective decision support tool for designing waste management facilities internal flows and available resources. Finally, for a recent review on internal vehicle scheduling problems in terminals the interested reader is referred to Wang (2020).

With this paper, we aim at two contributions. The first one illustrating how tactical decision making in waste collection planning can be done using a multimethodology approach that combines several analytical tools previously presented in the literature (Simonetto & Borenstein, 2007; Li et al., 2008; Van Engeland & Beliën, 2021). Contributing in this way to enrich the scarce literature of tactical planning for these systems and to show the potential benefits that can be achieved using these tools in a real-world application. Moreover, as a second contribution, we evaluate from a tactical point of view the impact of a new WTS in the operation of a real-world company, something that has not been reported before in the literature since previous works focus mainly on WTS location, integrated location-routing studies or vehicle routing problems with synchronization at the WTS (Beliën et al., 2014; Ghiani et al., 2014, 2021; Sulemana et al., 2018).

3. Problem statement and methodology

As stated above, this study addresses the redesign of a Colombian company's solid waste collection operation, based on the current operation and future requirements after the entry into operation of a new WTS. This section describes the problem under study and the business analytics tools used to support the decision-making process.

In a first step, we performed a statistical analysis of the behavior of solid waste generation. Additionally, the current solid waste collection process was analyzed in which a series of events are considered using compactor vehicles as the main resource. Figure 1 shows the process performed currently by this resource to transport solid waste from the defined collection routes to the final disposal site (a landfill located outside the city). In some cases, as seen in the figure, a vehicle can perform more than one route in a working day. However, most of the

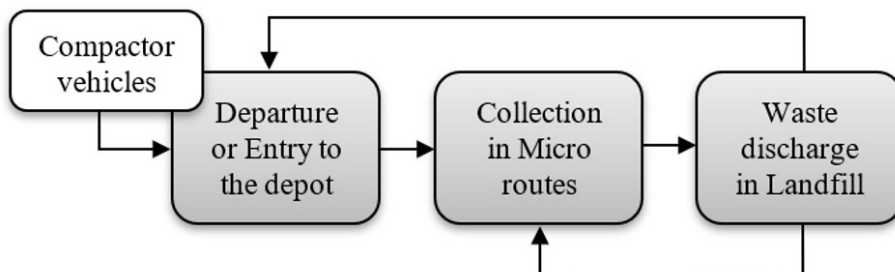


Figure 1. Current solid waste collection cycle.

trips of the vehicles take almost the entire working shift (approx. 8 hours) in a single collection cycle, including the departure from the depot to the collection routes and the return to the depot after discharge at the landfill.

With the entry into operation of the new WTS, the previous cycle changes because the compactor vehicles will be used to transport the solid waste within the city (from the collection routes to the WTS). As pointed out by Gonela et al. (2020), the use of a WTS generates positive impacts related to the compactor vehicle fleet, such as the reduction in travel times to landfills and unproductive times, at the same time, allowing a reduction in the operating costs. Consequently, the collection cycle with the WTS would present the improvement seen in the Figure 2. With this improvement, the compactor vehicles have the possibility to perform more collection routes in a shift with the potential of performing at least two collection routes in approximately 8 hours. Moreover, Figure 2 shows that a new resource (trucks with trailers) is needed for the transportation of waste from the WTS to the landfill.

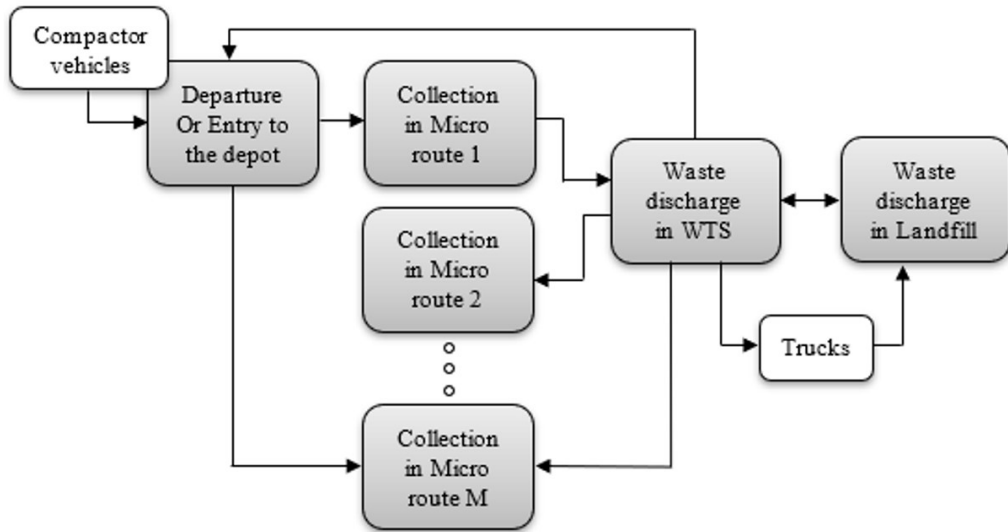


Figure 2. Expected solid waste collection cycle with the WTS.

Giving these changes in the collection cycle a series of questions arise to the managers of the waste collection process. The location of the new WTS (a strategic decision) is already fixed based on a previous study. Moreover, the design of current collection routes should not be changed strongly in the near future (an operational decision). However, several tactical decisions should be revised. Figure 3 summarizes these decisions and how the different business analytics tools are used to support this decision-making process.

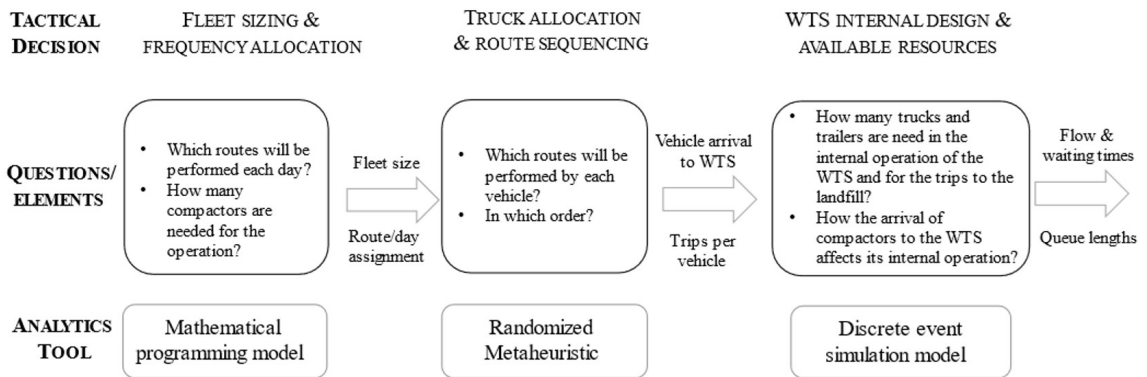


Figure 3. Decision making process and relations with the components of the methodology.

The first step of the proposed approach defines the optimal fleet size of compactor vehicles, for this a mathematical programming model was developed. In a second step, it is important to schedule the trips to be made by the compactor vehicles each day. This assignment and scheduling are done through a metaheuristic algorithm that consists of two phases (randomized construction and solution improvement). Finally, to determine the internal resources required to operate the new WTS (trucks and trailer), a discrete event simulation model was developed in the third step of the proposed approach. The following section describe each one of the components of the proposed multimethodology approach.

4. Prescriptive analytics tools

The three analytical tools described here were implemented using different specialized software. Particularly, the fleet sizing model was implemented in the Xpress Optimization Software using its Mosel Language. The metaheuristic procedure for the assignment and sequencing of collection routes was implemented in Visual

Basic for Applications (VBA) for Excel (Şeref & Ahuja, 2008). Finally, we used the Flexsim software to implement the discrete event simulation model.

4.1. Compactor fleet sizing model

WTSs allow the discharge of compactor vehicle waste to larger capacity containers or vehicles, this prevents compactor vehicles from traveling to landfills. The introduction of WTS generates a reduction in travel times and an increase in the number of trips that compactors can make to collect waste (also known as collection routes in this context). For a city that has defined the collection routes in which the operation is carried out, an implementation of a facility like this may lead to a reduction in the vehicle fleet and savings in operating costs. Therefore, we developed a mathematical programming model to determinate the optimal size of the compactor vehicle fleet.

The compactor fleet sizing was formulated as a lexicographic bi-objective optimization model, that finds the number of vehicles necessary to provide the service and, additionally, seeks to balance the number of tonnes collected during each day by these compactor vehicles. These objectives were combined lexicographically giving the reduction of the fleet size a higher priority.

Given a set $M = \{1, 2, \dots, |M|\}$ of collection routes in which the urban solid waste collection service is provided at a given frequency $F = \{1, 2, \dots, |F|\}$, each element of F represents a possible combinations of days $D = \{\text{Monday, Tuesday, } \dots, |D|\}$ that must be visited. The main decision of the proposed model is represented with the integer variable Y that is the maximum number of vehicles scheduled in a day, and by the binary decision variable X_{ij} that takes the value of 1 if the route $i \in M$ is assigned to a vehicle at frequency $j \in F$, and 0 otherwise. We also define the auxiliary binary variable C_i that takes the value of 1 if the route $i \in M$ changes frequency in the new planning, and 0 otherwise. Likewise, non-negative variables W_k represent the tonnes of waste collected on day $k \in D$. Finally, W_{min} and W_{max} are, respectively, the minimum and maximum tonnes of solid waste collected over the days of the week.

The parameters involved in this mathematical model are detailed in Table 1.

Using this notation, the optimization model is formulated as follows:

$$\text{Min } Y + \epsilon (W_{max} - W_{min}) \tag{1}$$

Table 1. Parameters and decision variables for the vehicle fleet optimization model.

| Parameters | |
|------------|--|
| n_j | Number of visits required in frequency $j \in F$ |
| r_i | Number of collections in the week required by route $i \in M$ |
| v_{kj} | Binary value equal 1 if the frequency $j \in F$ includes the day $k \in D$, 0 otherwise |
| d_i | Duration of the solid waste collection process in route $i \in M$ |
| t_i^{ET} | Time from WTS to start of route $i \in M$ |
| t_i^{BO} | Time from the depot to start of route $i \in M$ |
| f_i | Time from route $i \in M$ to WTS |
| tET | Service time in the WTS |
| tBO | Travel time from WTS to depot |
| m_i | Average tonnes of solid waste collected in route $i \in M$ |
| $freq_i$ | Current collection frequency on route $i \in M$ |
| dv | Time available of the compactor vehicles during each day to execute the solid waste collection process |
| mc | Maximum number of collection routes that can change their collection frequency |
| ϵ | Very small real number |

Subject to:

$$\sum_{j \in F} X_{ij} = 1 \quad \forall i \in M \quad (2)$$

$$\sum_{j \in F} n_j X_{ij} = r_i \quad \forall i \in M \quad (3)$$

$$\frac{1}{dv} \sum_{i \in M} \sum_{j \in F} v_{kj} X_{ij} \left(d_i + \max [t_i^{ET}, t_i^{BO}] + f_i + tET + tBO \right) \leq Y \quad \forall k \in D \quad (4)$$

$$\sum_{i \in M} \sum_{j \in F} t_{ij} X_{ij} v_{kj} = W_k \quad \forall k \in D \quad (5)$$

$$W_{min} \leq W_k \quad \forall k \in D \quad (6)$$

$$W_k \leq W_{max} \quad \forall k \in D \quad (7)$$

$$C_i \geq 1 - X_{ij} \quad \forall i \in M, j = freq_i \quad (8)$$

$$\sum_{i \in M} C_i \leq mc \quad (9)$$

$$Y \in Z^+ \quad (10)$$

$$X_{ij} \in \{0,1\} \quad \forall i \in M, j \in F \quad (11)$$

$$C_i \in \{0,1\} \quad \forall i \in M \quad (12)$$

$$W_k \geq 0 \quad \forall k \in D \quad (13)$$

$$W_{min}, W_{max} \geq 0 \quad (14)$$

The first term of the objective function (1) seeks to minimize the number of compactor vehicles, considering that this value will be enough to cover all collection routes, while the second term (multiplied by €) minimizes (lexicographically) the difference between the minimum and maximum tonnes collected throughout the days of the week, so that a balance in the waste collected daily is achieved. Constraints (2) and (3) guarantee that a route will only be assigned to a vehicle on a single frequency and that this frequency in turn will be compatible with the number of weekly collections in which the route must be visited. Expressions (4) ensures that there is sufficient fleet availability to serve all the collection routes, considering the start times of the operation in the collection routes (from the WTS or the depot), the duration of the route, the completion time of the operation, the unloading time in the WTS and the daily availability of the vehicle. Constraints (5) accumulate each day the tonnes of the collection routes assigned to frequencies that include this specific day of the week. The minimum and maximum amount of waste collected in the week is defined through constraints (6) and (7). Additionally, expressions (8) and (9) count and control the number of collection routes that change in their frequency, considering that they can only be changed for those that include the same number of weekly visits in constraints (3) and considering the current assignment of each route. Finally, expressions (10), (11), (12), (13), (14) define the domain of the decision variables.

4.2. Truck allocation and route sequencing

Once the fleet size has been defined and each route has been assigned to a compatible frequency, we follow with the detailed assignment of routes to compactor vehicles and the sequencing of collection routes that must be served by each vehicle during each day of the week. Initially, we formulated a mathematical programming model for this decision (Vargas et al., 2020). Being NP-hard (Van Engeland & Beliën, 2021), this sort of truck allocation and sequencing problems are intractable. Therefore, a commercial optimizer was unable to find even a feasible solution in reasonable times. Consequently, we opted to design a simple randomized metaheuristic algorithm to solve this problem.

The proposed metaheuristic was developed under the logic of the parallel machine sequencing problem (Elidrissi et al., 2018; Edis et al., 2013). The aim of this sequencing procedure is to assign the collection routes to the vehicles to balance their arrival at the WTS avoiding congestion that may be generated in the unloading facilities inside it. The metaheuristic is composed of a randomized construction phase and an improvement phase that tries to balance the number of routes that finish at each hour of the day.

Initially, the randomized construction phase consists of assigning the collection routes to the vehicles. After some data analysis we found that given the duration of the collection routes, a compactor vehicle can perform at most two routes in a single shift. The first one has as its starting point the depot, which is the place where these compactors start and end the operation. The second route departs from the WTS, this is carried out only if the vehicle has made its first route and has enough time to complete a second route without exceeding the shift duration. Algorithm 1 describes the general structure of the randomized construction phase.

Algorithm 1 Randomized construction phase: general structure

1. Random Shuffle (M)
2. while $M \neq \emptyset$ do
3. $i \leftarrow \text{SelectRoute}(M)$
4. $v \leftarrow \text{SelectVehicle}(V)$
5. $s(v) = s(v) \cup i$
6. $M = M - \{i\}$
7. end while
8. return $CV(S)$

The randomized construction algorithm starts with the random sorting of the collection routes set M (line 1). Once they are ordered, each route is assigned to an available compactor whose idle time at the WTS and remaining working time is feasible to complete another route. For this assignment procedure, the first unassigned route of set M that is taken (line 3), next, an available vehicle v is selected in line 4. The selection of the vehicle needs several feasibility verifications, namely, (i) the compactor has not performed the maximum number of routes of a shift (two in this case); (ii) the release time of vehicle v at the WTS or the depot is compatible with the time window of the zone of route i (i.e. the traveling time from the depot or the WTS to the beginning of route i allows the starting of the collection process within the time window of the zone of route i); (iii) the completion time of route r plus the travel time to the WTS and the processing inside it does not exceed the shift length. If this is true, the route is assigned to the compactor vehicle sequence ($s(v) = s(v) \cup i$) and it is removed from the set M of unassigned collection routes ($M = M - \{i\}$), lines 5 and 6, respectively. In this way, the collection routes are evaluated and assigned to the vehicles that are available. Dummy vehicles are added in case there is not an available feasible vehicle to perform a given route. Finally, once all collection routes are assigned ($M = \emptyset$), the algorithm uses function $CV(S)$ to calculate the peak hour where more vehicles arrive at the WTS and returns this number of vehicles as the objective function of solution S (in line 8) which can be seen as the set of sequences of all vehicles. The objective function (i.e., the number of vehicles arriving in the peak hour) of S seeks to balance the arrival of vehicles to the WTS during the day.

The improvement phase aims to minimizing the number of vehicles that arrive per hour at the facility, through two local search moves *change of start time* and *exchange of the visit order* in the collection routes of the same vehicle. Within these two moves, the *change of start time* move analyzes systematically the effect of displacing (in up to three 30 minutes steps forward or backward) the start time of the first route of each

compactor vehicle that is involved in the peak hour (i.e., $h^* = \operatorname{argmax}_{h \in H} \left\{ \sum_{i \in M} L_{ih} \right\}$, where L_{ih} equals 1 if the route

$i \in M$ arrives to the WTS at hour h in the planning horizon H (a working day of 24 hours beginning at 6 am in this case). When this first move fails to improve the solution, the move *exchange of the visit order* systematically exchanges the order of the collection routes of vehicles arriving in the critical time zone to search for further improvements. The improvement phase ends when a local optimum is found, that is, and improved result that reduces the number of vehicles arriving per hour at the WTS and none of the two moves can improve it further (i.e., a local optimum for the two improvement procedures). Algorithm 2 describes the general structure of the proposed metaheuristic.

Algorithm 2 Randomized + Improvement metaheuristic: general structure

1. $S \leftarrow \text{RandomizedAssignment}(M)$
2. improve = true
3. while improve = true do
4. $S' \leftarrow \text{ChangeStartTime}(S)$
5. if $CV(S') < CV(S)$
6. $S \leftarrow S'$
7. improve = true
8. else
9. $S' \leftarrow \text{ExchangeVisitOrder}(S)$
10. if $CV(S') < CV(S)$
11. $S \leftarrow S'$
12. improve = true
13. else
14. improve = false
15. end if
16. end if
17. end while
18. return $(S, CV(S))$

The algorithm starts with the initial solution using the randomized construction phase ($S \leftarrow \text{RandomizedAssignment}(M)$), (line 1). Then, the improvement procedure (lines 4 to 17) is executed as long as an improvement in the solution is achieved, and after this cycle the algorithm stops and returns the best result (solution and vehicles arriving in the peak hour).

Within the improvement cycle, the first step applies the *ChangeStartTime(S)*, move (line 4) described above. If this improvement fails (line 8), the *ExchangeVisitOrder(S)* move analyzes the vehicles arriving at the peak hour h (line 9). This move changes the order of visits of their routes. For each vehicle arriving in h^* , this move evaluates if its routes can be programmed in another order as long as they comply with the time windows of their corresponding zones. Once no improvement is found (improve = false), the final scheduling for each vehicle in S , and the number of vehicles that will arrive at the WTS in peak hour ($CV(S)$) is returned.

4.3. Discrete event simulation of the WTS

Using simulation models, it is possible to make decisions based on the sensitivity analyzes carried out on the critical variables of a system. The simulation model presented in this case study has as main entities the compactor vehicles and the trucks of internal and external movement in and from the WTS. For these resources we analyze the probability of queues generation, the length, and times in queue that compactors vehicles remain in each one of the processes carried out at the WTS. This model considers within its variables the number of solid wastes unloading points, the maximum number of vehicles that can remain in queues of each one of the internal processes, the maximum number of vehicles that can be unloaded simultaneously into the trucks, and the maximum amount of tonnes of waste that can be transported in a trailer.

The arrival of compactor vehicles to the WTS is given by the results of the metaheuristic described in the previous section. The results obtained from this algorithm are used as arrival distribution for the model. Additionally, for this model, random variables were defined for the time spent by compactor vehicles in each process, that is the time used for registration in the gateway of the WTS, for weighing on in and out scales, leachate, and solid waste discharge. In the case of trucks, random variables were defined such as the time for registration at the gateway of the WTS, time used for waste leveling and coverage before traveling to the landfill, travel time to the landfill and the respective discharge of solid waste there, and finally, the time it takes to return to the WTS. The values defined for the operation in the WTS, and the landfill are based on the times taken by the current operation.

The process followed by compactor vehicles (Figure 4) and trucks (Figure 5) in the WTS is presented. These flows present the internal operations that will be carried out in the WTS and the important decisions that must be taken when some areas of operation are full. These flow diagrams represent the logic that were implemented in our simulation model.

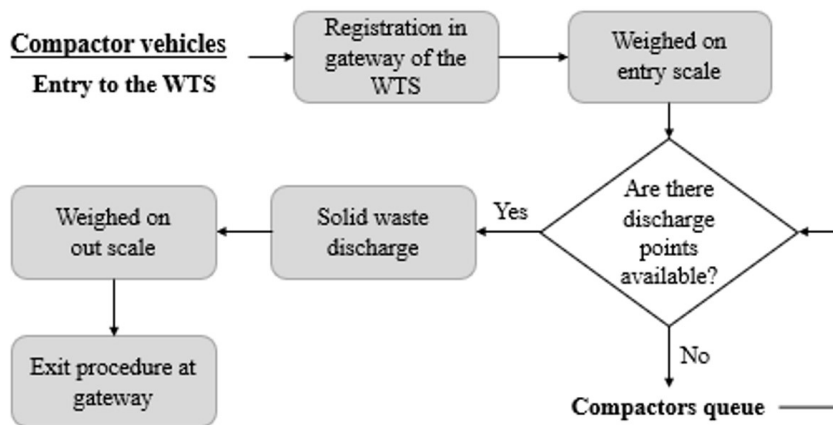


Figure 4. Compactor vehicles process flow in WTS.

The objective of the simulation model was to evaluate the effect of the sequencing metaheuristic in the internal operation of the WTS and to find a set of feasible solutions so that the WTS is operationally viable and the operating time of the compactors within it can be reduced. This implies determining from the simulation: number of trailers used to transfer solid waste collected by compactor vehicles, external trucks to hook up the trailers and transfer them to the landfill, internal trucks to move the trailers within the WTS and finally, to determine the size of the queues that can be generated for compactors and trucks, considering the internal processes and internal routes of the WTS. Figure 6 illustrates the discrete event simulation model; this 3D model allows the company to better understand how the operation will be in real life when the WTS starts its operation.

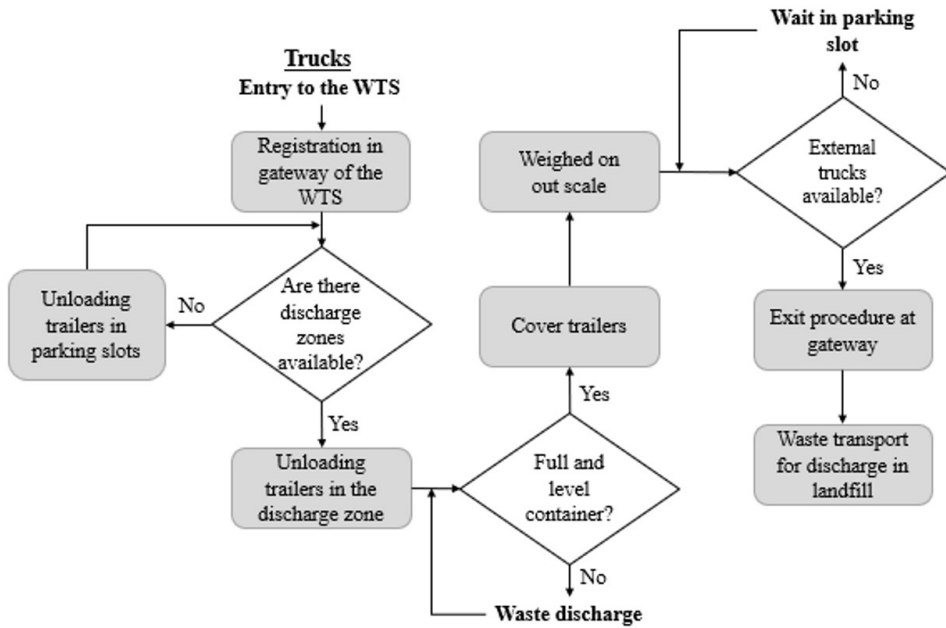


Figure 5. Truck's process flow in WTS.



Figure 6. WTS model in the Flexsim software.

5. Result analysis

This section presents the results of the case study. The data used to feed the models come from the records of the waste collection operation between 2019 and 2020 by the company under study. For the results, the projection of growth of the tonnes of solid waste generated in the city to the year 2038 is considered. Initially, we analyze the impact of the WTS in the system and compare the results with the current operation. Then, we perform several sensitivity analyses of key variables and constraints of the current and future operation.

5.1. Comparison with the current scenario

After applying the fleet sizing model, a reduction in the number of compactor vehicles between 10% and 30% was obtained with respect to the fleet that is currently in operation. This reduction is due to the decrease in time (about 40%) dedicated to the transport of solid waste with the new WTS. Being closer to the collection routes for the unloading of waste, the use of the WTS allows compactor vehicles to carry out more trips during the day compared to those performed today with long trips to the landfill. Figure 7 illustrates the number of compactor vehicles that are necessary to carry out the collection in the collection routes in the years following the entry into operation of the WTS and considering the projected volumes of solid waste for these years. This quantity considers the fleet needed to cover the scheduling performed by the metaheuristic procedure. In some cases, more vehicles were used when compared to those found with the initial mathematical model (1) – (13). Time windows constraints in the zones of the city made not possible to program all the collection routes with the initially determined fleet size. For instance, to ensure feasibility of the metaheuristic solution an increase of 4% of the initial fleet size was needed for the first projected year.

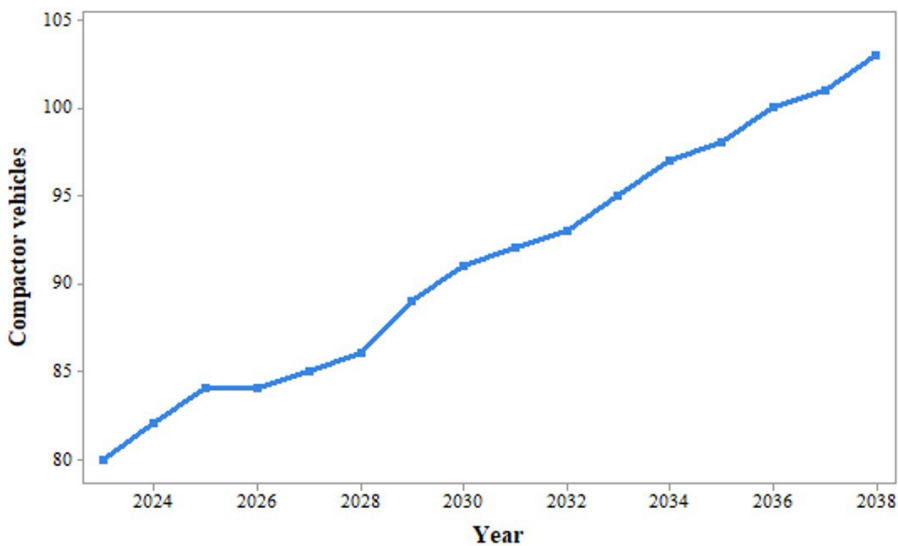


Figure 7. Compactor vehicle fleet size projection.

The results obtained with the assignment and sequencing metaheuristic for the first projected year of operation of the WTS will be discussed in the following. With the implementation of the randomized construction phase, approximately 17% of vehicles can carry out between one and two collection routes per day. However, for the operation in the new WTS, it is not profitable to operate a vehicle to make only one or two trips as they are currently used to transport and unload solid waste in a landfill located outside the city. Nevertheless, in our preliminary experiments we obtained that the order of the collection routes in the initial step (line 1 of Algorithm 1) is an influencing factor in the assignment and may be one of the reasons why some vehicles do not reach more than two collection routes a day. This objective is achieved after the improvement phase. By implementing both phases of the metaheuristic, the results indicate that 6.5% of the vehicle will carry out only two collection routes a day and the remaining 93.5% of vehicles will collect between three and four collection routes daily, increasing in this way the productivity of the system.

Additionally, the arrival of routes to the WTS must be analyzed. After implementing the randomized construction phase, we obtain the arrival of routes depicted in Figure 8, the critical hour occurs in the afternoon, in which 29 vehicles finish 12.3% of the collection routes and enter the WTS to carry out the respective discharge of solid waste, during this hour the queue generated inside the WTS increases since all vehicles go through internal unloading operations in which only one vehicle at a time is allowed.

Whereas, after the implementation of the two phases of the metaheuristic, the percentage of vehicles arriving at the WTS at the critical hour decreases by approximately 14%. Figure 9 illustrates this behavior. In this case, at the critical hour, the vehicles discharge (on average) the waste of 10.3% of the collection routes served daily.

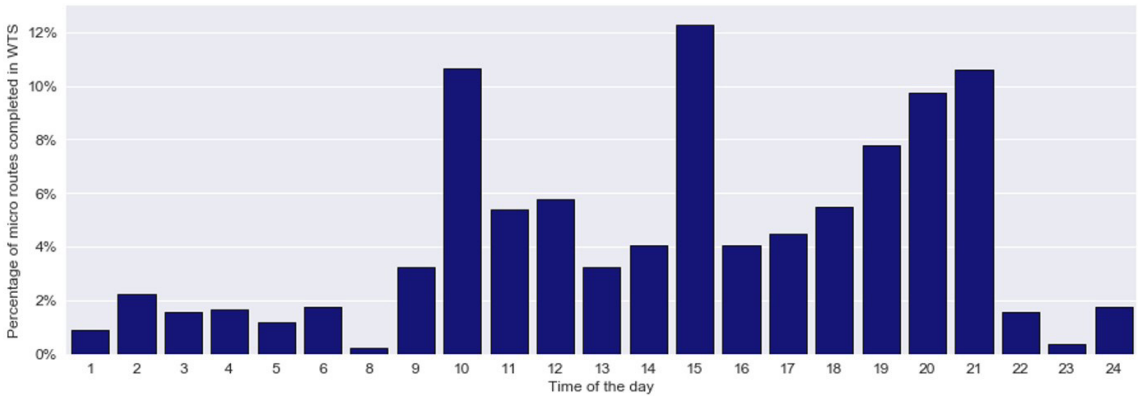


Figure 8. Hourly arrival of compactor vehicles to the WTS under the application of the randomized construction phase.

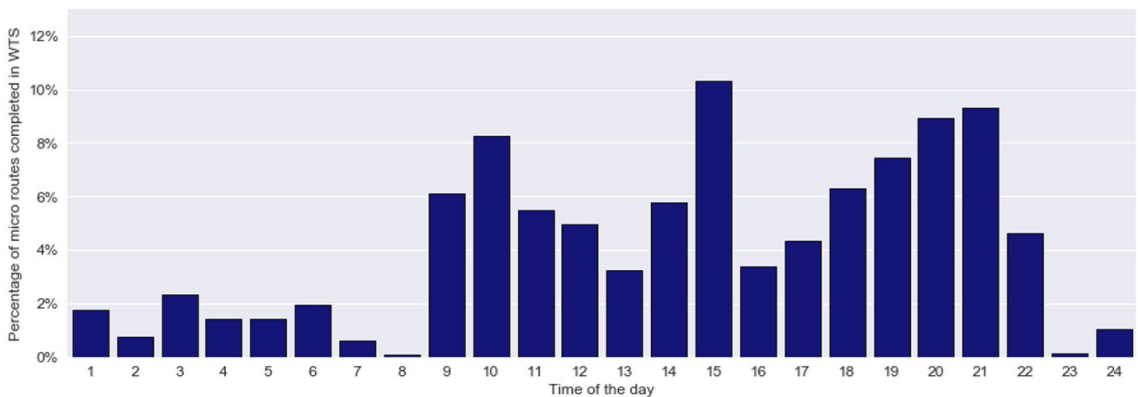


Figure 9. Hourly arrival of compactor vehicles at the WTS after the application of the two phases of the metaheuristic.

The comparison of Figures 8 and 9, reveals that by means of the randomized metaheuristic, it was possible to obtain a better balance in the arrival of vehicles at the WTS at critical times. However, the percentage of routes completed in each hour is still uneven, this is due to the constraints of the route assignment and scheduling process, mainly the time windows at the collection zones.

5.2. Sensitivity analysis

Once we have determined the fleet size that is necessary for the operation of the collection process and have scheduled the compactor vehicles, we set the fleet of trucks and trailers needed for the internal operation of the WTS. Additionally, we performed a sensitivity analysis on the impact of the availability of these resources on the internal operation of this facility. Moreover, the models used in the first two stages of the methodology allow the analysis of some (soft) changes in the system that enable achieving further reductions of the fleet size.

5.2.1. WTS available resources

The use of the discrete event simulation model allows the evaluation of the internal operation of the WTS, taking as input the balanced arrival of vehicles to the WTS obtained with the route allocation and sequencing metaheuristic. For this facility to be operationally viable, other elements must be considered: the number of waste discharge points, the number of internal trucks and trailers and for external use to transport the waste to the landfill, the parking slots for these resources and defined locations for scales, gateway capacity and other necessary spaces for the operation. Different scenarios were proposed considering the variation of the resources that will be used in the WTS, namely: internal and external trucks and available trailers. For these scenarios, we analyze their impact on several efficiency indicators of the WTS. For this case, we reported the maximum and average queues and the average flow times for processing the compactor inside the WTS depending on the number of available resources.

Table 2 shows the results obtained for a few of these scenarios. The queue analyzed corresponds to the one formed before the entrance scale for the compactor vehicles, this is a critical queue, and its formation depends on the availability of unloading points, trailers, and internal trucks, if at a given moment none is available or the scale is busy, a queue will begin to form inside the WTS.

Table 2. Simulation results.

| Trailers | External trucks | Internal trucks | Compactor vehicles | | | |
|----------|-----------------|-----------------|--------------------|---------------|---------------------------------|-------------------------------|
| | | | Maximum queue | Average queue | Average time in queue (minutes) | Average time in WTS (minutes) |
| 21 | 18 | 4 | 35 | 3.0 | 20 | 40 |
| 29 | 18 | 4 | 18 | 2.0 | 15 | 35 |
| 35 | 20 | 5 | 12 | 0.5 | 2 | 23 |
| 40 | 20 | 5 | 12 | 0.17 | 2 | 22 |

With the results of this analysis, we determined that the continuous operation of the WTS requires 35 trailers and for these vehicles the corresponding parking slots should be considered since they must wait while they pass to the unloading points. Additionally, 20 external and 5 internal trucks are required. With these available resources an average queue close to zero is obtained and a maximum queue of 12 compactors which will be obtained. This estimated queue length is below the capacity that the WTS will have internally for compactor vehicles. Likewise, when analyzing the cycle time of compactors inside the WTS we obtained an average time of 23 minutes and a maximum of 48 minutes, values that are consistent with those used for parameter (*tET*) in the fleet sizing model. Figure 10 shows an excerpt of the simulation output. It shows that in the morning there is a low probability of queue generation, while in the afternoon peaks are perceived, mainly after 5:00pm. According to this, Wednesday is one of the most critical days of the week since it is the one with most collection routes.

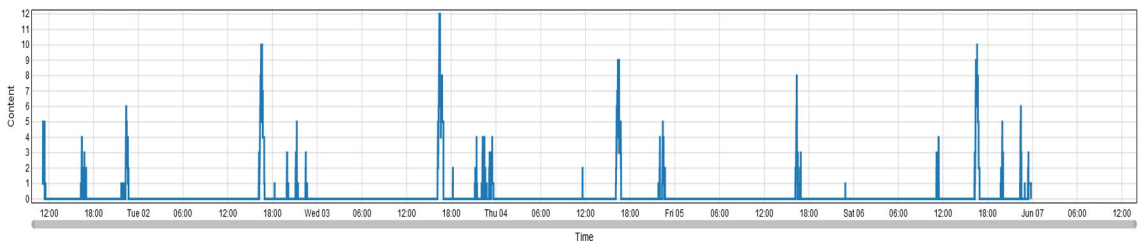


Figure 10. Compactor vehicles queue vs time.

A frequency change scenario was analyzed in the simulation model. In this scenario, a frequency change is made from two to three visits per week for home-type collection, this change implies an increase of 10% of the tonnes collected in the routes. Using the same number of resources considered in the baseline scenario, we get a 25% increase in generated queues and nearly double the maximum queue time for compactor vehicles. Carrying out the operation would take a maximum time of 66 minutes, which reduces the time of compactor vehicles to collect waste in the routes and leading to fewer trips being made during the day. In this case, the number of tonnes discharged in the sanitary landfill will increase and an increase in the use of trucks will be also needed.

Additionally, the behavior of the system for the year 2030 is analyzed as suggested by the managerial team of the company. The same indicators of Table 2 were analyzed considering the allocation of collection routes obtained by the heuristic, the same number of resources considered for 2023 and the current collection routes design. Under this waste collection grow scenario we found that the maximum queue of compactors doubles, which could be a complex issue since it exceeds the maximum queue allowed in the entrance scale. This in turn, leads to tripling the maximum flow time of these vehicles inside the WTS. However, this event happens very few times a week, with an average flow time of approximately 23 minutes. This scenario also implies an additional effort for the trucks, for which the average trips made per day would be increased by 12%. This behavior reinforces the need for a sequel study in which frequency changes and collection routes redesign is allowed to better control the arrival of compactors to the WTS.

5.2.2. Relaxing the constraints of the system

In this analysis we study the effect of relaxing some of the elements that were fixed in the initial models, namely frequency assignment, zone time-widows, and compactor vehicle available time. In a first scenario, we allow a change in the current frequencies of the collection routes (days of visits). This is obtained by modifying parameter mc in the mathematical model (1)-(13). In the previous experiments this value was fixed to $mc = 0$. By allowing a frequency change of a small number of routes a better balance of the tonnes collected daily can be obtained. Particularly, with only a 10% change in frequency of the collection routes ($mc = 55$ out of the 500+ routes of the system), a difference of less than one ton of collected waste can be achieved between the days of the week (i.e., the difference between the day of greatest collection and the day of least collection). By contrast, the solution with the current frequencies has a difference of 121 tonnes between the minimum and maximum collection days. This better balance of the collected waste brings an additional -4% reduction in the fleet size. However, the managerial team of the operation was not willing to make a change in the frequency of collection routes for the company. This change will be analyzed in a sequel study, but our results allow them to have an initial idea of the improvement that they can obtain with these small changes.

Likewise, the time slots for accessing the zones are an important constraint limiting the model to obtain a more balanced allocation of collection routes to vehicles. Therefore, we analyzed a second scenario in which time windows are wider. Figure 11 illustrates the hourly arrival of routes to the WTS under this scenario. As this figure shows, in the peak hour the percentage of completed routes is less than 8%. Moreover, with this flexibility it is possible to use the fleet size resulting from the mathematical programming model (without the need of additional dummy vehicles in the metaheuristic). This is a -4% additional reduction in the projected fleet size. By relaxing this constraint, the additional flexibility given to the system enables a more desirable balancing of the routes arriving to the WTS and a further reduction on the number of required vehicles.

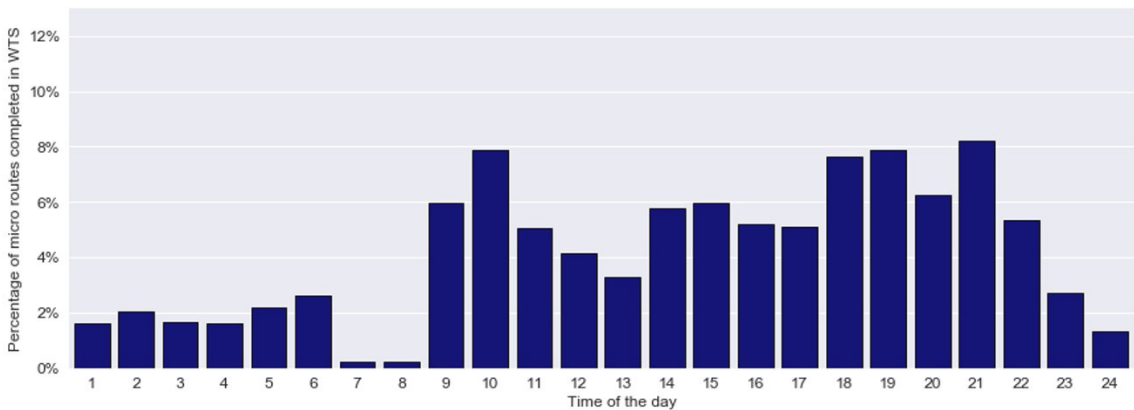


Figure 11. Hourly arrival of compactor vehicles at the WTS when the constraints in the collection time zones change.

Since these previous results reveal that the time windows of the city zones and the availability of the vehicles are a great limitation to assign the collection routes to the fleet size, we analyzed an additional scenario in which all constraints are relaxed simultaneously (frequency assignment, zone time-windows, and compactor availability). Figure 12 compares the number of vehicles needed for the operation under this scenario with four alternatives. In this figure, (i) the base-case scenario display the number of vehicles obtained by the mathematical model considering all the constraints (light blue line), (ii) the fleet size after the route scheduling obtained with the metaheuristic considering all the constraints of the operation (dark blue line), (iii) the fleet size obtained after a change of 10% of the routes using the mathematical programming model (gray line); and (iv) the fleet size of the relaxed scenario considering the change of 10% of the frequency of the routes and the relaxing of the time windows and vehicle availability, after using the metaheuristic for route scheduling (purple line). In cases (i) and (ii), where all constraints are considered, we find that in any year is not possible to schedule the routes with the vehicles obtained in the mathematical model and it is necessary to increase the quantity obtained between 4% and 5% to feasible schedule all routes. Conversely, when we compare scenarios (iii) and (iv) we realize that by relaxing these soft constraints, even fewer vehicles are required in the scheduling phase compared to those of the mathematical programming model. On average, relaxing these constraints all together offers a reduction of -13% of the fleet size when compared to the base-case results depicted on Figure 7. This final analysis

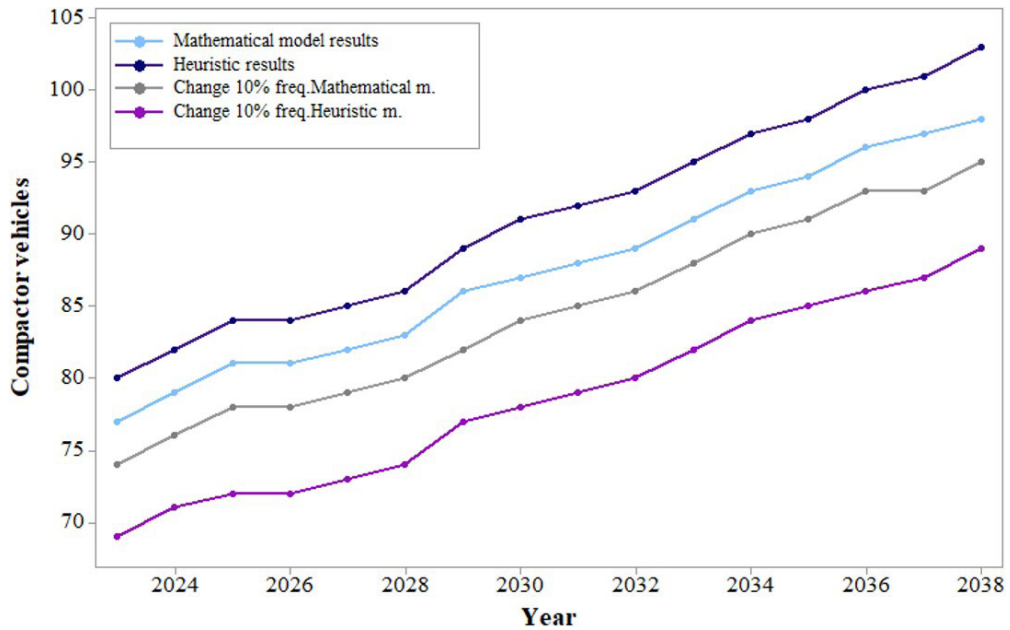


Figure 12. Compactor vehicles required under different scenarios.

unveils the importance of relaxing these (soft) constraints to achieve even better results after the introduction of the new WTS. To implement this scenario, it is important to evaluate if the change of time windows can be implemented in the zones of the city and if the availability of compactor vehicles can be increased considering that preventive maintenance activities should be kept on their corresponding days.

6. Conclusions

In this paper we present the analytical models used to support the tactical planning of the solid waste collection and transportation operation of a Colombian waste management company. Using a multimethodology approach we addressed different tactical decisions that must be revised due to the entry into operation of a new waste transfer station in the near future. Remarkably, we focus on a decision level that is seldom reported in the literature of waste collection.

The first component of this multimethodology approach is a mathematical programming model that assigns 500+ collection routes to different collection patterns to find the optimal fleet size of compactor vehicles to cover them and to balance the amount of solid waste entering the landfill during the days of the week. The second component is a randomized metaheuristic that assigns collection routes to compactors and schedule them during the working shift. The first phase of the metaheuristic consists of a randomized construction that assigns collection routes to the compactor vehicle while keeping the time windows of the zones and the available operating hours of the vehicles. The second phase improves the initial assignment to balance the arrival of vehicles at the WTS using two moves (that change the start time of the collection routes of a vehicle and exchange the order in which they are performed). Finally, the third component of the methodology is a discrete event simulation model that represents the operation of the waste transfer station. Using this model, it is possible to analyze the impact of the route schedules in the internal operation of this facility (length of queues and flow times of compactors in the discharge operation). This simulation model also allows the analysis of the required number of internal resources (trucks and trailers) needed for a proper discharge and final disposal at the landfill of the solid waste.

With the use of this multimethodology approach it was possible to foresee the positive impact of the new transfer station in the tactical planning of the waste collection process. This new facility allows a more productive use of the compactor fleet by allowing the execution of more routes per vehicle during the daily working shift, and consequently an important fleet size reduction (between 10% and 30% less vehicles when compared to the current operation). Moreover, this multimethodology approach enables a set of sensitivity analysis. In this analysis, we removed or relaxed some current tactical and operative constraints of the system. For instance,

a change of frequency of a given percentage of the routes, or the removal or enlargement of the collection time-windows of some districts of the city. Our analysis shows that by allowing these (soft) planning changes additional benefits could be obtained (an additional 13% of reduction in the fleet size and a more even flow of waste to the landfill during the week).

By contrast, in a future study the company will revise the routing of compactor vehicles in such a way as to reduce the times of completion of the routes to further reduce the fleet size. In such a case, the proposed simulation model could be used to validate how this change impacts the arrival of vehicles to the transfer station and its internal operation. Furthermore, this case study has some limitations, since some tactical (districting) and operative (routing and personnel scheduling) decisions were taken as fixed in our analysis. As proposed by Bruecker et al. (2018) the integrated scheduling of vehicles and crews could be included in the routing of the compactor vehicles. This will allow to better include the labor legislation that regulates the assignment of personnel to the operation and their well-being.

References

- Agalianos, K., Ponis, S. T., Aretoulaki, E., Plakas, G., & Efthymiou, O. (2020). Discrete event simulation and digital twins: review and challenges for logistics. *Procedia Manufacturing*, 51, 1636-1641. <http://dx.doi.org/10.1016/j.promfg.2020.10.228>.
- Aguirre-Gonzalez, E. J., & Villegas, J. G. (2017). A two-phase heuristic for the collection of waste animal tissue in a Colombian rendering industry. *Communications in Computer and Information Science*, 742, 511-521. http://dx.doi.org/10.1007/978-3-319-66963-2_45.
- Akbarpour, N., Salehi-Amiri, A., Hajiaghahi-Keshтели, M., & Oliva, D. (2021). An innovative waste management system in a smart city under stochastic optimization using vehicle routing problem. *Soft Computing*, 25(8), 6707-6727. <http://dx.doi.org/10.1007/s00500-021-05669-6>.
- Anagnostopoulos, T., Zaslavsky, A., & Medvedev, A. (2015). Robust waste collection exploiting cost efficiency of IoT potentiality in Smart Cities. In *2015 International Conference on Recent Advances in Internet of Things (RIoT)*, (pp. 1-6). USA: IEEE. <http://dx.doi.org/10.1109/RIOT.2015.7104901>.
- Banks, J., Carson II, J. S., Nelson, B. L., & Nicol, D. M. (2015). *Discrete event system simulation*. Harlow: Pearson.
- Baykasoğlu, A., Subulan, K., Taşan, A. S., & Dudaklı, N. (2019). A review of fleet planning problems in single and multimodal transportation systems. *Transportmetrica A: Transport Science*, 15(2), 631-697. <http://dx.doi.org/10.1080/23249935.2018.1523249>.
- Beliën, J., De Boeck, L., & Van Ackere, J. (2014). Municipal solid waste collection and management problems: a literature review. *Transportation Science*, 48(1), 78-102. <http://dx.doi.org/10.1287/trsc.1120.0448>.
- Bruecker, P., Beliën, J., Boeck, L., Jaeger, S., & Demeulemeester, E. (2018). A model enhancement approach for optimizing the integrated shift scheduling and vehicle routing problem in waste collection. *European Journal of Operational Research*, 266(1), 278-290. <http://dx.doi.org/10.1016/j.ejor.2017.08.059>.
- Carosi, S., Frangioni, A., Galli, L., Girardi, L., & Vallese, G. (2019). A matheuristic for integrated timetabling and vehicle scheduling. *Transportation Research Part B: Methodological*, 127, 99-124. <http://dx.doi.org/10.1016/j.trb.2019.07.004>.
- Edis, E. B., Oguz, C., & Ozkarahan, I. (2013). Parallel machine scheduling with additional resources: notation, classification, models and solution methods. *European Journal of Operational Research*, 230(3), 449-463. <http://dx.doi.org/10.1016/j.ejor.2013.02.042>.
- Elidrissi, A., Benmansour, R., Benbrahim, M., & Duvivier, D. (2018). MIP formulations for identical parallel machine scheduling problem with single server. In *Proceedings of the 2018 International Conference on Optimization and Applications, ICOA 2018* (pp. 1-6). USA: IEEE. <http://dx.doi.org/10.1109/ICOA.2018.8370596>.
- Fadda, E., Gobbato, L., Perboli, G., Rosano, M., & Tadei, R. (2018). Waste collection in urban areas: a case study. *Interfaces*, 48(4), 307-322. <http://dx.doi.org/10.1287/inte.2018.0943>.
- García-Ayala, G., González-Velarde, J. L., Rios-Mercado, R. Z., & Fernández, E. (2016). A novel model for arc territory design: promoting Eulerian districts. *International Transactions in Operational Research*, 23(3), 433-458. <http://dx.doi.org/10.1111/itor.12219>.
- Ghani, G., Laganà, D., Manni, E., Musmanno, R., & Vigo, D. (2014). Operations research in solid waste management: a survey of strategic and tactical issues. *Computers & Operations Research*, 44, 22-32. <http://dx.doi.org/10.1016/j.cor.2013.10.006>.
- Ghani, G., Manni, A., Manni, E., & Moretto, V. (2021). Optimizing a waste collection system with solid waste transfer stations. *Computers & Industrial Engineering*, 161, 107618. <https://doi.org/10.1016/j.cie.2021.107618>.
- Gonela, V., Zhang, J., Salazar, D., & Awudu, I. (2020). Solid waste management: a review from the supply chain perspective. *Journal of Supply Chain and Operations Management*, 18(2), 229-256.
- Kaza, S., Yao, L., Bhada-Tata, P., & Van Woerden, F. (2018). *What a waste 2.0: a global snapshot of solid waste management to 2050*. Washington, DC: World Bank Group.
- Knapčíková, L., Behúnová, A., & Behún, M. (2020). Using a discrete event simulation as an effective method applied in the production of recycled material. *Advances in Production Engineering & Management*, 15(4), 431-440. <http://dx.doi.org/10.14743/apem2020.4.376>.
- Korçyl, A., Książek, R., & Gdowska, K. (2019). A MILP model for the municipal solid waste selective collection routing problem. *Decision Making in Manufacturing and Services*, 13, 1-2.
- Kosacka-Olejnik, M., Kostrzewski, M., Marczevska, M., Mrówczyńska, B., & Pawlewski, P. (2021). How digital twin concept supports internal transport systems? – Literature review. *Energies*, 14(16), 4919. <http://dx.doi.org/10.3390/en14164919>.
- Larson, R. C., Minkoff, A. S., & Gregory, P. (1991). A computer simulation model for fleet sizing for the marine division of the New York City department of sanitation. *Waste Management & Research*, 9(1), 267-276. <http://dx.doi.org/10.1177/0734242X9100900138>.
- Lepenioti, K., Bousdekis, A., Apostolou, D., & Mentzas, G. (2020). Prescriptive analytics: Literature review and research challenges. *International Journal of Information Management*, 50, 57-70. <http://dx.doi.org/10.1016/j.ijinfomgt.2019.04.003>.

- Li, J., Borenstein, D., & Mirchandani, P. B. (2008). Truck scheduling for solid waste collection in the City of Porto Alegre, Brazil. *Omega*, *36*(6), 1133-1149. <http://dx.doi.org/10.1016/j.omega.2006.04.007>.
- Lima, J. P., Lobato, K. C. D., Leal, F., & Lima, R. S. (2015). Urban solidwaste management by process mapping and simulation. *Pesquisa Operacional*, *35*(1), 143-163. <http://dx.doi.org/10.1590/0101-7438.2015.035.01.0143>.
- Machado, C. R., & Hettiarachchi, H. (2020). Composting as a municipal solid waste management strategy: lessons learned from Cajicá, Colombia. In H. Hettiarachchi, S. Caucci & K. Schwärzel (Eds.), *Organic waste composting through nexus thinking* (pp. 17-38). Cham: Springer Nature.
- Mansini, R., & Speranza, M. G. (1998). A linear programming model for the separate refuse collection service. *Computers & Operations Research*, *25*(7-8), 659-673. [http://dx.doi.org/10.1016/S0305-0548\(97\)00094-4](http://dx.doi.org/10.1016/S0305-0548(97)00094-4).
- Mourão, M. C., Nunes, A. C., & Prins, C. (2009). Heuristic methods for the sectoring arc routing problem. *European Journal of Operational Research*, *196*(3), 856-868. <http://dx.doi.org/10.1016/j.ejor.2008.04.025>.
- Rada, E. C., Ragazzi, M., & Fedrizzi, P. (2013). Web-GIS oriented systems viability for municipal solid waste selective collection optimization in developed and transient economies. *Waste Management*, *33*(4), 785-792. <http://dx.doi.org/10.1016/j.wasman.2013.01.002>. PMID:23402896.
- Ramos, T. R. P., Gomes, M. I., & Barbosa-Póvoa, A. P. (2014). Planning a sustainable reverse logistics system: balancing costs with environmental and social concerns. *Omega*, *48*, 60-74. <http://dx.doi.org/10.1016/j.omega.2013.11.006>.
- Santos, C. H. D., Lima, R. D. C., Leal, F., Queiroz, J. A., Balestrassi, P. P., & Montevechi, J. A. B. (2020). A decision support tool for operational planning: a Digital Twin using simulation and forecasting methods. *Production*, *30*, e20200018. <https://doi.org/10.1590/0103-6513.20200018>.
- Şeref, M. M. H., & Ahuja, R. K. (2008). Spreadsheet-based decision support systems. In F. Burstein & W. Holsapple (Eds.), *Handbook on decision support systems* (pp. 277-298). Berlin: Springer Nature.
- Simonetto, E. O., & Borenstein, D. (2007). A decision support system for the operational planning of solid waste collection. *Waste Management*, *27*(10), 1286-1297. <http://dx.doi.org/10.1016/j.wasman.2006.06.012>. PMID:17005387.
- Sulemana, A., Donkor, E. A., Forkuo, E. K., & Oduro-Kwarteng, S. (2018). Optimal routing of solid waste collection trucks: a review of methods. *Journal of Engineering*, *2018*, 4586376.
- Van Engeland, J., & Beliën, J. (2021). Tactical waste collection: column generation and mixed integer programming based heuristics. *OR-Spektrum*, *43*(1), 89-126. <http://dx.doi.org/10.1007/s00291-020-00611-y>.
- Vargas, A. P., Jaramillo, S., Rangel, F., Villa, D., & Villegas, J. G. (2020, December 9-11). Optimization models for the tactical planning of the solid waste collection operation: case study in Colombia. In *10th International Conference on Production Research – Americas 2020*. Bahia Blanca, Argentina: ICPR.
- Wang, P. (2020). Vehicle scheduling problem in terminals: a review. In B. B. Hedia, Y. Chen, G. Liu & Z. Yu (Eds.), *International Conference on Verification and Evaluation of Computer and Communication Systems* (pp. 54-67). Cham: Springer. http://dx.doi.org/10.1007/978-3-030-65955-4_5.