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Research Article

A simulation-based optimization model for quality control in solid waste collection process

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Abstract

Paper aims: The Solid Waste Collection (SWC) process is fundamental to maintaining the healthiness of cities and protecting the environment. There is a lack of methodologies for integrating process quality control techniques to evaluate SWC performance. This article develops a methodological implementation with a simulation-based optimization technique to model SWC process.

Originality: Development of new simulation-based optimization techniques and tools that improve and complement the traditional analysis of variables in SWC Process.

Research method: Feasible solutions are obtained through an optimization stage and then solutions are used as inputs for the simulation stage.

Main findings: There is a high correlation between the total tons collected and the total time. It is possible to optimize the collection routes by integrating process quality control techniques to reduce the total travel time, which will reduce the operating costs and the environmental impact. Simulation results demonstrate a reduction in error of over 90% for each day, with an optimization of 55% in total times.

Implications for theory and practice: The methodology enables the collection of data and results that accurately reflect the behavior and performance of the SWC process. By studying the process variability and uncertainty, enhancing the reliability and robustness of the results.

Keywords

Goal programming applications. Monte Carlo simulation. Optimization model. Quality control model. Solid waste collection management.

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1. Introduction

Solid Waste Collection (SWC) is the process by which waste generated by human activity in urban areas is collected and transported (Tchobanoglous, 2009). This process is essential for maintaining hygiene and public health in cities, as it prevents the accumulation of waste in the streets and the spread of diseases. Thus, it has a significant impact on the quality of human life. First, the lack of waste collection can cause odors and attract insects and rodents, which can cause health problems in the nearby population (Ziraba et al., 2016; Hossain et al., 2011; Alam & Ahmade, 2013; Mangoro & Kubanza, 2023). In addition, waste accumulation can clog drainage systems and cause flooding in rainy seasons (Abd Manaf et al., 2009).

In recent years, some attention has been given to modelling, simulation, and optimization techniques for quality control capable of representing and improving waste collection processes (Cárdenas-Cuervo et al., 2023; Mascarenhas et al., 2021; Koot et al., 2021). These techniques support decision-making by helping to determine the best scenario in a combinatorial search space with stochastic variables (Sadati et al., 2024). Simulation-based optimization is used in a variety of quality control applications to find the best control parameter settings that maximize process efficiency and minimize errors and defects in the final product (Aljebory & Alshebeb, 2014; Volsuuri et al., 2023), evidencing that it is a valuable tool for designing and improving quality control processes, as it allows evaluating different scenarios and adjusting control parameters (Ahmad, 2018).

Quality control of SWC processes is essential to ensure public health, protect the environment, optimize the management of resources and costs, and fulfill the social responsibility to properly manage municipal solid waste (Saha et al., 2010). In addition, Zaccariello et al. (2015) state that quality indicators for process control and efficiency to measure the effectiveness of waste collection and disposal processes allow for evaluating the performance of SWC management.

Quality control still plays a vital function in the quality assurance of products and processes (Cogollo-Florez & Valencia-Mena, 2022; Valdés-Manuel & Cogollo-Flórez, 2022), as it allows for detecting and correcting errors before main problems occur. However, it can often be difficult to find solutions that balance the multiple and conflicting objectives that any operation may face, such as maximizing efficiency and quality, reducing costs, and optimizing cycle time (Sanjeevi & Shahabudeen, 2015; Purkayastha et al., 2019; Hannan et al., 2020).

One of the most viable techniques to provide solutions that balance multiple objectives is Goal Programming (GP) (Ignizio, 1983), an optimization technique that allows solving multi-objective problems by assigning priorities and assigning weights to each goal, which can be used to optimize different operations (Lyeme et al., 2017). For GP process quality control application, first, the optimization objectives are stated; then, weights and priorities for each goal are assigned based on their relative importance to the process; finally, the model performance is assessed and improved (Cherif et al., 2008). In those applications, techniques such as Monte Carlo Simulation (MCS) could be used for making informed decisions and optimizing results in different scenarios (Carrazza & Cruz-Martinez, 2020; Li et al., 2013).

Simulation-based optimization models applied to SWC provide several advantages over predictive models of fixed inputs since the ability to perform sensitivity analysis or calculate the correlation of inputs. Moreover, Tian et al. (2007) and Wajs et al. (2000) state that advanced technologies adoption and the appropriate policies implementation can significantly reduce the environmental impact and assess the economic feasibility of SWC (Martín-Pascual et al., 2020; Abdullah, 2023).

We note that there are several papers using GP and MCS to improve the SWC process (Lu et al., 2020; Zaeimi & Rassafi, 2021; Pamukçu et al., 2023). However, it is possible to find a gap in the integration of these two tools and their impact on SWC process control. To address this, we propose a methodology in Python for process quality control to minimize process time in SWC. This approach will allow for the improvement of computational efficiency, scalability, and accessibility, due to the versatility and popularity of the language. The integration of goal programming and Monte Carlo simulation (GP-MCS) will serve as the foundation for an industrial development that will assist the municipal SWC company in significantly improving its quality control process, time management, strategic planning, and decision-making based on reliable data. The paper is structured as follows: the methodology is in section 2, the results are in section 3, and the conclusions are in section 4.

2. Methodology

The study case was applied to an urban SWC operation in a medium-sized city in Colombia. The city has an area of 571.8 square kilometers and is divided into nineteen (19) districts with a total population of 565,527. The city has a single company for the collection service. The company divides its routes by day, with a collection frequency of two (2) times per week, from Monday to Saturday. This is done to ensure that the entire waste collection limit of the city is covered. The database used has a total of 80,513 actual records, corresponding to 172 routes, containing information on route and vehicle codes, collection date, day of the week, start and end time, total operating time, total operating kilometers, number of trips required, number of compactors, and amount of fuel used in tons.

As a preliminary step to the proposed methodology, it was necessary to process the data. The 80,513 records were divided according to the day of the week on which the route was run. The route operating time was used as the performance measure, and the data was cleaned by excluding those that were three standard deviations above or below the average operating time, resulting in a total of 59,671 records.

The Goal Programming – Monte Carlo Simulation methodology in SWC (GoProMoS-SWC) is based on Morán-Zabala & Cogollo-Flórez (2023a). This methodology (Figure 1) represents a novel approach to the field of SWC processes, offering the potential to enhance performance through the application of quality control techniques. It uses the real operation data to integrate optimization and simulation techniques achieving better results in total operation time. The methodology has two main stages: Stage 1: GP and Stage 2: MCS. Stage 1 (GP) seeks to provide a solution to the problem posed through a clear and hierarchical definition of the objectives directly, allowing the decision-making process and planning to adapt and find better solutions. In the first step of this stage, it is necessary to define and describe the variables that will be used within the model to define relationships and propose the mathematical formulation. A multiple regression analysis is then performed to model and understand the relationships between a dependent variable and several independent variables to provide accurate estimates and projections useful for decision making. Then, to improve the precision and quality of the model, the variables are transformed according to the specification limits and the regression equations are modified. Subsequently, the penalized equation is determined and subjected to a series of constraints to limit the feasible solutions and adapt them to certain conditions of the problem. Finally, the results of this stage are analyzed.

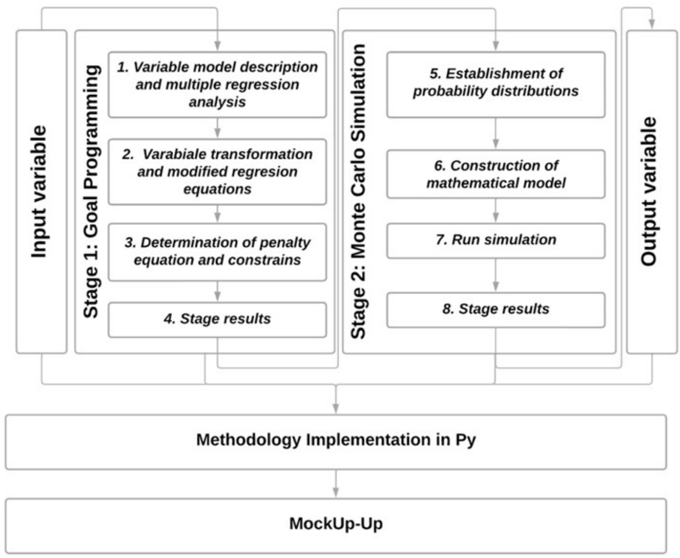

Figure 1. Methodology stages.
Source: own elaboration based on based on Morán-Zabala & Cogollo-Flórez (2023a).

The results of Step 1 serve as inputs to Step 2. First, the probability distributions are established to model the uncertainty associated with the model variables and reduce their variability, thereby improving the accuracy and reliability of the results. Then, the mathematical model of the simulation is built to describe the interactions between the components of the system, and finally, the simulation runs are performed to obtain the results and data that represent the behavior and performance of the process in different scenarios and conditions, in order to study the variability and uncertainty of the process and the model parameters, thus improving the robustness and reliability of the results.

This methodology was implemented in Python to reduce the computational cost, and as future research it is proposed to take it to an industrial development. Details of the methodology and results are presented in the next section.

3. Results

3.1. Stage 1: Goal Programming (GP)

To perform the optimization approach as a GP lexicographic problem and to establish the model, it is necessary to minimize the problem to the sum of the deviation of the variable (Equation 1) from the target concerning the constraints. Equation 2 details the adequacy of the sum of variances for the problem, where P_{Y_i}, P_{X_k} and P_{R_i} refer to the negative and positive penalty of output variables, input variables, and process variables, respectively, and n: [0, 1, 2, 3, 4, 5] (Sengupta, 1981; Cherif et al., 2008; Morán-Zabala & Cogollo-Flórez, 2023a).

$$\min \sum_{m=1}^{lkr} \left(\delta^{-}{}_{m} + \delta^{+}{}_{m}\right)_{n} \tag{1}$$

$$\boldsymbol{Min}\left\{ \boldsymbol{P_{Y_i}} \sum_{\boldsymbol{i}=0}^{\boldsymbol{l}} \left(\delta^{-}{}_{\boldsymbol{Y'}} + \delta^{+}{}_{\boldsymbol{Y'}}\right) + \boldsymbol{P_{X_k}} \sum_{\boldsymbol{j}=0}^{\boldsymbol{k}} \left(\delta^{-}{}_{\boldsymbol{X'}} + \delta^{+}{}_{\boldsymbol{X'}}\right) + \boldsymbol{P_{R_i}} \sum_{\boldsymbol{t}=0}^{\boldsymbol{r}} \left(\delta^{-}{}_{\boldsymbol{R'}} + \delta^{+}{}_{\boldsymbol{R'}}\right) \right\}_{\boldsymbol{n}} \tag{2}$$

Subject to:

Input goal constraint:

$$\left[X_i' + \boldsymbol{\delta}^{-}{}_{R_i'} - \boldsymbol{\delta}^{+}{}_{R_i'}\right]_n = \left[z'_{R_i}\right]_n \quad \left(for\, i = 1, 2, \ldots, r\right) \tag{3}$$

Process goal Constraints

$$\left[R_j' + \boldsymbol{\delta}^{-}{}_{x_j'} - \boldsymbol{\delta}^{+}{}_{x_j'}\right]_n = \left[z'_{x_j}\right]_n \quad \left(for\, i = 1, 2, \ldots, r\right) \tag{4}$$

Output goal Constraints

$$\left[Y_i' + \boldsymbol{\delta}^{-}{}_{\mathbf{Y}_i} - \boldsymbol{\delta}^{+}{}_{\mathbf{Y}_i}\right]_n = \left[z'_{Y_i}\right]_n \quad \left(for\, i = 1, 2, \ldots, r\right) \tag{5}$$

$$Y_i', x_j' \; and \; R_i^{'} \geq 0$$

where (3) is the input goal constrain, (4) is the process goal constrain, (5) is the output goal constrain, $\left[P_{Y_i}\right]_n$, $\left[P_{x_k}\right]_n$, and $\left[P_{R_i}\right]_n$ are the priority factors and $\left[z'_{R_i}\right]_n$, $\left[z'_{x_j}\right]_n$ and $\left[z'_{Y_i}\right]_n$ are the modified specification limits.

3.1.1. Variable model description and multiple regression analysis

Improving the capacity of the SWC process is vital to increase the quality of service and quality of life indices and to reduce inequalities between communities. For this purpose, the input variable considered in this study is Tons collected. The main quality characteristic to optimize and improve the process is the total time.

All process variables are measurable and controllable. The input variable is the number of tons collected (x). The greater the tons collected, the greater the workload and, therefore, the longer the time required to complete the process. Process variables such as total kilometers traveled (R_1), the trips number (R_2), compactions (R_3), and fuel tons consumption (R_4) are key indicators of the performance of the collection process. These variables provide insight into the utilization of resources and the efficiency of the process in terms of time and resources. By considering these input and process variables, areas for improvement and opportunities to optimize the collection process can be identified. These include reducing mileage or total collection time, increasing comparison efficiency, or improving route planning.

The output variables measured in hours correspond to the total time (Y_n) of the collection process for the six days studied. The estimation of the total SWC time provides a comprehensive measure of the performance of the collection process. The total collection time reflects the efficiency and effectiveness of the system and can be used as a key metric to evaluate performance and make comparisons between different collection scenarios or strategies. Details of the input variable, process variables, and quality characteristic are in Table 1.

To perform a multiple linear regression analysis for each day, a study of the capacity of the urban SWC process was carried out for a collection service provider. The matrix with the respective correlation coefficients between the variables is shown in Figure 2. Thus, the following Equations 6 to 11 were obtained:

$$Y_0 = 2.0450 + \left[0.2895x + 0.0384R_1 - 0.0994R_2 + 0.0034R_3 + 0.0329R_4\right]_0 \tag{6}$$

Table 1. Description of model variables.

Variable type	Variable	Specification limits	Variable classification
Input	(x) Tons collected	[9, 13]	Continuous
Process	(R_1) Total Km	[25, 45]	Continuous
	(R_2) Trips number	[0, 2]	Discrete
	(R_3) Compactions	[2,4]	Discrete
	(R_4) Fuel tons	[6, 8]	Continuous
Output	(Y_n) Total time	[6, 8]	Continuous

Source: own elaboration.

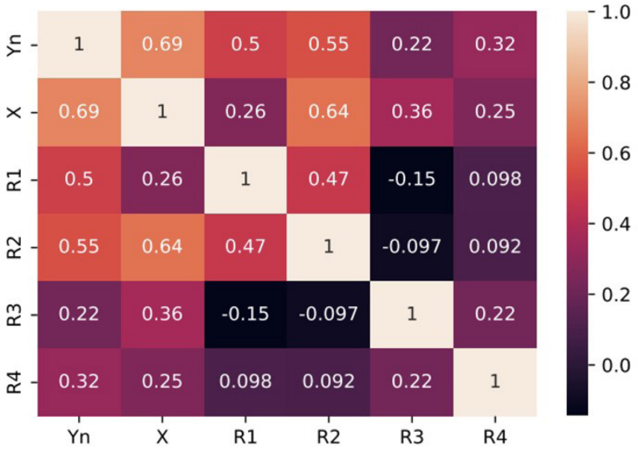

Figure 2. Correlation matrix variables.
Source: own elaboration.

$$Y_1 = 1.3188 + \left[0.17x + 0.0694R_1 + 0.06726R_2 - 0.0016R_3 + 0.051R_4\right]_1 \tag{7}$$

$$Y_2 = 0.8201 + \left[0.15x + 0.0499R_1 + 0.8110R_2 + 0.0063R_3 + 0.049R_4\right]_2 \tag{8}$$

$$Y_3 = 2.4326 + \left[0.24x + 0.0371R_1 - 0.1320R_2 + 0.0095R_3 + 0.04R_4\right]_3 \tag{9}$$

$$Y_4 = 1.7426 + \left[0.21x + 0.0649R_1 + 0.0856R_2 + 0.0047R_3 + 0.047R_4\right]_4 \tag{10}$$

$$Y_5 = 1.3138 + \left[0.133x + 0.0579R_1 + 0.5633R_2 + 0.0084R_3 + 0.045R_4\right]_5 \tag{11}$$

In addition, Figure 2 shows the results of the correlation coefficients between the input variable and the process variables. The x variable is highly correlated with Y and R_2, as well as R_1 and R_2 with Y. This indicates that there is a close relationship between the total tons collected and the total time required. This connection underscores the importance of considering these factors when effectively planning and managing harvesting operations, with the objective of optimizing efficiency and reducing total process times.

3.1.2. Variable transformation and modified regression equations

Transformation of variables to obtain one-side specifications and modify the constant terms in the regression equations according to (12) is shown from (13) to (18):

$$j' = j - ULS \le ULS - LLS \tag{12}$$

$$x' = x - 9 \le 4 \tag{13}$$

$$R_1' = R_1 - 25 \le 20 \tag{14}$$

$$R'_2 = R_2 - 0 \le 2 \quad (15)$$

$$R'_3 = R_3 - 2 \le 2 \quad (16)$$

$$R'_4 = R_4 - 6 \le 2 \quad (17)$$

$$Y'_n = Y_n - 8 \le 2 \quad (18)$$

Then, the modified regression for the six days equations applying $Y'_n = Coeficient + R' + x'_1 + x'_2 + x'_3 \ldots x'_m$ are the following:

$$Y'_0 = 5.8164 + \left[0.2895x + 0.0384R_1 - 0.0994R_2 + 0.0034R_3 + 0.0329R_4\right]_0 \quad (19)$$

$$Y'_1 = 4.8747 + \left[0.17x + 0.0694R_1 + 0.06726R_2 - 0.0016R_3 + 0.051R_4\right]_1 \quad (20)$$

$$Y'_2 = 3.7187 + \left[0.15x + 0.0499R_1 + 0.8110R_2 + 0.0063R_3 + 0.049R_4\right]_2 \quad (21)$$

$$Y'_3 = 5.8769 + \left[0.24x + 0.0371R_1 - 0.1320R_2 + 0.0095R_3 + 0.04R_4\right]_3 \quad (22)$$

$$Y'_4 = 5.5840 + \left[0.21x + 0.0649R_1 + 0.0856R_2 + 0.0047R_3 + 0.047R_4\right]_4 \quad (23)$$

$$Y'_5 = 4.2511 + \left[0.133x + 0.0579R_1 + 0.5633R_2 + 0.0084R_3 + 0.045R_4\right]_5 \quad (24)$$

3.1.3. Determination of penalty equations and constraints.

The minimization of the GP problem for the six days can be formulated as follows, considering that n: [0, 1, 2, 3, 4, 5]:

$$\begin{aligned}
Min\ z_{Ge}\colon \langle & P_{Y_0}(\delta^-_{Y_0} + \delta^+_{Y_0}) \\
& + \left[P_{R_1}(\delta^-_{R_1} + \delta^+_{R_1}) + P_{R_2}(\delta^-_{R_2} + \delta^+_{R_2}) + P_{R_3}(\delta^-_{R_3} + \delta^+_{R_3})\right. \\
& \left. + P_{R_4}(\delta^-_{R_4} + \delta^+_{R_4}) + P_x(\delta^-_x + \delta^+_x)\right]_0 \\
& + \left\{P_{Y_1}(\delta^-_{Y_1} + \delta^+_{Y_1})\right. \\
& + \left[P_{R_1}(\delta^-_{R_1} + \delta^+_{R_1}) + P_{R_2}(\delta^-_{R_2} + \delta^+_{R_2}) + P_{R_3}(\delta^-_{R_3} + \delta^+_{R_3})\right. \\
& \left.\left. + P_{R_4}(\delta^-_{R_4} + \delta^+_{R_4}) + P_x(\delta^-_x + \delta^+_x)\right]_1\right\} \\
& + \left\{P_{Y_2}(\delta^-_{Y_2} + \delta^+_{Y_2})\right. \\
& + \left[P_{R_1}(\delta^-_{R_1} + \delta^+_{R_1}) + P_{R_2}(\delta^-_{R_2} + \delta^+_{R_2}) + P_{R_3}(\delta^-_{R_3} + \delta^+_{R_3})\right. \\
& \left.\left. + P_{R_4}(\delta^-_{R_4} + \delta^+_{R_4}) + P_x(\delta^-_x + \delta^+_x)\right]_2\right\} \\
& + \left\{P_{Y_3}(\delta^-_{Y_3} + \delta^+_{Y_3})\right. \\
& + \left[P_{R_1}(\delta^-_{R_1} + \delta^+_{R_1}) + P_{R_2}(\delta^-_{R_2} + \delta^+_{R_2}) + P_{R_3}(\delta^-_{R_3} + \delta^+_{R_3})\right. \\
& \left.\left. + P_{R_4}(\delta^-_{R_4} + \delta^+_{R_4}) + P_x(\delta^-_x + \delta^+_x)\right]_3\right\} \\
& + \left\{P_{Y_4}(\delta^-_{Y_4} + \delta^+_{Y_4})\right. \\
& + \left[P_{R_1}(\delta^-_{R_1} + \delta^+_{R_1}) + P_{R_2}(\delta^-_{R_2} + \delta^+_{R_2}) + P_{R_3}(\delta^-_{R_3} + \delta^+_{R_3})\right. \\
& \left.\left. + P_{R_4}(\delta^-_{R_4} + \delta^+_{R_4}) + P_x(\delta^-_x + \delta^+_x)\right]_4\right\} \\
& + \left\{P_{Y_5}(\delta^-_{Y_4} + \delta^+_{Y_5})\right. \\
& + \left[P_{R_1}(\delta^-_{R_1} + \delta^+_{R_1}) + P_{R_2}(\delta^-_{R_2} + \delta^+_{R_2}) + P_{R_3}(\delta^-_{R_3} + \delta^+_{R_3})\right. \\
& \left.\left. + P_{R_4}(\delta^-_{R_4} + \delta^+_{R_4}) + P_x(\delta^-_x + \delta^+_x)\right]_5\right\}\rangle
\end{aligned} \quad (25)$$

Subject to:

Input constraint

$$\left[x' + \delta^{-}{}_{x} + \delta^{+}{}_{x}\right]_{n} = 4 \quad (26)$$

Process constraints

$$\left[R_1' + \delta^{-}{}_{R_1} + \delta^{+}{}_{R_1}\right]_{n} = 2 \quad (27)$$

$$\left[R'_2 + \delta^{-}{}_{R_2} + \delta^{+}{}_{R_2}\right]_{n} = 20 \quad (28)$$

$$\left[R'_3 + \delta^{-}{}_{R_3} + \delta^{+}{}_{R_3}\right]_{n} = 2 \quad (29)$$

$$\left[R_4' + \delta^{-}{}_{R_4} + \delta^{+}{}_{R_4}\right]_{n} = 2 \quad (30)$$

Output Constraints

$$\left[Y' + \delta^{-}{}_{Y} - \delta^{+}{}_{Y}\right]_{n} = 8; \quad i.e. \quad (31)$$

$$\left[0.2895x + 0.0384R_1 - 0.0994R_2 + 0.0034R_3 + 0.0329R_4\right]_0 = 2.1836 \quad (32)$$

$$\left[0.17x + 0.0694R_1 + 0.06726R_2 - 0.0016R_3 + 0.051R_4\right]_1 = 3.1253 \quad (33)$$

$$\left[0.15x + 0.0499R_1 + 0.8110R_2 + 0.0063R_3 + 0.049R_4\right]_2 = 4.2813 \quad (34)$$

$$\left[0.24x + 0.0371R_1 - 0.1320R_2 + 0.0095R_3 + 0.04R_4\right]_3 = 2.1231 \quad (35)$$

$$\left[0.21x + 0.0649R_1 + 0.0856R_2 + 0.0047R_3 + 0.047R_4\right]_4 = 2.416 \quad (36)$$

$$\left[0.133x + 0.0579R_1 + 0.5633R_2 + 0.0084R_3 + 0.045R_4\right]_5 = 3.7489 \quad (37)$$

The constraints (27) to (30) guarantee the fulfilment of the total kilometers target, the number of trips target, the number of compactions target, and tons of fuels target, respectively. Solving the lexicographic GP problem described in (25), the optimal solution to guarantee the ability of the process to meet the target specifications of the response variables for each day is shown in Table 2. If the optimization model for the SWC process does not meet the defined constraints, the negative effects can be significant. These include operational inefficiencies, increased costs, negative environmental impacts due to additional emissions and pollution, customer dissatisfaction due to delays or inconsistent service, and potential legal and regulatory risks such as fines or loss of licenses.

3.2. Stage 2: Monte Carlo Simulation (MCS)

3.2.1. Establishing of probability distributions

Based on the analysis of the available data, the parameters and probability distributions of the input and process variables must be configured (Morán-Zabala & Cogollo-Flórez, 2023b). As the data set for the simulation exceeded 5,000 observations, the Anderson-Darling goodness-of-fit test (AD-Test) was employed to assess the data fit to a specific distribution for each day. To this end, we fitted all the distributions and ranked their goodness-of-fit, from the most to least optimal, according to the weight of the area between the empirical and

Table 2. Optimal solution for each day.

Days	X	R_1	R_2	R_3	R_4	Y
Monday (Y_0)	9	32.37	1	2	6	6
Tuesday (Y_1)	9	31.59	1	4	6	6
Wednesday (Y_3)	9	38.44	2	2	6	6
Thursday (Y_4)	9	35.48	2	2	6	6
Friday (Y_5)	10.11	25	1	2	8	5.99
Saturday (Y_6)	9	35.74	2	2	6	6

Source: own elaboration.

the fitted cumulative distribution function (CDF). In this context, the smaller values corresponded to the more accurate fits. Table 3 shows the best fit distribution and parameters for days and variables. In addition, each distribution parameter for performing the simulation is shown. The adjustment made for each of the days and variables to find the best associated with the data is shown in Appendix A and the behaviour of the selected distributions in Appendix B.

3.2.2. Construction of the mathematical model

The general MCS mathematical model is based on (6) to (11) and presented in (38), considering the correlation coefficients (Figure 2) between variables and the probabilistic distributions, next, 10,000 simulation runs were performed.

$$
\begin{aligned}
Y_n = \sum_{0}^{n=5} 2.0450 + \{0.2895[x \rightarrow Skc(-0.67 + 16.34 + 1.79)] \\
&+ 0.0384[R_1 \rightarrow LA(0.76;\ 34.40;\ 11.08)] - 0.0994[R_2 \rightarrow Fc(99.41; 0.10; 0.02)] \\
&+ 0.0034[R_3 \rightarrow LA(1.81; 62.00; 11.60)] \\
&+ 0.0329[R_4 \rightarrow Br(3.82; 0.30; 0.02; 11.51)]\}_0 \\
&+ \{0.1700[x \rightarrow Gl(0.27; 16.07; 1.04)] + 0.0694[R_1 \rightarrow Jsu(0.79; 1.97; 13.53)] \\
&+ 0.0672[R_2 \rightarrow Nk(0.06; 2.00; 0.19)] - 0.0001[R_3 \rightarrow LA(1.57; 60.00; 10.89)] \\
&+ 0.0510[R_4 \rightarrow Fl(0.50; 2.17; 8.45)]\}_1 \\
&+ \{0.1500[x \rightarrow Mke(2.32; 10.88;\ -0.60; 18.41)] \\
&+ 0.0499[R_1 \rightarrow Dg(1.33; 38.61; 9.14)] + 0.8110[R_2 \rightarrow Nk(0.19; 2.00; 0.21)] \\
&- 0.0063[R_3 \rightarrow LA(1.56; 60.00; 11.73)] + 0.0490[R_4 \rightarrow ExN(0.50; 2)]\}_2 \\
&+ \{0.24[x \rightarrow Jsu(1.14; 1.07;\ 13.96; 1.86)] \\
&+ 0.0371[R_1 \rightarrow Dw(0.95; 36.10; 11.72)] - 0.1320[R_2 \rightarrow Fc(99.66; 0.26; 0.02)] \\
&+ 0.0095[R_3 \rightarrow Gl(0.31;\ 59.33;\ 5.66)] \\
&+ 0.04[R_4 \rightarrow Br12(1.59; 7.16; 0.03; 25.11)]\}_3 \\
&+ \{0.21[x \rightarrow Mke(3.20;\ 19.09;\ -1.80; 15.86)] \\
&+ 0.0649[R_1 \rightarrow SkN(-1.15; 38.10; 11.62)] \\
&+ 0.0856[R_2 \rightarrow GeN(0.29; 2.00; 0.00)] \\
&+ 0.0047[R_3 \rightarrow Br(16.15; 0.23;\ -21.68;\ 84.19)] \\
&+ 0.047[R_4 \rightarrow SkN(9.63; 1.35; 7.42)]\}_4 \\
&+ \{0.133[x \rightarrow GeN(2.75;\ 10.56;\ 5.93] \\
&+ 0.057[R_1 \rightarrow Br(8.01;\ 0.38;\ -0.29;\ 43.58)] \\
&+ 0.5633[R_2 \rightarrow Nk(0.04;\ 2.00;\ 0.02)] + 0.0084[R_3 \rightarrow LA(1.57; 60.00; 11.35)] \\
&+ 0.045[R_4 \rightarrow NiG(35.45;\ 35.26;\ -2.16;\ 0.99)]\}_5
\end{aligned} \tag{38}
$$

where *Skc* is Skewcauchy, *LA* is Laplace_Asimetric, *Fc* is Flodcauchy, *Br* is Burr, *Gl* is Genlogistic, *Jsu* is Johnsonsu, *Nk* is Nakagami, *Fl* is Fatiguelife, *Mke* is Mielke, *Dg* is Dgamma, *ExN* is Exponnorm, *Dw* is Dweibull, *Br12* is Burr 12, *SkN* is Skewnorm, *GeN* is Gennorm, and *NiG* is Norminvgauss.

3.2.3. Run simulations

Figure 3 shows the simulation histogram results for all the days measured in hours. The mean of the results for the 10,000 simulated days is 6.046 hours, indicating that the optimal solutions for these (see Table 2) are close to the current Lower Specification Limit (*LSL*) of six hours. With a 95% confidence interval estimation, the total times will vary with a standard deviation between 4.82 and 7.26 hours.

Although the simulation results include the current *LSL* and *USL* (Upper Specification Limit, 8 hours), they are located after the 50th percentile of the data distribution. Consequently, it is feasible to achieve total collection times of less than six hours in approximately 50% of cases. On the other hand, the output variable of the solid waste collection process (total time, *Y*) can be considered as a one-sided specification (the smaller the better), where the *USL* should be avoided to be exceeded.

Table 3. Parameters and distributions selected for each variable and each day.

	(Y_0)	(Y_1)	(Y_3)	(Y_4)	(Y_5)	(Y_6)
X	Skewcauchy (a=-0.67, loc=16.34, scale=1.79)	Genlogistic (c=0.27, loc=16.07, scale=1.04)	Mielke (k=2.32, s=10.88, loc=-0.60, scale=18.41)	Johnsonsu (a=1.14, b=1.07, loc=13.96, scale=1.86)	Mielke (k=3.20, s=19.09, loc=-1.80, scale=15.86)	Gennorm (beta=2.75, loc=10.56, scale=5.93)
R_1	laplace_asymmetric (kappa=0.76, loc=34.40, scale=11.08)	Johnsonsu (a=0.79, b=1.97, loc=37.21, scale=13.53)	Dgamma (a=1.33, loc=38.61, scale=9.14)	Dweibull (c=0.95, loc=36.10, scale=11.72)	Skewnorm (a=-1.55, loc=38.10, scale=11.62)	Burr (c=8.01, d=0.38, loc=-0.29, scale=43.58)
R_2	Foldcauchy (c=99.41, loc=0.10, scale=0.02)	Nakagami (nu=0.06, loc=2.00, scale=0.19)	Nakagami (nu=0.19, loc=2.00, scale=0.21)	Foldcauchy (c=99.96, loc=0.26, scale=0.02)	Gennorm (beta=0.29, loc=2.00, scale=0.00)	Nakagami (nu=0.04, loc=2.00, scale=0.04)
R_3	laplace_asymmetric (kappa=1.81, loc=62.00, scale=11.60)	laplace_asymmetric (kappa=1.57, loc=60.00, scale=10.89)	laplace_asymmetric (kappa=1.56, loc=60.00, scale=11.73)	Genlogistic (c=0.31, loc=59.33, scale=5.66)	Burr (c=16.15, d=0.23, loc=-21.68, scale=84.19)	laplace_asymmetric (kappa=1.57, loc=60.00, scale=11.35)
R_4	Burr (c=3.82, d=0.30, loc=0.02, scale=11.51)	Fatiguelife (c=0.50, loc=-2.17, scale=8.45)	Exponnorm (K=3.56, loc=2.46, scale=1.50)	burr12 (c=1.59, d=7.16, loc=0.03, scale=25.11)	Skewnorm (a=9.63, loc=1.35, scale=7.42)	Norminvgauss (a=35.45, b=35.26, loc=-2.16, scale=0.99)

Source: own elaboration.

In this case, it is not appropriate to calculate the potential capacity index, C_p, as it is only of practical interest to meet the *USL* and the target specification, *T*. Therefore, the index for the upper specification, C_{pu}, should be calculated. Then, when we calculated this index, the result is $C_{pu} = 0.69$. This implies that if the collection company employs the optimal solutions identified for each day, it should result in a decrease in the *LSL* to a value between 4.5 and 5 hours. Moreover, the capability analysis of this type of process should focus on assessing whether the distribution of the quality characteristic data is centered with respect to *T*. This can be achieved by calculating the process centering index, *K*.

Thus, when calculating the *K* index with the current specification limits, the result is *K* = -95.4%. Hence, the process mean is deviated 95.4% to the left of *T*, so the process centering, and the *USL* are inadequate and require adjustment. Based on the distribution of the data in Figure 3, *T* = 6 hours and *USL* = 7 hours are proposed as new specification limits. As a result, the new value of *K* is 4.6%, considered as an acceptable off-centering (Gutiérrez Pulido & De la Vara Salazar, 2013). That does not significantly affect the capability of the process to meet the target specification of 6 hours of total collection time in accordance with the optimal solutions found (see Table 2).

After that, a sensitivity analysis was performed to predict the optimal outcomes of the response variables, Y_n, considering the uncertainty conditions and using the Pearson ratio coefficient as a statistic to determine the strength of the relationship between the variables (Figure 4), showing that the variables that have the most influence in solid waste collection process total times are x and R_1.

These most influential variables have a significant impact on the environment, operational efficiency, logistics and process costs, since the more miles traveled, the more greenhouse gas emissions are generated and the higher the operating costs. In addition, as the number of tons collected increases, it becomes necessary to adjust collection routes and frequencies, which generates additional costs and demonstrates the need to improve the management and planning of the waste collection process.

The amount of waste collected during an operation is a critical factor that significantly affects operational efficiency, waste management capacity, environmental impact, and financial costs. Figure 4 shows that on Mondays, Tuesdays, Thursdays, and Fridays, the variable with the greatest impact on the routes is the number of tons collected (x). A higher number of tons collected may indicate an efficient operation, but it may also require proper management to avoid negative environmental impacts and increases in operating costs. The high number of tons collected is indicative of its significance for overall efficiency.

On the other hand, the total number of kilometres (R_1) travelled in the SWC process has significant operational, financial, and environmental implications. As this variable increases, as is the case on Wednesdays and Saturdays, operating costs tend to rise due to fuel consumption and vehicle maintenance.

In order to mitigate the impact of the collection process, the company would optimize collection routes, promote waste reduction at source through education and awareness, implement effective recycling programs, upgrade equipment to improve collection capacity, and adopt sustainable waste management practices.

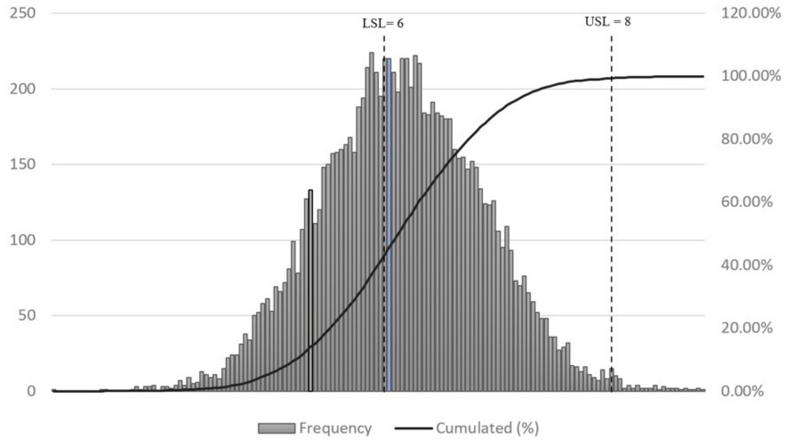

Figure 3. Simulation Histogram Results.
Source: own elaboration.

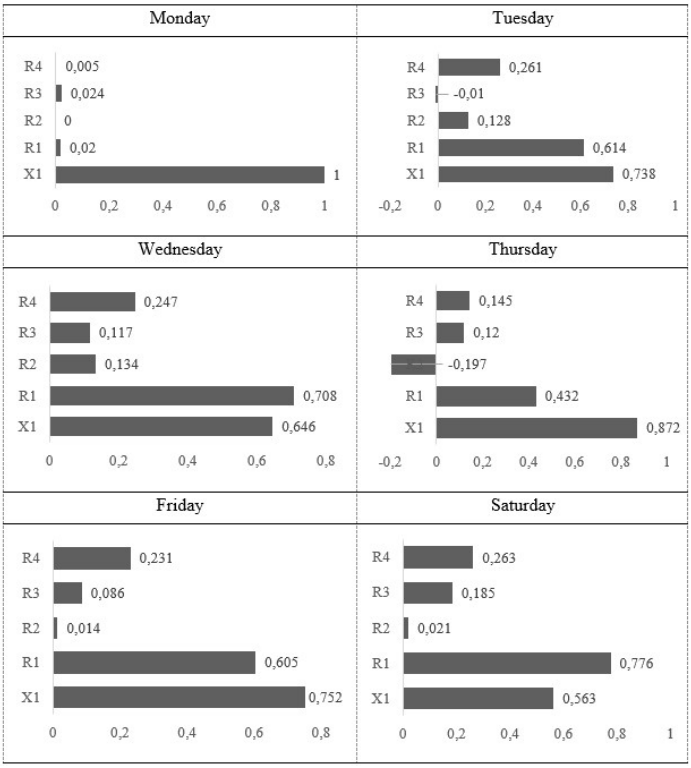

Figure 4. Pearson sensitivity analysis for the six days.
Source: own elaboration.

All variables are relevant to the methodological application. However, some variables have a greater impact on the established quality characteristics and compliance with specifications. Thus, it is possible to improve strategic decision-making to increase service quality based on scenario analysis of the uncertain behaviour of process variables. To verify the uncertain of the process variable a comparative analysis of the real error values for each day with the simulated errors was performed, showing a considerable decrease per day (see Table 4). These results will allow the waste collection company to define improvement actions that will allow them to find a balance between efficiency and sustainability in order to guarantee an effective and responsible collection process from an environmental point of view.

Table 4. Real vs Simulated errors.

Variable / Day	Real error	Simulated error	Decrease (%)
Y_0	1.1972	0.0197	94%
Y_1	1.2259	0.0135	92%
Y_2	1.0810	0.0123	93%
Y_3	1.0484	0.0126	95%
Y_4	0.9597	0.0099	96%
Y_5	1.0240	0.0090	98%

Source: own elaboration.

4. Conclusions

Process optimization helps to improve strategic decision-making to reduce costs and improve efficiency, thus obtaining the highest possible profit. GP provides greater flexibility in process modelling and optimization when there are many variations of constraints and priorities of objectives in multi-objective problems. Furthermore, MCS allows for dealing with uncertainty and performing risk analysis by creating new models of possible outcomes by permuting a series of values.

The GoProMoS-SWC Methodology allowed a complete mapping of the optimal operating ranges of process and response variables, reducing total times by up to 55%. In addition, the computational efficiency in optimization and simulation models application is of great importance as it can affect both the accuracy of the results and the time required to obtain them and in the probabilistic estimation of the process capability to meet multiple quality characteristics.

This methodology integrates the main variables of the SWC process, including the number of trips, distance traveled, number of compactions, fuel consumption, and tons collected, in order to minimize the total process time. It is possible to define different types of routes in the daily operations and quantify their impact on the performance of the process.

This work makes a significant contribution by integrating a quality control approach into the modelling and simulation of the waste collection process. The utilization of process capability indices in the evaluation of collection process performance provides additional insights into the operational ability to meet targets, adjust to established ranges, and facilitate data-driven decision-making, thereby enhancing the efficiency of operations.

The case study showed that longer collection distances lead to higher operational costs, increased emissions, and longer collection times. While the amount of waste collected reflects efficiency, it is important to have effective management to avoid environmental and financial problems. To tackle these issues, it is crucial to focus on route optimization, using efficient vehicles, and strategic planning based on waste patterns.

This work impacts on Quality Engineering since processes or services optimization helps the continuous improvement of organizations through decision-making. The main contribution of this work is the implementation and validation of a flexible lexicographic model using optimization and simulation tools for the resolution of complex problems of product and process quality profiling, which seek to provide new knowledge, skills, and abilities in the current context of the fourth industrial revolution and Artificial Intelligence (AI).

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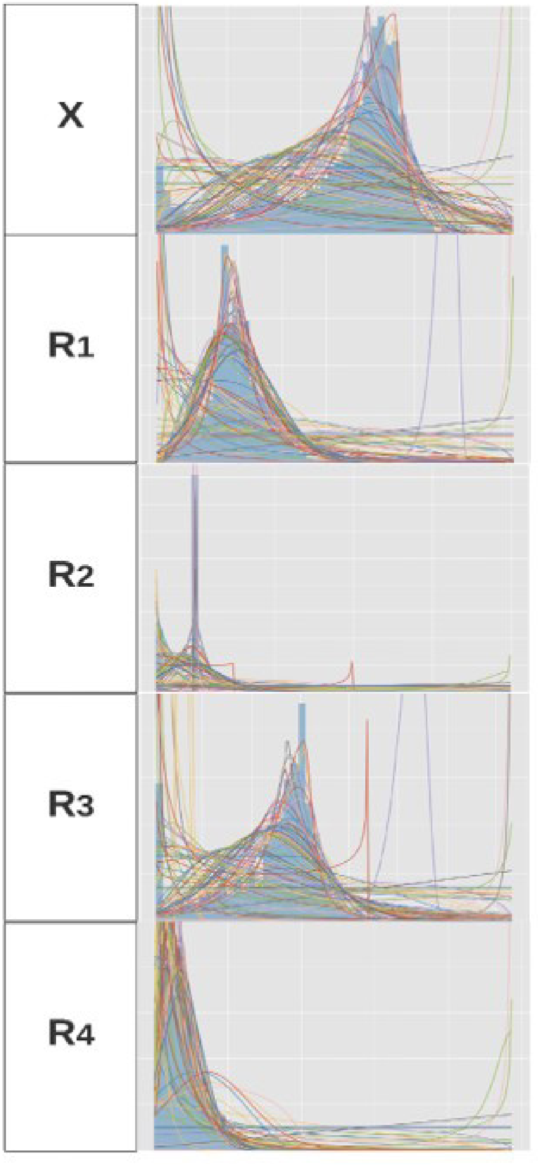
Appendix A. General selection of probability distributions that best-fit form 3.2.1.



Appendix B. Selection of probability distributions that best-fit each variable data.