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Analysis of Users' Requirements for Public Waste Management Services Using Fuzzy Inference

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Abstract
Municipalities play a key role in public waste management ensuring effective and efficient service performance. In Colombia, the public utilities sector has undergone significant changes since decentralization and the entry of private companies into the sector. In this study, our purpose is to analyze user perceptions and their willingness to pay for additional services regarding waste management. By using data analysis methods and a Mamdani fuzzy inference system, we were able to identify users' service requirements and expected quality. According to the results of our analysis, a combination of minimum coverage and low frequency resulted in a tariff increase of 7.05%. Furthermore, we recommend expanding the model to include other waste management services, such as solid waste collection, as well as to consider environmental aspects and sustainable practices.

Keywords: *Waste Management, Public Service, Service Requirements, Fuzzy Inference, Tariff, User Perceptions.*

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1 Introduction

In the context of waste management, municipalities play a vital role in ensuring the efficient and effective provision of various services, including waste collection, cleaning public areas, lawn mowing, washing public areas, tree pruning, and more. These services are essential for maintaining the cleanliness, hygiene, and aesthetic appeal of urban and suburban areas. While waste management services can be carried out by either public or private entities, municipalities bear the responsibility of overseeing and coordinating these activities. According to research in this domain [24, 28], municipalities act as key stakeholders, responsible for formulating waste management policies, allocating resources, and establishing regulations to ensure the proper functioning of waste management systems. However, the challenges faced by municipalities in delivering these services require a deeper understanding of the roles and responsibilities of both public and private entities involved in waste management.

Efficient waste management is crucial not only for maintaining the environmental integrity of communities but also for safeguarding public health and promoting sustainable development. As highlighted by studies conducted by Fried [16] and Zhang et al., [33] deficient waste management practices can result in environmental pollution, spread of diseases, and depletion of natural resources. Therefore, waste management services headed by municipalities becomes one important service towards achieving sustainable waste management goals. Citizens' perception of the price of public waste management services significantly influences their satisfaction and cooperation. Municipalities should consider aligning service costs with citizens' expectations to ensure fairness and transparency. Asare [9] highlight the importance of cost effectiveness in waste management, while Suryawan et al., [25] emphasize the need to understand citizens' attitudes towards service pricing. By addressing these factors, municipalities can enhance citizen satisfaction, foster cooperation in waste reduction efforts, and design equitable pricing models.

In Colombia, the public utilities sector has experienced significant growth since the reorganization of the country's administrative structure. Initially, during the 19th century, the prevailing model involved the government being responsible for service provision, aligning with the classical Keynesian welfare model—which fostered a government's monopoly over the sector and its intervention in service provision. However, the advent of the new constitution in 1991, which introduced a series of institutional reforms, brought in a substantial transformation of the sector's regulatory framework. Following this framework, there was a shift towards the decentralization of service operations and the involvement of private companies in the sector. This allowed for the creation of suitable conditions for the provision of public waste management services, along with a regulatory framework that defined the rights and obligations of both service users and providers, as well as all technical requirements [1]. The primary objective of this regulatory framework is to enhance service quality and meet the needs and expectations of users, without completely depriving the government of its responsibility to secure the provision of public utilities [26, 2].

Upon the enforcement of Decree 2981 of 2013 [3] in the country, waste management companies acquired new obligations regarding new services and coverage expansion of existing ones. This, indeed, led to an increase in operating costs and, consequently, higher tariffs for users, as stated in the proposed new tariff framework for public waste management services outlined in Resolution 831 of 2018 [4]. Such a scenario raises questions about users' perception of the service and the tariff increase they are willing to pay. Users who must pay monthly for waste management services would anticipate a comprehensive service in terms of coverage and frequency, as well as affordable rates. In fact, with the private sector intervening in the provision of these services, service quality must also be accompanied by profitability.

Given the foregoing, this study aims to identify, using data analysis methods and tools, the services, quality, and additional services (beyond those currently offered in cities and municipalities) that users expect from waste management companies and are willing to pay a higher price for. For data collection, we will use a questionnaire, which will serve as the basis for qualitative criteria, capturing users' expectations regarding waste management services and the price increases they would be willing to pay for service expansion. For data analysis, we will employ a Mamdani fuzzy inference system, which enables a straightforward and objective analysis of information that may be ambiguous, imprecise, or incomplete.

2 General Context

In recent years, the Colombian government has been evaluating the need for service expansion in the waste management sector. In fact, through Decree 2981 of 2013 [3], it introduced additional services such as cleaning and washing of public areas, lawn mowing, and tree pruning, and expanded the scope of waste utilization activities. These changes have provided a more comprehensive framework aligned with users' basic requirements, as depicted in Figure 1.

Yet, such increased activities performed by service providers translated to higher costs. Consequently, Resolution 643 of 2013 [5] and Resolution 664 of 2014 [6] presented a regulatory framework to evaluate the expected cost increase due to the inclusion of new service variables. This framework, in turn, aims to establish a tariff structure that ensures the sustainability of the service while complying with the obligations outlined in Decree 2981 of 2013 [3].

Since neither of those two regulations specifies the required service quality, a model must be developed to assess the coverage and frequency characteristics of such additional activities. Importantly, improvements in service quality cannot be excessive as this directly

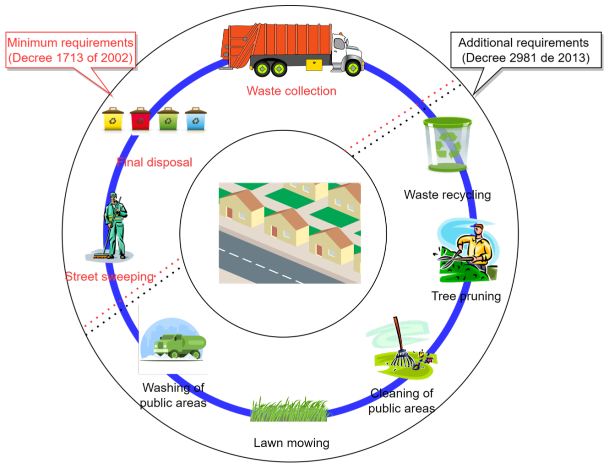

Figure 1: Public waste management services in Colombia.

impacts service costs and associated tariffs. Figure 2 illustrates a general framework for the provision of waste management services that facilitates decision-making based on users' service requirements while considering both service quality and regulatory provisions.

2.1 Analysis Using Fuzzy Logic

Fuzzy logic is a decision-making method that represents imprecise, vague, or ambiguous knowledge [29]. Unlike classical logic, this approach introduces uncertainty into human reasoning to provide responses based on more coherent concepts. Given the need of the modern world to find real solutions to problems where vagueness is prevalent, fuzzy logic has gained significance in various fields such as economics, social sciences, industry, and politics.

Among the most widely used fuzzy logic models are Fuzzy Inference Systems (FISs), which represent imprecise knowledge and data in a manner similar to human reasoning, offering valid responses even when the information provided to systems is incomplete [22]. The most well-known FISs are the Mamdani, relational or Pedryckz, and Takagi–Sugeno inference systems. In this study, we specifically focus on Mamdani systems, which employ if-then rules to map fuzzy input sets to output sets using fuzzy logic.

In the literature, fuzzy inference has been used to analyze customer preferences or perceptions regarding a product or service. For instance, authors such as [10] evaluated the quality perception of services provided to citizens in Osmaniye, Turkey. Their analysis covered basic services such as parking areas, roads and pavement, traffic, water supply and sewer services, and waste management. For their part [17], defined evaluations of customer demands for a product, which include intangible and difficult-to-measure elements such as environmental factors, ease of use, and smell. [12] presented a very similar case in the application of fuzzy ordinary regression for modeling customer preferences in tea maker design. Their proposed method can be

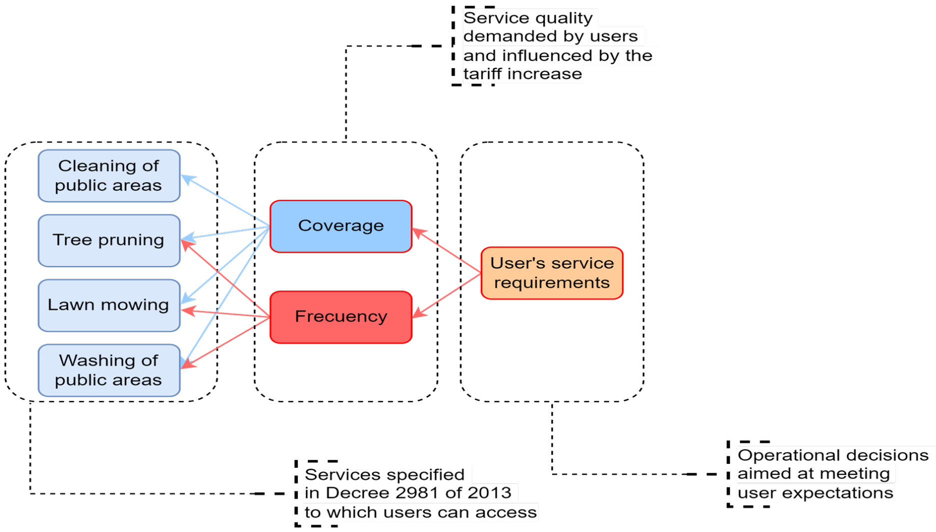

Figure 2: Model of users' service requirements for waste management services.

employed to develop models that are capable of addressing the two uncertainties in customer preferences: crispness and fuzziness.

Regarding the evaluation of service provision, [20] assessed and compared the quality of healthcare services provided by private and public hospitals in Ghana using a triangular fuzzy system integrated with a multiplicative multi-objective optimization by ratio analysis technique. Similarly, [14] employed fuzzy inference models to study hospital services in Taiwan. The author proposed a framework based on the fuzzy set theory to evaluate service quality in a fuzzy environment where uncertainty, subjectivity, and vagueness are addressed using linguistic variables parameterized by triangular fuzzy models. In such study, the author applied the fuzzy multi-criteria decision-making approach to determine the importance of each evaluation criterion and consolidate the service quality ratings. [19] also evaluated hospital service quality using fuzzy elements to reduce uncertainty and diversity in evaluation results. Given their distinctive features, fuzzy inference models can thus be regarded as suitable for evaluating users' perceptions, preferences, and requirements regarding a service.

In waste management topic, several studies have used fuzzy logic. In his paper [32] presented a multi-objective model for medical waste management during COVID-19. The model uses fuzzy programming to minimize costs, reduce environmental impact, and enhance the suitability of treatment technology. Strategic decisions, facility locations, waste flow, and transport are considered, addressing uncertainty using a possibilistic programming method. [21] used a fuzzy TOPSIS method to identify and prioritize key barriers to transitioning construction and demolition waste management to a circular economy including limited recyclable materials and ineffective waste processes, demanding proactive solutions. [11] used a fuzzy Delphi method to identify major barriers to maintain sustainable solid waste management practices classified by four main aspects: technical difficulties; information sharing and knowledge problems; human resource limitations; and financial and economic problems. [23] designed a sustainable municipal solid waste disposal system using a mixed-integer linear programming model to optimize the number and locations of construction sites for recycling centers and fuzzy programming to consider the uncertainty.

It is possible to find a significant number of studies on solid waste management municipal service using fuzzy logic, but few studies in the specialized literature, nevertheless, have focused on identifying users' requirements regarding waste collection and management services. In their study, [13] proposed a mixed-integer linear programming model combined with fuzzy sets to assess strategies for municipal solid waste collection, considering multiple objectives. Although the authors presented various management strategies, they did not specifically address the services required by users. In this regard, [18] introduced a tool for evaluating the performance of a recyclable material collection system that incorporates two fuzzy approaches: AHP-TOPSIS and AHP-VIKOR. [15], for their part, presented a fuzzy cognitive map as a method to develop strategies to optimize municipal waste management systems, taking into account systemic complexity and the participation of different stakeholders. Using a fuzzy logic expert system, [27] designed a performance measurement model for waste management systems that simultaneously considers profitability, financial characteristics, and efficiency. [30] employed fuzzy logic to address the complexities of sustainable solid waste management by handling qualitative information, uncertainties, and interrelationships among attributes. It identifies crucial causal links and emphasizes the role of political leadership in an analytic network. The authors focused on the hierarchical structure of fuzzy decision-making processes, but they did not consider the required ser-

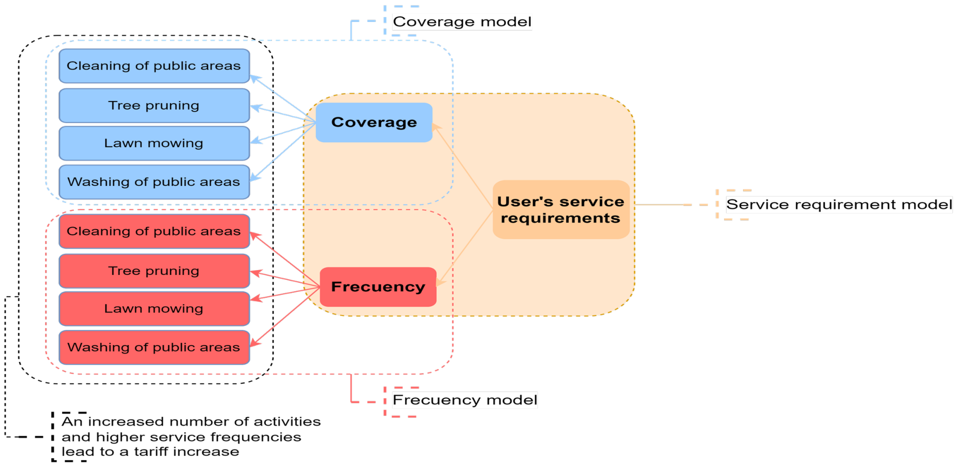

Figure 3: Proposed fuzzy inference model for evaluating waste management services.

vices and customer preferences. Finally, [31] employed a fuzzy chance-constrained programming model to plan pick-up, recycling, disposal, and transportation operations in a municipal solid waste management system They aimed to minimize costs and pollutant emissions while considering uncertainty, offering valuable insights for an efficient system. However, the authors did not address customer willingness to pay for these services.

From the literature, it is clear that fuzzy inference has been used to assess service quality or expected service quality. Yet, there exists a research gap in evaluating the necessary service coverage and frequency to identify specific service requirements and associated costs. Accordingly, this paper presents a model for measuring the quality of waste management services demanded by users in terms of desired coverage and frequency. The aim is to estimate the tariff increase for this service.

3 A fuzzy Inference-based Model for Analyzing Users' Service Requirements

For our analysis, primary data were collected through questionnaires administered to target groups in different municipalities in Colombia, where coverage expansion is planned for activities such as cleaning and washing of public areas, lawn mowing, and tree pruning. The designed questionnaire incorporated relevant operational variables such as service coverage and frequency, which were compared to the estimated tariff increase based on user-selected options.

Coverage evaluated users' needs in terms of service provision in specific zones and areas within these zones. This variable was evaluated for the following four services: cleaning of public areas, tree pruning, lawn mowing, and washing of public areas. Notably, cleaning of public areas and tree pruning were the services with the highest weight because service providers consistently demonstrated greater service level of user requirements. Frequency, for its part, assessed how often users felt that the services must be provided in the defined coverage areas. This variable was also evaluated for all four services. In this case, cleaning of public areas was the service with the highest weight, as increased service frequency is associated with greater service level of user requirements.

The data obtained from the administered questionnaires were analyzed using a three-step fuzzy inference model based on the Mamdani system (see Figure 3). In the first step of the proposed model, service coverage is measured by analyzing the number of areas served for the services required by users and specified in [16] (i.e., cleaning of public areas, tree pruning, lawn mowing, and washing of public areas). In the second step, the required frequency for these services is evaluated, which represents the number of times per unit of time that users consider the services should be provided. Finally, the results from the two previous steps give rise to the third part of the proposed model, which corresponds to users' service requirements. This part presents the relationship between coverage and frequency, as well as a rating of the services that users require and are willing to accept a tariff increase for.

The output of the proposed fuzzy inference model allows us to assess users' demands for the additional waste management services in terms of coverage and frequency and thus design operational plans that ensure the quality expected by users. Likewise, evaluating users' requirements provides valuable input for developing a tariff scheme that only applies a tariff increase acceptable to users for the requested services, ultimately enhancing their perception of the overall service. Figure 4 illustrates the stages (interaction and sequence of activities in each) for the evaluation of waste management services using the proposed fuzzy inference model.

3.1 Project Planning

After conducting the applicable conceptual and regulatory analysis, we verified that users' service requirements contribute to improving the quality of the overall service, particularly as service expansion includes additional services beyond the ones currently provided,

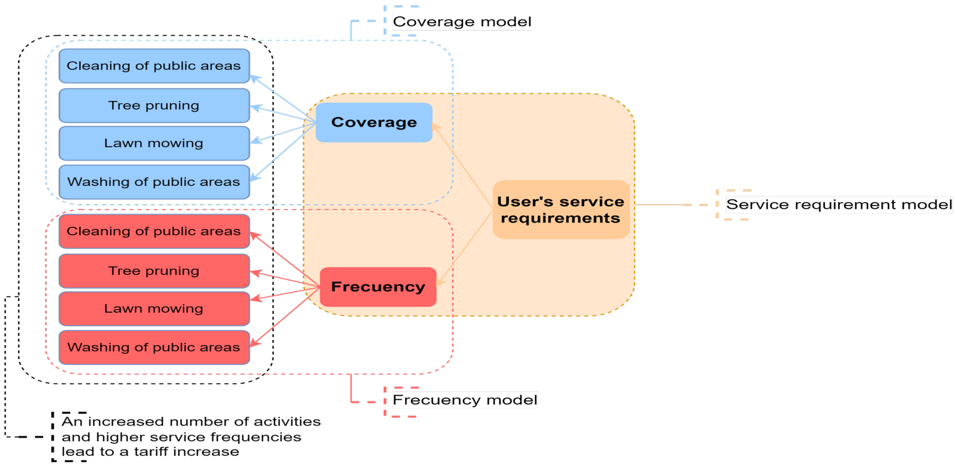

Figure 4: Stages for the evaluation of waste management services using the proposed fuzzy inference model.

as well as an increase in the areas being served. However, the cost of the waste management service will also experience an increment depending on factors such as the size of the area, the number of areas being served, users' demands, the value that users are willing to pay for the additional services, and the frequency of provision. This latter refers to the number of times the service is provided per unit of time based on the applicable operational conditions.

3.1.1 Calculation of Tariff Increase Based on the Operational Model

To estimate the expected tariff increase resulting from the expansion of coverage and frequency levels in the four services (i.e., cleaning of public areas, tree pruning, lawn mowing, and washing of public areas), we employed Resolution 643 of 2013 [5] and Resolution 664 of 2014 [6] for the municipalities under analysis, ensuring compliance with the obligations specified in Decree 2981 of 2013 [3].

In the tariff model presented in [5], the final tariff is calculated by adding up the individual tariffs per service. Hence, a suitable approximation involves estimating the percentage increase for each activity. After operationally evaluating the provision of the additional services requested by users, we defined the following three levels to determine the coverage of each service:

High: Applicable to all zones eligible for the service and to the entire involved area. In the case of tree pruning, it applies to all trees.

Medium: Applicable to all zones eligible for the service but limited to the main areas within them. In the case of tree pruning, it applies to the main trees.

Low: Applicable to the main zones eligible for the service but limited to the areas causing problems. In the case of tree pruning, it only applies to trees at risk for failure.

Service provision was estimated based on three equidistant linear coverage levels, ensuring a value proportional to the applied tariff according to users' required coverage. A high coverage results in the highest tariff increase, a medium coverage leads to a 2/3 increase, and a low coverage implies a 1/3 increase, with a minimum increase of 1% and a maximum increase of 9% due to coverage expansion. Table 1 reports the tariff increase for each service depending on the level of coverage expansion.

The tariff increase based on the frequency of service provision was also defined using three levels. For the cleaning of public areas service, a high frequency results in a 100% tariff increase, a medium frequency leads to a 50% increase, and a low frequency implies a 25% increase. For the other services, a high frequency results in a 100% tariff increase, a medium frequency leads to a 2/3 increase, and a low frequency implies a 1/3 increase, as shown in Table 2.

Furthermore, the relationship between the expected coverage of an additional service and the frequency with which users require it leads to a tariff increase adjustment. This adjustment depends on the combination of the coverage levels (high, medium, or low) and frequency levels (high, medium, or low) requested by users. The point at which a required coverage intersects with an expected frequency indicates the percentage tariff increase that users are willing to accept. The highest increase occurs at position HH (high coverage and high frequency), while the lowest increase occurs at position LL (low coverage and low frequency). Table 3 presents the model used to determine the tariff increase, which ranges from 2.0% for services with low coverage and low frequency to 20% for services with high coverage and high frequency.

3.2 Questionnaire Design and Administration

A questionnaire, which included the services mandated in [3], was designed and administered to waste management service users, who were asked to indicate their preferred coverage and the frequency at which they require each service.

Table 1: Tariff increase based on coverage expansion.

Service	Level of coverage expansion		
	High	Medium	Low
Cleaning of public areas	9.0%	6.0%	3.0%
Tree pruning	3.0%	2.0%	1.0%
Lawn mowing	6.0%	4.0%	2.0%
Washing of public areas	2.0%	1.5%	1.0%

Table 2: Tariff increase based on frequency of service provision.

Service	Level of coverage expansion		
	High	Medium	Low
Cleaning of public areas	100%	50%	25%
Tree pruning	100%	66%	33%
Lawn mowing	100%	66%	33%
Washing of public areas	100%	66%	33%

Table 3: Tariff increase based on coverage and frequency expansion.

		Coverage		
		High	Medium	Low
Frequency	High	20%	14%	7%
	Medium	12%	8%	5%
	Low	6%	4%	2%

A simple random sampling method was employed for the purposes of this study, and the sample was selected using a stratified model with allocation proportional to the number of users in each municipality. Data were collected through interviews with the users. All the collected data were organized and tabulated to facilitate grouping and weighting of user responses, which were then inputted into the MATLAB's fuzzy inference engine.

3.2.1 Sample Size and Distribution

The target population consisted of residential waste management service users from socioeconomic strata 1 and 2 across 11 municipalities in Colombia (Finlandia, La Tebaida, Montenegro, Facatativá, Duitama, Tumaco, Tunja, Yumbo, Popayán, Montería, and Soacha). In each municipality, a questionnaire was administered to a sample of users, which was estimated based on the parameters outlined below.

As of December 2016, the population size (N) of interest was 261,087 (SUI, 2016) [7]. The desired confidence level was set at 95%, which corresponds to a z-value of 1.96 assuming a normal distribution. The desired margin of error (e) for this study was 5%. Based on these parameters, the calculated sample size was as follows:

$$n = 383.6 \approx 384$$

Therefore, a total of 384 questionnaires were administered, with proportional distribution across the 11 municipalities based on their respective share in the total population.

3.2.2 Users' Desired Coverage and Frequency

User responses regarding the desired coverage and frequency were tabulated and assessed for each of the provided services (j: cleaning of public areas, tree pruning, lawn mowing, washing of public areas) and their corresponding evaluated factors (k: coverage and frequency) within different service levels (l: high, medium, and low) for each user (i). This evaluation was carried out using the equation (1).

$$W_{jk} = \frac{\sum_{1}^{n} x_{ijk}^{l} * w_l}{n} \quad (1)$$

Where x_{ijk}^{l} is a binary variable that takes a value of 1 when user i responds to a question related to service j and service factor k regarding a specific level l (high, medium, or low), and w_l denotes the weight assigned to each service level: $w_h = 1$, $w_m = 0.67$, and $w_l = 0.33$.

3.2.3 Questionnaire Results

The results obtained for each W_{jk} are presented in Table 4 and represent user requirements in terms of coverage and frequency for each of the services specified in Decree 2981 of 2013.

Table 4: Classification of the results obtained regarding users' service requirements.

Service (j)	K = coverage	K = frequency
Cleaning of public areas	0.78	0.756
Tree pruning	0.684	0.618
Lawn mowing	0.572	0.572
Washing of public areas	0.542	0.546

3.3 Fuzzy Inference Model

The fuzzy inference model proposed in this study follows the Mandani inference system, which consists of three stages: fuzzification, fuzzy inference, and defuzzification. This model uses a fuzzy reasoning engine that incorporates inference rules based on expert knowledge. In addition, it integrates three analysis components aiming to determine the tariff increase based on the coverage and frequency of the four services under analysis (see Figure 1). Each component was individually designed with independent technical and tariff criteria.

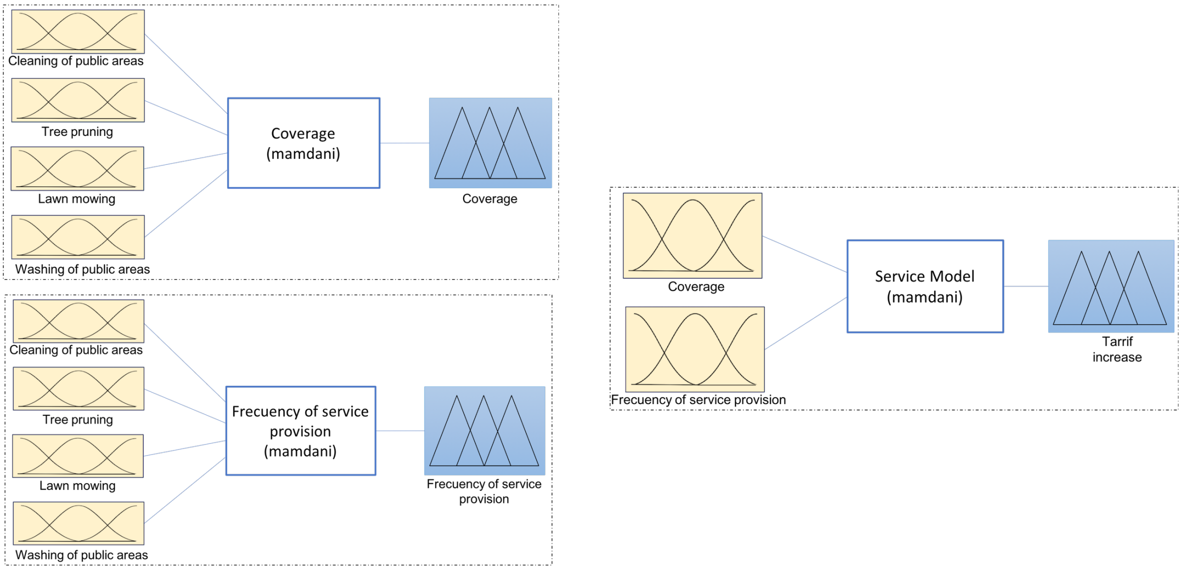

Figure 5: Fuzzy inference model proposed in this study to evaluate tariff increase for waste management services.

The first and second components took cleaning of public areas, tree pruning, lawn mowing, and washing of public areas as input variables, which were evaluated in terms coverage and frequency (sj1 and sj2, respectively), and the required service levels for coverage and frequency (S1 and S2, respectively) as output variables. In the third component, the input variables were S1 and S2; and the output variable, the tariff increase. The fuzzification of these variables is detailed below.

3.3.1 Fuzzification

Input variable Wjk for the services (j) and their factors (k) was classified into the following levels: high, medium, and low. This classification is denoted by variable s_{jk}, whose high, medium, and low levels are defined as fuzzy sets with the membership functions shown in equations (2)-(4). Variable s_{jk} represents the classification of factor k in service j.

$$Low = \begin{cases} 1 & W_{jk} < 0.4 \\ \frac{0.6-W_{jk}}{0.6-0.4} & 0.4 < W_{jk} < 0.6 \\ 0 & W_{jk} > 0 \end{cases} \quad (2)$$

$$Medium = \begin{cases} 0 & W_{jk} < 0.4 \\ \frac{W_{jk}-0.4}{0.6-0.4} & 0.4 < W_{jk} < 0.6 \\ 1 & 0.6 < W_{jk} < 0.7 \\ \frac{0.7-W_{jk}}{0.85-0.7} & 0.7 < W_{jk} < 0.85 \\ 0 & W_{jk} > 0.85 \end{cases} \quad (3)$$

$$High = \begin{cases} 0 & W_{jk} < 0.7 \\ \frac{0.7-W_{jk}}{0.85-0.7} & 0.7 < W_{jk} < 0.85 \\ 1 & W_{jk} > 0.85 \end{cases} \quad (4)$$

Hence, the first level, for example, corresponds to the fuzzy treatment of the coverage factor, where the classifications in terms of coverage (s_{j1}) for the four evaluated services are combined at the high, medium, and low levels (see Figure 6).

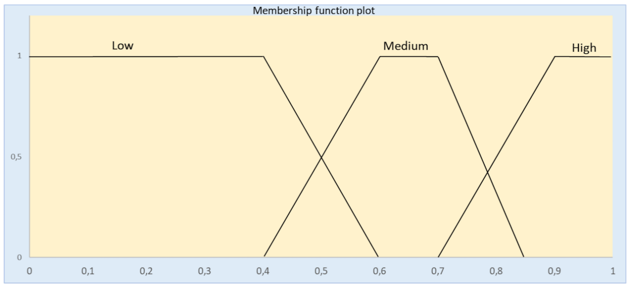

Figure 6: Membership function for service (W_{jk}).

The output variable for the coverage factor (S_1) was classified into four different levels (poor, minimum, sufficient, and wide), which are defined as fuzzy sets with the membership functions depicted in Figure 7.

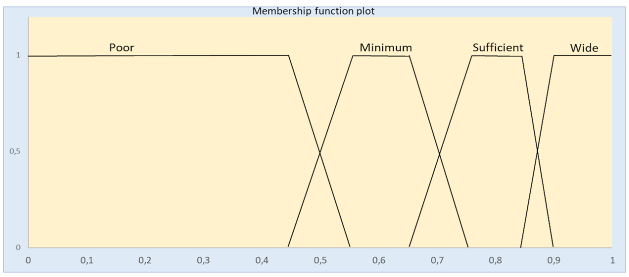

Figure 7: Membership function for the coverage factor (S_1).

The output variable for the frequency factor (S_2) was classified into the following levels: high, medium, and low. These levels are defined as fuzzy sets with the membership functions shown in Figure 8.

The third component corresponded to the inference model for the tariff increase, which gathered the results of the previous models and evaluated users' require-

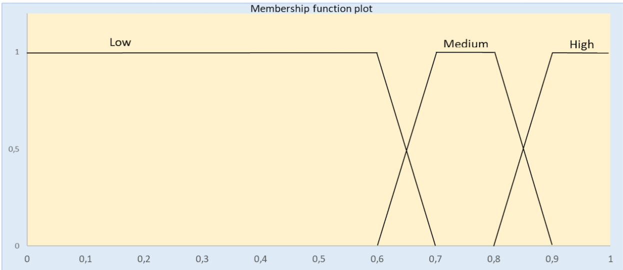

Figure 8: Membership function for the frequency factor (S_2).

ments for the required service and its configuration in terms of coverage and frequency. This model was configured with the ratings obtained from the two previous models using the measurement scales for coverage (poor, minimum, sufficient, and wide) and those for frequency (high, medium, and low). The tariff increase was a value between 20% and 2.0% and was classified into three levels (high, medium, and low), which are fuzzy sets with the membership functions depicted in Figure 9.

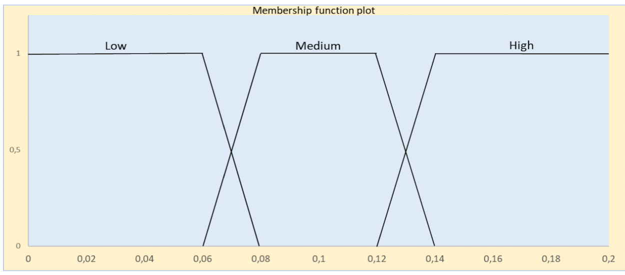

Figure 9: Membership function for the tariff increase factor.

3.3.2 Inference Engine

To configure the fuzzy inference engine for the three components of the model, we worked together with the technical-operational department of a waste management company. The configuration obtained for each component is described below.

The inference engine for the first component (coverage) resulted from the combination of the three possible levels (high, medium, low) across the four evaluated services (cleaning of public areas, tree pruning, lawn mowing, and washing of public areas). Its output was classified into the following fuzzy categories: wide, sufficient, minimum, and poor. A total of 81 (3^4) fuzzy rules were obtained, which are summarized in Table 5, Table 6 and Table 7.

The set of fuzzy rules for the second component (frequency) were defined in a similar manner, resulting in a total of 81 (3^4) fuzzy rules. Table 6 provides a summary of these rules.

Finally, the inference engine for the third component included the set of fuzzy rules presented in Table 7.

Table 5: Inference rules for the coverage component.

s_{11}: Cleaning of public areas	s_{21}: Tree pruning	s_{31}: Lawn mowing	s_{41}: Washing of public areas	S_1: Coverage
High	High	High	High	Wide
High	High	High	Medium	Wide
High	High	High	Low	Wide
High	High	Medium	High	Sufficient
High	High	Medium	Medium	Sufficient
High	High	Medium	Low	Sufficient
High	High	Low	High	Sufficient

Table 6: Inference rules for the frequency component.

s_{12}: Cleaning of public areas	s_{22}: Tree pruning	s_{32}: Lawn mowing	s_{42}: Washing of public areas	S_2: Coverage
High	High	High	High	High
High	High	High	Medium	High
High	High	High	Low	High
High	High	Medium	High	High
High	High	Medium	Medium	High
High	High	Medium	Low	Medium
High	High	Low	High	High

Table 7: Inference rules for the frequency component.

S_1: Coverage	S_2: Frequency	Tariff increase
Wide	High	High
Wide	Medium	High
Wide	Low	Medium
Sufficient	High	High
Sufficient	Medium	Medium
Sufficient	Low	Medium
Minimum	High	High
Minimum	Medium	Medium
Minimum	Low	Low
Poor	High	Medium
Poor	Medium	Low
Poor	Low	Low

3.3.3 Fuzzification

The three fuzzy inference models were implemented in MATLAB®, where the set of if-then rules for the three models was defined to obtain a linguistic result for the output variables based on input variable values[1]. This was done using the Mamdani implication, which employs the fuzzy min operator to establish relationships between two fuzzy sets: A and B ($\mu A \to B(x, y) = min\{\mu A(x), \mu B(y)\}$).

The process of combining the fuzzy sets that represent the outputs of each fuzzy rule is known as aggregation, which results in a fuzzy set in the universe of discourse of the fuzzy variable [8].

3.3.4 Defuzzification

In this stage, a fuzzy set is defuzzified to a single value that serves as the solution to the evaluated fuzzy model. The centroid method, which is denoted by the equation (5) is one of the most widely used defuzzification techniques.

$$\text{Center of gravity} = \frac{\int x\mu(x)dx}{\int \mu(x)dx} \tag{5}$$

4 Results

The responses to the questionnaire administered to the target sample provided the input data for the coverage model of each of the services provided by the waste management company. Once the coverage data for each service was inputted into the model (cleaning of public areas: 78.0; tree pruning: 57.2; lawn mowing: 68.4; and washing of public areas: 54.2), we obtained a coverage level of 0.687, placing this variable in the minimum and sufficient levels. Figure 10 shows the evaluation of the fuzzy rules for the coverage factor.

Likewise, the input data for the frequency model were derived from the questionnaires applied to the target sample. Based on the inputted values (cleaning of public areas: 75.6, tree pruning: 57.2, lawn mowing: 61.8, and washing of public areas: 54.6), the fuzzy inference model yielded a frequency result of 0.586, which places this variable in the low level.

When the coverage and frequency results were incorporated into the third component of the fuzzy inference model, we obtained a tariff increase of 0.705%, placing this increase in the low and medium levels according to the membership function. Figure 12 illustrates the set of fuzzy inference rules used in the model to evaluate users' service requirements, encompassing four coverage levels and three frequency levels.

Based on the analysis of users' service requirements, *coverage* obtained a rating of 68.7/100, placing it in the *minimum* level, while *frequency* was rated at 58.6/100, placing it in the low level. The combination of these two service requirements leads to a tariff increase of 7.05%.

[1]The code for this inference models can be found at https://github.com/Crisgo11/FuzzyWaste_Management_Service-.git

Figure 13 presents the surface plot for the main tariff increase model based on users' service requirements. We used this plot to evaluate the two variables (coverage and frequency) assessed by users and described in previous sections. As observed, there is a clear relationship between frequency and coverage (on the x- and y-axes) and tariff increase (on the z-axis). For frequency values above 0.5, the tariff increase starts to rise. This also occurs with coverage, but from values close to 0. When the values of these two components exceed 0.0 and 0.5, respectively, the tariff increase begins to rise at a higher proportion than with lower values for both variables.

5 Conclusion

Fuzzy inference is a method that provides a straightforward approach to draw conclusions from input information that is vague, uncertain, imprecise, noisy, or incomplete. It allows for summarizing user perceptions of a service they require but lack the expertise to establish a comparison criterion, which makes it impossible for them to evaluate the quality of the service or rate it in terms of coverage and frequency. Thus, the model designed in this study enables inferences to be made about the desired service, considering what users aim to obtain for their desired price without requiring them to consider all the factors involved.

The analysis obtained from the proposed model supports operational and tariff decision making to meet user requirements regarding the new activities defined for waste management services in Colombia, considering two measurement variables: coverage and frequency. In this particular case, combining minimum coverage with low frequency resulted in a tariff increase of 7.05%. Although tariff increase was found to be directly proportional to frequency and coverage, it was notably more sensitive to expansions in coverage than in frequency.

As future work, the model could be extended to incorporate additional waste management services provided by similar companies, such as solid waste collection, which would require further considerations for optimizing said service. By considering factors like optimal route selection, truck capacity, and the adoption of advanced technologies, the model's expansion would make it possible to evaluate and enhance the efficiency of waste collection. Additionally, further research could consider environmental aspects, such as promoting source separation of waste and implementing sustainable waste management practices. Such model's expansion would contribute to an overall improvement in waste management services by promoting increased operational efficiency and reducing environmental impact while also satisfying the changing needs of users.

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Figure 10: Evaluation of the fuzzy rules for the coverage factor.

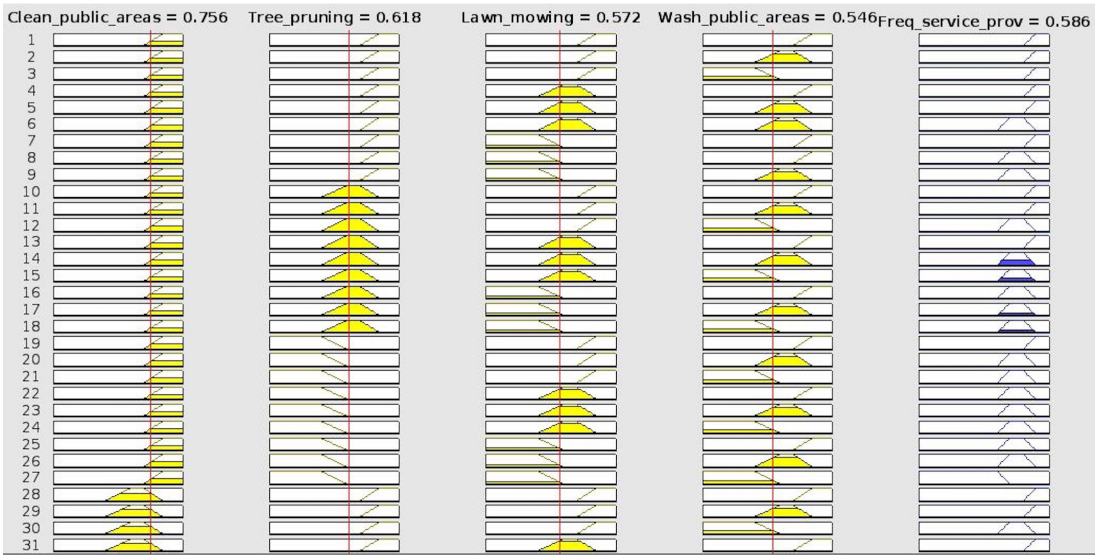

Figure 11: Evaluation of the fuzzy rules for the frequency factor.

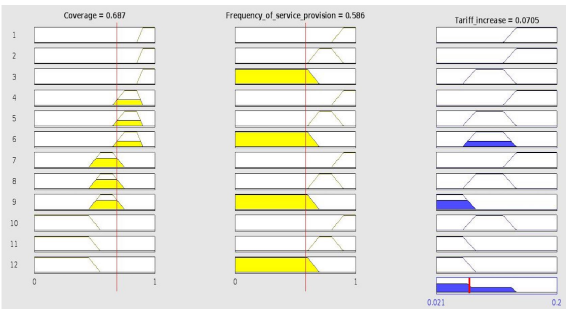

Figure 12: Evaluation of the fuzzy rules for the tariff increase factor.

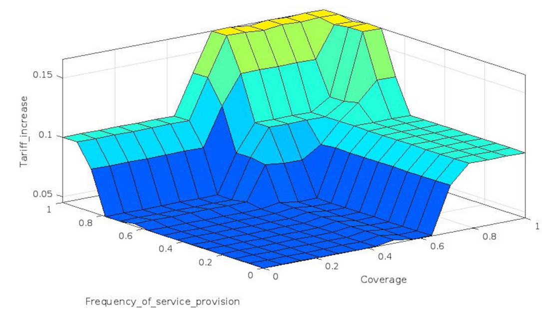

Figure 13: Surface plot for tariff increase according to coverage and frecuency.

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