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Methodological Planning to Determine the Technological Expansion of Smart Metering Systems for Utilities

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Abstract: This research uses data analysis and mining techniques to determine the technological expansion of measurement systems in a public service company. It integrates technical, economic, geographic, and social variables into the analysis using machine learning techniques to discover patterns and relationships in large data sets. The fuzzy logic methodology is applied using the MATLAB programming tool "Fuzzy Logic" to build algorithms that allow for the correct selection of measurement, achieving greater efficiency and precision in the assignment of meter types. The results show that 98% of the metering systems in the significant part are electronic meters, with the "Residential BT" rate being the most extensive data set. Implementing the "fuzzy logic" technique recognizes that more than 60% of the meters are electronic, with the registration of active energy, reactive energy, and demand, allowing for greater control over the marketing variables of the distribution system operator. This research suggests that a future restructuring of electrical metering systems benefits the company and its users. By applying the analysis, a portfolio of viable projects for the replacement of measurement systems is obtained, and they are grouped into two clusters based on the total cost of the technological change.

Keywords: fuzzy logic; distribution systems; advance metering infrastructure; planning; measurement systems

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1. Introduction

Electrical distribution systems are essential for ensuring the efficient and safe delivery of electrical energy from distribution substations to final consumption points, providing power to homes, companies, and industries [1]. This theoretical framework's primary focus is the methodological planning of measurement systems for utilities, with a particular emphasis on electrical measurement systems and the methodological application of fuzzy logic with its main theoretical foundations.

Electrical energy measurement technology is crucial for accurate and fair billing to end consumers and ensuring the quality of the electrical supply. Electronic and smart meters are currently the most widely used technologies due to their high accuracy and advanced communication capabilities [2]. However, the choice of the type of energy meter depends on the specific needs of each electrical distribution system operator and user [3]. They can be used for various applications in electrical distribution systems, such as electrical energy billing, identifying electrical grid faults, and detecting electrical power quality problems [4]. The information collected by energy meters can be used to improve energy efficiency and reduce energy consumption in homes and businesses [5].

Ecuador has initiatives to implement smart meters that allow more precise measurement and greater efficiency in electrical energy management [6]. These smart meters are equipped with communication technology that allows for real-time data transmission and better management of electrical energy consumption [7,8].

The transformation of the electrical energy system is occurring worldwide, moving from a conventional unidirectional structure to one that is more open, configurable, and participatory by consumers and other actors in the sector [9]. Since 2010, the electricity sector has experienced essential changes in using and implementing new technologies to allow better use and greater efficiency in generating, transporting, and distributing electricity [10]. This change has culminated in the emergence of a broader electricity market [11,12].

Some of the most common applications of electric energy meters in electrical distribution systems include detecting system failures [13], monitoring power quality [14], demand management [15], selecting appropriate measuring devices based on the company's specific needs [16], designing a measurement system that allows energy consumption to be measured and analyzed in real-time [17], and monitoring and controlling systems [18]. Implementing a well-designed electrical energy metering system can generate significant savings in energy costs and improve the operational efficiency of utilities [19].

Evaluating the effective and robustness of electrical energy measurement systems is essential to determine whether they are meeting the objectives for which they were implemented. Different evaluation techniques can be used, such as comparing results with theoretical values or performing performance tests under adverse conditions [20].

Most utilities in Latin America and the Caribbean lack planning for integrating advanced measurement systems to improve marketing processes. The average energy loss rate in Latin American and Caribbean countries is 15.65% [21]. In Ecuador, technical investments and data analysis models achieved a significant reduction of 25.04% in 2008 to 13.03% in 2018 [22]. Investment in energy loss reduction programs has been limited due to the need for more public policies, laws, and regulations governing distribution systems [23]. This social and cultural inequality is causing a reduction in metering systems to reduce electricity bills. Electricity providers must maintain accurate records of measurement system readings in real-time to offer optimal operation and service.

In electrical engineering, fuzzy logic has been used to optimize the control of electrical energy generation and distribution systems, such as regulating frequency and voltage, active and reactive power, and protecting electrical systems [24]. Examples of the application of fuzzy logic in different fields include the automation of industrial processes, decision-making in expert systems, robotics, computer vision, artificial intelligence, and electrical engineering [25].

In the context of electrical energy measurement systems, fuzzy logic can be applied to model and control variables such as energy consumption, electrical demand, and energy efficiency. For instance, one of the most common applications of fuzzy logic is in fuzzy demand control, which involves implementing a control system that adjusts energy consumption in real time based on the needs of the user system fuzzy demand control. This involves implementing a control system that adjusts energy consumption in real-time. This application, as demonstrated in a study by Ramos and Sun, can generate significant savings in energy costs and improve the utility's operational efficiency. Another practical application of fuzzy logic is predicting energy consumption, as shown in a study by Atef. In this study, fuzzy logic is applied in voltage measurement in electrical energy distribution systems. A study developed by Akbari et al. [26,27] presents a voltage measurement technique in electrical power distribution systems that uses fuzzy logic to improve measurement accuracy. A study by Kumar et al. [28] presents a power quality measurement technique that uses fuzzy logic to improve measurement accuracy.

The practical applications of fuzzy logic in electrical energy measurement systems are numerous and significant. It enables the modeling of complex and non-linear systems, the handling of imprecise or uncertain information, and the incorporation of expert knowledge and prior experience into the design of measurement systems [29]. This, in turn, enhances system accuracy and efficiency. Fuzzy logic also offers greater flexibility and adaptability to different conditions and environments, as it can automatically adjust measurement system rules and parameters in real-time in response to changes in power consumption and other external factors. However, it is important to note that fuzzy logic does have its limitations. For instance, it may not provide a clear explanation of the relationship between variables, which can make it challenging to interpret the results. Additionally, it can be computationally expensive and time-consuming in complex systems, which may limit its practicality in certain applications. Lastly, it is based on assumptions and approximations, which may lead to less-accurate results in some cases. Despite these limitations, fuzzy logic remains an essential tool in electrical energy measurement systems and has proven useful in various applications.

This work uses fuzzy logic to determine the methodological planning that influences the technological expansion of utility measurement systems. The specific objectives include using analytics and data mining techniques to define the types of measurement systems, applying fuzzy logic to validate variable use in planning, and evaluating the selection methodology based on a portfolio of projects.

The contribution of this research is the use of the fuzzy logic tool to determine the methodological planning that influences the technological expansion of smart metering systems for utilities. Through the use of data analytics techniques, it validates the use of variables in planning and evaluates and generates a portfolio of projects that must be implemented according to the utility investments.

This article aims to present a comprehensive review as follows: Section 2 describes an in-depth analysis of the variables involved in the methodology to analyze and determine utility patterns. Section 3 describes the methods used in the case study. In Section 4, an analysis is carried out, and the results of the methodology are discussed. Section 5 reports conclusions based on the results obtained from the methodological implementation and the potential applications in the electrical industry.

2. Statistical Analysis of Data

This statistical analysis aims to analyze the electricity consumption in five regions of Cuenca, divided into urban and rural areas. Variables such as consumption group, economic and geographic aspects, electricity consumption stratum, tariff type, and meter brands will be considered to provide a clear understanding of electricity consumption behavior in these zones. The data used in the statistical analysis were sourced from a company that sells and distributes electricity, ensuring accurate information on consumption. The company uses rigorous processes to ensure data quality and accuracy, including verification of meter accuracy and regular calibration of measurement equipment. Descriptive statistical methods identify patterns, trends, and relationships, reducing the margin of error and improving the representation of results, as seen in Table 1.

Table 1. Literature review and methodology used in fuzzy logic.

Methodology	Concept	Algorithm/Method	Reference
Theoretical study			[1,23,25,30]
Fuzzy logic	Smart meters	Smart meters	[2,3,16]
		System AMI	[6,19]
		Local and regional analysis	[7,8,21,22]
		Opportunities with smart meters and smart grids	[4,10,15]
		Data analysis with smart meters and smart grids	[13,14,17]
	Fuzzy logic	Management and energy measurement	[26,28]
		Energy management in buildings and homes	[31,32]
		Network reconfiguration for energy saving	[32,33]
		Control and automation	[24,34,35]

2.1. Geographic Area Analysis

This study analyzed 220,000 users from an electric power distribution system operator's data set, as shown in Table 2, dividing the sample into five groups based on socioeconomic characteristics. The data were analyzed using MATLAB, allowing for a wide range of analyses to explore relationships between variables and provide a deeper understanding of the collected data. This study aimed to compare electricity consumption patterns across different geographical areas.

Table 2. Representative data of the sample.

Location	Number of Samples
El Batán	1000
Monay	1000
San Sebastian	1000
Totoracocha	1000
Valle	1000
Total	5000

Figure 1 corresponds to a scatter diagram, where it is possible to differentiate the variables of the selected geographical areas.

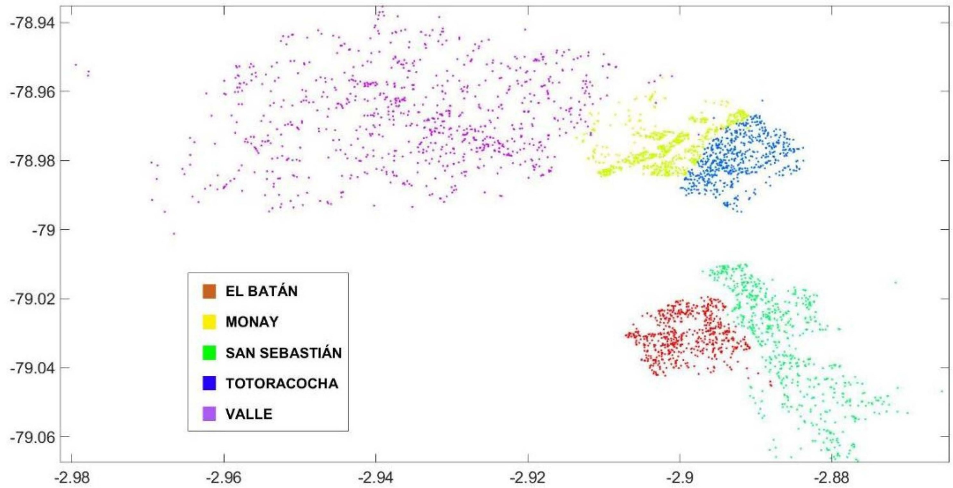


Figure 1. Scatterplot of regions.

2.2. Analysis of Electric Meter Brands

The statistical analysis involves analyzing each sample separately and studying its characteristics. A significant sample size helps identify patterns and trends in energy consumption in each region based on the type of meter brand, as shown in Table 3.

The analysis of meter brands in the regions reveals that Hexing has the highest frequency (56%), followed by Xili (14%) and Lintin 8%. Wasion and Sunrise have lower frequencies (6% and 4%, respectively). This information can help utility companies make strategic decisions about meter management and equipment. A word cloud representation, as shown in Figure 2, can be used to visualize the frequency of different brands in region measurements, guiding supplier selection and equipment maintenance decisions.

This study analyzed the brands and types of 5000 m, finding that 98% were electronic and 2% were electromechanical. The Hexing brand was the preferred electronic meter, while the Xili, Lintin, Wasion, and Sunrise brands offered both electronic and electromechanical meters. Most of the meters were electronic, indicating a trend toward modern technology in energy consumption measurements. The results suggest a trend towards electronic meters across all brands.

Table 3. Meter brands.

Meter Brand	Quantity	Meter Brand	Quantity
ABB	3	Landis	1
Aeg	1	Lintin	386
Aem	60	Nansen	1
Conteleca	4	Ningbo	3
Elster	40	Sanxing	1
Fae	26	Schneider	1
Galileo	1	Sco	19
General Electric	1	Siemens	3
Hexing	2815	No known brand	2
Hiking	6	Songhe	173
Holley	22	Star	158
Honeywell	3	Sunrise	213
Intech	52	Wasion	312
Krizik	1	Xili	679
		Nummissing	13

Figure 2. Word cloud of meter brands.

2.3. Analysis of the Types of Electrical Connections

The analysis of electrical connection types revealed that 5% of the connections were single-phase, 87% were two-phase, and 8% were three-phase. These data helps in understanding the utilities.

2.4. Analysis of Electricity Consumption Groups

This section examines a significant variable, categorized into residential, commercial, and industrial consumption groups, as shown in Table 4. The table highlights their unique usage patterns, requirements, and electrical energy consumption.

Table 4. Division according to consumption group.

Consumer Group	Quantity	Frequency
Commercial	394	8%
Residential	4499	90%
Industrial	69	1%
Others	38	1%

The analysis revealed that 58% of the connections were two-phase, with the Hexing brand being the most used in the residential sector, accounting for 90% of electricity consumption in the regions analyzed. Different meters and connections could influence the commercial sector's 8% consumption, requiring further analysis to identify trends. The low percentage of consumption in the industrial sector and others suggests they are not significant in electricity consumption.

2.5. Analysis of the Types of Electricity Tariffs

This section analyses the consumption trends of electricity tariffs in the regions, focusing on residential groups. The BT residential tariff was the most used, accounting for 85% of the total sample. The analysis revealed that most consumers belonged to this group, accounting for 84% of the total. The LV commercial tariff was the second-most used, followed by the LV residential tariff for the PEC program and the BT industrial artisanal tariff. The consumption tariff can influence electricity consumption and its cost to consumers. The LV residential tariff was the most used, accounting for 84% of the total. The presence of the LV commercial and PEC residential tariffs was also significant; 6% each. The BT industrial artisanal tariff stands out, with 1%, indicating a low presence of electricity consumption in the industrial sector.

2.5.1. Analysis of the BT Commercial Tariff

The BT commercial tariff was analyzed with a 6% relevance, and its performance was predominant in Totoracocha, with 95 customers. The other regions were El Batán with 82 customers, San Sebastián with 66 customers, Monay with 35 customers, and Valle with 26 customers. The analysis reveals that the region with the highest membership level in this tariff was Totoracocha. Most regions had similar customer numbers, except for Totoracocha, which had the highest number of customers, indicating higher commercial activity. San Sebastian had the lowest number of customers, indicating lower commercial activity in the urban area. The analysis suggests that the LV commercial tariff is a significant factor in the area's commercial activity.

2.5.2. Analysis of the LV Residential Tariff

The analysis of commercial tariffs revealed that residential tariffs were 90% relevant in all regions, with the LV residential tariff being the most used. The number of customers with this tariff was balanced across all regions, with no region significantly impacting the electric voltage levels used for households and small industries. The results are presented in Table 5.

Table 5. LV residential tariffs by region.

LV Residential Tariff	Residential	PEC Program	Ind. Artisanal
El Batán	19%	17%	31%
Monay	20%	28%	24%
San Sebastián	20%	16%	13%
Totoracocha	20%	14%	20%
Valle	21%	26%	11%

2.6. Analysis of Electricity Consumption Strata

The analysis identifies five electricity consumption strata: E, D, C, B, and A, each with a specific monthly consumption range. Stratum E has the lowest consumption (1–60 kWh), while stratum A has the highest (310+ kWh). This analysis helps identify the distribution of electricity consumption in different regions and its relationship with consumption groups and corresponding electricity tariffs, as shown in Figure 3.

The strata are categories based on a user's electricity consumption and ability to pay, which are used to apply different tariffs. Figure 3 shows outliers with mean data that are greater than the median, providing relevant data for monthly readings in kW/h for each client. The analysis reveals that Valle has the lowest consumption stratum, with a higher percentage of low electricity consumption. This suggests a potential for energy conservation initiatives in this area. El Batán, on the other hand, has a higher concentration of customers in higher-consumption strata, indicating a need for increased energy supply and infrastructure in this area. This could lead to higher electricity consumption costs. These findings can be used to inform energy planning and policy decisions, particularly in the context of commercial and industrial projections for El Batán compared to other regions.

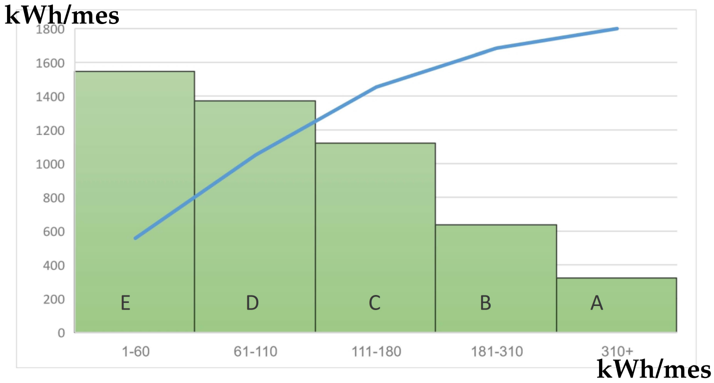


Figure 3. Distribution of electricity consumption strata in each region.

Furthermore, the analysis of meter types and their behavior in each region can be used to create a new distribution of meters based on their electricity consumption stratum, as illustrated in Table 6. This study found that 98% of meters in the area were electronic, with the remaining 2% being electromechanical. The distribution of electronic meters across different electricity consumption strata indicates that electricity consumption is evenly distributed among different socioeconomic groups, suggesting a higher level of technology and efficiency in recording consumption compared to electromechanical meters. This is significant, as it indicates a more accurate and efficient way of measuring and managing electricity consumption.

The analysis of electricity consumption strata using electronic meters revealed that 98% of the metering system was electronic. In the residential tariff, Table 6 shows that stratum E had 27% of the customers, followed by stratum D (26%), stratum C (21%), stratum B (11%), and stratum A (4%). These results are specific to electronic meters and suggest a lower consumption strata.

Table 6. Distribution of electricity consumption strata based on electronic meters.

Strata	kWh	Electronic Meters	Residential	Commercial	Industrial
E	1–60	1505	1338	131	18
D	61–110	1353	1289	49	6
C	111–180	1098	1043	45	5
B	187–310	615	556	41	16
A	>301	307	187	99	2

The analysis of electronic meters in the commercial tariff reveals that stratum E had the highest frequency at 3%, followed by stratum A at 2%. Strata D, C, and B had frequencies of 1% each. The total number of meters in the commercial tariff was significantly lower than in the residential tariff, indicating differences in stratum frequencies. The low percentage of meters in stratum A may indicate lower energy consumption among commercial consumers. Interestingly, stratum E had the highest frequency, suggesting that customers in this tariff are on par with those in the residential tariff.

2.7. Economic Variable Analysis

In previous sections, we analyzed various variables, including the electricity consumption strata, meters used, consumption groups, and tariffs applied to the sample. The focus is now on analyzing the economic variable based on different electricity consumption strata, as shown in Table 7. This analysis helps us to understand how electricity costs are distributed in different strata, providing significant implications for planning and decision-making related to electricity consumption.

Table 7. Billing distribution according to electricity consumption strata.

Strata	Residential	Commercial	Industrial	El Batán	Monay	San Sebastián	Totoracocha	Valle
E	13,587	3129	508	2056	2500	2315	2789	3933
D	22,482	1498	209	4290	5206	3679	4208	5099
C	31,124	1751	269	6453	7062	5766	6206	5637
B	24,015	2474	1124	5743	5327	4480	4345	4120
A	16,197	18,280	5211	5085	2736	3927	2438	2011

The billing analysis reveals that most customers are in strata D and C, with higher total billing compared to other strata. Additionally, stratum B has higher billing, while stratum E has the lowest. The residential consumption groups show that strata C and B have the highest billing, while stratum A has the lowest. Commercial tariff billing is lower than residential, with stratum A representing the most significant revenue. The commercial tariff also contributes significantly to revenue, especially in stratum A. In the commercial tariff, stratum A has the highest billing, with USD 18,279.58, while the other strata have significantly lower billing. In the industrial tariff, stratum A has the highest revenue, followed by stratum B. However, strata C, D, and E have lower contributions to the total revenue.

Table 7 shows the analysis of billing by stratum for each region, identifying regions with the highest electricity consumption for resource distribution and energy planning. The analysis of residential rates in the city reveals that Valle has the highest billing, with a total of USD 3932.72. El Batán, the lowest-billing region, has a significant value of USD 2055.80, indicating electricity consumption in that area. In stratum D, Monay has the highest total billing value, followed by the rural region of Valle and El Batán and Totoracocha. San Sebastián has the lowest turnover value, costing USD 3678.86.

Stratum C has the highest total billing value, followed by Monay and El Batán. The total billing value increases as the stratum and energy consumption increase. However, in San Sebastian, the total billing value is lower than the other strata, suggesting lower energy consumption.

In stratum A, El Batán has the highest value, followed by Monay and San Sebastián. The total values correspond to consumption of over 310 kWh, which is higher in this stratum. Lower strata have lower bills, while higher strata have higher bills.

Similarly, according to the commercial consumption group, the billing development of each region is analyzed. The data on commercial rates in Cuenca's strata is of significant importance, as they reveal the variations in energy consumption patterns. In stratum E, which corresponds to 1–60 kWh consumption intervals, rates are relatively low, with San Sebastian having the highest rate. In stratum D, which corresponds to a consumption interval of 61–110 kWh, rates are higher but still relatively low, with El Batán having the highest rate. In stratum C, which corresponds to a consumption interval of 111–180 kWh, rates are higher but still relatively low, with Totoracocha having the highest rate. In stratum B, which corresponds to a consumption interval of 181–310 kWh, rates are even higher, with El Batán having the highest tariffs. In stratum D, the lowest rate is in St. Sebastian, while the lowest rate is in stratum D. In stratum A, which corresponds to a consumption interval of more than 310 kWh, rates are the highest, with Totoracocha having the highest rate. In conclusion, commercial rates in Cuenca vary significantly according to strata and region, with higher rates in higher consumption strata and certain regions.

2.8. Analysis of Total Turnover

A detailed analysis of the total billing for each region, as depicted in Figure 4, was conducted to better understand the distribution of electricity costs across different geographic areas.

The data show that El Batán had the highest contribution to total income, with USD 33,317.05. San Sebastian followed with USD 31,845.41, while Monay had USD 30,432.04. Totoracocha and Valle had lower contributions to the total revenue, with USD 29,687.81

and USD 23,732.20, respectively. The data suggest that regions with higher socioeconomic and commercial levels contribute more to the energy utility distribution revenue. The higher strata in El Batán and San Sebastián had the highest residential and commercial rates, indicating higher electricity consumption and a significant presence of companies and businesses. Lower-strata regions like Monay, Totoracocha, and El Valle had lower rates, indicating lower electricity consumption and a less significant presence of businesses.

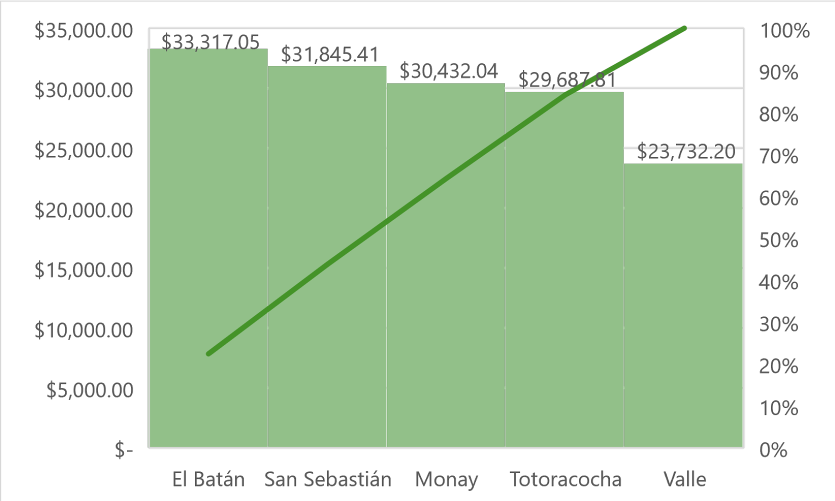


Figure 4. Distribution of the total turnover of each region.

3. Methodology

This research uses analytical and data mining techniques and fuzzy logic algorithms to select metering systems for utilities. The methodology helps in decision-making regarding the planning and technological expansion of metering systems, considering market trends and limitations. The application of fuzzy logic validates the use of variables in planning technological expansion, allowing for more accurate and efficient results. MATLAB 2021b software is chosen due to its ability to implement fuzzy logic algorithms and complex data processing, making it suitable for analyzing electrical metering systems. The Fuzzy Logic toolbox add-on provides a wide range of tools and functions for designing, simulating, and analyzing control systems based on fuzzy logic. As shown in Figure 5.

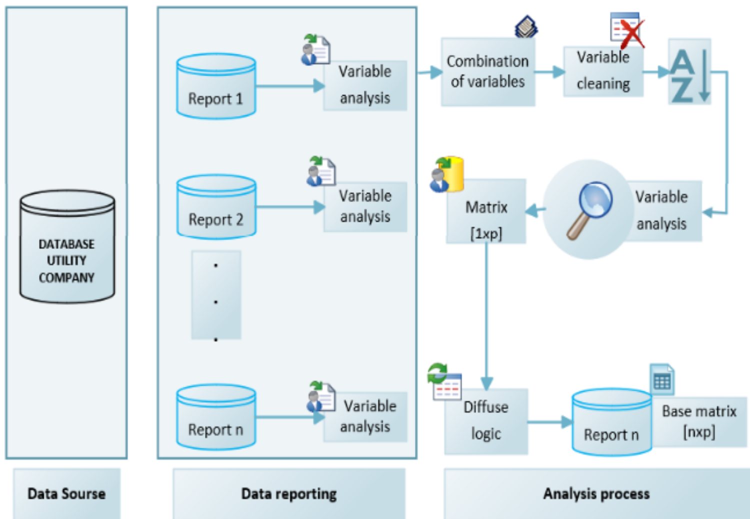


Figure 5. Collection and process integration diagram.

3.1. Development of the Fuzzy Logic Model

The fuzzy logic algorithm uses billing in USD and consumption in KWh as input variables. Billing is divided into three membership functions (low, medium, and high) [30], ranging from $0 to $500, and consumption into three membership functions (minor, medium, and major), ranging from 0 to 400 KWh. These variables are crucial for planning metering system expansion and making informed decisions.

The fuzzy logic algorithm uses a meter-type variable with five membership functions as an output variable. These functions are electronic; electronic with active, reactive, and demand (ARD) register; electronic with ARD and radio frequency register; electronic multirate radio frequency; and AMI electronic meter. The range of values and their membership functions are shown in Table 8.

Table 8. Definition of output parameters.

Output Parameters	Belonging Function	Range
Output	Electronic	0∼0.2
	Electronic with ARD	0.2∼0.4
	Electronic with RF reg.	0.4∼0.6
	Multi-rate RF electronics	0.6∼0.8
	Electronic AMI	0.8∼1

The output variable chosen for this fuzzy logic algorithm is the type of meter, which aims to determine the ideal meter for each user in each region.

3.2. Fuzzy Logic Implementation in MATLAB

The default fuzzy logic editor window appears as shown in Figure 6.

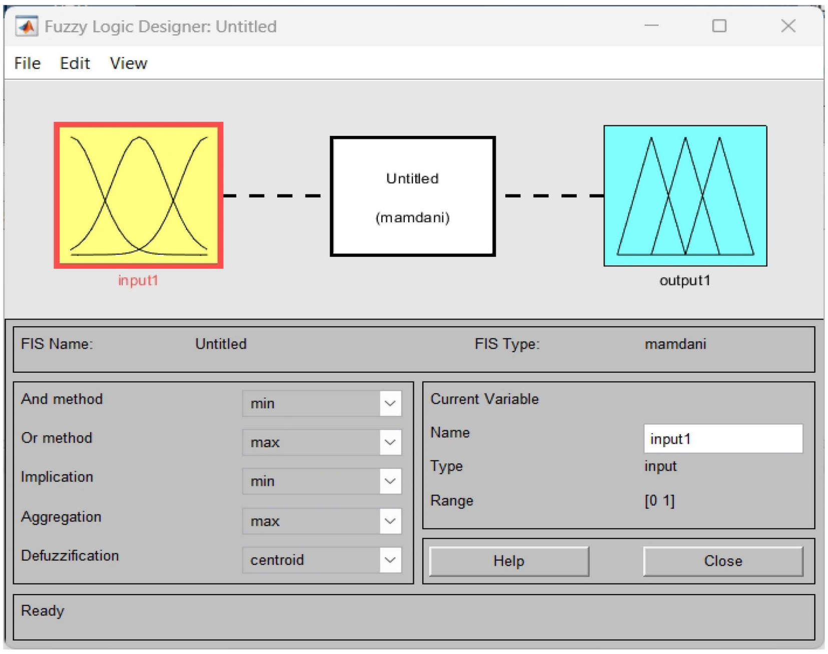


Figure 6. Fuzzy logic MATLAB editor window.

We load the Fuzzy Logic toolbox plug-in in the development environment to design and simulate fuzzy logic systems. The Fuzzy Logic plug-in in MATLAB defined two input variables, billing in USD and consumption in KWh, and an output variable, the meter type. The Fuzzy Tools add-on in MATLAB is valuable for defining these variables and their membership functions intuitively and efficiently. This helps in determining the ideal meter type for each region, ensuring accurate and useful results in fuzzy logic decision making.

3.3. Definition of Membership Functions

The parameterization using fuzzy logic involves defining membership functions for each input variable and output variable, such as turnover in USD and billing in USD, as shown in Table 9.

Table 9. Definition of invoicing input parameters.

Membership Function		Degrees of Membership	Degrees of Membership
Under	Triangular	Minimum value: 0 Maximum value: 125 Peak value: 250	Minimum value: 0 Maximum value: 100 Peak value: 50
Medium	Triangular	Minimum value: 0 Maximum value: 375 Peak value: 250	Minimum value: 50 Maximum value: 200 Peak value: 125
High	Triangular	Minimum value: 250 Maximum value: 500 Peak value: 500	Minimum value: 150 Maximum value: 400 Peak value: 275

Triangular membership functions exhibit abrupt transitions between values, maximizing overlap for a uniform and smooth output surface graph. They have a triangle shape, with the lowest membership value at the minimum, the highest at the maximum, and the maximum at the middle.

For the input variable "Consumption in KWh", the following membership functions are defined in Table 9.

For the output variable "Meter type", the following membership functions are defined, as shown in Table 10.

Table 10. Definition of output parameters for meter type.

Membership Function		Degrees of Membership
Electronic	Triangular	Minimum value: 0 Maximum value: 0.1 Peak value: 0.05
Electronic with ARD	Triangular	Minimum value: 0.1 Maximum value: 0.3 Peak value: 0.2
Electronic with RF reg.	Triangular	Minimum value: 0.3 Maximum value: 0.5 Peak value: 0.4
Multirate RF Electronics	Triangular	Minimum value: 0.5 Maximum value: 0.7 Peak value: 0.6
Electronic AMI	Triangular	Minimum value: 0.7 Maximum value: 1 Peak value: 0.85

3.4. Application of Fuzzy Rules to the Model

The fuzzy logic algorithm uses fuzzy sets to map the input values to the degrees of membership, representing uncertainty or vagueness. This is implemented in MATLAB as a 5000X1 matrix. The input variables represent billing in USD and consumption in kWh for 5000 users. This allows the fuzzy logic application to determine the relationship between billing and other variables, such as meter type or electricity consumption. The fuzzy rules for inference and defuzzification are established, obtaining a discrete value for the output variable. The membership function assigns fuzzy values to a set, representing uncertainty in membership. Rules are transferred to the fuzzy logic algorithm to make decisions based on input data, such as planning metering system expansion.

3.5. Defuzzification Process in the Fuzzy Algorithm Model

Defuzzification converts the fuzzy logic system's fuzzy output into a valid numerical value. The centroid method is a widely used method, where the centroid of the membership function from fuzzy inference is calculated and used as the system's output value.

Defuzzification Method Centroid

In the centroid method, the centroid or center of gravity of the membership function of the output variable is calculated. The centroid is defined as the sum of the products of the membership functions and their corresponding membership values divided by the total sum of the membership values. The MATLAB Fuzzy toolbox uses the centroid method to defuzzify an output fuzzy set, calculating the corresponding centroid using the weighted area centroid algorithm. This weighted measure calculates the centroid of the output area by weighing the degree of membership at each point with its respective value. This results in a 2D plot of consumption in kWh vs. the type of meter, as shown in Figure 7. The result shows an increasing trend in consumption in KWh, indicating that higher consumption necessitates meters with higher capacities and functionalities. This is reflected in the graph as an expanding surface.

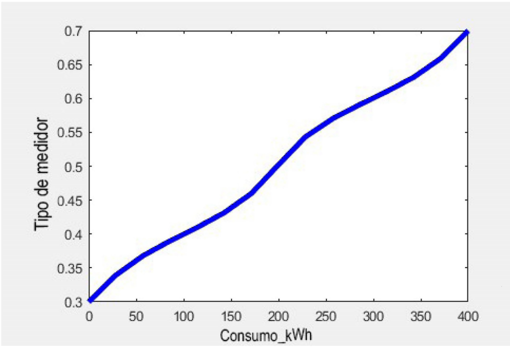


Figure 7. Two-dimensional graph of the relationship between consumption and meter type in the fuzzy logic model.

Figure 8 shows the relationship between meter type and billing in dollars, calculated by weighting the output surface's membership degrees. The graph shows an increasing trend as billing in USD increases, indicating an increase in the required meter type. These data align with the statistical analysis in Section 2. The centroid is calculated and used as the output value of the fuzzy system, but it may not correspond to any linguistic value in the discourse universe.

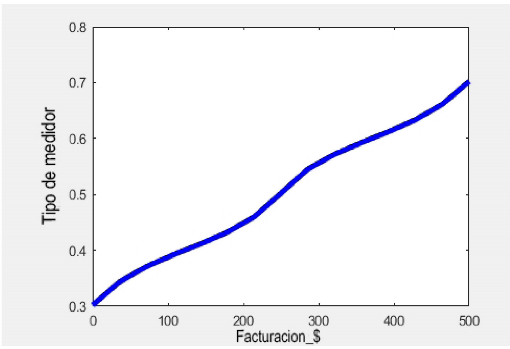
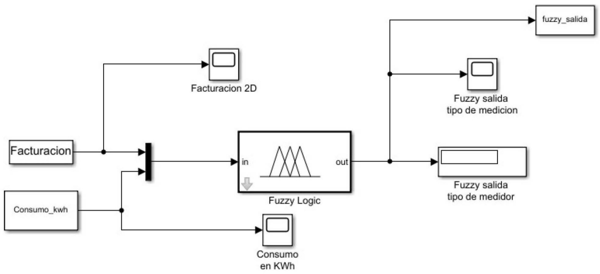


Figure 8. Two-dimensional graph of the relationship between billing and meter type in the fuzzy logic model.

3.6. Simulink Model

The Simulink block model is developed to analyze a fuzzy logic system for selecting an electronic counter based on customer billing values and electricity consumption. A block diagram with feedback is designed as shown in Figure 9, with blocks corresponding to billing in dollars and consumption in kWh added to the diagram.



Rango de Salida	Tipo de sistema de medición
0~0.2	Electrónico
0.2~0.4	Electrónico ARD
0.4~0.6	Electrónico con Reg y RF
0.6~0.8	Electrónico Multitarifa RF
0.8~1	Electrónico AMI

Figure 9. Block diagrams of the fuzzy logic model.

After the fuzzy logic algorithm is run, the results are visualized and exported to a matrix for further analysis. This process allows for the simulation of 5000 clients, enabling planning decisions for metering system expansion. The results can then be exported to an analysis program for further interpretation, providing a comprehensive understanding of the system's performance and potential areas for improvement. Figure 10 displays the billing curves for 5000 users in five regions, displaying the billing input variable in dollars and meter type values for each utility user.

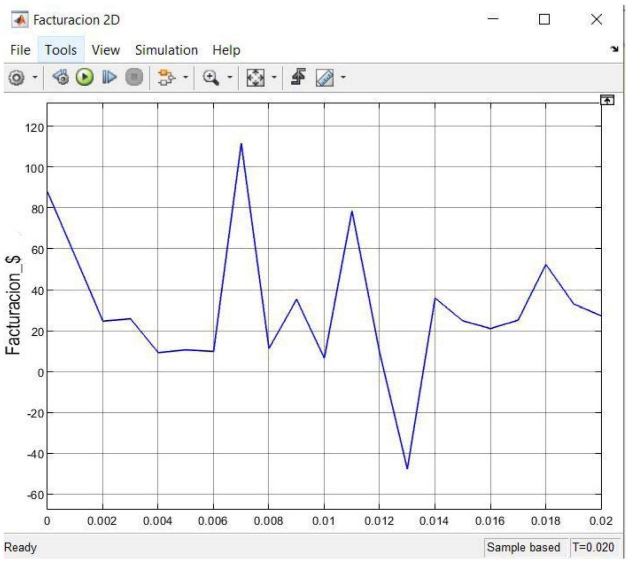


Figure 10. Diagram of fuzzy logic billing.

Figure 11 displays the kWh consumption curves for 5000 users in five regions, displaying the consumption density in kWh and degrees of membership corresponding to meter type, with the y-axis representing kWh usage density.

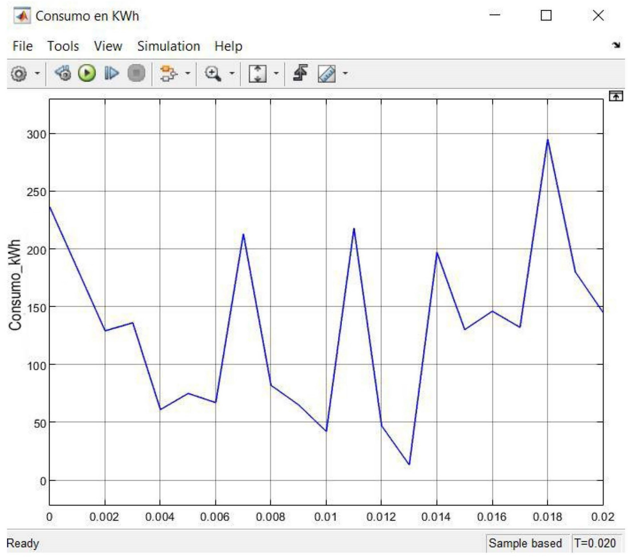
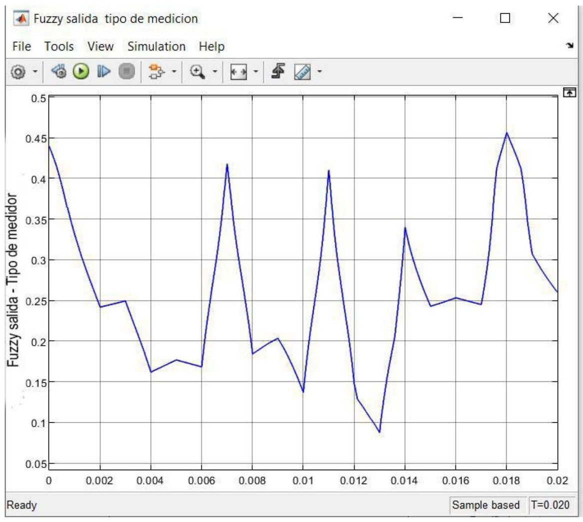


Figure 11. Diagram of consumption in kWh of fuzzy logic.

Using the results obtained from the input variables of the model, the output variable indicates the membership values obtained, along with their range of membership, as shown in Figure 12.



Rango de Salida	Tipo de sistema de medición
0~0.2	Electrónico
0.2~0.4	Electrónico ARD
0.4~0.6	Electrónico con Reg y RF
0.6~0.8	Electrónico Multitarifa RF
0.8~1	Electrónico AMI

Figure 12. Two-dimensional output diagram of the fuzzy logic meter type.

The fuzzy logic model shown in Figure 12 shows a significant decrease in electronic meter usage in the sample cluster, with 98 % of users currently using electronic meters. However, an increase is observed in the range of 0.2 to 0.4, corresponding to the Active, Reactive, and Demand Register (ARD) meter type, which has a significant sample for the data set. A smooth curve is observed for electronic meters with register and radio frequency, indicating few or no meters for selected users. The results can be exported to an Excel file for further data analysis, allowing for precise meter types and other relevant information to improve the model for future applications.

4. Analysis of Results

This section analyzes the fuzzy logic results for technological planning for meters, determining economic feasibility based a cost–benefit analysis. It provides valuable information for decision-making in metering system technology upgrade projects for electricity distribution system operators and generates ideas for service quality improvement. In Section 2, the data analysis revealed that 98% of urban and rural regions have electronic meters, while only 2% use electromechanical meters. The distribution of these meters is based on a significant sample of 5000 users, with only 2% using electromechanical meters.

The majority of meters in certain areas are electronic, except in San Sebastian, where there are more electromechanical meters than in other regions. This suggests that San Sebastian's electrical infrastructure may influence the choice of the type of meter.

Figure 13 corresponds to a heatmap representing the current status of the measurement systems in the regions, correlating with the electronic meters distributed in each region.

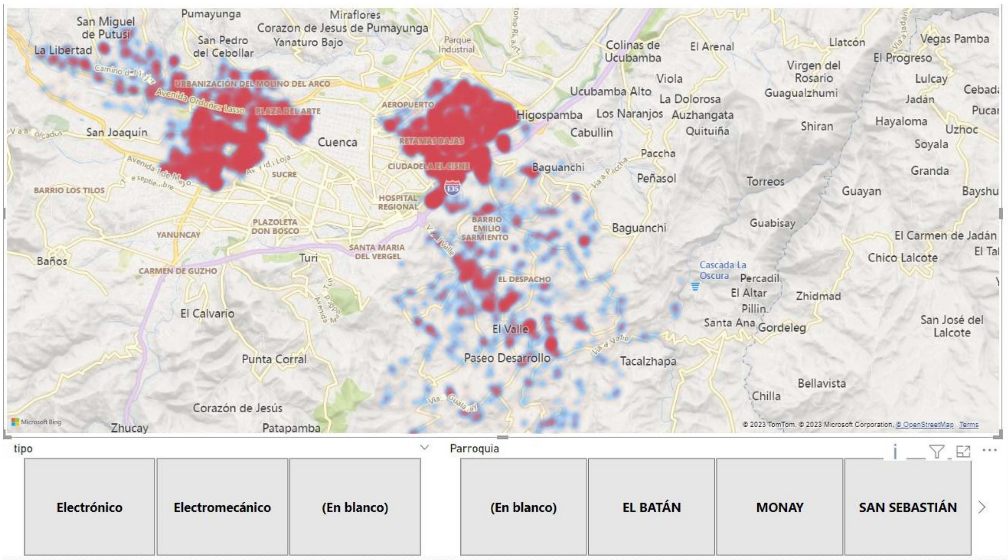


Figure 13. Heatmap of the distribution of electronic meters in the regions.

4.1. *Application of Fuzzy Logic*

Table 11 presents a frequency distribution analysis revealing the frequency of electronic meters affecting fuzzy logic implementation. The Active, Reactive, and Demand Recording (ARD) type is the highest frequency, with 3010 and 60% relative frequencies. The second-most-common frequency is the 1575 frequency, followed by the 32% relative frequency. The least-common frequency is the 415 frequency and 8% relative frequency. Currently, 98% of electronic meters are used, resulting in a 66% decrease in all regions. This study highlights the importance of frequency distribution in implementing fuzzy logic.

Table 11. Distribution of meters based on fuzzy logic results across different regions.

Meter Type	Frequency	Relative Frequency
Electronic	1575	32%
Electronic ARD	3010	60%
Electronic1 ARD with RF	415	8%
TOTAL	5000	100%

The majority of users (32%) are suited for electronic meters, with 60% of these being equipped with electronic meters with ARD and 8% with ARD and radio frequency. However, no results were obtained for electronic multi-rate radio frequency and AMI meters, suggesting a lack of potential customers for energy demand for the selected samples. The heatmap in Figure 14 can help provide a more precise study projection.

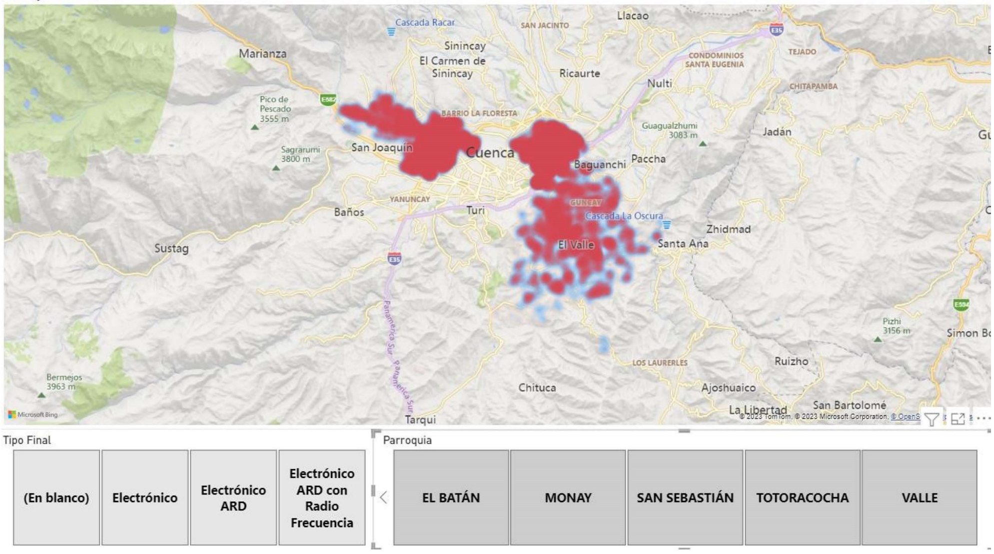


Figure 14. Heatmap of the final distribution of electric meters.

4.2. Analysis of Meter Distribution in Each Region

Analyzing electric energy consumption in each region using fuzzy logic reveals that the electronic and ARD electronic meters have similar frequencies. However, the ARD electronic meter with radio frequency is lower, as shown in Table 12. In El Batán, San Sebastián, and Totoracocha, the electronic meter with an ARD register is the most used, while in Monay, the electronic meter is the most common. The most common meter in Valle is the electronic meter with an ARD register, with a relative frequency of 61%. Although rural regions have less favorable results for electronic meters, they have the highest use rate of 5% for ARD registers with radio frequency. This indicates a remarkable growth projection above urban regions, with 90% of meters being electronic.

Figure 15 presents a heatmap for both electronic and electronic meters with ARD recording.

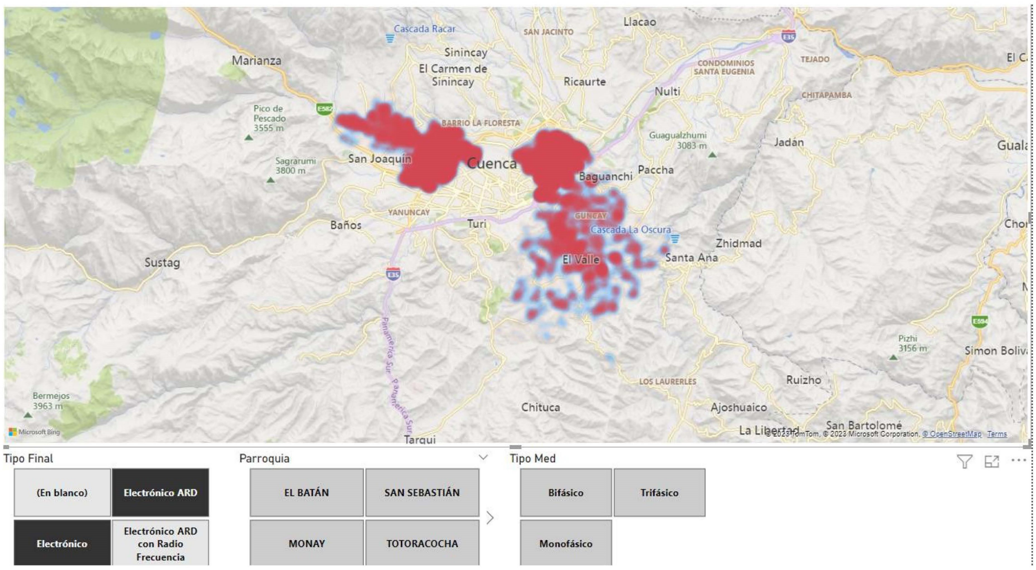


Figure 15. Heatmap of electronic meters and ARD in each region.

Table 12. Distribution of meters in each region.

Regions	Electronic	Electronic ARD	Electronic ARD with Radio Frequency
El Batán	104	790	106
Monay	544	426	30
San Sebastian	536	449	15
Totoracocha	391	609	0
Valle	0	736	264
TOTAL [%]	**31.5%**	**60.2%**	**8.3%**

4.3. Analysis by Type of Consumption

The fuzzy logic methodology was used to analyze the frequency of meter types based on consumption type in each region, as shown in Table 13. The most commonly used type was the electronic meter with an ARD register for two-phase consumption, with a relative frequency of 53%. This rate was predominant in all regions, with 27% for convention and electronic meters. The three-phase tariff had a lower presence, with a relative frequency of 5% in ARD electronic meters and 3% in conventional electronic meters.

Table 13. Distribution of meters according to type of electricity consumption.

Meter Type	Single-Phase	Two-Phase	Three-Phase
Electronic	88	1345	142
Electronic ARD	137	2641	232
Electronic ARD with radio Frequency	20	378	17
TOTAL [%]	5%	87%	8%

4.4. Analysis by Type of Consumption in Each Region

The analysis of electricity consumption in different regions primarily focuses on two-phase and three-phase consumption due to their significant role in electricity consumption, as depicted in Figure 16 as a heatmap of metering systems.

Using the fuzzy logic methodology, the frequency and relative frequency of each meter are determined, and their relationship with the type of consumption will allow us to make more relevant decisions to the study, as detailed in Table 14.

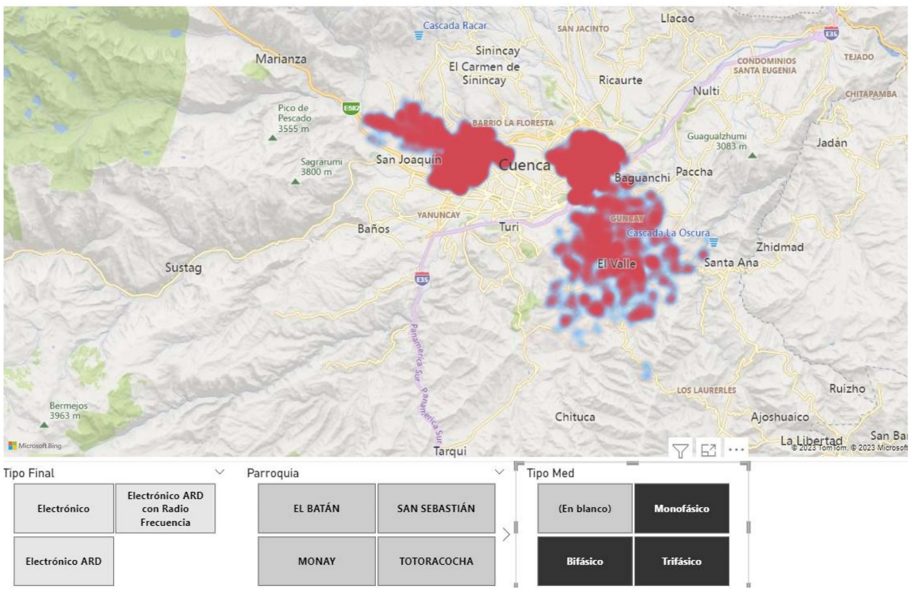


Figure 16. Heatmap of the distribution of electric meters by type of meter.

Table 14. Distribution of meters by type of meter in each region.

	Two-Phase			Three-Phase		
Region	**Electronic**	**Electronic ARD**	**Electronic ARD with Radio Frequency**	**Electronic**	**Electronic ARD**	**Electronic ARD with Radio Frequency**
El Batán	2%	14%	2%	0%	1%	0%
Monay	10%	7%	1%	1%	1%	0%
San Sebastian	8%	7%	0%	1%	1%	0%
Totoracocha	7%	11%	0%	1%	1%	0%
Valle	0%	14%	5%	0%	0%	0%

4.4.1. Analysis of Two-Phase Consumption Type

The type of two-phase meter in the regions is primarily determined by its ARD register. The Totoracocha region has the highest relative frequency of the two-phase meters, with 12% for electronic meters with ARD registers and 11% for electronic meters. San Sebastian has the lowest relative frequency for both meters, with 7% for electronic meters with ARD registers and 8% for electronic meters. These data are crucial for planning and managing electric service in each region. Generally, the type of meter with an ARD register has a higher frequency in the two-phase tariff, suggesting it may be more suitable for this type of tariff.

4.4.2. Analysis of Three-Phase Consumption Type

The three-phase tariff type has a lower frequency than the two-phase tariff type, with the relative frequency of three-phase meters being less than 2% in all regions except Valle. San Sebastian has the highest number of three-phase meters, while Totoracocha has the lowest number. A significant heat projection is also detected in San Sebastian, which has the highest number of three-phase meters.

4.5. Analysis Based on Consumption Group

The analysis focuses on the contribution of commercial, residential, and industrial electricity consumption groups to total electricity consumption in each region. It identifies patterns and trends based on their geographical areas, thereby providing valuable insights into overall electricity consumption patterns, as seen in Table 15.

Table 15. Distribution of meters according to electricity consumption group.

Meter Type	Commercial	Residential	Industrial
Electronic	132	1415	23
Electronic ARD	240	2697	41
Electronic ARD with RF	22	387	5
Total	394	4499	69

The residential consumption group is the most prevalent in terms of the number of meters installed in the regions, with 28% for electronic meters, 54% for electronic meters with ARD registration, and 8% for electronic meters with radio frequency. On the other hand, the commercial consumption group is representative of 3% for electronic meters, 5% for electronic meters with ARD registers, and 0% for electronic meters with ARD registers with radio frequency. The industrial consumption group is the least representative, with 0% for electronic and radio frequency meters and 1% for electronic meters with ARD registers.

4.5.1. Analysis of Commercial Consumption Group by Region

The most common type of meter for commercial consumption is the electronic meter with an ARD register, accounting for 5% of the total number. San Sebastian has the highest number of meters for all three types, followed by Totoracocha, as shown in Table 16.

Table 16. Distribution of meters according to commercial consumption group.

Location	Electronic	Electronic ARD	Electronic ARD with Radio Frequency
El Batán	10	84	14
Monay	28	17	1
San Sebastian	58	44	2
Totoracocha	36	74	0
Valle	0	21	5
Total [%]	34%	61%	6%

The electronic meters in Monay, San Sebastian, and Totoracocha have a higher relative frequency than the other regions, accounting for 1% of the total number of meters for this consumption group. El Batán and Totoracocha have a higher relative frequency of electronic meters with ARD registration, representing 2% and 1% of the total number, respectively.

Finally, in the case of the electronic meters with ARD registers with radio frequency, El Batán has the highest number of meters of this type, representing 0.2% of the total meters for the consumption group. Variations in the frequency of meters by region may indicate differences in consumption patterns among different geographic areas, as shown in Figure 17.

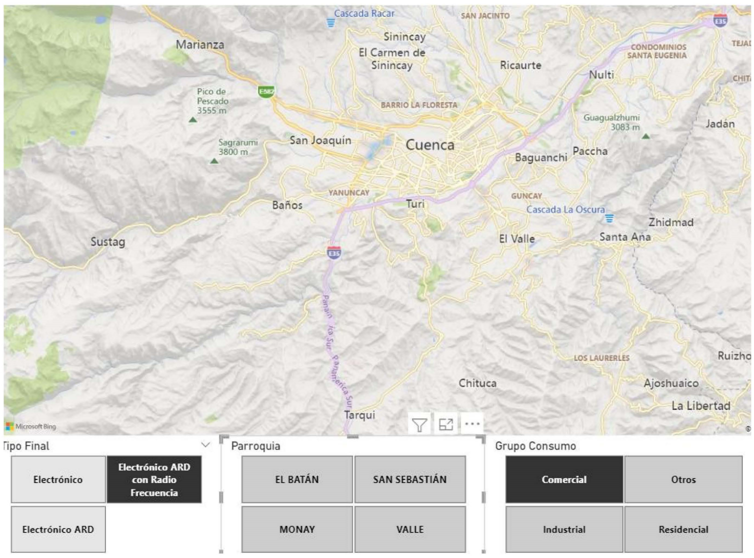


Figure 17. Heatmap of the distribution of ARD electronic meters with radio frequency according to commercial consumption group.

4.5.2. Analysis of the Residential Consumption Group

The data depicted in Table 17 show that the most commonly used meter for residential consumption is the electronic meter with ARD register, followed by the electronic meter, and finally, the electronic meter with an ARD register with radio frequency. However, as shown in Figure 17, Valle does not use electronic meters.

Table 17. Distribution of meters according to residential consumption group.

Location	Electronic	Electronic ARD	Electronic ARD with Radio Frequency
El Batán	92	682	89
Monay	508	397	28
San Sebastian	470	389	13
Totoracocha	345	525	0
Valle	0	704	257
Total	1415	2697	387
Total [%]	31%	60%	9%

The Valle region also has a higher use of meters in this consumption group, with 14% of users using the electronic meter with an ARD register with radio frequency, as shown in Figure 18.

In general, the residential consumption group is the one that represents the highest percentage of users, with 90% of the installed meters. The urban regions of Monay and El Batán use electronic ARD registers with radio frequency, despite representing a minority of users. However, the rural region of Valle significantly exceeds these regions in meter usage, as shown in Figure 19. The electronic meter with ARD recording is the most widely used, possibly due to its accuracy in measurement and ability to record the energy consumed over time. The rural region of Valle also significantly exceeds these regions in meter usage.

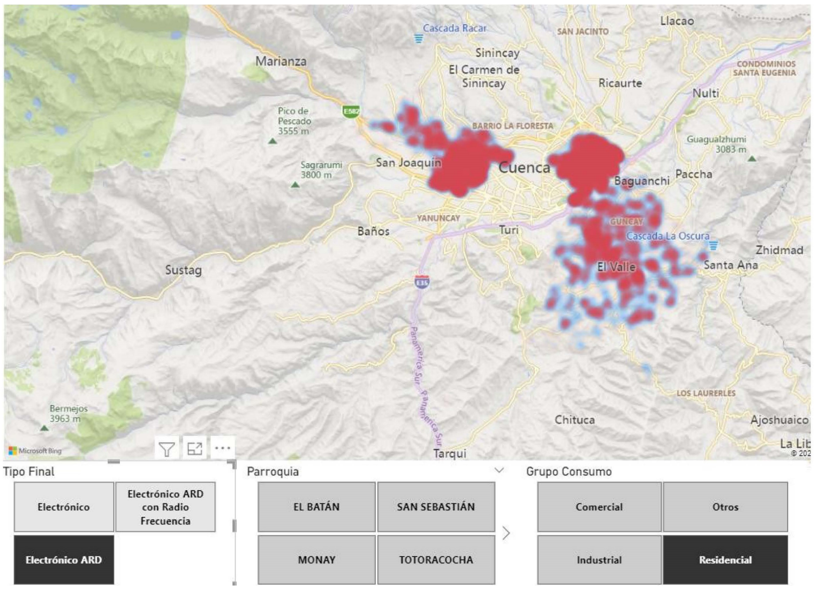


Figure 18. Heatmap of the distribution of ARD electronic meters according to residential consumption group.

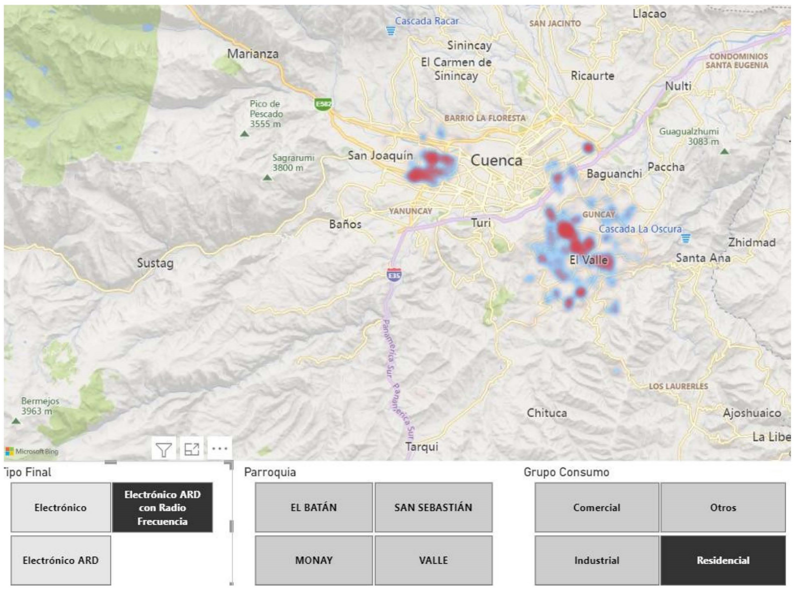


Figure 19. Heatmap of the distribution of ARD electronic meters with radio frequency according to residential consumption group.

4.5.3. Analysis of the Industrial Consumption Group

The data provided show that electricity consumption in the industrial consumption group is deficient across all regions, representing less than 1% in most cases, as shown in Table 18.

Table 18. Distribution of meters according to industrial consumption group.

Location	Electronic	Electronic ARD	Electronic ARD with Radio Frequency
El Batán	0	18	2
Monay	7	8	1
San Sebastian	7	2	0
Totoracocha	9	6	0
Valley	0	7	2
Total [%]	45%	45%	10%

This could be because the economic activities in these areas do not require significant electrical energy consumption, or they could be using energy sources other than electricity, but there is almost no visual representation, as indicated in Figure 20.

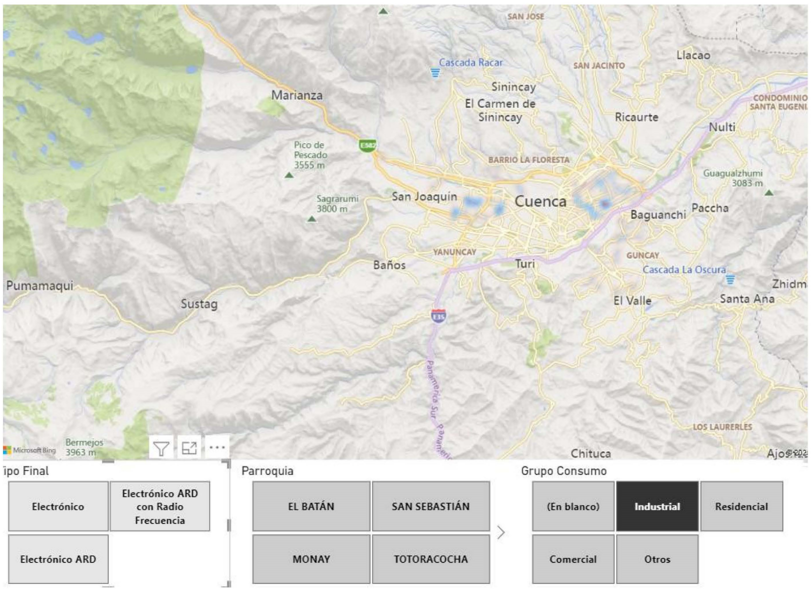


Figure 20. Distribution heatmap according to industrial consumption group.

The data provided may not accurately represent the total electricity consumption in each region, as they are based on electronic meters from a random sample of 1000 users per region. Fuzzy logic techniques are used to estimate actual consumption. Trends can be identified by comparing the results of the three consumption groups. The residential consumption groups have the highest number of meters in each category, with most belonging to the electronic ARD category. The commercial consumption groups have significant numbers of electronic ARD meters, while residential consumption groups have similar numbers. The industrial consumption groups have lower numbers of meters than the other groups.

4.6. Analysis Based on Type of Electricity Tariff

The analysis of the fuzzy logic results of electricity consumption in different regions reveals that the kind of tariff may vary depending on the amount of energy consumed. For commercial consumption, 2% of the electronic meters belonged to the LV commercial tariff, while 4% belonged to the ARD register category. The MT commercial tariff with demand had a 1% presence in both electronic meters and ARD-registered electronic meters in several regions, indicating significant commercial demand.

Residential consumption showed that 51% of users belonged to the BT residential tariff group, followed by 27% and 7% of electronic meters with ARD registration and radio frequency. This suggests that consumers may opt for more advanced electronic meters for residential use.

In the residential LV tariff for the PEC program, only 3% of consumers had electronic ARD meters, while only 2% had electronic meters, and 1% had electronic meters with ARD and radio frequency. This suggests that consumers in the PEC program are less willing to use advanced electronic meters.

In summary, the majority of residential consumers would opt for advanced electronic meters, while industrial companies would use only 1% of ARD electronic meters in the BT industrial artisanal tariff. A more generalized approach is needed to identify patterns and trends in tariff behavior in the region and design appropriate project planning strategies for electricity metering systems in different sectors.

5. Conclusions

In conclusion, after performing the corresponding analysis and research, obtaining significant patterns and relevant relationships from a conglomerate of data is of great importance in the technological analysis of the metering system of an energy distribution and commercialization utility company. Using the fuzzy logic methodology, it was determined that the change in technology of the metering system could be considered for medium- or long-term planning. The sample analysis was carried out for 5000 users, where more than 60% were deemed suitable for the changeover to the electronic meter with Active, Reactive, and Demand Register (ARD), and only 36% would continue using the conventional electronic meter. At present, 98% of these metering systems are electronic meters, and the remaining 2% belong to the electromechanical category.

Two-phase connections represented most of the sample population, comprising 87% of the sample.

Finally, based on the data provided, based on a logical and coherent inference, the highest strata (B, C, and A) were found in the regions of El Batán and San Sebastián, which are considered more affluent areas. These regions have the highest residential and commercial rates, indicating higher electricity consumption. In addition, the industrial tariff was also higher in El Batán, suggesting that there is a significant presence of companies and businesses in this area. Therefore, these regions contribute more to the overall revenue of the electric utility companies, and more technological changes are represented in these regions using the fuzzy logic methodology.

The rural region of Valle showed significant growth in population and energy consumption. According to the fuzzy logic methodology, no variable is required, whether it represents its consumption group, the type of tariff, or conventional electronic meters. As a result, electronic meters with active, reactive, and ARD demand registers are considered ideal for this rural region.

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Abbreviations

The following abbreviations are used in this manuscript:

NTL	Non-technical losses
GIS	Geographic information system
CIS	Customer information systems
SAP	System application products
CENTROSUR	Empresa Eléctrica Regional Centro Sur C.A.
TPR	True positive rate
FPR	False positive rate
TP	True positives
TN	True negatives
FP	False positives
FN	False negatives
k-NN	k-nearest neighbor
ANN	Artificial neural network
SVM	Support vector machine
OPF	Optimum path forest
AUC	Area under the curve

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