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FACULTAD DE INGENIERÍAS

MAESTRÍA EN BIG DATA Y CIENCIA DE DATOS

TEMA:

PROYECCIÓN DE LA ADOPCIÓN DE SISTEMAS FOTOVOLTAICOS Y SU IMPACTO EN UNA RED DE DISTRIBUCIÓN ELÉCTRICA UTILIZANDO LÓGICA DIFUSA.

Trabajo de Titulación previo a la obtención del título de Magíster en Big Data y Ciencia de Datos.

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A mi mayor tesoro, Magui, Patricio, Karito y Nicole.

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A Dios, por brindarme la sabiduría, fortaleza, y salud para afrontar todos los retos de mi vida.

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ÍNDICE DE CONTENIDOS

ÍNDICE DE TABLAS

ÍNDICE DE GRÁFICOS

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RESUMEN EJECUTIVO

La creciente adopción de sistemas fotovoltaicos plantea nuevos retos para la planificación energética y la estabilidad de la red. Este estudio propone una metodología basada en lógica difusa para identificar a los potenciales adoptantes de sistemas fotovoltaicos mediante la integración de variables como el consumo de energía, la tarifa eléctrica, la radiación solar y el nivel socioeconómico. El enfoque se aplicó a una red de distribución real y se comparó con un método presentado anteriormente que selecciona a los usuarios basándose únicamente en el elevado consumo de energía. El modelo de lógica difusa demostró un rendimiento superior al identificar el 77,03 [%] de los adoptantes reales, superando a la estrategia de selección anterior. Además, el estudio evalúa el impacto técnico de la integración fotovoltaica en la red de distribución mediante simulaciones de flujo de potencia, analizando las pérdidas de energía, perfiles de voltaje y la cargabilidad de los activos. Los resultados ponen en evidencia que, si bien los sistemas fotovoltaicos reducen las pérdidas de energía, también pueden plantear problemas de regulación del voltaje en condiciones de alta penetración. La metodología propuesta es una herramienta de apoyo a la toma de decisiones para las empresas eléctricas y los entes de control, ya que mejora la precisión de las previsiones de adopción y sirve de base para la planificación de infraestructura. Su flexibilidad y su naturaleza basada en reglas la hacen adaptable a diferentes entornos normativos y técnicos, lo que permite replicarla en todo el mundo para iniciativas de transición energética sostenible.

DESCRIPTORES: Adopción fotovoltaica; lógica difusa; tarifa eléctrica; consumo de energía; recursos energéticos distribuidos.

ABSTRACT

UNIVERSIDAD TECNOLÓGICA INDOAMÉRICA

FACULTY OF ENGINEERING

MASTER'S IN BIG DATA AND DATA SCIENCE

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ABSTRACT

PROJECTION OF PHOTOVOLTAIC SYSTEM ADOPTION AND ITS IMPACT ON AN ELECTRIC DISTRIBUTION NETWORK USING FUZZY LOGIC

The increasing use of photovoltaic systems creates new challenges for energy planning and grid stability. This study proposes a fuzzy logic-based methodology to identify potential adopters of photovoltaic systems by integrating variables such as energy consumption, electricity rate, solar radiation, and socioeconomic level. The method was applied to a real distribution network and compared to a previously presented approach that selects users based solely on high energy consumption. The fuzzy logic model demonstrated superior performance by identifying 77.03% of actual adopters, outperforming the earlier selection strategy. Additionally, the study evaluates the technical effects of photovoltaic integration on the distribution network through power flow simulations, analyzing energy losses, voltage profiles, and asset loading. The results highlight that, while photovoltaic systems reduce energy losses, they may also cause voltage regulation issues under high penetration conditions. The proposed methodology serves as a decision-support tool for electric utilities and regulatory entities, as it improves the accuracy of adoption forecasts and provides a foundation for infrastructure planning. Its flexible and rule-based nature allows adaptation to various regulatory and technical environments, enabling global replication for sustainable energy transition initiatives.

KEYWORDS: Distributed energy resources, electricity rate, energy consumption, fuzzy logic, photovoltaic adoption *sustainability*

MDPI

Article

Projection of Photovoltaic System Adoption and Its Impact on a Distributed Power Grid Using Fuzzy Logic

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Abstract: The increasing adoption of photovoltaic systems presents new challenges for energy planning and grid stability. This study proposes a fuzzy logic-based methodology to identify potential PV adopters by integrating variables such as energy consumption, electricity tariff, solar radiation, and socioeconomic level. The approach was applied to a real distribution grid and compared against a previously presented method that selects users based solely on high energy consumption. The fuzzy logic model demonstrated superior performance by identifying 77.03 [%] of real adopters, outperforming the previous selection strategy. Additionally, the study evaluates the technical impact of PV integration on the distribution grid through power flow simulations, analysing energy losses, voltage stability, and asset loadability. Findings highlight that while PV systems reduce energy losses, they can also introduce voltage regulation challenges under high penetration. The proposed methodology serves as a decision-support tool for utilities and regulators, enhancing the accuracy of adoption projections and informing infrastructure planning. Its flexibility and rule-based nature make it adaptable to different regulatory and technical environments, allowing it to be replicated globally for sustainable energy transition initiatives.

Keywords: photovoltaic adoption; fuzzy logic; electricity tariff; energy consumption; distributed energy resources

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1. Introduction

1.1. Context

The global growth of distributed energy resources (DER), particularly photovoltaic (PV) systems, has been driven by the need to reduce dependence on fossil fuels and mitigate climate change impacts [1–3]. As installation costs decrease and technological advancements improve efficiency, solar energy has emerged as a viable alternative for both residential and commercial consumers [4,5]. However, PV adoption is influenced by more than just economic factors; psychological, social, and regulatory elements also play a significant role [6–8]. Moreover, recent studies have emphasized the need to consider behavioural, psychological, and contextual factors in PV adoption, particularly in regions facing socioeconomic barriers [9,10].

Additionally, government incentives and stable energy policies have been critical drivers of PV adoption, with countries implementing successful policy frameworks experiencing higher growth rates [11–13]. Nonetheless, in Ecuador, regulatory hurdles, government-subsidized tariffs, and bureaucratic permitting have been identified as major obstacles to widespread PV implementation [14]. However, the recent energy crisis has triggered a noticeable increase in PV system adoption, as frequent power outages have pushed consumers to seek more reliable and autonomous energy solutions [15]. Consequently, this shift illustrates how external pressures, such as supply instability, can temporarily outweigh structural barriers and accelerate the transition toward distributed renewable energy. Furthermore, unlike previous studies that correlate PV adoption with high energy consumption, recent evidence suggests that even moderate energy consumers are adopting PV technology, challenging traditional user selection models [15,16]. This underscores the need for context-aware methodologies capable of integrating qualitative factors beyond economic metrics, especially in response to crisis-driven adoption behaviours [17].

Moreover, while numerous studies have analysed the impact of distributed energy resource (DER) integration on power distribution systems, most have focused on highly simplified grid segments, such as a single feeder or substation [18], gradually increasing PV penetration until reaching the grid's operational limits. However, these localized analyses fail to account for the broader, system-wide effects of high PV penetration, particularly in the selection of potential adopters, which is crucial for projecting a more realistic generation capacity and accurately assessing its impact on distribution grids.

Therefore, this study aims to provide a comprehensive assessment of DER integration across an entire real distribution grid, enabling long-term planning strategies that ensure the continuous and high-quality supply of electricity to all users. By evaluating DER deployment at a full-grid scale, this research offers a more accurate representation of adoption trends, allowing for a deeper understanding of the technical challenges and operational measures required to maintain grid stability, power quality, and infrastructure resilience under increasing PV penetration. Additionally, this aligns with recent literature emphasizing the importance of integrated planning and operational strategies to manage the reliability and stability challenges posed by high levels of renewable energy penetration in power systems [19].

1.2. State of Art

The adoption of PV systems is influenced by multiple economic, social, and regulatory factors. Principal drivers include cost savings, energy independence, and environmental impact [1,6,20]. Additionally, energy self-consumption has emerged as a strategy to maximize solar generation benefits, although government incentives and regulatory frameworks play a crucial role in determining feasibility [21–23]. Countries with stable energy policies exhibit higher PV adoption rates, whereas regulatory uncertainty hinders market growth [11,12,15]. In Ecuador, for instance, regulatory hurdles, government-subsidized tariffs, and bureaucratic permitting have been identified as major obstacles to widespread PV implementation [14].

Nevertheless, despite its benefits, PV adoption is not homogeneous as it varies according to socioeconomic status, access to financing, and consumer perception [20,24]. Older populations tend to show less interest in PV systems due to long investment payback periods, while lower-income households face economic barriers, reinforcing the need for financing programs [7,13,20]. Furthermore, education levels and financial stability have been identified as key determinants of adoption behaviour [25].

From a social perspective, peer influence and trust in technology significantly impact adoption decisions [26–28]. Studies have shown that PV adoption is higher in communities where solar systems have already been installed, indicating a diffusion effect [16,24,26]. This effect refers to the social phenomenon whereby the adoption of a new technology by some members of a community increases the likelihood of its adoption by others. In the context of PV systems, seeing Neighbors or peers adopt solar technology builds trust, reduces perceived risk, and thus encourages imitation. This social networking effect is further reinforced when economic benefits are shared among consumers within the same community [8,24]. In this regard, future assessments may benefit from analysing collective PV adoption models in residential apartments, particularly in settings where individual installation faces spatial or ownership constraints [29]. Recent analyses have shown that user perception, social trust, and awareness campaigns are pivotal in shaping adoption behaviours, especially in emerging markets [9,10].

Furthermore, several methodological approaches have been applied to model the adoption of photovoltaic (PV) systems, including machine learning algorithms [30], agent-based modelling [28], multi-criteria decision analysis [24], and fuzzy logic frameworks [31]. In particular, recent reviews have highlighted that the suitability of these methods depends on data availability and the interpretability required for decision-making [32]. In this context, the authors in [30] developed a machine learning-based model using Gradient Boosting Decision Trees to predict potential PV adopters, addressing issues of data imbalance and limited samples through focal-loss supervision and synthetic data generation. Their work demonstrated high predictive capability when detailed consumer profile datasets were available.

However, such data-driven approaches are often unsuitable in contexts with limited historical information or incomplete user records, as is the case in many developing regions. Specifically, in Ecuador, where PV adoption is still emerging, utilities do not yet maintain comprehensive datasets on user characteristics, installation patterns, or system performance. This restricts the applicability of supervised learning methods that rely on large-scale, labelled data for effective training. Consequently, fuzzy logic emerges as a practical and adaptable alternative for such contexts. It remains effective in environments with data scarcity and also enables planners to integrate expert judgment through interpretable rule-based reasoning [33–35]. Moreover, fuzzy systems provide transparency and flexibility using linguistic variables and simple membership functions such as triangular and trapezoidal shapes [36], making them suitable for utilities that require intuitive models to support decision-making and policy planning. Its ability to handle vagueness and model dynamic, real-world phenomena through flexible rule-based structures and hybrid models combining expert knowledge with data-driven techniques further reinforces its applicability in complex environments [37].

Nevertheless, although advantageous, the mass adoption of PV systems presents challenges for distribution grids. Studies have shown that high PV penetration can cause voltage stability issues, increased transformer loads, and potential overloading of grid assets [22,28,38]. Additionally, in some scenarios, PV adoption has led to the “death spiral” phenomenon, where self-generation reduces the customer base of electric utilities, leading to tariff increases and further incentivizing PV adoption [38,39].

Moreover, recent simulation studies have demonstrated that the use of advanced modelling tools, such as the CYMDIST simulator, enables better evaluation of PV system impacts on the grid, identifying areas for improvement and mitigation strategies [40]. Thus, to address voltage stability issues, reactive power compensation and advanced inverter control strategies have been proposed [15,41]. Furthermore, integration of PV systems in real-world distribution networks has also been analysed using detailed simulations to assess their impact on voltage profiles, losses, and asset ageing, showing the need for adaptable planning tools [17,42].

Despite the variety of methodologies previously explored, there is a noticeable gap in the literature regarding the use of fuzzy logic to predict photovoltaic system adoption under real distribution grid conditions. This study contributes to filling that gap by presenting a methodology that is both technically rigorous and suitable for developing countries, where data availability is often limited. The proposed approach offers a comprehensive framework that begins with user selection based on multiple contextual variables and integrates expert knowledge through the configuration of fuzzy rules such as the 2024 energy crisis in Ecuador. This adaptability makes it suitable for replicating in different technical and regulatory environments. Moreover, the use of quasi-static simulation enables the dynamic behaviour of the grid to be assessed during solar influence hours by incorporating typical daily load curves scaled to the coincident peak demand day and the generation profile of a typical PV system [43]. This planning criterion captures the most critical grid conditions and allows for realistic assessment of voltage stability, loadability, and energy losses [44]. The methodology thus provides an interpretable and scalable tool to support long-term planning decisions, helping utilities in emerging economies to identify infrastructure vulnerabilities, prioritize reinforcements, and develop effective policies for DER integration.

In this context, an adoption model based on fuzzy logic is proposed, integrating energy consumption with other variables such as electricity tariff, solar radiation, and socioeconomic level to identify users with a higher probability of adopting PV systems. Four different models were developed, each combining energy consumption with one or more of these variables to determine the most accurate predictive approach [45,46]. Furthermore, a comparative analysis was conducted against a previous study that used a fixed consumption threshold for user selection, evaluating both methodologies against real adoption data [15]. Finally, the impact of DER on critical electrical parameters of the distribution grid was modelled, simulated, and analysed. This assessment considered voltage profile, infrastructure loadability, and energy losses, providing valuable insights into the long-term challenges and benefits of PV system penetration in distribution grids. This work provides a valuable tool not only for energy planning and public policy formulation but also for supporting the sustainable expansion of cities, contributing to population development aligned with long-term environmental and social sustainability goals. Therefore, through the application of advanced prediction, the results obtained can be used by electric utilities in Ecuador and governmental entities to design strategies that encourage the adoption of solar energy and guarantee the long-term stability of the electric grid. Thus, this paper is structured as follows: Section 2 describes the materials and methods used; Section 3 presents the results and the discussion of the main findings. Finally, Section 4 summarizes the conclusions drawn from the study.

2. Materials and Methods

This research work has been developed using information from the electrical distribution grid of Ecuador (EEASA), located in the north-central area of the country. To achieve the objective, five fundamental stages have been carried out, described in Figure 1, which allow the selection of adopters of PV systems and assess the impact of energy distributed with self-supply PV systems in the distribution grid.

In the first stage, data acquisition and preprocessing, information is collected from the geographic information system (GIS) and the national business system SAP/CIS, in addition to an exploratory analysis of the data. Then, in the second stage, the selection of candidates for the adoption of PV systems is carried out by fuzzy logic, considering multiple variables such as energy consumption, tariff type, socioeconomic level, and solar radiation of the area. This phase also includes the estimation of adoption probabilities using inference rules and a comparative analysis of the developed scenarios.

In the third stage, the annual distribution of PV system adopters is determined using the innovation diffusion model, which allocates the number of customers selected by the fuzzy logic model throughout the analysis planning period. In the fourth stage, the modelling and simulation of the distribution grid is performed, where the nominal power of the PV systems and their integration into the grid are simulated using Cymdist software. Finally, in the fifth stage, a comparative analysis with a previously presented study is conducted and insights into the evaluated electrical parameters are presented.

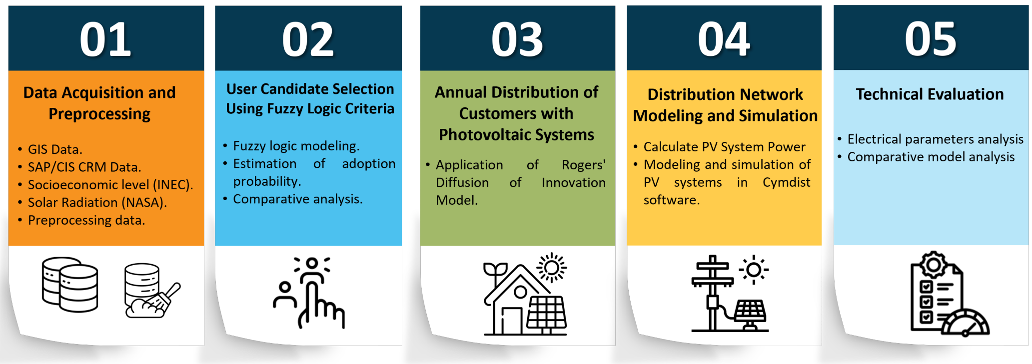

Figure 1. Methodology to evaluate the impact of distributed generation with PV systems for self-consumption.

2.1. Data Acquisition and Preprocessing

The first stage of the project consisted of collecting data from various sources. Georeferenced customer information, such as their location, account number, and distribution transformers to which they are connected, was extracted from EEASA using ArcGIS. On the other hand, from the distribution company's commercial system, SAP/CIS CRM, the average monthly energy consumption for the last year for each user was obtained, as well as the commercial tariff associated with each one. Solar radiation data was obtained through access to NASA (National Aeronautics and Space Administration) APIs, while socioeconomic data were extracted from INEC (National Institute of Statistics and Census).

The database used in this study corresponds to the users of the distribution company, which covers approximately 318,000 customers. To identify the customers most likely to adopt PV systems, the uniqueness of account numbers was verified and duplicate records were eliminated. Subsequently, those users whose average monthly consumption in the last year was higher than 110 kWh were selected. This selection is justified by the fact that customers with consumption below this threshold receive economic subsidies from the Ecuadorian State, which reduces their incentive to adopt distributed generation systems.

Likewise, the commercial rate for public lighting was not considered, since these meters only register the energy consumption for public lighting. As a result of the filtering, 103,568 subscribers were identified as ideal candidates for the integration of DER with PV self-consumption. Figure 2 shows the distribution of customers by type of tariff, classifying them as residential, commercial, industrial, other and EV (electric vehicles). This figure shows that the residential tariff is the predominant one, representing approximately 77.7% of the total number of customers with a consumption of more than 110 kWh. On the other hand, the commercial tariff represents 16.0%, while the industrial and others have a lower share, with 4.1% and 2.2%, respectively. Finally, the EV (electric vehicle) rate does not have a significant incidence.

Figure 3 shows the distribution of total energy consumption by type of tariff for customers with consumption of over 110 kWh. In this case, although the residential tariff has the largest number of customers, its share of total energy consumption is 36.3%, which indicates that its consumption does not have a greater incidence than that of other segments. On the other hand, the commercial rate represents 25.7% of total consumption and the industrial rate reaches 24.5%, which confirms that these sectors have a more significant energy consumption. The other tariff represents 13.5%, while the EV tariff does not show a significant incidence in consumption.

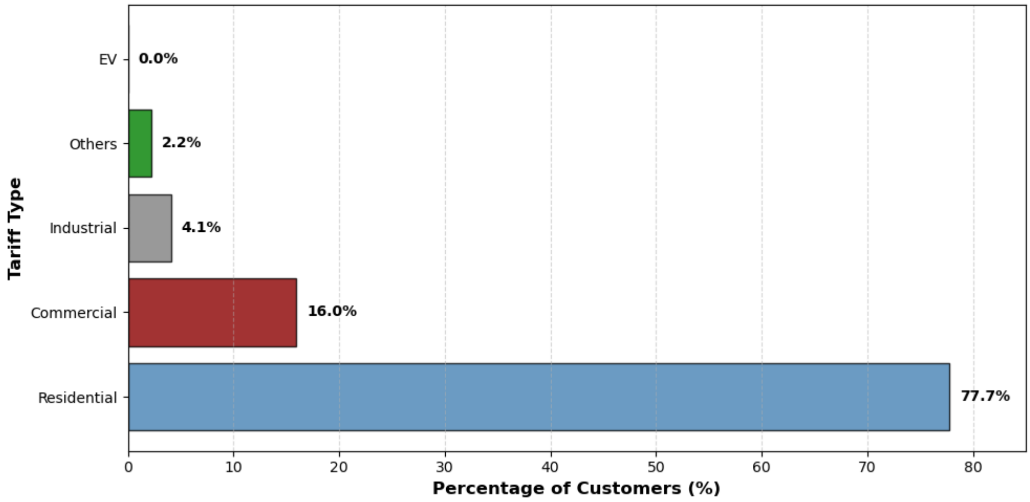

Figure 2. Distribution of customers with consumption above 110 kWh by tariff type.

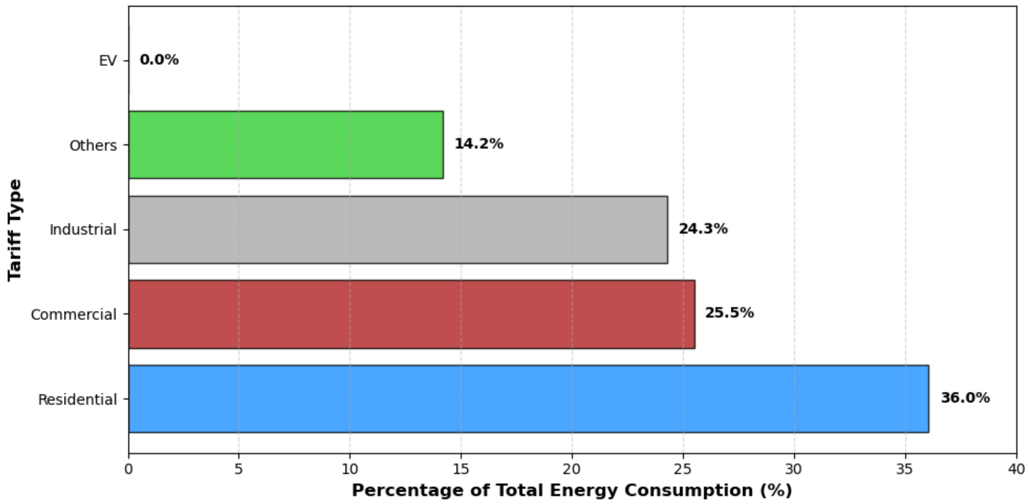

Figure 3. Distribution of energy consumption of customers with consumption above 110 kWh by tariff type.

Then again, in Figure 4, most of the users under the residential tariff have a consumption ranging from 111 to 500 kWh, with a total of 93,206 customers in this segment. For higher consumptions, the industrial tariff has a greater incidence in the 1001–5000 kWh range, which evidences its high-energy-consumption character. On the other hand, the commercial tariff shows presence in all consumption ranges, standing out in the 1001–5000 kWh segment, which means that this sector has a more distributed energy demand. Other and EV tariffs have a marginal share in all consumption ranges, suggesting that these customers do not represent a significant segment within the consumption profile of the distribution company.

This information was combined with external data obtained from NASA and INEC, which were extracted in shapefile format. To assign each user a radiation value and socioeconomic level, a spatial intersection was performed between the georeferenced database of EEASA users, the radiation polygons provided by NASA and the irregular polygons of INEC that segment the population into socioeconomic levels; the scheme of this process is visualized in Figure 5. During the spatial intersection process, it was identified that socioeconomic data from INEC is only available for provincial urban areas, covering approximately 66% of the study region. As a result, a significant portion of rural zones lacked defined classification. To address this limitation, users without available socioeconomic information were assigned a placeholder category labelled Indefinite. While this treatment introduces a degree of uncertainty, it is important to note that the urban sectors with complete socioeconomic data coincide with areas of higher load density and commercial or industrial activity. These zones are typically associated with customer types that exhibit higher potential for photovoltaic adoption. Therefore, the missing data primarily affects low-density rural areas with lower adoption likelihood. Moreover, to mitigate potential bias, multiple fuzzy logic models were developed using different combinations of input variables. This modelling strategy ensures robustness by avoiding reliance on a single variable and allows the assessment of adoption potential.

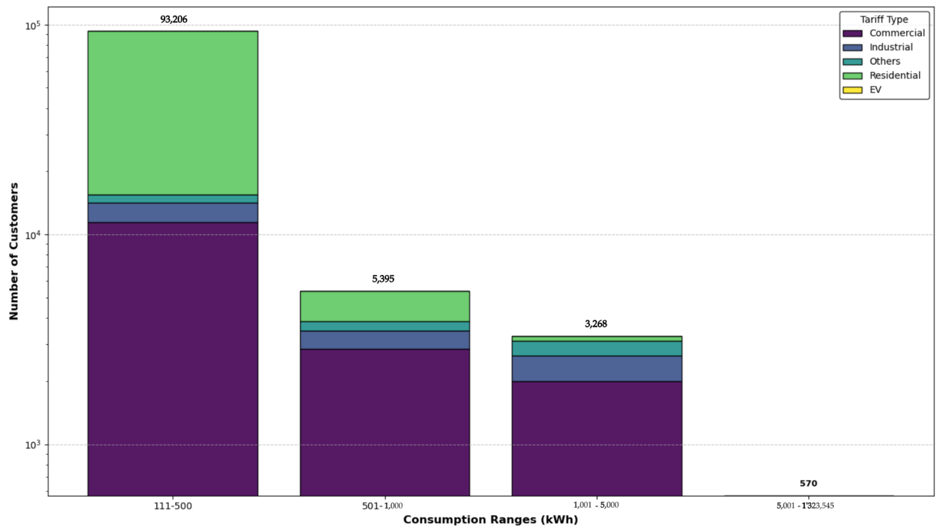

Figure 4. Number of customers by consumption ranges with tariff distribution.

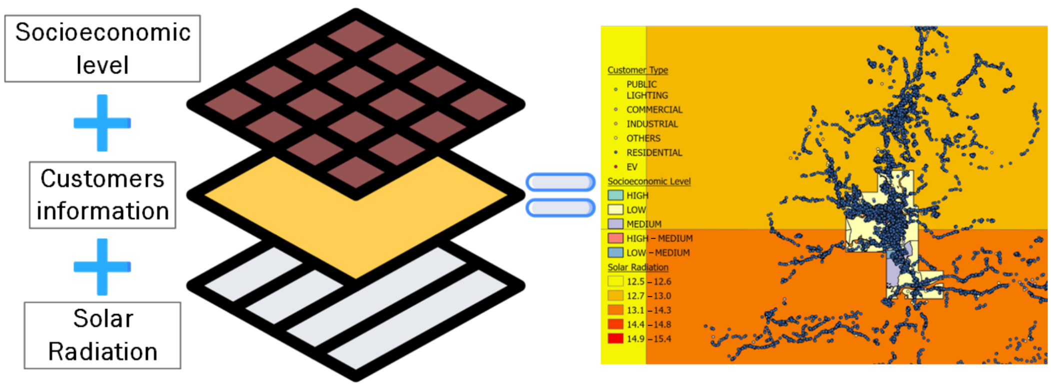

Figure 5. Spatial intersection layers of customers, solar radiation and socioeconomic level data.

2.2. *Selecting Candidate Users Using Fuzzy Logic Criteria*

To assess the probability of PV system adoption in the EEASA distribution grid, a fuzzy inference approach based on Mamdani's method was implemented [33]. This model is particularly suitable for decision-making problems in which the experience and judgment of the planner are essential, as it allows the use of linguistic variables and interpretable if–then rules to represent complex and uncertain relationships.

In the Ecuadorian context, where energy rationing has occurred in recent years, the selection of users is not primarily guided by economic criteria but rather by the need to guarantee energy comfort and autonomy. This sociotechnical condition highlights the importance of methodologies that can incorporate expert knowledge and the planner's criteria into the decision-making process. Mamdani-type fuzzy systems are advantageous in this regard, given their capacity to reflect human reasoning through flexible rule structures [39].

Furthermore, the use of fuzzy logic is supported by the lack of sufficient historical data on photovoltaic adoption in the country. Since this technology is relatively new in Ecuador, there is still no robust dataset that captures user behaviour, performance trends, or socioeconomic profiles of customers who have implemented PV systems. This limitation prevents the use of advanced machine learning models such as LSTM or deep neural networks, which typically require large and structured datasets for effective training [2,31].

Fuzzy logic, on the other hand, offers a robust and interpretable framework that remains effective in data-scarce environments. By using simple membership functions such as triangular and trapezoidal types, the model ensures computational efficiency and transparency, while allowing flexible integration of planner knowledge and qualitative variables [34–36]. These characteristics make it a practical and scalable solution for real-world applications in distribution utilities facing data limitations and emerging adoption patterns.

2.2.1. Definition Model

In order to evaluate user interest in adopting PV systems, four fuzzy logic models were designed and implemented, each based on different combinations of relevant variables:

- Model 1: Based on energy consumption and electricity tariff;
- Model 2: Considers energy consumption and solar radiation;
- Model 3: Combines energy consumption and socioeconomic level of the user;
- Model 4: Integrates energy consumption, electricity tariff, and socioeconomic level.

Each model was built using a Mamdani-type fuzzy inference system, in which specific fuzzy functions and fuzzy rules were defined for each combination of variables, with the aim of estimating the probability of PV system adoption for each user, as can be seen in Figure 6.

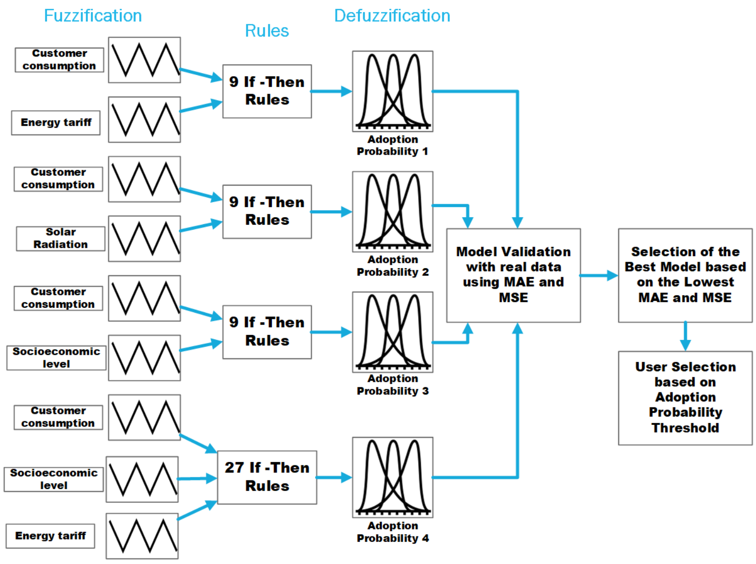

Figure 6. Framework for assessing PV adoption using fuzzy logic and validation.

2.2.2. Input Membership Functions (Fuzzification)

The input variables of energy consumption, electricity tariff, solar radiation, and socioeconomic level were transformed into fuzzy values through membership functions. Two commonly used membership function types were employed: triangular and trapezoidal. These functions were chosen because of their simplicity, computational efficiency, and interpretability, which make them suitable for modelling gradual transitions in fuzzy inference systems [34]. Figure 7 shows the graphical representation of the triangular and trapezoidal membership functions used in this study.

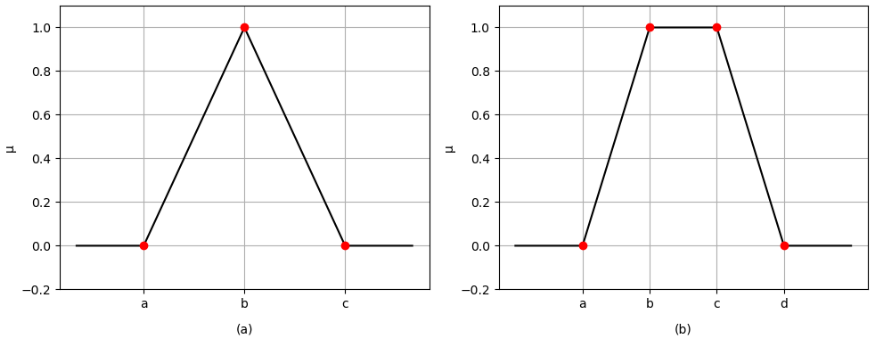

Figure 7. Membership function types: (**a**) triangular; (**b**) trapezoidal.

These functions are defined mathematically as

$$\mu_{\text{triangle}}(x; a, b, c) = \begin{cases} 0, & x \leq a \\ \frac{x-a}{b-a}, & a < x \leq b \\ \frac{c-x}{c-b}, & b < x \leq c \\ 0, & x > c \end{cases} \tag{1}$$

$$\mu_{\text{trapezoid}}(x; a, b, c, d) = \begin{cases} 0, & x \leq a \\ \frac{x-a}{b-a}, & a < x \leq b \\ 1, & b < x \leq c \\ \frac{d-x}{d-c}, & c < x \leq d \\ 0, & x > d \end{cases} \tag{2}$$

The trapezoidal membership functions were used for the energy consumption variable due to their ability to model broader plateaus, allowing smoother transitions at the boundaries. In contrast, triangular membership functions were applied to electricity tariffs, solar radiation, and socioeconomic levels, which exhibit sharper distinctions between categories and benefit from the simplicity and interpretability of triangular shapes [34,35]. This choice balances the model's interpretability and flexibility, as confirmed by established research showing that triangular and trapezoidal membership functions are effective even in more complex fuzzy systems [36].

The consumption variable refers to the average electricity consumption of each customer, measured in kilowatt hours (kWh). To model this variable within the fuzzy logic system, three levels of consumption were defined: low, medium and high. Trapezoidal belonging functions were used, since extreme values present a nonlinear progression and require an extended transition range, as shown in Figure 8. Table 1 details how these levels are classified according to the consumption ranges.

Table 2 shows the types of electricity tariffs; these tariffs refer to the type of use that customers make of energy in their daily activities. In addition, Figure 9 shows the categorization of these tariffs, which were classified into three levels: low, medium and high. Triangular membership functions were used, since the values have a more defined transition between each category.

Figure 10 shows the categorization of the solar radiation variable, which was considered at three levels: low, medium and high. Since the solar radiation data have a more limited distribution, triangular belonging functions were used.

Table 1. Classification of the level of energy consumption according to the monthly consumption range.

Category	Consumption Range (kWh)	Description
Low	111–260	Customers with low electricity consumption, typically residential customers of low socioeconomic status or with reduced consumption.
Middle	261–750	Customers with average energy consumption representing moderate use in residential or small commercial sectors.
High	>750	Customers with high levels of consumption, including industrial or commercial customers with high energy demand.

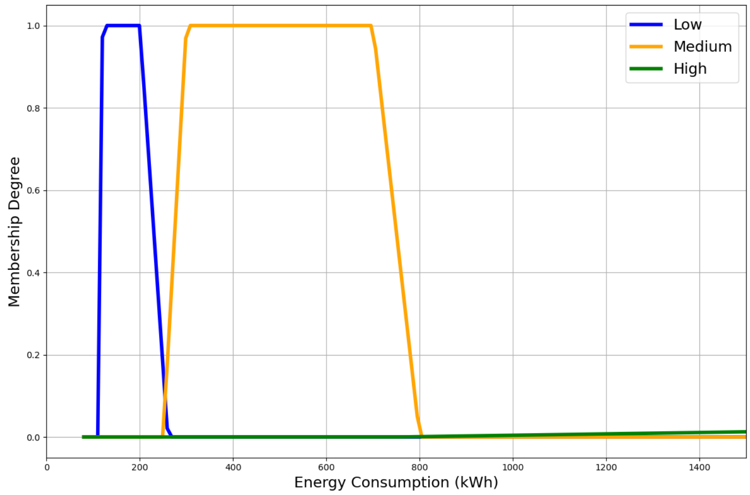

Figure 8. Membership functions—energy consumption.

Table 2. Classification of customers according to the type of commercial rate.

Customer Type	Assigned Rate Value	Description
EV	1	Customers with EV charging infrastructure.
Others	2	Customers with special features that do not fit into the other categories.
Residential	3	Typical residential users with domestic consumption.
Industrial	4	Industrial customers with high energy demands.
Commercial	5	Commercial customers with significant consumption related to economic activities.

Table 3 shows the classification with which INEC has segmented the population in terms of socioeconomic level; for users located in areas without defined socioeconomic classification, a separate category labelled Indefinite was created and included in the model. Although this may introduce some degree of uncertainty, its influence is limited because most undefined zones correspond to low-density rural areas, whereas the available data covers urban centres where electricity demand and PV adoption potential are highest.

For the analysis, the socioeconomic level has been categorized into three fuzzy sets: low, medium, and high. For this, triangular membership functions were employed due to the progressive nature of transitions between levels, as illustrated in Figure 11. The low category is represented by a triangular function ranging from level 0 to 3, with its peak at 1. The medium category spans the interval from 2 to 4, reaching its maximum membership at

3. The high category is defined over the range of 3 to 5, with its peak at 5. This overlapping structure effectively captures the smooth transition between classes, enhancing the model's capacity to handle uncertainty and variability in the socioeconomic classification.

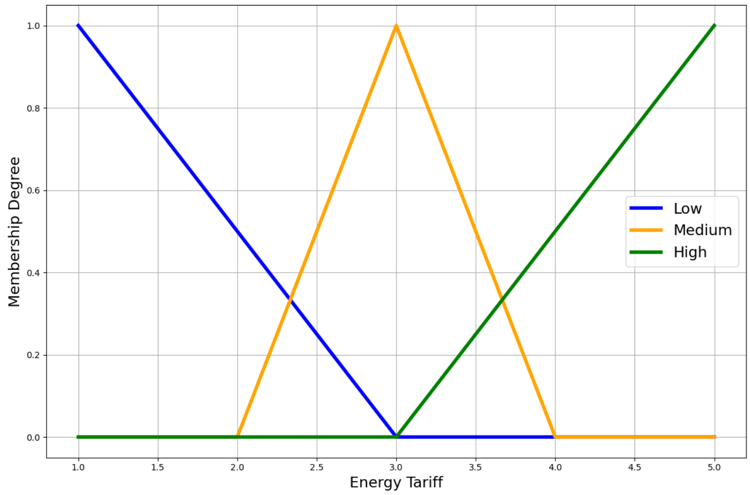

Figure 9. Membership functions—energy tariff.

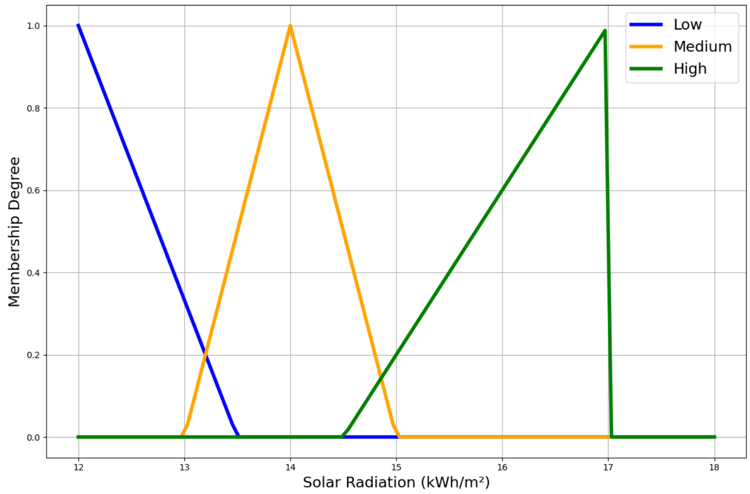

Figure 10. Membership functions—solar radiation.

Table 3. Classification of the socioeconomic level variable.

Socioeconomic Level	Assigned Level of Socioeconomic Status	Description
Indefinite	0	Customers whose socioeconomic category has not been defined or classified.
Low	1	Clients with a low socioeconomic status, with limited access to basic resources and services.
Medium Low	2	Clients with a medium-low socioeconomic level, with access to basic but limited services.
Middle	3	Customers with a medium socioeconomic level, with access to a wide range of services and resources.
Medium High	4	Clients with a medium-high socioeconomic level, with a stable quality of life and access to advanced services.
High	5	Customers with a high socioeconomic level, with privileged access to goods, services, and resources.

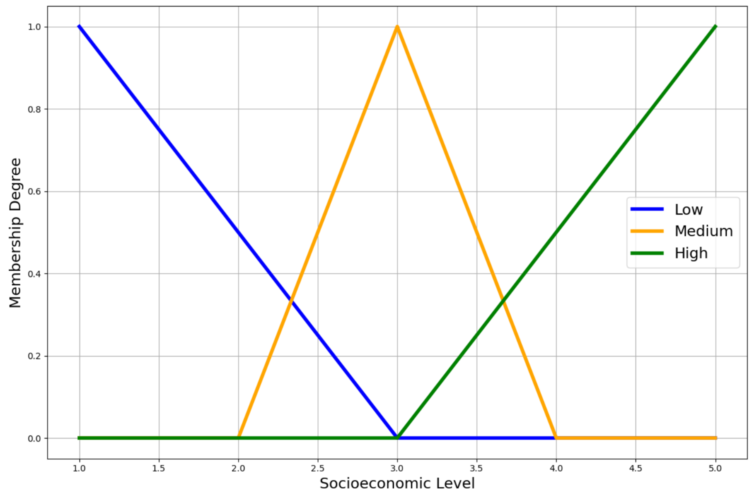

Figure 11. Membership functions—socioeconomic level.

2.2.3. Fuzzy Inference

Linguistic rules were established for each combination of variables, which were evaluated using AND operators. An important advantage of fuzzy logic is its ability to incorporate expert knowledge through flexible and intuitive rule construction. This feature allows the system to replicate human reasoning and supports its adaptation to various contexts and datasets, making it especially suitable for modelling complex decision-making processes such as photovoltaic adoption [33].

1. Model 1: Energy Consumption with Electricity Tariff.
   In this scenario, the probability of PV adoption is defined as a function of energy consumption and electricity tariff. Users with high consumption levels and high tariffs such as commercial and industrial are expected to have a greater predisposition to adopt a PV system, since the long-term energy cost reduction is more significant. On the contrary, customers with low consumption and low tariffs show less interest, since the potential savings do not justify the investment in solar generation. Table 4 shows if–then fuzzy rules for the model considering energy consumption (E) and electricity tariff (T).

Table 4. Fuzzy rules for model 1, energy consumption (E) and electricity tariff (T).

	Low (E)	**Medium (E)**	**High (E)**
Low (T)	Low (L)	Low (L)	Medium (M)
Medium (T)	Low (L)	Medium (M)	High (H)
High (T)	Medium (M)	High (H)	High (H)

2. Model 2: Energy Consumption with Solar Radiation.
   This model assesses the relationship between energy consumption and solar radiation in the probability of adopting a PV system. It is assumed that greater solar radiation increases interest, since the efficiency of the system will be greater. However, if the radiation is low, interest decreases, especially among customers with lower energy consumption, who may not consider the investment in solar panels profitable. Table 5 shows if–then fuzzy rules for the model considering energy consumption (E) and solar radiation (R).
3. Model 3: Energy Consumption with Socioeconomic Level.
   This model analyses how socioeconomic level influences the adoption of PV technology. It is expected that customers with higher economic capacity and high energy

consumption will have a greater interest in adoption, since they have the financial resources to invest in the installation of the system. On the contrary, users with low socioeconomic status could have a lower probability of adoption, regardless of their energy consumption. Table 6 shows if–then fuzzy rules for the model considering energy consumption (E) and socioeconomic level (S).

Table 5. Fuzzy rules for model 2, energy consumption (E) and solar radiation (R).

	Low (E)	**Medium (E)**	**High (E)**
Low (R)	Low (L)	Low (L)	Medium (M)
Medium (R)	Low (L)	Medium (M)	High (H)
High (R)	Medium (M)	High (H)	High (H)

Table 6. Fuzzy rules for model 3, energy consumption (E) and socioeconomic level (S).

	Low (E)	**Medium (E)**	**High (E)**
Low (S)	Low (L)	Low (L)	Medium (M)
Medium (S)	Low (L)	Medium (M)	High (H)
High (S)	Medium (M)	High (H)	High (H)

4. Model 4: Energy Consumption with Electricity Tariff and Socioeconomic Level. This scenario integrates three variables, energy consumption, electricity tariff and socioeconomic level. The interaction of these variables is modelled to assess the accuracy in predicting interest in PV systems. It is assumed that customers with high tariffs, high consumption and higher socioeconomic status have the highest probability of adoption. In contrast, those with low tariffs and lower economic status have less incentive to invest in solar energy, regardless of their energy consumption. Table 7 shows if–then fuzzy rules for the model considering energy consumption (E), socioeconomic level (S) and electricity tariff (T).

Table 7. Fuzzy rules for model 4, energy consumption (E), socioeconomic level (S), and electricity tariff (T).

	Low (E)	**Medium (E)**	**High (E)**
Low (T) and Low (S)	Low (L)	Low (L)	Medium (M)
Medium (T) and Medium (S)	Medium (M)	Medium (M)	High (H)
High (T) and High (S)	High (H)	High (H)	High (H)

2.2.4. Defuzzification

Fuzzy inference has been performed by applying a set of if–then rules, which combine the input variables to generate a fuzzy output. Subsequently, a defuzzification method is applied to convert the output into a numerical value. The output of the system is the probability of PV system adoption, which is classified into three levels: low, medium and high. Triangular membership functions were used to represent this variable, as shown in Figure 12.

Once the fuzzy system has evaluated the rules, the centroid method is applied to obtain a numerical value of adoption probability, which allows users to be ranked according to their interest in implementing PV systems. In order to validate the performance of the proposed models, the estimated PV adoption probabilities were compared with the actual data of users who installed PV systems. This process made it possible to quantify the degree of accuracy of each model in predicting interest in the adoption of this technology.

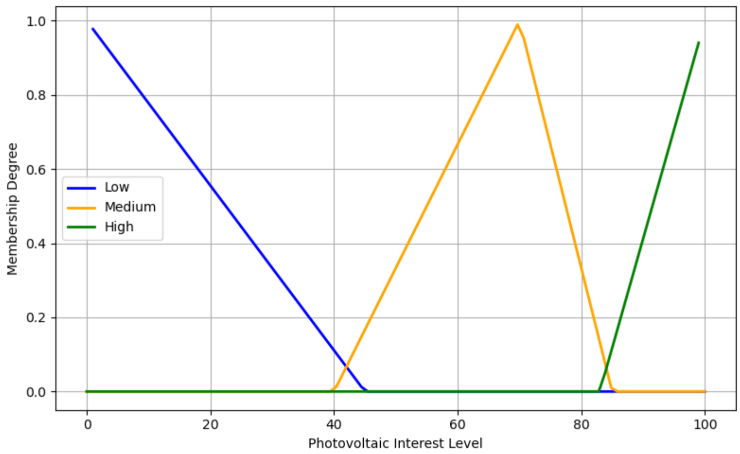

Figure 12. Membership functions—PV interest.

The evaluation employed two commonly used error metrics in predictive modelling, namely Mean Absolute Error (MAE) and Mean Squared Error (MSE). MAE provides a straightforward measure of the average magnitude of prediction errors, without considering their direction, thus indicating how far predictions typically deviate from actual values. In contrast, MSE assigns greater weight to larger errors by squaring the deviations, making it particularly effective at identifying models prone to generating outlier predictions. These metrics are especially relevant in this context as they quantify both the accuracy and consistency of adoption probability estimates across the proposed models. Together, they offer complementary insights into model performance, revealing not only which model yields more accurate predictions on average but also which demonstrates greater robustness to extreme values [31].

- MAE represents the average of the absolute differences between the probabilities estimated by the model and the real values of adoption (in this, 100%); its calculation is expressed by Equation (1).

$$\mathrm{MAE} = \frac{1}{n} \cdot \sum_{i=1}^{n} |Y_{\mathrm{dif},i} - Y_{\mathrm{real},i}|, \tag{3}$$

- MSE, similar to MAE but with the differences squared, penalizes large errors more severely. It is shown in Equation (2).

$$\mathrm{MSE} = \frac{1}{n} \cdot \sum_{i=1}^{n} (Y_{\mathrm{dif},i} - Y_{\mathrm{real},i})^2, \tag{4}$$

where
$Y_{\mathrm{dif},i}$ is the probability of adoption estimated by the model for user i.
$Y_{\mathrm{real},i}$ is the actual adoption value (100% for customers who did adopt).
n is the total number of customers evaluated.

2.2.5. Determination of the Adoption Threshold

Once the most accurate model was identified, a probability threshold was established to determine which customers have a high probability of adopting a PV system. The threshold was defined based on the actual adoption data, selecting the 75th percentile of the probabilities estimated in the model with the lowest MAE and MSE. This means that potential adopters were considered those users whose estimated probability of adoption was above the third quartile, ensuring that the criterion was based on a realistic distribution of customers who installed solar panels. This analysis has determined how many customers could adopt this technology.

2.3. Annual Distribution of Customers with PV Systems

A ten-year analysis horizon was defined for this study. To understand user adoption behaviour, Everett Rogers' theory of the diffusion of innovations was considered [47,48]. This model classifies the members of a social system according to their rate of adoption of new technologies into five categories: Innovators (2.5%), Early Adopters (13.5%), Early Majority (34%), Late Majority (34%) and Laggards (16%).

To quantitatively model the adoption over time, the Bass diffusion model was applied [24]. This model incorporates innovation and imitation effects, allowing the estimation of the number of adopters at each point in time. The mathematical formulation is shown in Equation (5).

$$\frac{dN(t)}{dt} = \left[p + q\frac{N(t)}{m}\right][m - N(t)], \tag{5}$$

where
$N(t)$: Number of adopters at time t.
m: Sample size.
p: Innovation coefficient.
q: Imitation coefficient.

2.4. Distribution System Modelling and Power Flow Simulation

2.4.1. Installed PV Systems Power

The users selected as candidates for the implementation of PV systems in their buildings should be modelled with the purpose of analysing the impact that their incorporation could generate in EEASA's distribution system. However, it has been identified that a determining factor that may restrict the maximum generation power is the availability of physical space in their facilities. To address this limitation, the criteria described in [15] have been applied, which establish that the maximum generation power can be determined by Equations (6) and (7). These equations consider essential parameters such as average energy consumption, solar irradiance, PV panel efficiency and installation capacity in the available space. From both estimates, the lowest value is selected, ensuring a conservative approach that avoids overestimating the installed PV system capacity, whether limited by the user's energy consumption or by the physical constraints of the infrastructure.

$$P_p = \frac{E_D \cdot G_{\text{STC}}}{G_{\text{annual}} \cdot PR}, \tag{6}$$

where
P_p: Peak power of PV System [kW].
E_D: Annual energy consumption [kWh].
G_{STC}: Solar irradiance under standard conditions, 1 [kW/m^2].
G_{annual}: Annual solar irradiance for the area.
PR: Performance ratio of the installation, considering losses in energy efficiency due to temperature, wiring, parameter dispersion and dirt losses, errors in maximum power point tracking, and inverter energy efficiency, among others.

$$P_p = P_n \cdot \frac{E_D \cdot f_e}{A_p}, \tag{7}$$

where
P_p: Peak power of PV System [kW].
P_n: Nominal power of one panel [kW].
E_D: Average monthly energy consumption [kWh].
f_e: Physical space factor related to monthly energy consumption [m^2/kWh].
A_p: Area of the selected panel [m^2].

2.4.2. Distribution Grid Modelling and Load Flow Simulation

For modelling EEASA's distribution grid, including the integration of the PV systems of the selected customers, the CYMDIST power grid simulation software was used. This tool, developed by EATON under the CYME suite, is widely employed for the steady-state and dynamic analysis of electrical distribution systems [49]. The analysis in this study was performed using CYMDIST version 9.4 rev2, under the institutional software license held by EEASA.

The objective of this study is to evaluate the impact that PV generation has on the grid during the production hours of PV systems. For this purpose, it has been necessary to model typical load curves of customers, considering their commercial tariff and their consumption behaviour within EEASA's service area. Figure 13 shows the representation of these curves, which were normalized in per-unit [p.u.] terms and are fundamental for the analysis of the interaction between distributed generation and system demand.

Customer profiles were stored in a database in a format compatible with CYMDIST software. Subsequently, EEASA's distribution system grid information was extracted from the GIS (geographic information system) in ASCII format, allowing direct import into CYMDIST for analysis. Since modelling each selected customer individually would be a highly time- and resource-demanding process, an automated procedure was developed in Python 3.11.11 for the mass modelling of all candidate users. This approach allowed the technical parameters of the PV systems associated with each customer to be created and modified efficiently. For reference, Figure 14 shows an example of the parameters corresponding to a PV system of a customer in the industrial sector.

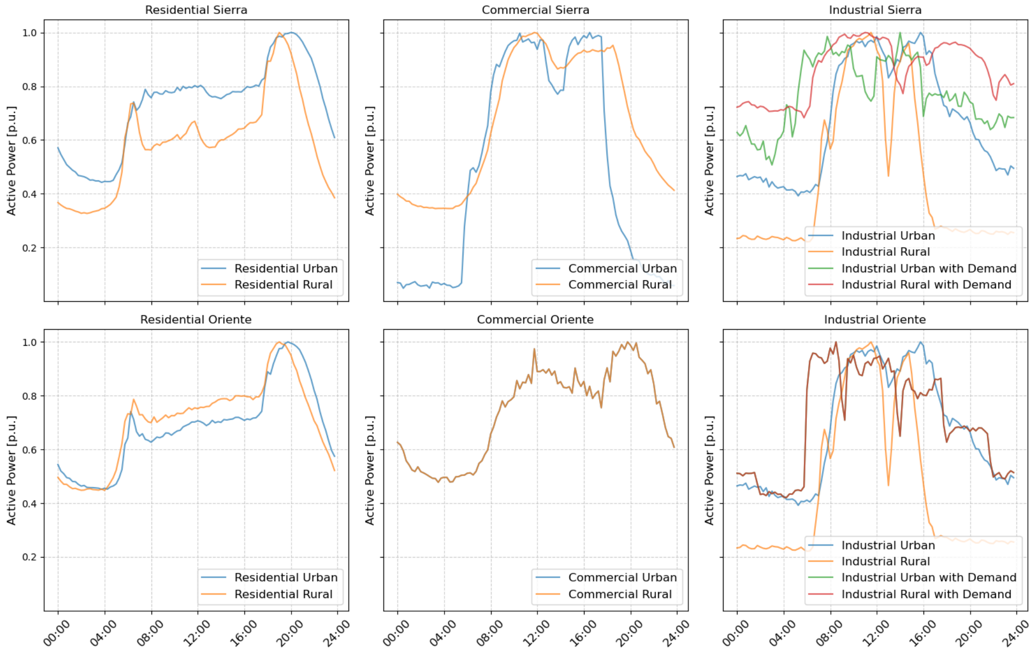

Figure 13. Typical daily load curves of customers in the EEASA service area.

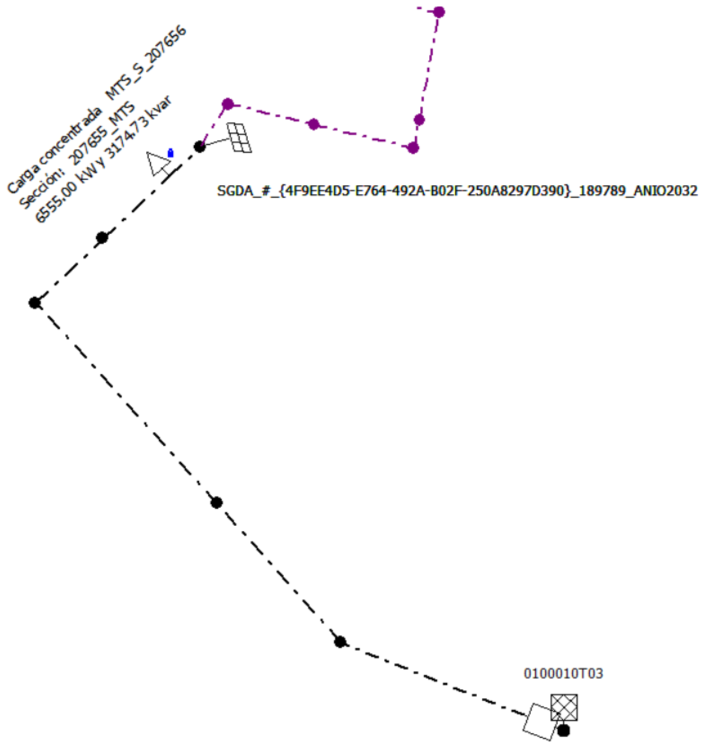

Figure 14. Modelling of an industrial user's PV system using Python coding in ASCII files.

In order to evaluate the dynamic interaction between photovoltaic generation and system demand, load flow simulations were performed using typical daily load curves classified by customer type. This approach allowed modelling of time-varying power demand at each load point, enabling a quasi-static simulation that reflects realistic operating conditions throughout the day [43].

The simulation was carried out for the system's coincident peak demand day of the most recent year. This planning criterion is supported in the literature and ensures the evaluation of the grid under its most stressed condition, which is essential to identify infrastructure vulnerabilities and define appropriate mitigation strategies [44]. By combining the shape of a typical daily load profile with each customer's peak demand, the simulation captures a realistic approximation of time-varying consumption at every node in the distribution network, capturing the most critical scenario in terms of voltage and loading behaviour.

The photovoltaic generation profile was modelled as time-dependent, acknowledging that both energy supply and demand exhibit dynamic variations throughout the day. This temporal resolution enables the simulation to capture the interaction between generation and consumption with more accuracy, particularly during periods of active solar production.

To capture long-term demand evolution and support distribution system planning, a two-percent annual growth rate was applied to all existing loads over a ten-year horizon, based on historical trends provided by EEASA. Although spatial network expansion and new customer connections were not included, future iterations of this study could incorporate such changes as historical data for new users becomes available. This simulation framework thus offers a flexible and scalable foundation for assessing the technical impact of DER integration under changing load conditions.

2.5. Comparative Analysis and Technical Evaluation

In order to evaluate the effectiveness of the fuzzy logic-based user selection methodology, a comparative analysis was conducted against a previous study presented in [15].

This evaluation employed three performance metrics: Mean Absolute Percentage Error (MAPE), Theil's U-Statistic, and the Area Under the Receiver Operating Characteristic Curve (AUC-ROC).

MAPE quantifies the average percentage deviation between predicted and actual values, providing an intuitive and widely used measure of forecasting accuracy. Lower MAPE values indicate a closer correspondence between model predictions and observed outcomes, which is particularly valuable for assessing the practical applicability of adoption models.

Theil's U-Statistic benchmarks model performance against a naive forecast. Values below one suggest the model performs better than a simple baseline, while values equal to or exceeding one imply no added predictive value. This metric is especially relevant when validating whether the complexity introduced by the fuzzy logic approach translates into meaningful predictive improvements.

AUC-ROC measures the model's capacity to distinguish between adopters and non-adopters across varying probability thresholds. It captures the trade-off between true and false positive rates, with values approaching one indicating strong discriminatory ability. This makes AUC-ROC highly pertinent for applications where accurately identifying potential adopters is essential for targeted interventions.

The combined use of these three metrics provides a comprehensive evaluation of model performance, balancing predictive accuracy and classification effectiveness. Their application ensures that both the quantitative forecasting quality and the operational utility of the model are adequately assessed [31]. Table 8 presents a summary of the comparative results obtained for each metric.

For technical evaluation, one of the most critical parameters in this study is voltage level stability, which is essential for the proper operation of the distribution system. According to Ecuadorian regulations, medium-voltage primary feeders must maintain voltage variations within an acceptable range of ±6% of the nominal value. Additionally, energy losses were analysed for each year of the planning period, comparing scenarios with and without PV system adopters. Lastly, equipment loadability was assessed to determine whether long-term asset management actions are required in the EEASA distribution grid.

Table 8. Comparative analysis methodology metrics.

Metric	Equation	Variable Descriptions
MAPE	$\text{MAPE} = \frac{100}{n}\sum_{i=1}^{n}\left\lvert\frac{A_i - P_i}{A_i}\right\rvert$	A_i is actual value, P_i is predicted value, n is number of observations
Theil's U-Statistic	$U = \frac{\sqrt{\frac{1}{n}\sum_{i=1}^{n}(A_i - P_i)^2}}{\sqrt{\frac{1}{n}\sum_{i=1}^{n}A_i^2} + \sqrt{\frac{1}{n}\sum_{i=1}^{n}P_i^2}}$	A_i is actual value, P_i is predicted value, n is number of observations
AUC-ROC	$AUC = \int_0^1 TPR(FPR)\,d(FPR)$	$TPR = \frac{TP}{TP+FN}$ (True Positive Rate), $FPR = \frac{FP}{FP+TN}$ (False Positive Rate)

3. Results and Discussion

3.1. User Selection

Applying the proposed methodology, the estimated adoption probabilities were compared with the actual data of customers who installed PV systems. To evaluate the accuracy of each model, two metrics were calculated, Mean Absolute Error (MAE) and Mean Square Error (MSE). These metrics made it possible to identify the model with the best performance in predicting the probability of adoption. After the analysis of the four scenarios proposed, model 1, consumption with electricity tariff, was selected as the most accurate, since it presented the lowest values in both metrics, with an MAE of 0.22 and an MSE of 0.10, as shown in Table 9.

Table 9. MAE and MSE results for different models.

Models	MAE	MSE
Model 1	0.228603	0.101165
Model 2	0.363955	0.145799
Model 3	0.433780	0.280699
Model 4	0.312055	0.179482

With this information, an adoption threshold was established, under which potential adopters were considered those customers whose probability of interest in model 1 exceeded a certain value. To define this threshold, the third quartile (Q3) of PV interest adoption of model 1 was considered, resulting in a value of 65%. This threshold was selected as it allows focusing on the top 25% of users with the highest adoption probabilities, ensuring the inclusion of those most likely to adopt PV systems. The use of Q3 provides a statistically sound and conservative cutoff that balances selectivity with representativeness, avoiding overly restrictive or excessively broad classifications. Under this criterion, 24,330 customers with high adoption potential were identified within the concession area of EEASA. However, some of these customers belong to commercial buildings where multiple users share the same physical space, which limits the availability for the installation of solar panels. After excluding these spatially constrained users, the total number of customers with real adoption potential dropped to 21,093 users.

3.2. Annual Distribution of PV System Users Selected

Figure 15 shows the annual distribution of 21,093 selected customers that could adopt PV systems over the analysis horizon, calculated using the Bass model and based on the diffusion of innovation.

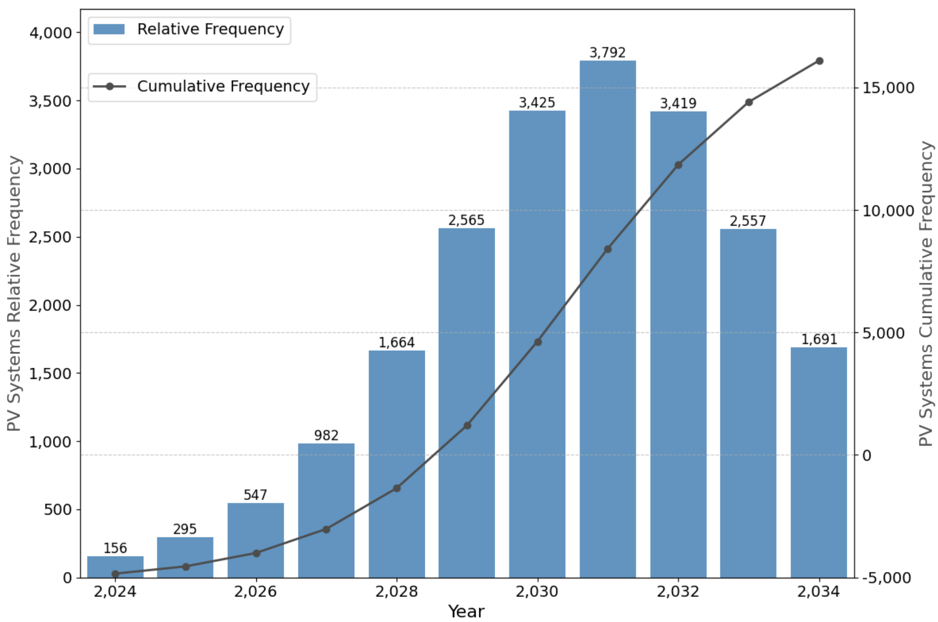

Figure 15. Annual distribution of selected users for adopting PV systems.

3.3. Comparative Analysis

In order to validate the proposed methodology, a comparative analysis has been carried out with the study presented in [15], which selects as adoption criteria those users whose energy consumption exceeds the last decile (≥500 kWh) within EEASA's concession area. During 2024, EEASA registered 21 feasibility requests for the connection of self-consumption PV systems. However, due to the energy rationing that occurred in the last quarter of the year, it has been identified through consumption records that a significantly higher number of customers have adopted PV technology without prior notification to the distributor. This phenomenon is mainly attributed to the lack of regulatory incentives and the interest of users to avoid lengthy administrative procedures, which may delay the implementation of PV systems. As a result, a total of 209 customers have been counted as having installed PV systems in 2024, a figure well above the number of official data.

Since the analysis horizon considers a ten-year planning period, and actual information is currently only available for the year 2024, the comparative analysis between both methodologies, fuzzy logic and last decile, has been performed considering only this first year. To evaluate the accuracy of each methodology in identifying actual adoption, three validation metrics have been used: MAPE, Theil´s U-Statistic, and AUC-ROC. Table 10 shows the values obtained for the first two metrics, while Figure 16 illustrates the AUC-ROC curves for each methodology, and Figure 17 presents a consolidated graphical comparison of all performance indicators.

Table 10. MAE and MSE results for different models.

Metric	Fuzzy Logic Method	Last Decile
MAPE (%)	18.181818	90.151515
Theil's U-Statistic	0.083333	0.820690

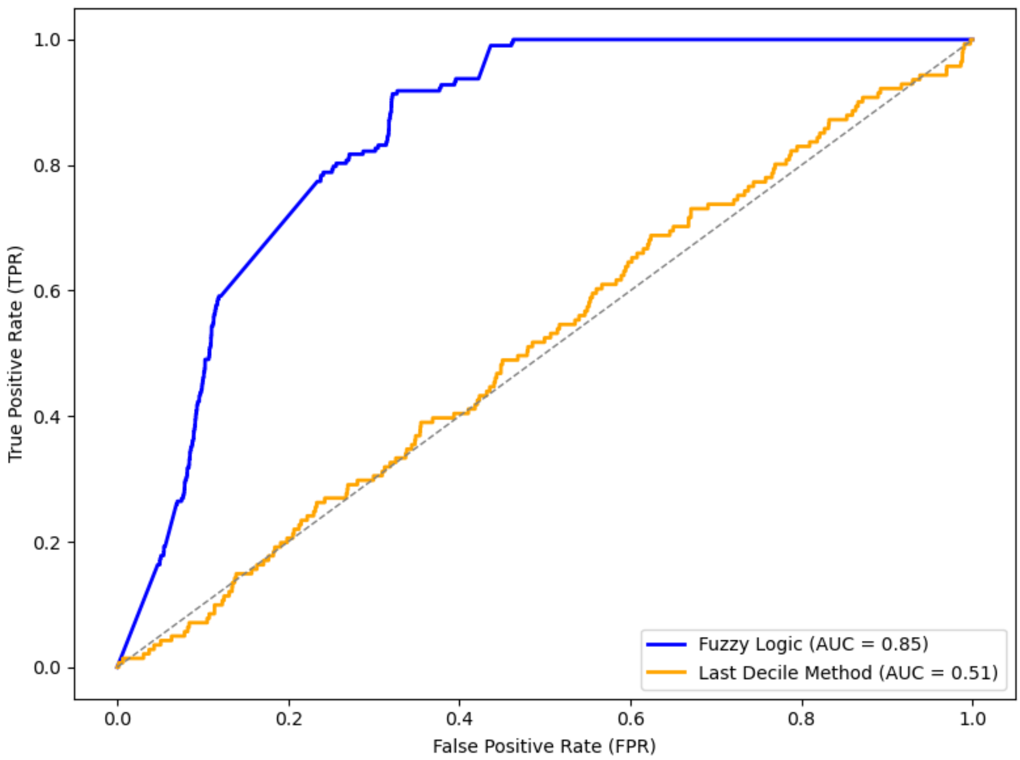

Figure 16. ROC curve—fuzzy logic vs. last decile method.

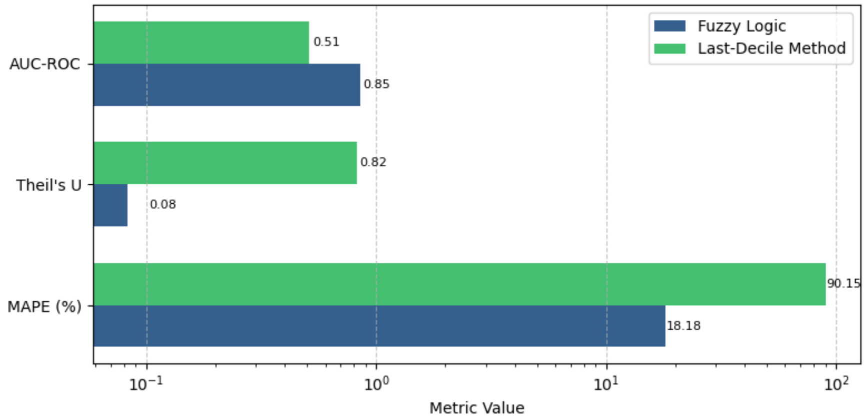

Figure 17. Comparative performance metrics, MAPE, Theil's U, and AUC-ROC for the fuzzy logic model and the last decile consumption-based model.

Additionally, an assessment was conducted to determine whether customers who have already adopted PV systems are included among the candidates identified by both methodologies. Table 11 presents the success rate of each approach.

Table 11. Comparison of adoption methodologies.

Methodology	Total Real Adopters	Correctly Identified Adopters	Success Rate (%)
Fuzzy Logic	209	161	77.03
Last Decile	209	141	67.46

3.4. Electrical Grid Analysis

To evaluate the impact of PV system integration on the distribution grid, two scenarios were analysed for a typical day, without PV systems and with PV systems, both considering annual load growth. This assessment was conducted using load flow simulations in CYMDIST software module of CYME 9.4, incorporating demand and generation profiles. The simulated grid was composed of a total of 163,205 nodes and the evaluation focused on three parameters, namely energy losses, equipment loadability, and voltage profile.

1. Energy Losses: Figure 18 illustrates the evolution of energy losses in the distribution grid over the period 2024–2034, comparing two scenarios: without PV systems (blue line) and with PV systems (orange line). Both scenarios exhibit a gradual increase in energy losses over time. However, the scenario without PV systems consistently shows higher losses than the scenario with PV systems. The divergence between the two curves becomes more pronounced as the years progress, with a steeper increase in losses in the absence of PV systems. In the final years (2032–2034), the gap between both scenarios reaches its peak, indicating a growing disparity in grid efficiency depending on PV system integration.
2. Loadability: Figure 19 illustrates the evolution of equipment loadability in the distribution grid over the period 2024–2034, comparing both scenarios. A progressive increase is observed in the number of overloaded assets and the severity of overloading in both cases. In the early years, loading conditions remain relatively stable, with values close to 100% of rated capacity. However, from 2027 onwards, greater variability emerges, indicating an increasing disparity in loadability across different assets. In the final years of the analysis (2032–2034), significantly higher loadability levels are observed, along with a growing presence of outliers, suggesting that some equipment is experienced critical overloading conditions.

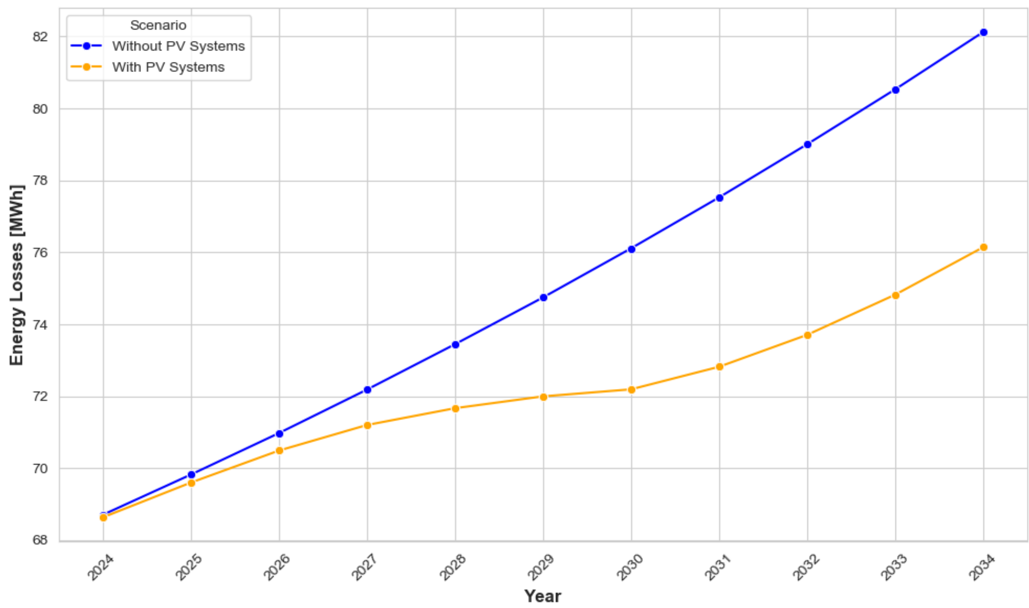

Figure 18. Annual energy losses over the planning period.

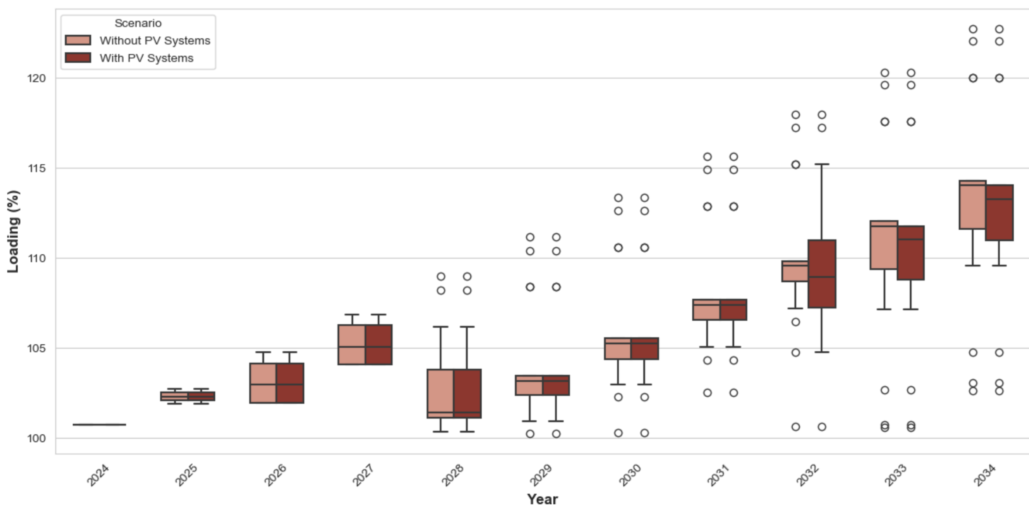

Figure 19. Equipment loading over the planning period.

3. Voltage Profile: Figure 20 presents the voltage profile over a 24 h period in the year 2034, comparing two scenarios: without PV systems (blue) and with PV systems (brown). The boxplots illustrate the distribution of voltage magnitudes at different times of the day, expressed in per-unit (p.u.) values. The acceptable voltage range under Ecuadorian regulations is ±6% of the nominal voltage, corresponding to the interval [0.94 p.u., 1.06 p.u.], which is indicated by the red dashed lines. Additionally, an upper reference of 1.08 p.u. is marked in blue. Throughout the day, voltage levels exhibit significant variations, with instances of both undervoltage (below 0.94 p.u.) and overvoltage (above 1.06 p.u.) occurring in both scenarios. In particular, early-morning and nighttime hours show a large number of undervoltage violations, whereas midday hours display outliers beyond the upper limit, suggesting localized overvoltage events due to PV generation.

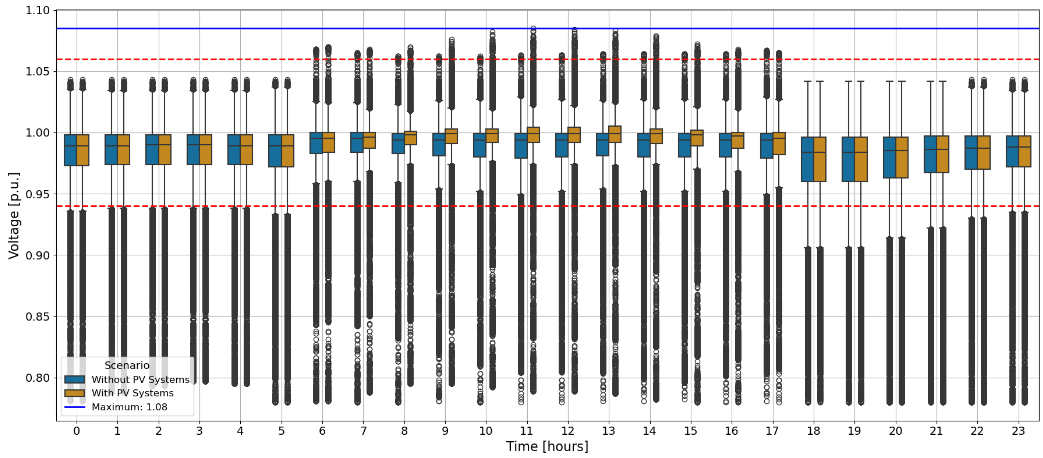

Figure 20. Voltage profile on a typical day in the EEASA distribution grid, fuzzy logic criterion.

3.5. Discussion

This study highlights how data analysis can enhance the long-term planning of distribution grids under high penetration of renewable energy sources. The proposed methodology employs fuzzy logic criteria and evaluates four models that integrate principle variables such as energy consumption, electricity tariff, solar radiation, and socioeconomic level to estimate the probability of PV adoption systems. Through the formulation of if–then rules, it was determined that the model combining energy consumption with electricity tariff yields the lowest MAE (0.22) and MSE (0.1) when compared to real PV adopters. This outcome is primarily attributed to the fact that, according to the classification used, commercial and industrial tariffs play a significant role in PV system adoption due to the economic impact experienced during the energy rationing events of 2024 in Ecuador. Based on this model, a 65% threshold was established to identify 21,093 potential adopters of PV systems.

A previous study considered an energy consumption threshold of 500 kWh as the sole selection criterion [15]. While this method captures high energy consumers who may find PV adoption economically viable, it fails to account for users with lower consumption who have also chosen to install PV systems. Excluding these users could lead to an underestimation of infrastructure requirements in long-term distribution system planning. To address this, the fuzzy logic-based methodology was compared with the last decile method, and both were validated against actual PV adoption data from EEASA in 2024. Three evaluation metrics were used: MAPE, Theil's U-Statistic, and AUC-ROC.

Metrics show that the fuzzy logic-based model significantly outperforms the last decile method in predictive accuracy. The MAPE for the fuzzy logic method is 18.18%, whereas the last decile method exhibits a considerably higher error of 90.15%. A lower MAPE reflects greater model accuracy, confirming that the fuzzy logic approach is far more effective in identifying potential adopters. Conversely, the last decile method demonstrates an error rate nearly five times higher, indicating that selecting customers solely based on an energy consumption threshold does not accurately represent actual PV adoption patterns within EEASA's concession area.

Additionally, Theil's U-Statistic, which assesses the accuracy of the methodologies against a naïve prediction, further supports these conclusions. The fuzzy logic-based approach achieved a value of 0.083, indicating high precision in identifying real adopters. In contrast, the last decile method yielded a value of 0.82, suggesting its performance is only marginally better than a simple extrapolation without additional selection criteria. These findings underscore that the fuzzy logic model significantly improves the identification of users with high adoption potential, while relying solely on a fixed consumption threshold is not a reliable predictor of PV adoption.

Moreover, the AUC-ROC metric provides further validation of the superiority of the fuzzy logic approach. The fuzzy logic model achieved an AUC of 0.85, indicating strong discriminative ability in distinguishing between adopters and non-adopters. In contrast, the last decile method obtained an AUC of only 0.51, which is close to random classification (AUC = 0.50), further demonstrating its poor predictive power. The higher AUC for the fuzzy logic model confirms that incorporating electricity tariffs beyond energy consumption significantly enhances the model's ability to accurately predict PV system adoption.

It was observed that the fuzzy logic-based method with the first model successfully identified 161 adopters out of a total of 209, achieving a success rate of 77.03%. In contrast, the last decile method correctly identified only 141 adopters, corresponding to a success rate of 67.46%. These results further confirm that the fuzzy logic approach outperforms the consumption-based selection criterion by correctly identifying 10% more real adopters. This improvement stems from the method's ability to integrate planner criteria, providing a strongest comprehensive representation of adoption behaviour. In contrast, the last decile method excludes users who, despite having lower energy consumption, have opted for PV adoption due to external drivers such as the ongoing energy crisis and the desire for energy independence.

Beyond the selection of PV adopters, the study also analysed the impact of DER on the distribution grid. Results indicate that a high penetration of DER does not necessarily alleviate overloading conditions in grid assets. Instead, DER integration appears to increase load variability and contribute to extreme overload events. The high dispersion and presence of outliers in later years suggest that the distribution grid may not be adequately designed to accommodate large-scale DER penetration, leading to increased stress on infrastructure and a heightened risk of operational failures. These findings emphasize the necessity for strategic grid planning, infrastructure reinforcements, and advanced operational measures to effectively manage DER penetration, maintain power quality, and ensure long-term system reliability.

Additionally, results indicate that distributed generation contributes to reducing energy losses over time, as PV systems help decrease the overall loss profile by supplying local demand and minimizing long-distance power flows. However, energy losses continue to rise in both scenarios analysed, suggesting that growing grid demand cannot be entirely offset by DER. This highlights the need for complementary solutions such as grid reinforcements, voltage regulation strategies, and energy storage integration to further optimize power distribution efficiency under high DER penetration levels.

By 2034, when all selected customers will have adopted PV systems, it is anticipated that voltage profiles will be altered, but this alone will not fully resolve regulation violations. While PV generation improves voltage levels during peak solar hours, it fails to eliminate undervoltage conditions in off-peak periods. The high dispersion of voltage values, particularly the prevalence of undervoltage occurrences below 0.90 p.u., indicates that the distribution grid may not be adequately prepared to manage high PV penetration without additional voltage control mechanisms. To comply with Ecuadorian voltage regulations, it is necessary to implement reactive power compensation, voltage regulators, or advanced inverter control strategies. These findings emphasize the need for coordinated grid planning to integrate DER effectively while maintaining voltage quality and grid stability.

4. Conclusions

The findings of this study demonstrate the effectiveness of fuzzy logic-based methodologies in predicting the adoption of PV systems compared to traditional consumption-based selection criteria. The proposed approach, which integrates variables such as energy consumption and electricity tariffs, has proven to be a more reliable predictor of PV adoption than the conventional method based solely on high energy consumption thresholds. This is evident from the lower Mean Absolute Percentage Error (MAPE) and Theil's U-Statistic, as well as the higher AUC-ROC, which confirm the superior predictive performance of the fuzzy logic model.

By applying the fuzzy logic-based model, a 77.03% success rate was achieved in identifying real PV adopters, surpassing the 67.46% success rate obtained with the last decile method. These results confirm that a multivariable selection approach significantly enhances the ability to predict potential adopters, particularly in emerging markets with dynamic energy policies and external factors influencing adoption, such as the ongoing energy crisis in Ecuador. The study further highlights that relying exclusively on energy consumption as a selection criterion excludes a significant portion of adopters, leading to inaccurate demand projections and suboptimal infrastructure planning.

Furthermore, this research emphasizes the impact of DER on power distribution grids. While high PV penetration contributes to energy loss reduction and local demand balancing, it also introduces new challenges related to voltage regulation and infrastructure stress. The observed increase in voltage fluctuations and undervoltage occurrences suggests that additional control measures, such as reactive power compensation, voltage regulation devices, and advanced inverter control strategies, are necessary to maintain grid stability. These findings underscore the importance of strategic planning for DER integration, ensuring that distribution grids can accommodate large-scale PV deployment while maintaining operational reliability and regulatory compliance.

The methodology developed in this study enables utilities to assess the resilience of their distribution networks under increasing PV penetration. Although this research did not incorporate network expansion, the simulation environment was built using a full migration of EEASA's distribution grid from GIS to CYMDIST. This modelling framework allows future iterations by updating the network model whenever significant grid changes occur. Additionally, future research could incorporate spatial load forecasting techniques to progressively include new customer connections and evaluate their impact on the distribution grid. Thus, utilities can periodically reassess the technical impact of DER by integrating updated consumption profiles, topology changes, and new load growth projections into the CYME simulation environment.

The socioeconomic classification was derived from INEC shapefiles, available only for provincial urban areas, covering approximately 66% of the study region. This limitation introduces uncertainty, particularly in rural or cantonal zones lacking defined classification. Future work will explore data imputation techniques, geostatistical interpolation, and clustering methods to infer socioeconomic levels based on correlated variables such as electricity consumption, tariff type, and geographic proximity. Additionally, long-term projections could be enhanced by incorporating multi-year datasets, especially to account for potential market saturation or disruptive technological trends.

Although cadastral information would significantly enhance the precision of rooftop PV capacity estimations, its integration in this study was limited by the lack of unified and comprehensive cadastral databases across EEASA's service area. Most municipalities do not provide detailed land use records or rooftop surface data, hindering accurate assessments of installable PV area. For future research, it is essential to incorporate variables related to the available installation space, potentially obtained through municipal cadastral systems or alternative sources such as satellite imagery and remote sensing technologies. Establishing partnerships with local authorities to access or develop these datasets is a critical step forward.

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Nomenclature

List of Acronyms and Terms Used in the Manuscript.

AUC-ROC	Area Under the Curve—Receiver Operating Characteristic
CYMDIST	Electrical distribution system modelling and simulation software
DER	Distributed Energy Resource
EEASA	Empresa Eléctrica Ambato Regional Centro Norte S.A.
EV	Electric Vehicle
GIS	Geographic Information System
INEC	Ecuadorian National Institute of Statistics and Census
MAE	Mean Absolute Error
MAPE	Mean Absolute Percentage Error
MSE	Mean Squared Error
PV	Photovoltaic
SAP/CIS	Nationally standardized commercial software for electric utilities

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