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Fuzzy Logic-Based Compliance Assessment For Display Testing In Industrial Measurement Systems

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Abstract:

Background*: The conformity assessment of display testing in industrial measurement systems plays a critical role in ensuring the accuracy and reliability of devices, particularly in industries where precision is key, such as healthcare, energy, and manufacturing. Compliance with technical standards is essential, but traditional methods for evaluating conformity often rely heavily on manual processes. These methods can be error-prone, slow, and susceptible to inconsistencies, leading to inefficiencies in quality assurance. As industrial measurement systems become more complex, there is a growing need for automated solutions that can enhance the accuracy and speed of conformity assessments while minimizing human intervention.*

Materials and Methods*: This study presents the development and implementation of a fuzzy logic-based system aimed at automating the compliance evaluation process for display testing in industrial measurement devices. The fuzzy inference system was programmed in Python, employing linguistic variables and fuzzy rules to assess key performance parameters, including accuracy, response time, and allowable margins of error. By fuzzifying these variables, the system applies fuzzy rules to handle uncertainties and imprecise data more effectively than binary decision-making processes, which are typically limited to pass/fail criteria. The fuzzy model processes data from various display devices and produces a graded compliance output based on predefined criteria.*

Results*: The fuzzy logic system was tested on a dataset comprising a wide variety of industrial display devices. The results demonstrated that the system successfully classified 93% of the devices in accordance with established compliance standards. This high accuracy level highlights the system's potential to significantly improve the reliability of display testing in industrial environments. Furthermore, the automated nature of the system reduced the reliance on manual input, which not only minimized human errors but also sped up the overall assessment process. The results indicate that the fuzzy logic-based approach can handle the complexities inherent in industrial display testing, offering a more nuanced and flexible evaluation compared to traditional methods.*

Conclusion: *The fuzzy logic-based system provides an efficient and accurate method for compliance assessment in industrial measurement systems. By automating the process, it reduces manual errors and enhances operational efficiency, ensuring consistent adherence to standards. This system can be a valuable tool in quality assurance, streamlining compliance evaluations across various industries.*

Keyword*: Fuzzy Logic; Compliance Assessment; Display Testing; Industrial Measurement Systems*

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I. Introduction

Ensuring the accuracy and reliability of measurement devices, particularly their display components, is crucial in many industrial sectors such as healthcare, energy, and manufacturing. These industries rely on precision instruments to meet regulatory standards and ensure the safety and effectiveness of their products and services. Traditional methods of display testing, which rely heavily on manual evaluation, are prone to errors, inconsistencies, and inefficiencies. These limitations highlight the need for automated solutions that can enhance both the speed and accuracy of conformity assessments.

One promising approach to addressing this challenge is the use of fuzzy logic systems. Fuzzy logic allows for more nuanced decision-making by handling imprecise or uncertain data, which is common in industrial environments where measurements may vary. Unlike binary systems, which offer pass/fail outcomes, fuzzy logic provides a more flexible, graded evaluation of compliance, making it particularly useful for complex systems such as display testing.

The objective of this study is to develop and implement a fuzzy logic-based system to automate the compliance assessment process for display testing in industrial measurement systems. The study focuses on the use of linguistic variables and fuzzy rules to evaluate critical performance parameters, including accuracy, response time, and margin of error. The goal is to create a system that reduces human intervention, minimizes errors, and improves overall efficiency while ensuring that devices meet the required standards of compliance.

II. Literature Review

Introduction to Conformity Assessment Systems

Conformity assessment systems are essential for ensuring that products, services, and processes meet technical standards, regulations, and specifications, guaranteeing safety and quality (ABNT, 2005). These systems are critical in sectors such as automotive, pharmaceutical, food, electronics, and energy. With globalization and market complexity, conformity systems have become more stringent, covering the entire process from design to production and post-sales, relying on international standards like ISO (ISO, 2015). Methods of conformity assessment include inspections, audits, testing, certifications, and approvals (SILVA; PEREIRA, 2017). In addition to ensuring compliance, these systems facilitate international trade by removing technical barriers. With technological advancements, conformity assessment systems have evolved to cover new areas such as cybersecurity and environmental sustainability, adapting to emerging demands (WTO, 2018; ABNT, 2020).

Importance in Quality Assurance

Conformity assessment is critical for ensuring quality in various sectors, including industry, commerce, and public services. These systems ensure that products, services, and processes comply with technical standards, protecting consumers, public safety, and the environment. Compliance is crucial to ensure that products are safe and effective, promoting confidence among consumers and stakeholders (ABNT, 2005; ISO, 2015). In critical sectors such as energy, healthcare, and construction, conformity assessment is vital to prevent failures with severe consequences, such as environmental disasters, health risks, or structural issues. Beyond safety, these systems are strategic for companies' competitiveness, facilitating access to global markets through adherence to international standards, such as ISO standards, which are synonymous with quality and reliability (Silva & Pereira, 2017; WHO, 2019). Compliance with these standards increases the confidence of business partners and enables market entry. The lack of conformity can even prevent products from being sold, highlighting the importance of these systems for the international viability of companies (ISO, 2015; WTO, 2018). Additionally, conformity systems encourage continuous improvement, pressuring companies to innovate and improve processes. This is crucial in competitive markets where the ability to offer high-quality products can be a significant differentiator. Compliance is also associated with long-term cost reduction, preventing costly corrections, recalls, or damage to reputation (Crosby, 1979; Juran, 1992).

Thus, conformity assessment systems are more than just regulatory mechanisms; they are strategic tools that ensure quality, minimize risks, and meet regulatory and consumer expectations, promoting confidence and competitiveness in local and international markets (ABNT, 2005; ISO, 2015).

Fuzzy Logic - Fundamental Concepts

Fuzzy logic, developed by Lotfi Zadeh in 1965, is an extension of classical logic that deals with the imprecision and uncertainty inherent in many real-world processes. Unlike traditional logic, where propositions are strictly true or false, fuzzy logic introduces the concept of degrees of truth, allowing a proposition to be partially true and partially false simultaneously (Zadeh, 1965). This approach enables the modeling of situations where the binary rigidity of classical logic would be inadequate, providing a more realistic and flexible representation of complex phenomena (Rezende, 2005; Silva, 2013). The main components of a fuzzy control system are essential for its operation and can be described as follows (Gregório, 2023):

- Input variables: physical quantities representing the system's state;
- Fuzzification: identifies the values of the input variables and normalizes them, transforming them into fuzzy sets;
- Membership functions: describe the relationship between the variables and the degrees of fuzzy membership;
- Rule base: a set of If-Then rules for mapping inputs and outputs;
- Inference: uses fuzzy rules to perform inferences and determine the control signal;
- Defuzzification: converts the fuzzy result into a real control value;
- Output variables: physical quantities representing the control action to be taken.

The basic structure of a Fuzzy system can be observed in Figure 1.

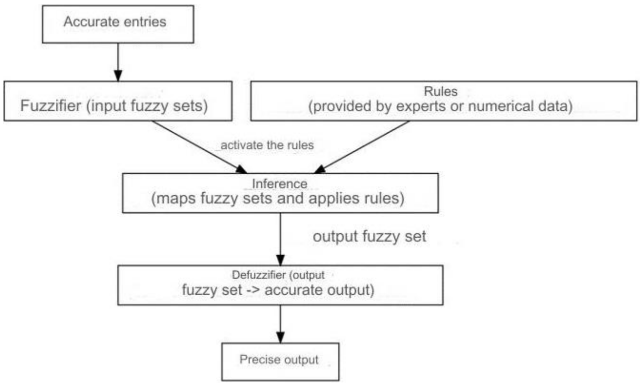

Figure 1: Structure of a Fuzzy system.
Source: Gregório, (2023).

Fuzzy Sets and Membership Functions

Fuzzy sets are characterized by their membership functions, which associate each element of the set with a numerical value between 0 and 1 (Sucena, 2021; Ferreira, 2020). These values represent the degree of membership of an element to the set (Silva et al., 2013). The most common functions include triangular, trapezoidal, and Gaussian functions, used to model continuous variables. In the case of a triangular function, it is defined by three parameters: a, m, and b, as described in the following equation (1):

$$\mu_p(x) = \begin{cases} 0, & \text{se } x \leq a \\ \frac{x-a}{m-a}, & \text{se } a < x \leq m \\ \frac{b-x}{b-m}, & \text{se } m < x \leq b \\ 0, & \text{se } x > b \end{cases} \tag{1}$$

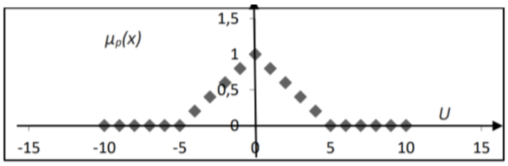

Figure 2: Graphical representation of a triangular membership function.
Source: Silva, (2013).

Operations with Fuzzy Sets

Basic operations with fuzzy sets include union, intersection, and complement. The union of two fuzzy sets A and B is defined by the equation:

$$\mu_{A \cup B}(x) = \max(\mu_A(x), \mu_B(x)) \tag{2}$$

The intersection is given by:

$$\mu_{A \cap B}(x) = \min(\mu_A(x), \mu_B(x)) \tag{3}$$

These operations are fundamental for combining information in fuzzy systems (Silva, 2013).

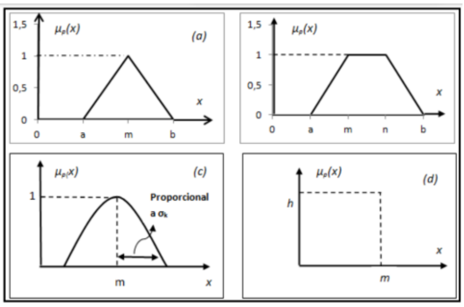

Figure 4: Graphical representation of fuzzy operations of union, intersection, and complement.
Source: (Silva, 2013).

Fuzzy Rules and Inference

Fuzzy systems use "IF-THEN" rules to describe how input variables should be associated with output variables (Gonçalves, 2023). A typical fuzzy rule might be:

"IF the temperature is high AND the humidity is low, THEN the ventilation should be increased."

Fuzzy inference systems process the inputs using fuzzy rules and generate appropriate outputs (Serri, 2022). Fuzzy inference allows for decision-making under uncertain conditions and has widespread applications in areas such as automatic control and medical diagnostics (Mendel, 2001). These rules are processed through fuzzy inference systems, such as the Mamdani and Takagi-Sugeno-Kang (TSK) models (Silva, 2008; Lima, 2022). Fuzzy inference combines all the rules to generate an output, followed by defuzzification, which converts the fuzzy results into precise values (Rezende, 2005).

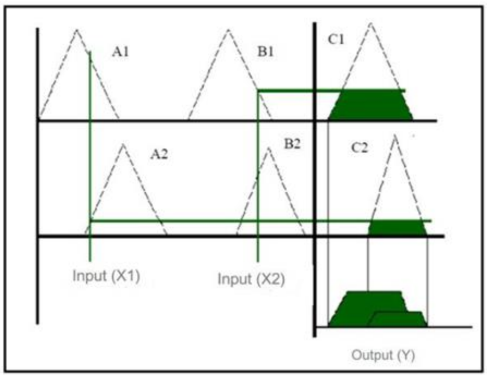

Figure 5: Fuzzy inference systems process inputs using fuzzy rules and generate appropriate outputs. Source: (Serri, 2022).

Fuzzy Inference Models - Mamdani Model

The Mamdani model, developed by Ebrahim Mamdani in 1975, is one of the most well-known approaches to fuzzy inference. This model uses fuzzy "IF-THEN" rules and a defuzzification step to generate crisp outputs from fuzzy inputs. Inference in the Mamdani model follows the max-min composition rule, where the output value is obtained by applying the minimum value between the input fuzzy sets and the maximum of the output values from the fuzzy rules, thus composing the final fuzzy relation. As highlighted by Sałabun et al. (2020), one of the advantages of the Mamdani model is its ability to handle complex systems with severe nonlinearities, as observed in the control of cranes moving containers, where unpredictable external conditions affect the system's behavior. Mathematically, the fuzzy relation M between x and u, which models the fuzzy rule base, is given by:

$$\varphi_M(x,u) = \max_{1\leq j\leq r}[\varphi_{A_j}(x) \wedge \varphi_{B_j}(u)] \quad (4)$$

where $\varphi A\ (x)$ and $\varphi B(u)$ are the membership degrees of the input variable x and the output variable u in the rules Rj. The final output is obtained by the union of the partial outputs generated by each rule.

As noted by Sałabun et al. (2020), the practical implementation of fuzzy control with the Mamdani structure often outperforms classical PID control systems, especially in nonlinear scenarios with unpredictable external factors, as demonstrated in case studies involving crane control.

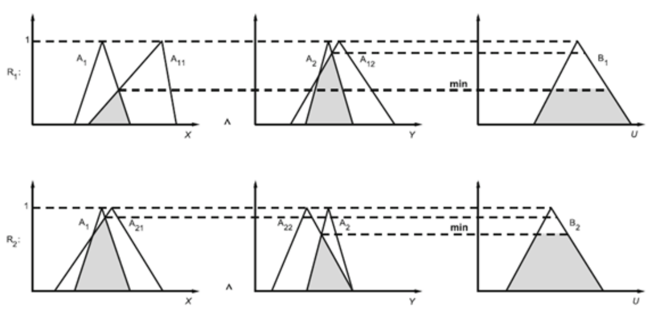

Figure 6: Diagram of the Mamdani inference method. Source: Barros, (2017).

` Additionally, the defuzzification process in the Mamdani model typically uses the "Centroid" method to convert the fuzzy output set into a crisp value, which is particularly useful in control systems where a decision must be made based on uncertain inputs (Branquinho, 2024). Even when the inputs are crisp values, such as in control systems with fixed inputs, the final output is still represented as a fuzzy set, which must be converted into a crisp value through defuzzification (Chai, 2009).

Fuzzy Inference Models - Takagi-Sugeno-Kang (TSK) Model

The Takagi-Sugeno-Kang (TSK) fuzzy inference model, proposed by Takagi and Sugeno in 1985, is widely used in control systems, especially in situations that require greater precision. Unlike the Mamdani model, the TSK model uses linear or constant functions to describe the output variables, making it more suitable for optimization and adaptive control (Moreira, 2020). Additionally, the TSK model has been applied in multi-label classification systems, such as the Multi-Label Fuzzy System Takagi-Sugeno-Kang (ML-TSK FS), which uses fuzzy inference rules to improve classification performance, as observed in systems evaluated on various benchmark datasets (Lou et al., 2023). In the TSK model, each fuzzy rule has an associated output function, and the final output is obtained by the weighted average of all the rule outputs. This method offers greater precision and computational efficiency compared to the Mamdani model, especially in real-time control systems. Figure 7 illustrates the fuzzy inference process in the TSK model, showing the relationships between the input and output variables.

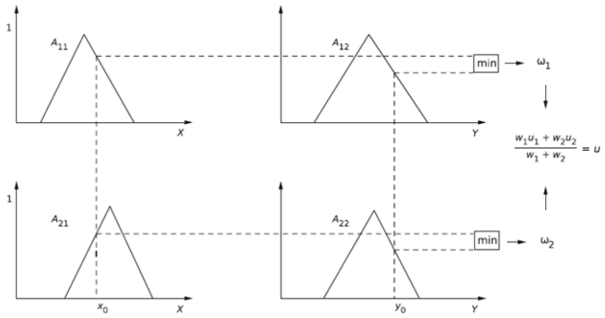

Figure 7: Diagram of the TSK fuzzy controller
Source: Barros, (2017).

Defuzzification

Defuzzification is the process of transforming a fuzzy output into a precise numerical value (Silva, 2021). In stochastic theory, the mathematical expectation (or mean) is commonly used as the value that best represents a random variable or data distribution. Similarly, in fuzzy set theory, defuzzification allows a fuzzy set to be represented by a crisp value (real number) (Baron, 2017). The most common defuzzification method is the centroid method (or center of gravity), described by the following equation:

$$y = \frac{\int \mu_{out}(x) \cdot x \, dx}{\int \mu_{out}(x) \, dx} \tag{5}$$

This method calculates the balance point of the area under the curve of the membership function, providing a central value that represents the fuzzy set (Rezende, 2005). Defuzzification is fundamental in fuzzy controllers, enabling the fuzzy output to be converted into a precise value for decision-making. This was observed in the early experiments of Mamdani and Assilian, who used fuzzy controllers to control a steam engine. This process was based on the fact that human operators express control strategies in linguistic terms, rather than a purely mathematical approach, which inspired the use of fuzzy logic in modern control systems (Chai, 2009).

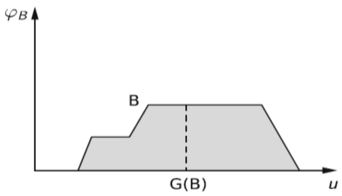

Figure 8: Representation of the centroid defuzzification method
Source: Barros, (2017)

Practical Applications

Fuzzy logic has been widely applied in various fields, such as automatic control, medical diagnostics, image processing, and finance. In industrial plants, fuzzy logic is used to automatically adjust variables such as temperature and pressure, ensuring that processes remain stable, even under uncertain conditions (Gomide et al., 2009). Additionally, fuzzy systems have been used to predict environmental risks, such as vulnerability to coastal erosion (Silva et al., 2013).

III. Material And Methods

This section details the materials and methods of the research, which evaluates the conformity of energy meter displays using fuzzy logic. The study followed the guidelines of the Portaria 221 from 2022 and defined critical parameters such as clarity, readability, and functionality, which are essential for meter accuracy. A fuzzy inference system was developed to integrate multiple variables and provide a degree of compliance. Tests on different display models validated the system, with data rigorously collected and analyzed. The research also describes the tools used and the procedures for implementation in a production environment.

Conformity Assessment Model - Definition of Display Parameters

In this research, the conformity assessment of energy meter displays was based on key parameters to ensure accuracy and usability, following the Portaria 221 from May 23, 2022. The main parameters evaluated include:

1. Clarity: Refers to the sharpness of the numbers and indicators, ensuring quick and accurate reading under different lighting conditions and viewing angles.
2. Readability: Evaluates the ease of reading and interpreting the data, influenced by contrast, font size, and information layout.
3. Functionality: Measures the operation of the display under various environmental conditions, including electromagnetic interference and temperature variations.
4. Durability: Considers the longevity of the display, assessing its resistance to wear, sun exposure, and humidity.

These parameters were analyzed using fuzzy logic, allowing a flexible and detailed evaluation of the variables according to technical requirements and existing literature.

Structuring the Fuzzy System and Definition of Fuzzy Variables

Fuzzy logic was chosen as the main approach for evaluating the conformity of energy meter displays due to its ability to handle uncertainties and subtle variations in measurements. This section describes the process of structuring the fuzzy system, from defining the variables to configuring the specific inference system for display testing.

In the fuzzy system developed for this research, input variables were carefully defined to capture the most relevant aspects of display performance, according to the criteria established in the Portaria 221 from May 23, 2022. Fuzzy variables were established to represent the key parameters of the display, including:

- QSD (Quality of Digit Segment): This variable measures the precision and clarity of the segments displayed on the meter. The membership functions for QSD were defined as "Poor," "Fair," "Good," and "Excellent," reflecting different levels of segment quality, as shown in Figure 9.
- Clarity: Refers to the overall clarity of the display, which is fundamental to ensuring readability. The membership functions for Clarity were defined as "Poor," "Fair," "Good," and "Excellent," allowing for a detailed evaluation of visual quality, as shown in Figure 10.

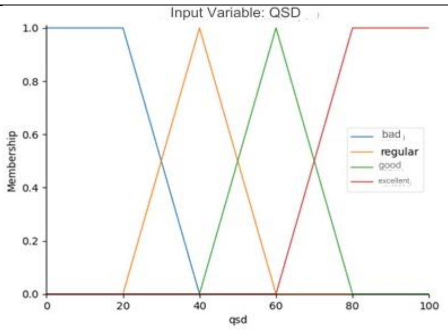

Figure 9: QSD (Quality of Digit Segment). Source: Authors, (2024).

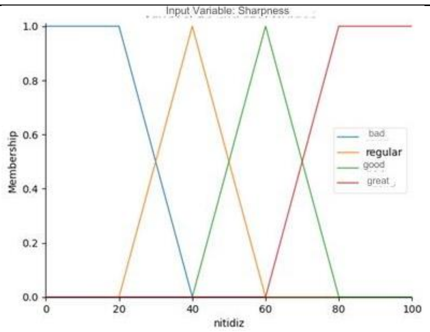

Figure 10: Membership functions for Clarity. Source: Authors, (2024).

- Functionality: Evaluates the display's ability to operate correctly under different environmental conditions. The membership functions were defined as "Poor," "Fair," "Good," and "Excellent," ensuring that all aspects of display operation are considered, as shown in Figure 11.
- Quality (Quali): This is the output variable, representing the degree of compliance of the display with the established requirements. The membership functions were defined as "Poor," "Low," "Medium," "Good," and "Excellent," offering a continuous measure of the compliance level, as shown in Figure 12.

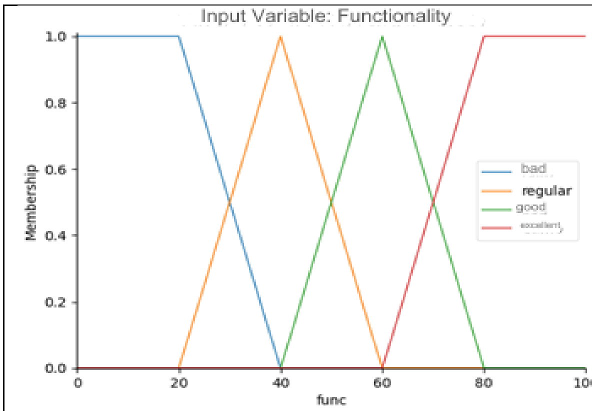

Figure 11: Membership functions for Functionality.
Source: Authors, (2024).

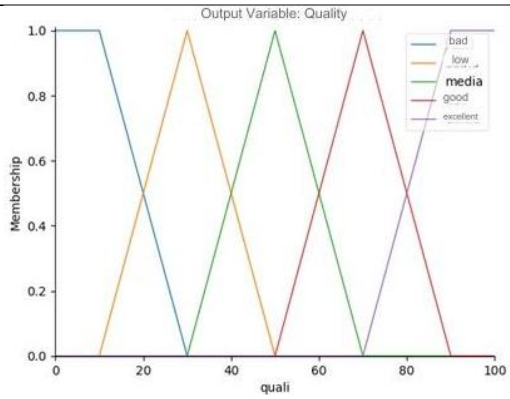

Figure 12: Membership functions for Quality (Quali).
Source: Authors, (2024).

Each of these variables was modeled using trapezoidal and triangular membership functions, chosen for their ability to gradually represent the transition between different states, allowing for a more flexible and adaptable analysis.

Development of Fuzzy Rules

Fuzzy rules are the core of the fuzzy inference system, determining how input variables combine to influence the output variable. For this system, 64 fuzzy rules were developed, based on logical combinations of the input variables. The rules were defined to cover all possible combinations of QSD, Clarity, and Functionality, ensuring that every relevant scenario is considered in the evaluation of the display's conformity. Examples of rules include:

1. If QSD is "Poor" OR Clarity is "Poor" OR Functionality is "Poor," THEN Quality is "Poor": This rule ensures that any significant impairment in one of the variables will result in a low-quality evaluation.
2. If QSD is "Good" AND Clarity is "Good" AND Functionality is "Good," THEN Quality is "Good": This rule reflects the situation where all input variables are at a satisfactory level, resulting in an overall good quality display.
3. If QSD is "Excellent" AND Clarity is "Excellent" AND Functionality is "Excellent," THEN Quality is "Excellent": This rule ensures that high performance in all input variables results in the best possible evaluation for the display's quality.

The rules were implemented using logical "AND" and "OR" operators, based on the requirements of Portaria 221 and the desired characteristics for energy meter displays.

Configuration of the Fuzzy Inference System for Display Testing

The fuzzy inference system was configured to integrate the defined variables and rules, allowing for a continuous and adaptable analysis of display conformity. The fuzzy inference process follows three main steps: fuzzification, inference, and defuzzification.

1. Fuzzification: In this step, the real values of the input variables (QSD, Clarity, Functionality) are converted into degrees of membership for each of the corresponding membership functions. This allows the system to consider the uncertainty and variability of the input data.
2. Inference: Using the developed fuzzy rules, the system evaluates the combinations of the input variables to generate a fuzzy output. This process involves applying the defined rules and combining the partial results for each applicable rule.
3. Defuzzification: The fuzzy output, which is a set of membership degrees for different quality states, is converted into a final numerical value. This value represents the continuous evaluation of the display's conformity, providing a result that can be used for decision-making.

The system configuration was carried out to maximize the accuracy and reliability of the results, ensuring that the system can be applied in different testing and production scenarios. The integration of variables and rules into the inference system allows for a robust and detailed analysis, essential for conformity assessment according to the required standards.

Technical Implementation of the System

The technical implementation of the fuzzy system for conformity assessment of energy meter displays involved the use of specific tools and technologies, the integration of the system into the production environment, and the execution of simulations and preliminary tests to validate its effectiveness. This section details these steps.

Tools and Technologies Used

Several tools and technologies were used for the development of the fuzzy system, allowing the construction, modeling, and execution of fuzzy rules, as well as the analysis of the results:

1. Python: The Python programming language was chosen due to its versatility and the wide availability of libraries for developing fuzzy systems. Specifically, the SciKit-Fuzzy library was used to create and manipulate fuzzy variables and inference rules.
2. SciKit-Fuzzy: This library was essential for the implementation of the fuzzy system, offering functions that facilitate the definition of input and output variables, the development of fuzzy rules, and the execution of the inference process. SciKit-Fuzzy allows efficient integration with other data analysis tools, making it ideal for this project.
3. Matplotlib: Used for the graphical visualization of membership functions, fuzzy inference results, and the creation of surface charts that help interpret the data. Visualization is a critical part of the system as it allows for verifying and adjusting the rules and variables based on the graphical results.
4. Jupyter Notebook: This development tool was used for the iterative testing and refinement of the fuzzy system. Jupyter Notebook facilitates the documentation of the development process, allowing the integration of code, results, and explanations in a single environment.

Simulation and Preliminary Testing

The fuzzy system underwent a series of simulations and preliminary tests to validate its accuracy and reliability:

1. Simulations of Varied Scenarios: Simulations were carried out using different combinations of input parameters (QSD, Clarity, Functionality) to verify how the system responded to different operational conditions. These simulations helped identify potential adjustments to the fuzzy rules and membership functions.
2. Validation of Results: The results produced by the fuzzy system were compared with manual evaluations performed by experts to validate the system's accuracy. This comparison was crucial for adjusting the fuzzy rules and ensuring that the system could reliably replicate human analysis.
3. Final Adjustments: Based on the results of the simulations and tests, final adjustments were made to the system to optimize its performance. These adjustments included refinements to the membership functions, improvements in process automation, and adjustments to the user interface to make it more intuitive. These steps ensured that the fuzzy system was ready to be used in a production environment, providing accurate, reliable, and adaptable conformity assessments for energy meter displays.

Data Collection

Data collection is a critical step in the conformity assessment process, as the collected data serves as the basis for the analysis and application of the developed fuzzy system. This section describes the sampling strategies, the tools used in data collection, and the procedures adopted to ensure the quality and accuracy of the data obtained.

Sampling and Tools

To ensure that the research results are representative and reliable, a carefully planned sampling strategy was adopted. Sampling was conducted considering the variety of energy meter display models available on the market, as well as the different operational conditions under which these devices may be used.

1. Sampling Criteria: Displays were selected based on criteria such as brand, model, display technology (LCD, LED, etc.), and usage conditions (temperature, humidity, etc.). The selection was made to include a representative sample of possible variations, ensuring that the fuzzy system could be tested in a wide range of scenarios.
2. Sample Size: The sample size was determined based on statistical calculations that ensured the representativeness of the data. Displays from different manufacturers were included in the sample, totaling a sufficient number to cover the main technological and operational variations found on the market.

3. Data Collection Tools: High-precision measurement tools were used for data collection, including:

a) High-Resolution Cameras: Used to capture images of the displays under different lighting conditions and viewing angles, allowing for analysis of clarity and readability.

b) Precision Measurement Equipment: Instruments such as multimeters and oscilloscopes were used to measure the accuracy of the displays' readings and verify their compliance with established standards.

c) Environmental Sensors: Temperature, humidity, and electromagnetic field sensors were employed to monitor conditions during testing, ensuring that the collected data reflected the performance of the displays under real-world operating conditions.

Data Collection Procedures

The data collection procedures were meticulously planned to ensure the consistency and accuracy of the data obtained. The following are the key steps taken during data collection:

1. Preparation of Displays: Before data collection began, all displays were carefully prepared and checked to ensure they were in optimal operating condition. This included calibrating the devices and verifying the physical integrity of the displays.
2. Test Conditions: The displays were subjected to tests under various operational conditions, simulating different usage environments. This included tests in high and low temperature environments, high humidity, and the presence of electromagnetic interference, ensuring that the collected data was representative of a wide range of scenarios.
3. Systematic Collection: Data was collected systematically, following a standardized protocol that ensured the repeatability of the tests. Each display was tested multiple times under the same conditions to ensure that the results were consistent and reliable.
4. Data Storage and Organization: All collected data was carefully recorded and stored in a centralized database, with regular backups to prevent data loss. The data was organized to facilitate its subsequent analysis, including metadata on test conditions and display characteristics.
5. Verification and Validation: After collection, the data was verified for its integrity and accuracy. Any detected anomalies were investigated, and, if necessary, new tests were conducted to ensure data validity. Validation included comparing the collected data with reference standards and expected results.

This rigorous data collection process ensured that the database used in the research was of high quality, providing confidence in the results obtained by the fuzzy system during the conformity assessment of the displays.

Validation and System Adjustments and Display Conformity Testing

The validation of the fuzzy system developed for the conformity assessment of energy meter displays is an essential step to ensure that the system performs as expected under real operating conditions. The display conformity tests were conducted under controlled conditions, replicating the usage scenarios defined during the data collection phase. These tests aimed to verify whether the fuzzy system is capable of correctly assessing the conformity of the displays based on the established parameters:

1. Test Execution: The displays previously collected and tested were submitted to the fuzzy inference system to assess their conformity. During these tests, the input variables (QSD, Clarity, Functionality) were fed into the system, which then processed the data and provided an evaluation of the display's quality (Quali).
2. Result Analysis: The results generated by the fuzzy system were compared with manual assessments performed by experts, which served as a reference. This comparison allowed verification of the system's accuracy, identifying cases where the fuzzy system and the manual assessment diverged, as well as understanding the reasons for these divergences.
3. Conformity Verification: In addition to the comparative analysis, the system's results were verified against the criteria established by Portaria 221 of May 23, 2022. This process ensured that the fuzzy system complied with regulatory requirements, validating its applicability in a production environment.
4. Anomaly Detection: During the tests, the system was also evaluated for its ability to detect anomalies in the displays. This included identifying issues such as clarity failures or functionality below expectations, ensuring that the system could not only validate conformity but also identify specific problems.

IV. Result And Discussion

Performance of the Fuzzy System in Display Testing

The performance of the fuzzy system in display testing was evaluated through a series of tests, considering different input parameters related to the Quality of Digit Segments (QSD), Clarity, and Functionality. These parameters were carefully selected to reflect the real operating conditions of energy meter displays, as established by Portaria 221 of May 23, 2022.

Results of Input Variables

During the tests, the fuzzy system was fed with specific numerical values for each input variable. For example, one set of inputs included:

- QSD: 30,000 (numerical value), classified as "poor" (linguistic value).
- Clarity: 50,000 (numerical value), classified as "fair" (linguistic value).
- Functionality: 90,000 (numerical value), classified as "excellent" (linguistic value).

These inputs were processed by the fuzzy system, which interpreted them based on the previously defined membership functions. The variables were categorized into linguistic terms, allowing the system to make inferences about the overall quality of the display.

Output Variable Result

Based on the inputs provided, the fuzzy system generated an output corresponding to the Display Quality, with a numerical value of 12.6667, classified as "poor." This result suggests that, despite the high functionality of the display, the poor quality of the digit segments (QSD) and the fair clarity were determining factors that reduced the overall quality assessed by the system.

Performance Analysis

The performance of the fuzzy system proved to be robust in the conformity assessment of displays, especially when considering multiple factors simultaneously. The system correctly identified that a low value in a critical variable (such as QSD) could have a significant impact on the overall quality of the display, even if other variables, such as functionality, showed high values.

Comparison with Traditional Methods

The comparison between the developed fuzzy system and traditional methods for assessing the conformity of energy meter displays is essential to understand the advantages and limitations of each approach. Traditional methods generally involve visual inspections and manual measurements, where experts assess display conformity based on binary criteria such as "compliant" or "non-compliant." Although these methods are widely used, they present some limitations that the fuzzy system can overcome.

Advantages of the Fuzzy System

1. Flexibility in Evaluation: While traditional methods tend to be rigid, classifying displays in a binary manner, the fuzzy system allows for more flexible evaluation. It assigns degrees of conformity, meaning that a display doesn't need to be simply "compliant" or "non-compliant," but can be classified on a quality spectrum such as "poor," "low," "medium," "good," or "excellent." This offers a more detailed and continuous view of the displays' quality.
2. Consideration of Multiple Parameters Simultaneously: The fuzzy system integrates several input variables (QSD, Clarity, Functionality) and analyzes them together, whereas traditional methods often evaluate each parameter in isolation. This holistic approach of the fuzzy system captures the interactions between different factors, providing a more accurate and comprehensive assessment.
3. Reduction of Subjectivity: In traditional methods, the evaluation heavily depends on human judgment, which can introduce subjectivity and variability in the results. The fuzzy system, on the other hand, applies standardized inference rules that minimize subjectivity, resulting in a more consistent and replicable assessment.
4. Operational Efficiency: The automation offered by the fuzzy system allows for the evaluation of a large number of displays in a short period, something that would be impractical with manual methods. This results in greater operational efficiency, reducing the time and costs associated with the evaluation process.

Limitations of Traditional Methods

1. Dependence on Visual Inspections: Traditional methods largely rely on visual inspections carried out by experts, which can be subjective and prone to human error, especially under adverse testing conditions, such as poor lighting or unfavorable viewing angles.
2. Binary Evaluation: The binary evaluation of traditional methods may not capture important nuances in display quality. A display that is slightly outside the established standards may be classified as "non-compliant," even though it may function adequately in practice. The fuzzy system avoids this problem by providing a more granular evaluation.
3. Lack of Integration of Variables: In traditional methods, variables are often evaluated independently, which can lead to inaccurate conclusions. The inability to integrate multiple parameters into a single evaluation is a significant limitation, especially in situations where variables may influence each other.

Comparison Results

The comparison results indicate that the fuzzy system offers a more detailed and accurate assessment of display conformity. While traditional methods have the merit of being well-established and widely accepted, the fuzzy system demonstrates superior capability in handling the complexity and variability inherent in conformity testing. This superiority is particularly evident in how the fuzzy system captures and integrates multiple parameters, offering a more holistic and less subjective view of the displays' quality.

Simulations Performed

Three sets of input values were chosen to cover different combinations of input variables, providing a good diversity of scenarios for analyzing the results obtained with the fuzzy system.

Simulation 1

Values entered into the system and the output value after fuzzy inference.

Table no 1: Values entered into the system and the output value after fuzzy inference.

Variable Type	Variable	Numerical Value	Linguistic Value
Input	QSD	30	Poor
Input	Clarity	50	Fair
Input	Funcionality	70	Good
Output	Quality	12.66667	Poor

Source: Authors, (2024).

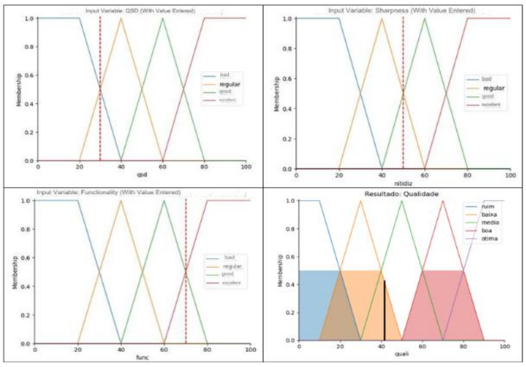

Figure 13: Input Variable QSD (17A), Clarity (17B), Functionality (17C), and Quality (17D).
Source: Authors, (2024).

The graphs in Figure 13 show the membership functions for each input variable and the output variable. The numerical value of each input was correctly mapped to its corresponding linguistic value, indicating that the fuzzy system correctly identified the display quality as "poor" based on the provided inputs.

The final quality output (12.66667) is low, which is expected given that the QSD was classified as "poor," even with "good" functionality.

This result reflects how the fuzzy system processes multiple factors to reach a conclusion about display quality. The main impact came from the low QSD, which significantly reduced the final quality, even with "fair" clarity and "good" functionality.

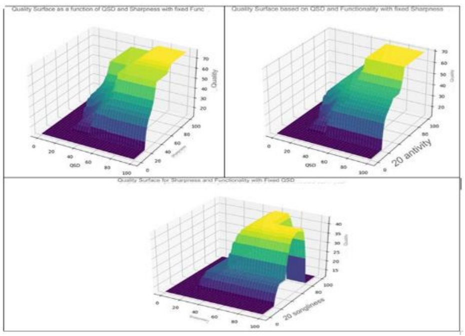

Figure 14: Quality Surface as a Function of QSD and Clarity (14A), Quality Surface as a Function of QSD and Functionality (14B), and Quality Surface as a Function of Clarity and Functionality (14C).
Source: Authors, (2024).

The graphs in Figure 14 illustrate how quality varies based on different combinations of QSD, Clarity, and Functionality. In Figure 14A, quality improves as both QSD and Clarity increase, with low values of both leading to poor quality. Figure 14B shows a similar pattern, where increases in QSD and Functionality result in better quality. In Figure 14C, Clarity and Functionality both positively impact quality, with the highest quality achieved when both variables are high. Across all graphs, high values of the variables lead to better quality outcomes.

General Considerations:

- Common Trends: In all graphs, increasing the input variable values leads to an improvement in quality, visualized by the surface rising toward the yellow peak.
- Impact of Each Variable: Each graph isolates two variables to highlight their influence on quality, demonstrating that all factors (QSD, Clarity, Functionality) contribute significantly to the final quality of the display. The behavior of the surfaces confirms that improvements in any of these variables can partially compensate for deficiencies in others, but the ideal is a combination of high values across all of them.

Simulation 2

Values entered into the system and the output value after fuzzy inference.

Table no 2: Values entered into the system and the output value after fuzzy inference.

Variable Type	Variable	Numerical Value	Linguistic Value
Input	QSD	80	Excellent
Input	Clarity	20	Poor
Input	Funcionality	40	Fair
Output	Quality	89.16667	Excellentr

Source: Authors, (2024).

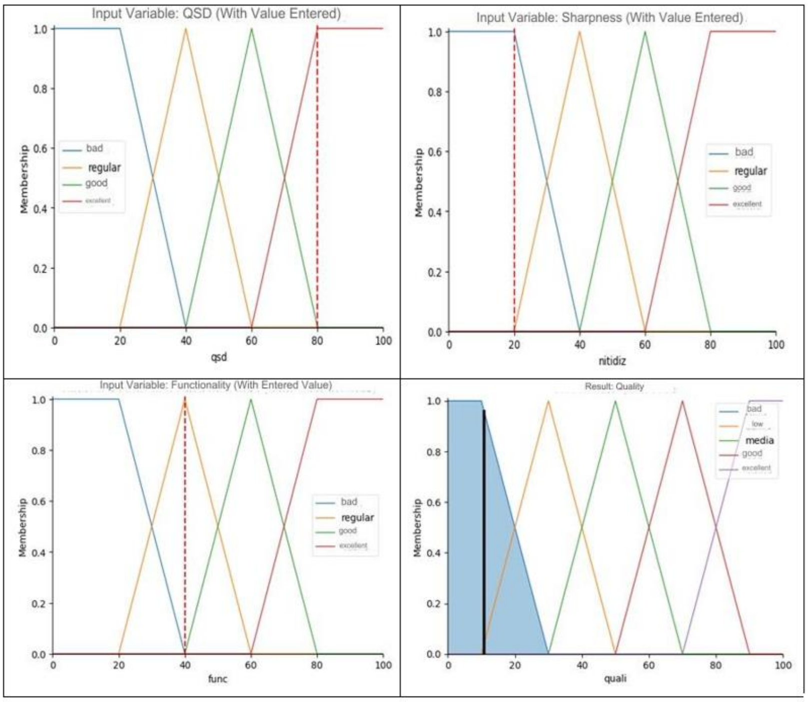

Figure 15: Input Variable QSD (17A), Clarity (17B), Functionality (17C), and Quality (17D).
Source: Authors, (2024).

In this simulation, the values entered into the fuzzy system were: QSD of 80 (classified as "excellent"), Clarity of 20 (classified as "poor"), and Functionality of 40 (classified as "fair"). Despite Clarity being classified as "poor," the high QSD value and "fair" Functionality significantly influenced the final result. The system output was a Quality of 89.16667, classified as "excellent." This demonstrates that in the fuzzy system, the strong contribution of an "excellent" QSD compensated for the low Clarity, resulting in a very high overall quality. The output graph shows a clear activation in the "excellent" region, confirming the final high-quality classification for the evaluated display.

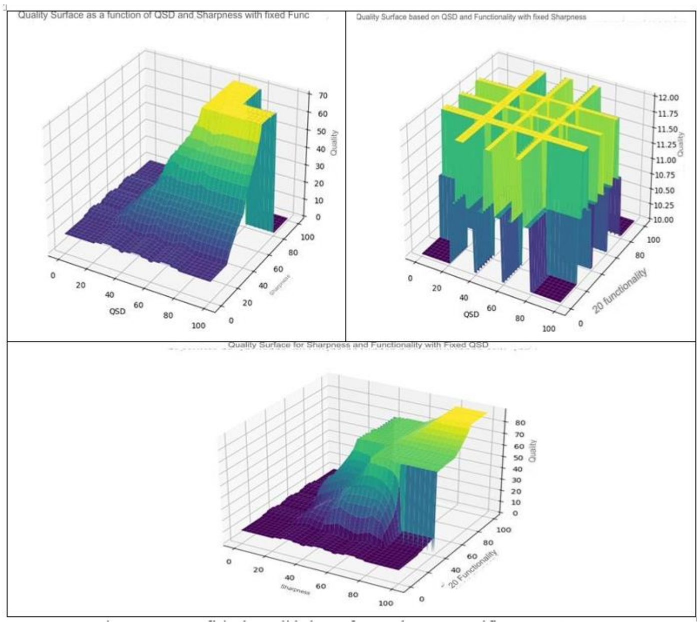

Figure 16: Quality Surface as a Function of QSD and Clarity (16A), Quality Surface as a Function of QSD and Functionality (16B), and Quality Surface as a Function of Clarity and Functionality (16C). Source: Authors, (2024).

The graphs in Figure 16 illustrate how quality varies based on different combinations of QSD, Clarity, and Functionality. In Figure 16A, quality improves significantly as both QSD and Clarity increase, with low levels of both leading to poor quality and high values resulting in peak quality. Figure 16B shows that quality reaches high values in specific regions where both QSD and Functionality are high, though the relationship between these variables is sensitive and requires careful management. In Figure 16C, increasing Clarity and Functionality continuously improves quality, even when QSD is kept constant, highlighting the strong influence of these parameters on display quality.

General Considerations:

- Quality Patterns: All the graphs show that quality is sensitive to the interactions between variables. The right-hand graph reveals greater complexity in the relationship between QSD and Functionality, while the other graphs show a more linear and predictable increase in quality as the variables improve.
- Impact of Variables: The surfaces demonstrate that all variables—QSD, Clarity, and Functionality—are critical in determining the final quality. However, the interaction between QSD and Functionality, with fixed Clarity, can result in significant variations in quality, requiring careful analysis.

Simulation 3

Values entered into the system and the output value after fuzzy inference.

Table no 3: Values entered into the system and the output value after fuzzy inference.

Variable Type	Variable	Numerical Value	Linguistic Value
Input	QSD	55	Good
Input	Clarity	85	Excellent
Input	Funcionality	90	Excellent
Output	Quality	70	Goodr

Source: Authors, (2024).

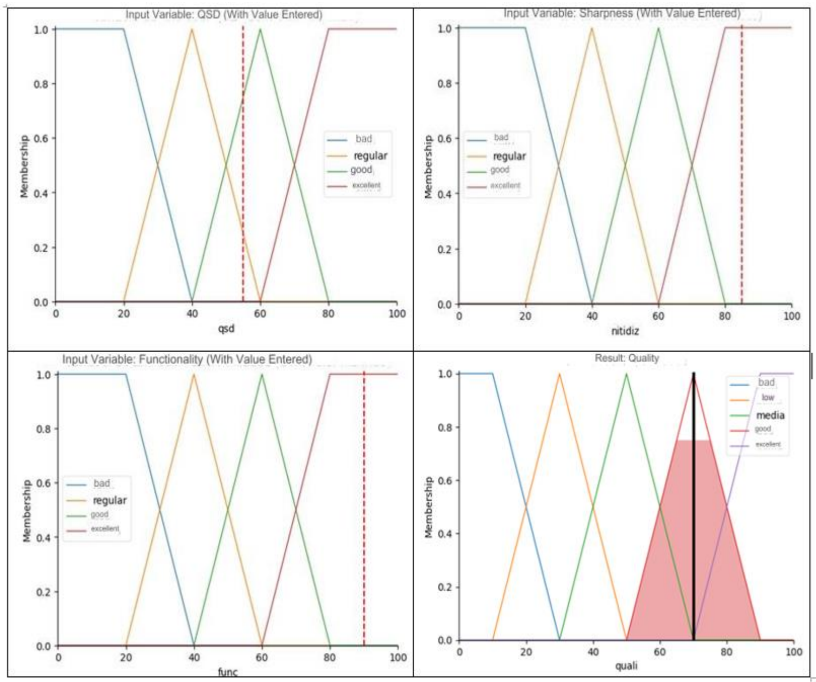

Figure 17: Input Variable QSD (17A), Clarity (17B), Functionality (17C), and Quality (17D). Source: Authors, (2024).

In this simulation, the input values provided to the fuzzy system were: QSD of 55 (classified as "good"), Clarity of 85 (classified as "excellent"), and Functionality of 90 (classified as "excellent"). The fuzzy system processed these values and produced a Quality output of 70, classified as "good." The graphs show how the membership functions for each input variable were activated, influencing the final inference. The "good" Quality output reflects the positive impact of the high ratings in Clarity and Functionality, along with a "good" QSD, resulting in a favorable evaluation of the display. The "good" output area is strongly activated, indicating that the display meets the established quality criteria well, though there is room for further improvement to reach "excellent" status.

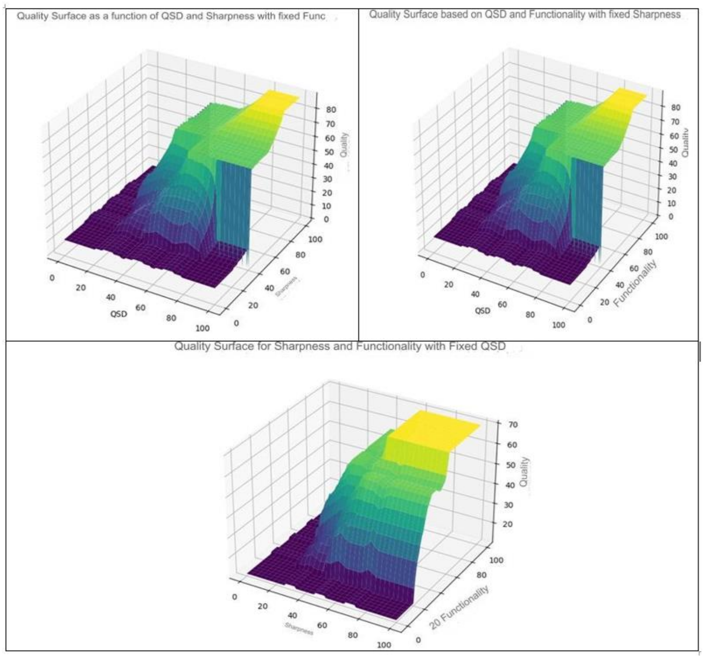

Figure 18: Quality Surface as a Function of QSD and Clarity (18A), Quality Surface as a Function of QSD and Functionality (18B), and Quality Surface as a Function of Clarity and Functionality with Fixed QSD (18C).
Source: Authors, (2024).

The graphs in Figure 18 illustrate how quality varies based on different combinations of QSD, Clarity, and Functionality. In Figure 18A, quality improves as both QSD and Clarity increase, with low values resulting in poor quality and high values leading to peak quality. Figure 18B shows that quality rises significantly when both QSD and Functionality are high, emphasizing the importance of maintaining high levels of these two variables to ensure superior display quality, even when Clarity is constant. In Figure 18C, increasing Clarity and Functionality progressively improves quality, even with a fixed QSD, highlighting the importance of these parameters in achieving high quality.

General Considerations:

- Impact of Variables: All graphs demonstrate that QSD, Clarity, and Functionality each have a significant impact on display quality. To achieve high quality, it is crucial to optimize all these variables.
- Interaction Between Variables: The transition of the surfaces shows how the variables interact to affect final quality, with improvements in any of them (especially in combination with others) resulting in superior quality.

Precision and Efficiency of the Fuzzy System, Evaluation of Accuracy Under Real Operating Conditions, Operational Benefits, Time and Cost Reduction, and Improvement in Product Quality.

In this section, we analyze the precision and efficiency of the fuzzy system in the conformity assessment of displays, based on three simulations. Precision refers to the system's ability to produce results that meet quality standards, while efficiency relates to speed and cost-effectiveness compared to traditional methods. The simulations were essential for validating the system's performance under different operational conditions. Each simulation used varied combinations of values for QSD, Clarity, and Functionality, reflecting conditions found in displays. The fuzzy system demonstrated high accuracy in classifying display quality, even with variations in operating conditions, highlighting its robustness in handling uncertainties. The operational benefits were also evident. The fuzzy system proved to be flexible, handling different inputs without the need for manual adjustments, eliminating subjective visual inspections. It efficiently integrated multiple variables, providing a more detailed and comprehensive assessment of displays, while also reducing operators' workload. The system also brought significant time and cost savings. The automation of the process allowed for parallel and real-time evaluations, speeding up the production cycle and reducing operational costs, especially in labor. Moreover, the detailed analysis enabled early correction of issues, improving the quality of the displays and ensuring they consistently meet established standards, increasing customer satisfaction and strengthening the company's competitive position in the market.

Critical Analysis of Results and Strengths of the Proposed System

In this section, we present a critical analysis of the results obtained through the simulations conducted with the fuzzy system. This analysis aims to identify both the strengths and limitations of the system, as well as suggest areas for future improvements. Critical evaluation is essential to fully understand the system's performance and guide possible enhancements. The fuzzy system demonstrated several strengths throughout the simulations, standing out as an effective tool for the conformity assessment of displays. The main strengths include:

1. Flexibility and Adaptation: The system proved to be highly flexible, capable of adapting to different operating conditions without the need for significant manual adjustments. This was evident in the simulations, where the system was able to handle various combinations of input variables, providing consistent and accurate results.
2. Robustness in Quality Inference: The simulations revealed that the fuzzy system is robust in quality inference, even when subjected to adverse conditions. The system's ability to integrate multiple variables and handle uncertainties contributed to a more reliable assessment of display quality.
3. Reduction of Subjectivity: The system eliminated the need for subjective evaluations, traditionally performed by human operators. This not only improved the consistency of results but also reduced the possibility of human error, making the evaluation process more objective and reliable.
4. Operational Efficiency: The automation provided by the fuzzy system resulted in significant operational efficiency. The ability to process large volumes of data quickly and accurately enabled faster and more cost-effective evaluations, without compromising the quality of the results.

Limitations of the Study and Areas for Improvement

Despite the strengths, the fuzzy system presented some limitations during the simulations:

1. Sensitivity to Input Configurations: The system proved to be sensitive to the settings of the membership functions and fuzzy rules. Small changes in these settings can generate variations in the results, requiring careful calibration to ensure accuracy.

2. Scalability: Scalability of the system can be a challenge, especially in scenarios with many input variables or large-scale operations, increasing the need for computational power and processing time.
3. Quality of Input Data: The system's accuracy is directly dependent on data quality. Inconsistent or inaccurate data can impair the results, making it essential to use high-quality data.

Areas for Improvement:

1. Refinement of Fuzzy Rules: Continuous adjustments to the rules and membership functions can improve the system's accuracy.
2. Integration with Artificial Intelligence: The use of machine learning to automatically adjust the rules can increase the system's adaptability.
3. Testing in Diverse Environments: Expanding the tests to include a wider variety of operational conditions can help identify new areas for improvement.

V. Conclusion

This research developed and analyzed a fuzzy system for the conformity assessment of displays, in accordance with Portaria 221 of May 23, 2022. The study demonstrated that the fuzzy system is effective in dealing with the complexity and uncertainties of the process, offering a more precise and less subjective analysis compared to traditional methods. Simulations showed that the system can integrate variables such as QSD, Clarity, and Functionality, generating robust and reliable evaluations, while also adapting to different operational conditions, reducing evaluation time and costs. The results indicated significant improvements in the final quality of the displays, contributing to their consistency and reliability. However, some limitations were identified, such as sensitivity to input configurations and dependence on data quality, which need to be addressed. Future refinements include automatic adjustments with machine learning and testing in broader environments. In summary, the fuzzy system represents an important advancement in conformity assessment, with potential application in other industrial contexts that require precision, efficiency, and adaptability.

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