Journal of Engineering and Technology for Industrial Applications

ITEGAM-JETIA

ISSN ONLINE: 2447-0228

Manaus, v.12 n.57, p. 465-482. January/February, 2026.
DOI: https://doi.org/10.5935/jetia. v12i57.3098

RESEARCH ARTICLE OPEN ACCESS

A SYSTEM FOR DETECTING NON-CONFORMITIES IN INDUSTRIAL MANUFACTURING PROCESSES IN THE AUTOMOTIVE SECTOR USING FUZZY LOGIC

Roberto Ferreira de Lima[1]*, Helder Kiyoshi Miyagawa[2] and Rivanildo Duarte Almeida[3]

[1]Federal Institute of Amazonas – IFAM. Manaus – Amazonas, Brazil
[2]The Institute of Technology of the Federal University of Pará (PPGEP-ITEC-UFPA). Avenida Augusto Correa, 01. Belém, Pará – Brazil.
[3]Instituto de Tecnologia e Educação Galileo da Amazônia. Manaus – ITEGAM. Manaus, Amazonas - Brasil

[1]https://orcid.org/0009-0000-3771-8807, [2]http://orcid.org/ 0000-0001-9346-4696, [3]http://orcid.org/ 0000-0001-9454-2393

Email: *roberto.lima@ifam.edu.br, helderkm@ufpa.br, duartiot@gmail.com

ARTICLE INFO

Article History
Received: December 10, 2025
Revised: December 20, 2025
Accepted: January 1, 2026
Published: January 31, 2026

Keywords:
Fuzzy Logic,
Non-Conformities,
PPM,
Process Control, Industry.

ABSTRACT

Increasing industrial competitiveness demands stable and continuously monitored production processes. This work presents a Non-Conformance Detection System based on Fuzzy Logic, applied to quality control in manufacturing. Using the PPM (Parts Per Million) indicator, the system evaluates process performance and identifies the risk level of non-conformities. Scenarios with PPM between 20 and 11,000 were analyzed, covering conditions from ideal to critical situations. The fuzzy model, composed of triangular and trapezoidal membership functions, expert rules, and centroid defuzzification, showed smooth transitions and greater sensitivity compared to deterministic methods. The results confirm its practical applicability in the automotive industry, assisting in risk identification, rapid decision-making, and continuous process improvement.

I. INTRODUCTION

Quality control in industrial manufacturing systems has been a recurring theme since the advent of mass production in the Industrial Revolution, when the standardization of processes and products became essential to meet the growing market demand. In recent decades, with globalization, Industry 4.0, and the increased complexity of production processes, fault detection and non-conformity prevention have become critical factors for the competitiveness and sustainability of organizations [1]. The problem under study is directly related to the non-detection of non-conformities in industrial manufacturing processes, which can lead to rework, waste of resources, increased costs, and, above all, compromised customer satisfaction. The literature points out that the absence of effective monitoring mechanisms can lead to the repetition of errors and the loss of reliability of the production system [2]. The current demands of Industry 4.0 require increasingly precise, flexible, and sustainable processes. The absence of effective fault detection mechanisms compromises productivity and quality, negatively impacting the competitiveness of companies. In this sense, the adoption of techniques based on Artificial Intelligence and Fuzzy Logic is highly aligned with the needs of the sector, as it allows for the handling of uncertainties and variabilities common in industrial processes. In this context, several methodologies and theories have been used to minimize such problems. Among the most relevant approaches are statistical process control techniques, Lean Six Sigma methodologies, and, more recently, intelligent systems based on computational intelligence [3], [4]. Among these techniques, fuzzy logic stands out for its ability to handle imprecise and uncertain information, offering a model closer to human decision-making. The objective of this dissertation is to develop a system for detecting nonconformities in industrial manufacturing processes, based on fuzzy logic to integrate process signals and quality criteria, reducing the non-detection rate and the response time of inspections.

II. INDUSTRIAL MANUFACTURING SYSTEM

Production systems are defined as socio-technical systems responsible for transforming inputs into products through structured and organized processes [5]. Production involves interrelated technical and human functions, based on systems theory and cybernetics, considering human, social, technical, and organizational subsystems integrated into the environment [6]. Value creation requires organized processes and operations such as machining, assembly, testing, and transportation, performed by people and equipment [7]. With the development of the Toyota Production System, a holistic approach to Lean Production Systems (LPS) emerged, combining strategic principles, operational methods, and tools aimed at eliminating waste and continuous improvement [5]. These systems guide all processes towards the customer and seek the systematic reduction of activities that do not add value [8]. Manufacturing has evolved through four industrial revolutions: mechanization; adoption of new energy sources and combustion engines; automation with electronics and computing; and, more recently, Industry 4.0, marked by cyber-physical systems, IoT, cloud computing, and cognitive resources [9]. Companies aligned with Industry 4.0 are considered "smart," with flexible, precise, digitized, and logistically integrated systems[10]. Digital transformation occurs in four stages—digitization, virtualization, connectivity, and autonomization—leading to new scenarios of human-machine cooperation in smart factories [5].

II.1 INTELLIGENT MANUFACTURING SYSTEM

Intelligent manufacturing is an advanced production model that uses information technologies, sensors, data analysis, and intelligent systems to optimize all stages of a product's life cycle, from design to final integration. Its goal is to increase the efficiency, quality, and competitiveness of companies in dynamic markets [11]. The advancement of automation, driven by the evolution of machines and computers, has led to the emergence of concepts such as flexible cells, computer-integrated manufacturing, and, finally, intelligent manufacturing. Since the 1990s, international programs—especially in Japan, the USA, and Europe—have driven research and cooperation to develop this new productive paradigma [12]. Smart manufacturing integrates communication technologies, data science, systems engineering, and automation to connect people, machines, and processes. This integration occurs through detection, interconnection, analysis, learning, and autonomous decision-making, allowing the optimization of three central elements (people, management, and technology) and five fundamental flows (information, logistics, capital, knowledge, and service) [13]. According to [14], smart manufacturing relies heavily on data, sensors, and advanced analytics, integrating Operational Technology (OT) and Information Technology (IT). According to [12] organizes the concept into six fundamental pillars:

1) Manufacturing technologies and processes – including additive manufacturing, new materials, hybrid processes, and smarter robots.
2) Materials – use of new materials, biomaterials, and resource recovery at the end of the life cycle.
3) Data – massive collection and advanced analysis, basis for predictive models and knowledge preservation.
4) Predictive engineering – creation of digital models to predict future behaviors and support strategic decisions.
5) Sustainability – development of sustainable products and processes, valuing remanufacturing, reuse, and impact reduction.
6) Resource sharing and networking – cooperation between companies to share equipment, software, and knowledge.

Artificial Intelligence is essential in SMI, enabling real-time monitoring, automated decision-making, intelligent scheduling, and increasingly advanced human-machine integration [11]. In Industry 4.0, SMI uses service-oriented architecture (SOA) and platforms connected via the Internet, forming an integrated ecosystem where technical, managerial, and organizational processes operate collaboratively, flexibly, and reconfigurably.

II.1.1 Sistema de Manufatura Flexivél

A flexible manufacturing system (FMS) can be defined as a computer-controlled production system capable of processing a variety of part types, characterized by the ability of production to be adapted to the production of multiple parts, small or medium batches, and there are several flexible manufacturing systems categorized according to the target process being improved. These categories are addressed below [9]:

a) Variant flexibility: Ability to manufacture or assemble more variants of a product. (Product flexibility)
b) Quantity flexibility: Ability to adapt the production system to fluctuating volumes.
c) Technology flexibility: The ability of the manufacturing and assembly system to be used for a range of technologies.
d) Successor flexibility: Ability to use equipment or parts also for future products.

II.2 QUALITY IN THE INDUSTRIAL MANUFACTURING SYSTEM

Quality in industrial production involves the ability of a production system to generate goods that meet or exceed technical standards, requirements, and customer expectations, from conception to delivery [15] and [16]. This concept encompasses conformity, reliability, and continuous improvement throughout the production process.

II.2.1 Quality Management System (QMS)

The Quality Management System (QMS) promotes the standardization of processes with a focus on continuous improvement and customer value [15]. Implementing a QMS means documenting procedures, monitoring performance, and correcting deviations systematically, ensuring that all products meet the established requirements.

II.2.2 Evolution towards Industry 4.0 and Quality 4.0

The transition to Industry 4.0 has transformed quality approaches: integrated systems and connectivity have become fundamental, characterizing what is now called Quality 4.0 [16]. Technologies such as automation, intelligent sensors, and real-time data analysis allow for greater efficiency and reliability [17]. Digital integration enables preventive actions and data-driven decisions, increasing the competitiveness of the industry.

II.2.3 Quality Tools and ISO 9001

The implementation of ISO 9001:2015 requires the establishment of an effective QMS, capable of documenting processes, reducing failures, and ensuring conformity [18]. In the Brazilian context, the application of tools such as PDCA, 5S, and statistical methods proves essential to reduce costs, rework, and improve customer satisfaction [19].

II.2.4 Quality Tools

Quality tools are essential instruments for monitoring, analyzing, and improving processes in industrial environments. Below are the main ones:

a) Pareto Diagram

The Pareto Diagram organizes defects in descending order of frequency, allowing the identification of the most relevant causes according to the Pareto principle, which indicates that a few factors are responsible for the majority of problems. Thus, prioritizing the main causes allows for a greater impact on process improvement [20]. Diagram is shown in the figure 1.

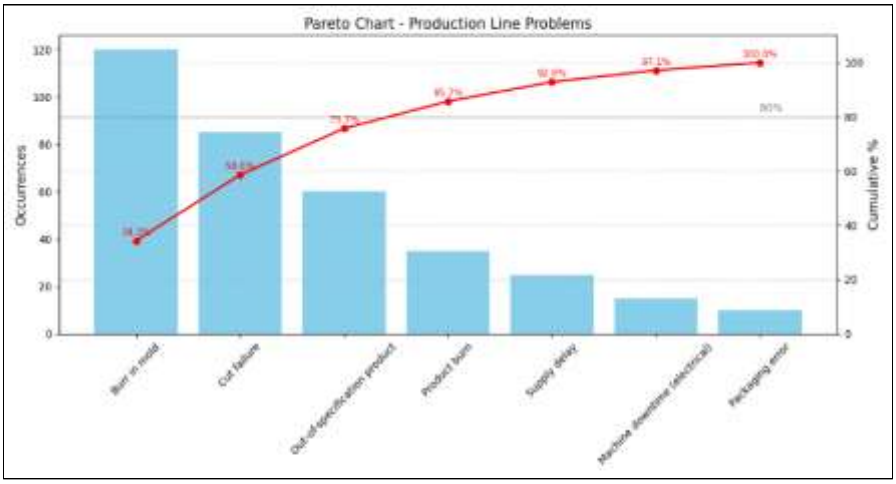

Figure 1: Pareto Diagram.
Source: Authors, (2026).

b) Control Chart

The Control Chart is used to monitor the stability of a process over time. It presents upper and lower control limits, as well as a centerline. When the points remain within these limits, the process is considered stable; values outside the limits indicate a need for intervention [21]. The control chart is shown in the figure 2.

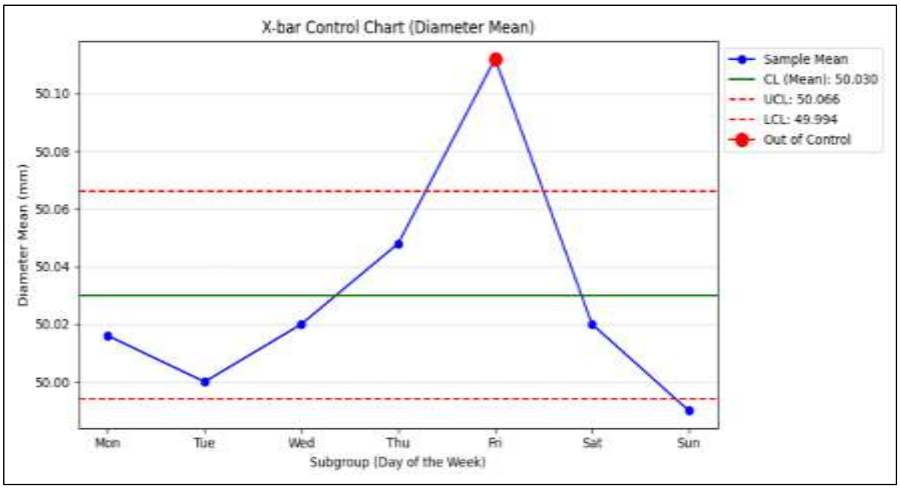

Figure 2: Iron bar production.
Source: Authors, (2026).

c) Ishikawa Diagram

The Ishikawa Diagram, or cause-and-effect diagram, assists in the systematic identification of the possible causes of a problem, organizing them into categories such as methods, machines, manpower, materials, measurements, and environment. This facilitates understanding the origins of a nonconformity [22]. The Ishikawa Diagram is shown in the figure 3.

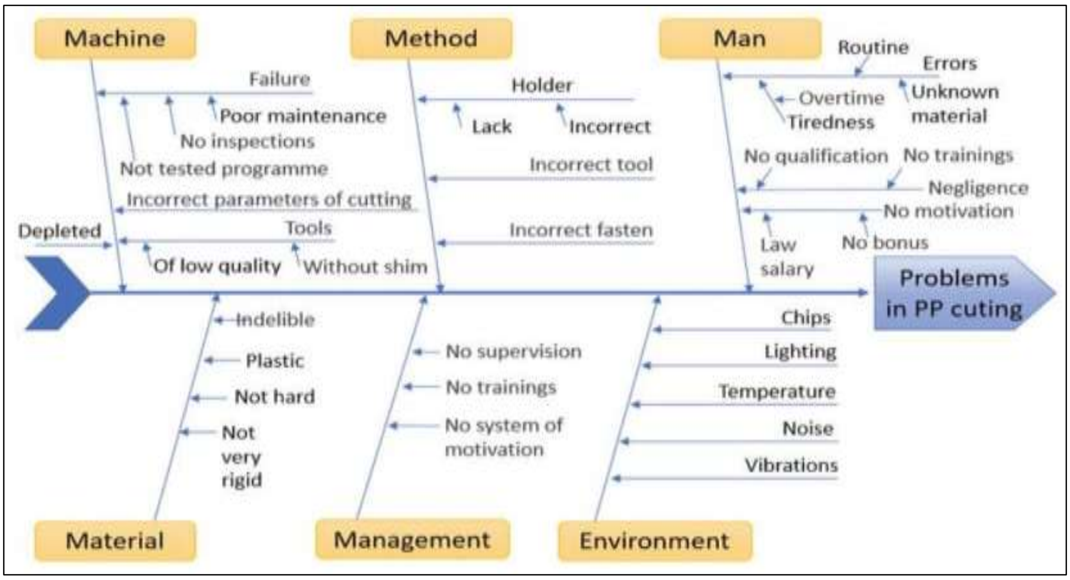

Figure 3: Ishikawa diagram for polypropylene cutting.
Fonte: [22].

d) Flowchart

Finally, the flowchart graphically represents the steps of a process, allowing you to visualize the logical sequence of activities, identify critical points, and support operational improvements. This tool is fundamental for standardizing procedures and understanding the production flow clearly. The figure below shows an example of a flowchart.

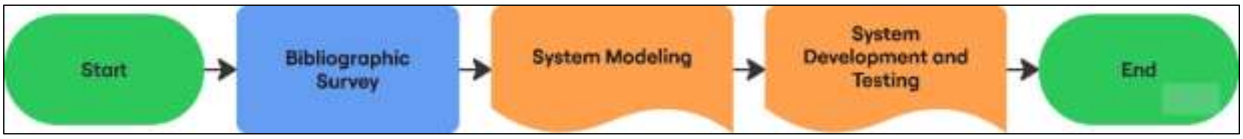

Figure 4: Methodological flow.
Source: Authors, (2026).

II.3 TÉCNICAS DE INTELIGÊNCIA ARTIFICIAL

This topic will cover the most commonly used techniques in industrial processes. Fuzzy Logic, Simple Linear Regression, Decision Trees, and Artificial Neural Networks are widely used in intelligent systems for decision support, process control, and modeling of industrial phenomena.

II.3.1 Fuzzy Logic

Fuzzy Logic allows working with imprecision and subjectivity, representing variables by degrees of membership between 0 and 1. Unlike traditional Boolean logic, it allows an element to partially belong to several sets. This approach is applied in different stages of manufacturing, such as temperature control, defect reduction, and injection parameter adjustment. The operation of a fuzzy system involves three fundamental steps: fuzzification, which converts numerical values into linguistic terms; inference, which applies "If-Then" rules defined by experts; and defuzzification, which transforms the fuzzy result into a precise numerical value. The most common membership functions are triangular, trapezoidal, and Gaussian, with the triangular function being the most used due to its simplicity and computational efficiency [23]. The linguistic variable is a variable whose elements are names of fuzzy sets. Its main function is to provide a way to characterize the complexity of phenomena and the lack of clarity. This allows the treatment of more complex systems to be analyzed using traditional mathematical terms [24]. The most common forms of fuzzy membership functions are: triangular fuzzy, trapezoidal fuzzy, and Gaussian fuzzy. See figures 5, 6, and 7, respectively.

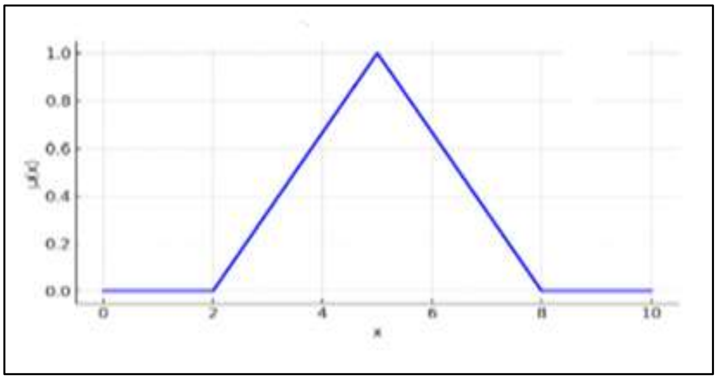

Figure 5: Fuzzy Triangular Membership Function.
Source: Authors, (2026).

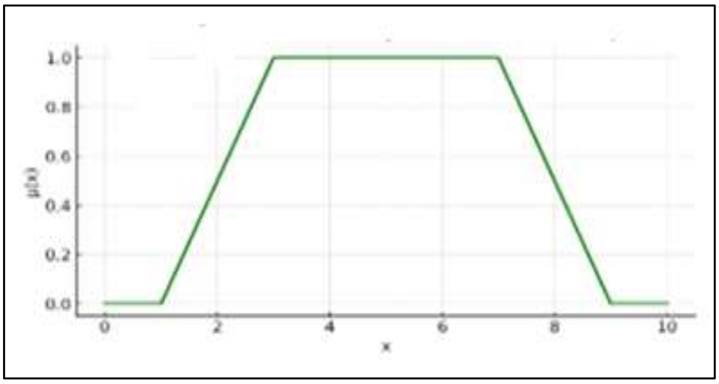

Figure 6: Fuzzy Trapezoidal Membership Function.
Source: Authors, (2026).

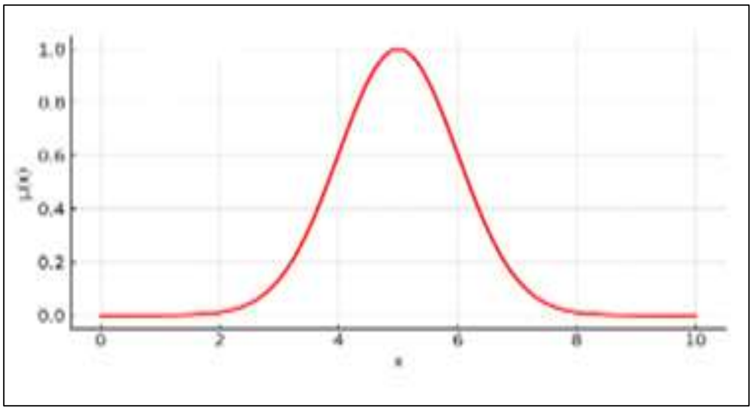

Figure 7: Fuzzy Gaussian Membership Function.
Source: Authors, (2026).

II.3.2 Simple Linear Regression

Simple linear regression models the relationship between two variables one explanatory and one response using a straight line defined by the intercept (α) and slope (β) parameters. This model allows for predicting future behaviors and identifying trends, being widely applied in production processes, demand forecasting, costs, or operational performance. The error term (ei) represents the random variation not explained by the equation. Despite its simplicity, this technique is effective when there is a linear correlation between the variables and provides a clear interpretation of how changes in x affect y. Figure 8 shows the graph of a linear function [25].

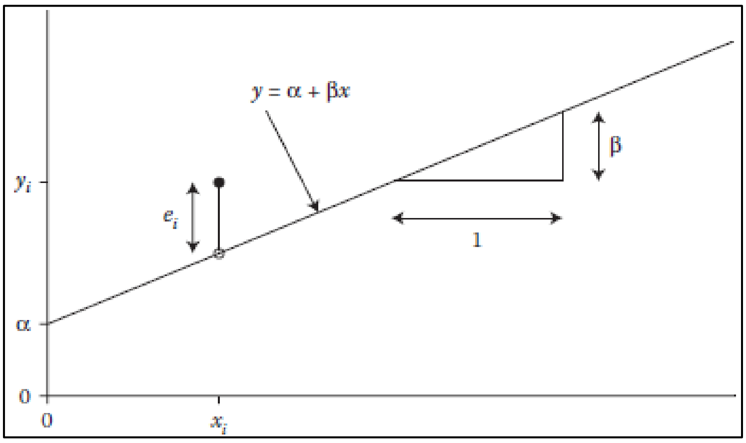

Figure 8: Simple linear regression model.
Source: [25].

II.3.3 Decision Tree

A Decision Tree is a supervised learning method used for classification or regression. It functions like a flowchart, where each node represents a decision test, each branch is a result, and each leaf indicates a class or prediction. Among its main advantages are ease of interpretation, low computational cost, and the ability to handle imperfect or redundant data. The construction of the tree involves the recursive partitioning of data until stopping criteria are met, followed by a pruning step, which avoids overfitting and improves the generalization of the model. This type of technique is widely used in medical applications, risk analysis, quality analysis, and industrial decision-making. Figure 9 depicts an example of a decision tree designed for classification, obtained by running the J48 (C4.5) algorithm applied to the Weka "contact lenses" dataset [26].

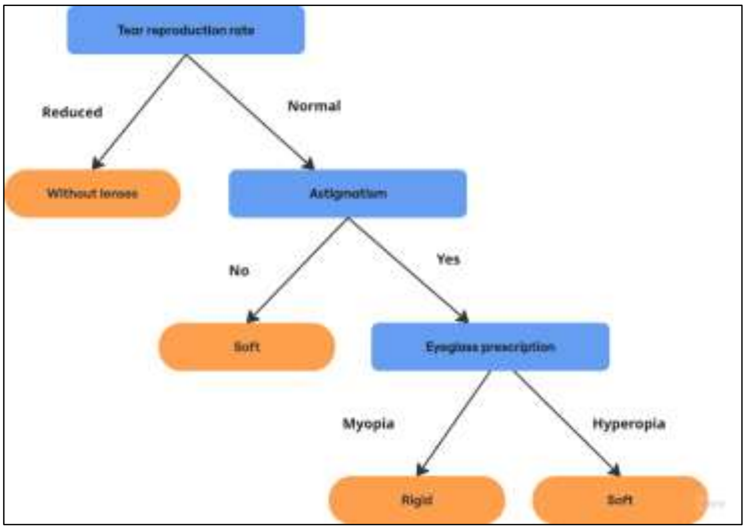

Figure 9: An example of a decision tree.
Source: Authors, (2026).

II.3.4 Artificial Neural Networks

Artificial Neural Networks are models inspired by the functioning of the human brain and are capable of learning complex patterns. They are formed by layers of interconnected artificial neurons that process information by multiplying inputs by weights and applying activation functions. The learning process occurs through backpropagation of error, adjusting the weights to improve accuracy. ANNs are especially effective in problems that require pattern recognition, time series prediction, complex classification, and decision-making based on large volumes of data. Due to their flexibility, they are widely used in computer vision, industrial automation, intelligent control, and predictive systems [27]. Figure 10 shows the neuron function.

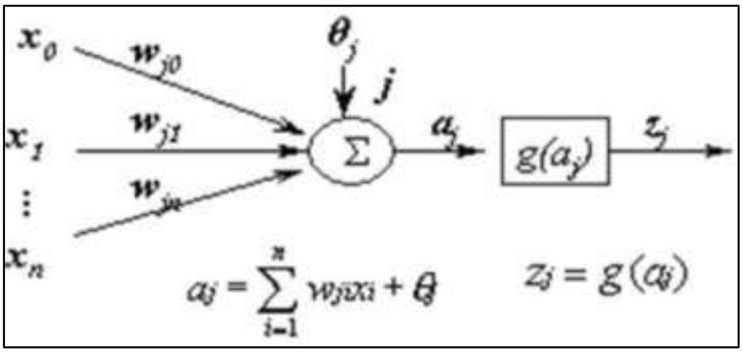

Figure 10: Neuron function.
Source: [27].

III. MATERIALS AND METHODS

For the development of the proposed system, the following computational tools and resources were used:

a) Programming language: Python;
b) Development environment: Visual Studio Code (VS Code);
c) Python libraries: NumPy, Matplotlib, and scikit-fuzzy (for fuzzy modeling and inference);
d) Auxiliary software: Miro (for creating flowcharts and modeling diagrams);
e) Simulation environment: Windows 11 operating system.

The use of the Python language is justified by its wide application in scientific research and the availability of libraries specialized in fuzzy logic and data analysis, which facilitates the implementation of intelligent systems and the handling of large volumes of information. The use of the Visual Studio Code (VS Code) IDE is justified because it is the most widely used IDE for software and embedded projects in the world. The methodology proposed in this dissertation is based on applied and experimental research, since its objective is the development and validation of a computational system aimed at detecting nonconformities in industrial manufacturing processes. The applied nature of the study is justified by seeking a solution to a real problem in the industrial area, which is the early identification of failures in the production process through monitoring the Parts Per Million (PPM) indicator. In addition, the research has an experimental and exploratory character, as it involves the conception, implementation, and evaluation of a computational prototype based on fuzzy logic, developed to simulate typical conditions of an industrial environment. The experimental approach allows testing the system's behavior in the face of different input scenarios, making it possible to analyze its inference and response capacity in nonconformity situations. The technique used in the methodology of this dissertation is the computational intelligence technique Fuzzy Logic.

Fuzzy logic is a theory proposed by Lofti Zadeh in 1965, which is based on sets that have degrees of membership and are encoded in unit intervals; that is, they have a membership function whose values are compatible with these sets in degrees of membership from 0 to 1, differing from classical logic theory, since the data are complex, that is, a piece of data has membership in a set, "all or nothing", which is based on sets whose inclusion is resolved in degrees of "true or false", 0 or 1, all or nothing; unlike fuzzy logic, where a piece of data is part of a set to a certain extent, to a higher degree (0), sometimes to a medium degree (0.5) or can increase or decrease its vagueness, and may even be empty [28].

III.1 RESEARCH STAGES

The development of this dissertation was structured in three main stages. These are:

a) Bibliographic survey

This stage consisted of conducting theoretical and documentary research on the main concepts related to industrial quality, process control, performance indicators (especially the Parts Per Million KPI), as well as the fundamentals of fuzzy logic and its applications in decision support systems. Academic sources, scientific articles, dissertations, and books addressing the topic were consulted in order to support the conceptual and technical development of the proposed system.

b) Fuzzy system modeling

In this phase, the input and output parameters of the fuzzy system were defined, based on variables relevant to the evaluation of the quality of the production process. The modeling involved the elaboration of membership functions, the definition of fuzzy rules (e.g., If cost LOW and benefit HIGH then cost-benefit HIGH), and the structuring of the inference mechanism, in order to approximately represent human reasoning in making decisions about the conformity or non-conformity of the process. The Miro software was used to design the flowcharts representing the system's operational logic and data flow, contributing to the visualization of the decision-making process.

c) System Development and Testing

After modeling, software was developed in Python, using the Visual Studio Code (VS Code) IDE, to implement the non-conformity detection and KPI monitoring system Parts Per Million (PPM). The program was structured to collect and process simulated production data, apply the fuzzy model, and return a monitoring graph of the indicator, allowing the user to identify failure trends and make corrective decisions more quickly. Computational simulation tests were performed, in which different data scenarios were entered into the system to evaluate its robustness, coherence of fuzzy inferences, and reliability of results. This step was essential to verify the adherence of the proposed model to the expected behavior in a real industrial environment.

Figure 11 shows the research steps represented in a methodological flow adopted to achieve the established objectives.

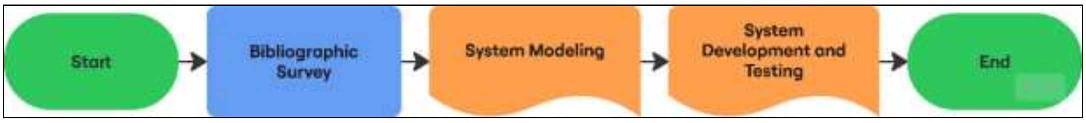

Figure 11: Methodological flow.
Source: Authors, (2026).

The system validation was performed in a simulated manner, using datasets representative of an industrial manufacturing process. The simulations allowed us to verify the consistency of the fuzzy system outputs in relation to the input conditions and to analyze the correlation between the KPI PPM (Parts Per Million) values and the compliance levels identified by the model. The results were evaluated based on performance criteria related to the accuracy in detecting non-conformities, the stability of the inferences, and the clarity of the information presented in the monitoring graph. This analysis made it possible to verify the viability of the system as a decision support tool in production processes.

III.2 FUZZY SYSTEM DEVELOPMENT

This topic presents all the steps used in the implementation of the fuzzy system based on Fuzzy Logic to monitor the Parts Per Million (PPM) indicator in manufacturing processes in the automotive supply chain. The objective is to transform numerical process data into an intelligent risk interpretation, capable of adaptively anticipating nonconformities. The introduction of this fuzzy system allows for the evaluation of quality levels even in imprecise scenarios or with natural process fluctuations, something that traditional methods cannot adequately represent.

III.2.1 General system architecture

The application was structured in a logical flow composed of four main steps:

a) Input: actual value of the PPM indicator collected in the industrial process.
b) Fuzzy processing: composed of fuzzification, rule base, and inference.
c) Defuzzification: transformation of the fuzzy result into a numerical index.
d) Output: Risk Index (0 to 100), indicating the degree of compliance of the process.

The system architecture can be represented as shown in figure 12.

Figure 12: System architecture flowchart.
Source: Authors, (2026).

III.2.2 Definition of the fuzzy input variable – PPM

The PPM indicator is widely used in industry to measure the number of defective parts in relation to the total produced. Table x abaixo presents the limits for PPM indicators according to the IATF 16949 standard.

Table 1: Limits for PPM indicators – IATF 16949 standard.

Level	PPM Range	Interpretation
Excellent	0 – 100 ppm	Very capable process
Good	100 – 500 ppm	Proper control
Acceptable	500 – 1.000 ppm	As expected, but with caution.
Warning	1.000 – 5.000 ppm	It requires investigations and corrective actions.
Bad	> 5.000	Process out of control.
Critic	>10.000	High risk – possible customer account suspension.

Source: Authors, (2026).

Based on this classification, six fuzzy sets were defined for the PPM:
Unit: parts per million (PPM). Universe considered: 0 20,000 PPM (sufficient to cover >10,000).

a) **Excellent:** 0 – 100 ppm (Very capable process)
b) **Good:** 100 – 500 ppm (Proper control)
c) **Acceptable:** 500 – 1.000 ppm (As expected, but with caution.)
d) **Warning:** 1.000 – 5.000 ppm (It requires investigations and corrective actions.)
e) **Bad** > 5.000 ppm (Process out of control)
f) **Critic:** > 10.000 ppm (High risk – possible customer account suspension)

Each set represents a region of the PPM space with smooth transitions between boundaries, a fundamental characteristic of fuzzy systems.

III.2.3 Membership functions of the PPM variable

The membership functions were defined to reflect industrial logic, using triangular and trapezoidal functions.

a) **Excellent:** — trapezoidal: (a=0, b=0, c=25, d=100) **-** High relevance in very low PPMs; decreases down to 100.
b) **Good:** — triangular: (100, 300, 500) **-** Peak at 300, base 100–500.
c) **Acceptable:**— triangular: (500, 750, 1000) **-** Peak at 750, base 500–1000.
d) **Warning:** — triangular: (1000, 3000, 5000) **-** Peak at, base 1000–5000.
e) **Bad** — triangular: (5000, 7500, 10000) **-** Peak at 7500, base 5000–100000.
f) **Critic:** — trapezoidal: (10000, 11000, 12000, 12000) **-** Starts to increase from 10k, becomes strong above 15k.

III.2.4 Fuzzy output variable – Risk index (0–100)

The output variable does not represent PPM values. It represents a fuzzy interpretation of the current process risk. For this reason, the output is defined on a universal scale of 0 to 100, widely used in risk analysis systems. Output universe: 0 …100 (0 = zero risk; 100 = maximum/critical risk). Fuzzy output sets (with triangular/trapezoidal shapes):

a) **Very Low** — tri (0, 10, 20)
b) **Low** — tri (10, 25, 40)
c) **Moderate** — tri (30, 50, 70)
d) **High** — tri (60, 75, 85)
e) **Very high** — tri (80, 90, 95)
f) **Critical** — trap (90, 95, 100, 100)

III.2.5 Construction of fuzzy rules

The rules were constructed based on a direct interpretation of the PPM classification table:

IF 0 ≤ PPM <= 100 It is **Excellent** → Risk Index Is **Very Low**
IF 100 ≤ PPM <= 500 It is **Good** → Risk Index Is **Low**
IF 500 ≤ PPM <= 1,000 It is **Acceptable** → Risk Index Is **Moderate**
IF 1,000 ≤ PPM <= 5,000 It is **Alert** → Risk Index Is **High**
IF PPM >= 5,000 It is **Bad** → Risk Index Is **Very High**
IF PPM >= 10,000 It is **Critical** → Risk Index Is **Critical**

These rules ensure that the system responds gradually, avoiding abrupt jumps in the ranking.

III.2.6 Fuzzy Inference Process

The Mamdani inference method was used, a method traditionally employed in industrial applications due to its robustness and interpretability.

AND operator used: minimum (typical in Mamdani).
Implication: clipping of the consequent's moiety by the degree of activation (minimum).
Output Aggregation: maximum (take union / sup) between the clipped sets.
Flow for a specific PPM:

a) Calculate the PPM membership level in each input set.
b) For each rule, obtain the activation level = membership of the antecedent.
c) Clip the MF of the corresponding output set at the activation level.
d) Aggregate (max) all clipped output MFs to obtain the aggregated fuzzy MF of the risk index.

III.2.7 Defuzzification

To transform the output fuzzy set into a numerical value, the following method was used:

Centroid – Center of Gravity (COG)
This method calculates the "center of mass" of the resulting area, providing a final risk index between 0 and 100.

IV. RESULTS AND DISCUSSIONS

This topic presents the results obtained from the implementation and testing of the fuzzy system developed for detecting nonconformities in industrial manufacturing lines. The results were organized, interpreted, and compared with industrial quality control practices, especially the use of metrics such as PPM (Parts Per Million), widely used for monitoring process performance. Obtaining real PPM data for the project was not possible due to the difficulty of accessing industrial information, which is usually confidential. To enable testing and maintain methodological consistency, simulated data were used, realistically constructed to represent different process situations. This approach allowed the system to be validated and its operation demonstrated, making the use of simulated data a necessary and justifiable alternative. The simulations were performed using PPM values obtained or defined in representative industry scenarios: 20, 150, 400, 800, 2500, 6000, and 11000. Each value was processed by the fuzzy system, resulting in an aggregate risk level and indicating the probability of the process exhibiting compliance, intermediate risk, or severe non-compliance.

The tests were conducted with the objective of verifying the fuzzy system's ability to:

a) Interpret PPM levels reported by the production process;
b) Add expert knowledge through fuzzy rules;
c) Automatically classify the degree of non-compliance risk;
d) Indicate recommended actions for each situation.

IV.1 IMPLEMENTAÇÃO COMPUTACIONAL DO SISTEMA FUZZY

This topic presents the implementation of a fuzzy system to monitor the PPM indicator in a production process in the automotive industry. The development was carried out in Python, chosen for its simplicity, readability, versatility, and large ecosystem of libraries, which facilitates prototyping and maintenance. The IDE used was Visual Studio Code, a lightweight, free, and highly extensible editor that offers features such as debugging, support for multiple languages, Git integration, and a built-in terminal. After defining all the implementation steps in topic 3.2.3, the execution of the system developed in Python is presented. Figure 13 exemplifies the behavior of the input variable in the system, demonstrating that the PPM variable has six membership functions (PFs), two trapezoidal (Excellent and Critical) and four triangular (Good, Acceptable, Alert, and Bad).

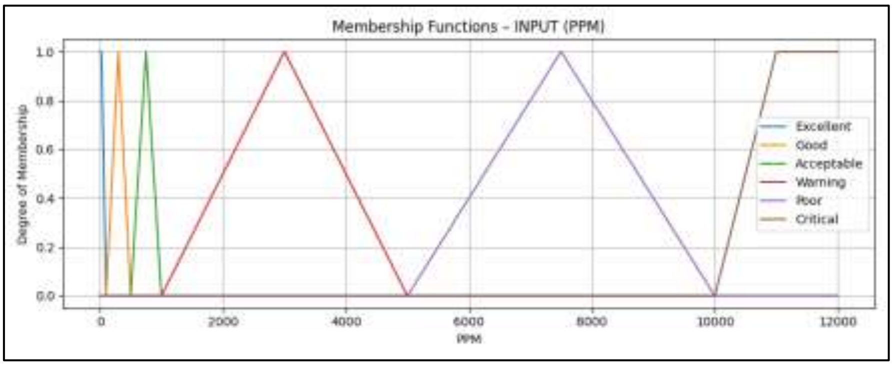

Figure 13: Input membership functions.
Source: Authors, (2026).

Figure 14 illustrates how the output variable is admitted in the proposed fuzzy system, considering that the Risk Index output variable, related to the PPM input, also has six membership functions (PFs), one trapezoidal (Critical) and five triangular (Very low, Low, Moderate, High, Very High).

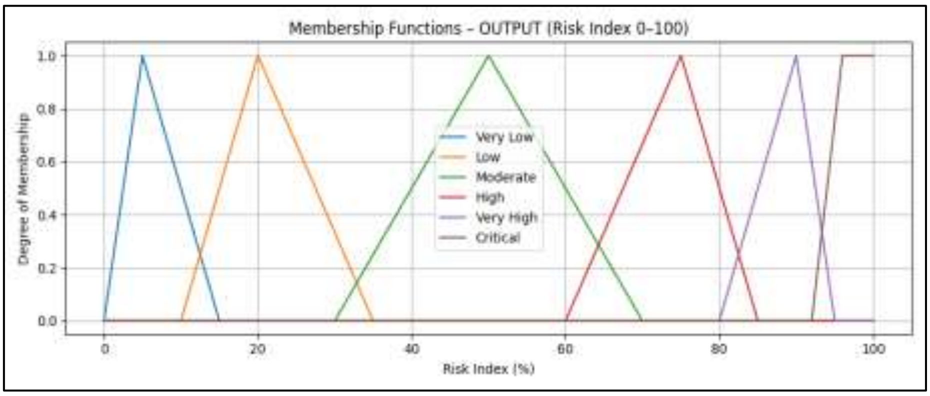

Figure 14: Output membership functions.
Source: Authors, (2026).

IV.1.1 How the fuzzy system works

As discussed earlier in topic IV, the operation of the developed fuzzy system was tested with simulated PPM input values, reflecting real industrial process values. The simulated values were a vector with the values [20, 150, 400, 800, 2500, 6000, 11000], thus covering all possible scenarios of an industrial process. Below, all tests with the aforementioned input values will be presented.

a) For PPM = 20

In Figure 15, it can be observed that the value PPM = 20 belongs almost entirely to the "Excellent" set, showing a high degree of membership. The other sets ("Good", "Acceptable", "Alert", "Bad", and "Critical") have zero membership, indicating that the process is exclusively framed within the best quality condition.

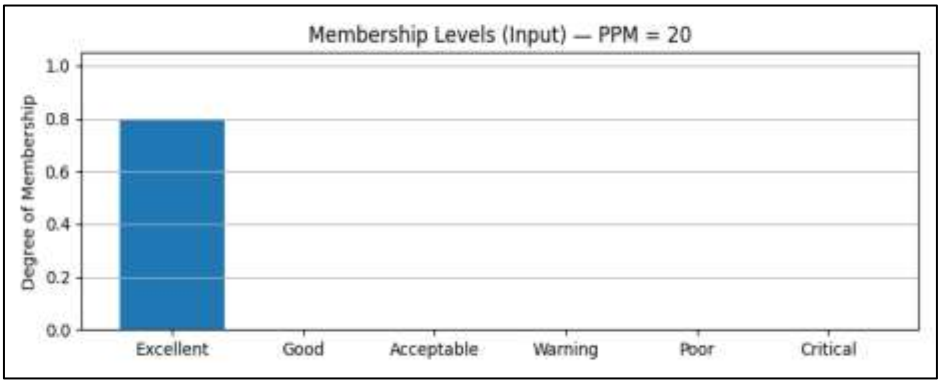

Figure 15: Degree of membership for PPP = 20.
Source: Authors, (2026).

In Figure 16, only the rule associated with the "Excellent" set is activated. The strength of this rule is equivalent to the degree of relevance calculated in the input, demonstrating that the system exclusively uses knowledge related to high-performing processes to generate its output. No other rule contributes to the final calculation, reinforcing the natural classification of the process as low-risk.

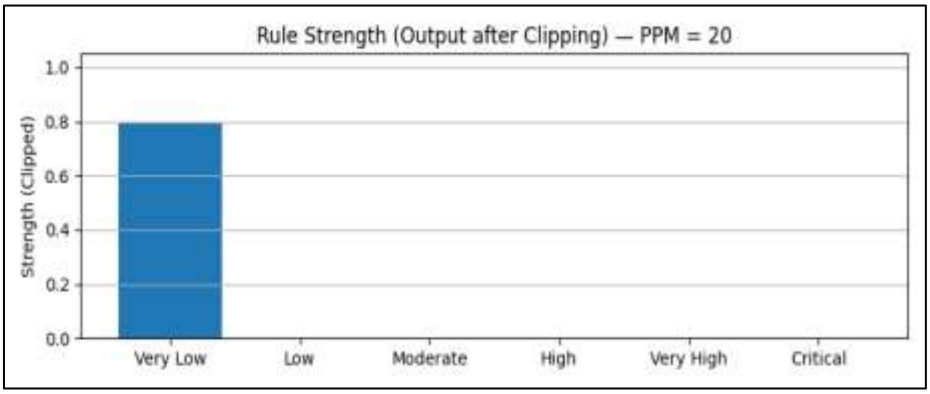

Figure 16: Rule strength for PPP = 20.
Source: Authors, (2026).

In figure 17, the graph shows that the output surface is predominantly shaped by the "Very Low Risk" set, resulting in an aggregate curve concentrated at the beginning of the risk axis. The dashed line indicates the defuzzified value, which approaches a small value, representing an extremely low risk index.

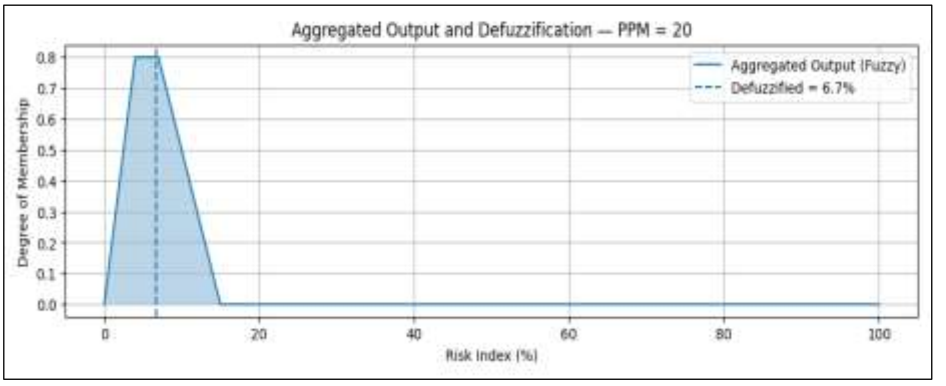

Figure 17: Aggregate output for PPP = 20.
Source: Authors, (2026).

b) For PPM = 400

In Figure 18, it can be observed that the value PPM = 400 belongs to the "Good" set, presenting a membership degree of 0.50. The other sets ("Excellent", "Acceptable", "Alert", "Poor", and "Critical") have zero membership, indicating that the process is exclusively framed within the best quality condition.

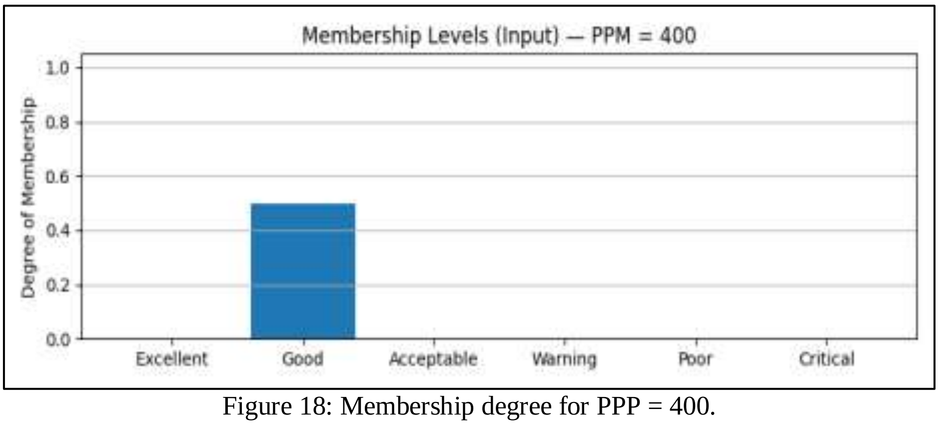

Figure 18: Membership degree for PPP = 400.
Source: Authors, (2026).

In Figure 19, only the rule associated with the "Low" set is activated. The strength of this rule is equivalent to the degree of membership calculated in the input, which demonstrates that the system exclusively uses knowledge related to high-performance processes to generate its output. No other rule contributes to the final calculation, reinforcing the natural classification of the process as low risk.

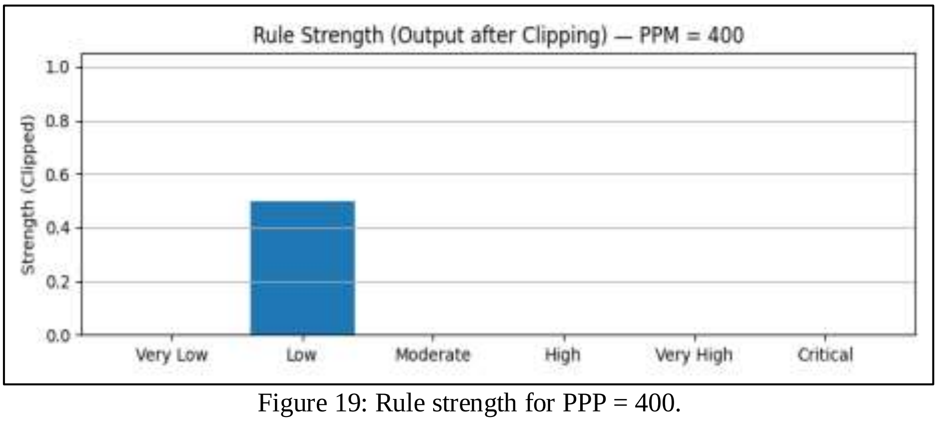

Figure 19: Rule strength for PPP = 400.
Source: Authors, (2026).

In figure 20, the graph shows that the output surface is predominantly shaped by the “Low Risk” set. The dashed line indicates the defuzzified value, which approaches a small value, representing an extremely low risk index.

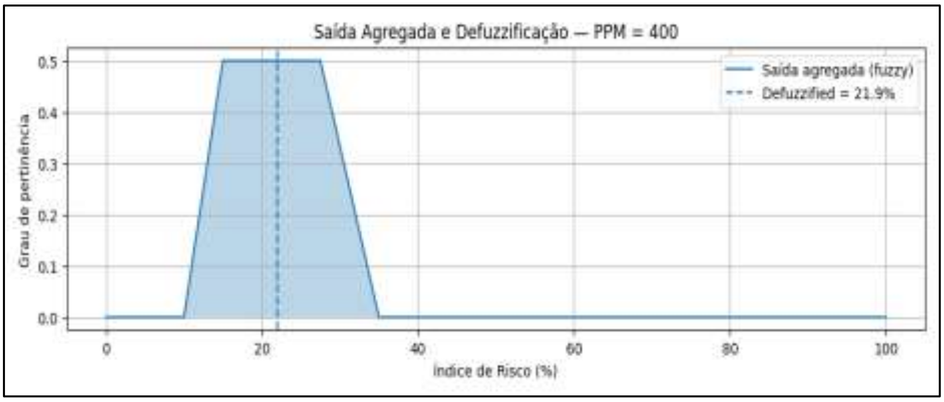

Figure 20: Aggregate output for PPP = 400.
Source: Authors, (2026).

c) For PPM = 800

In Figure 21, it can be observed that the value PPM = 800 belongs entirely to the "Acceptable" set, presenting a membership degree of 0.80. The other sets ("Excellent", "Good", "Alert", "Bad" and "Critical") have zero membership, indicating that the process is exclusively classified as acceptable.

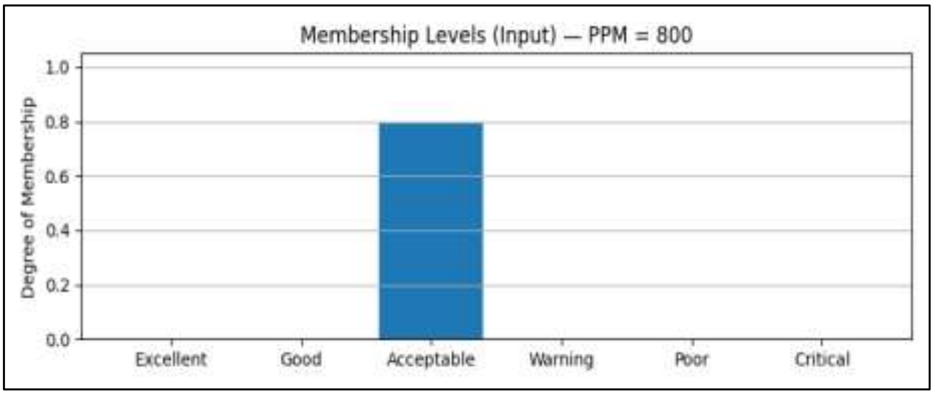

Figure 21: Membership degree for PPP = 800.
Source: Authors, (2026).

In Figure 22, only the rule associated with the "Moderate" set is activated. The strength of this rule is equivalent to the degree of relevance calculated in the input, which demonstrates that the system exclusively uses knowledge related to high-performance processes to generate its output. No other rule contributes to the final calculation, reinforcing the natural classification of the process as moderate risk.

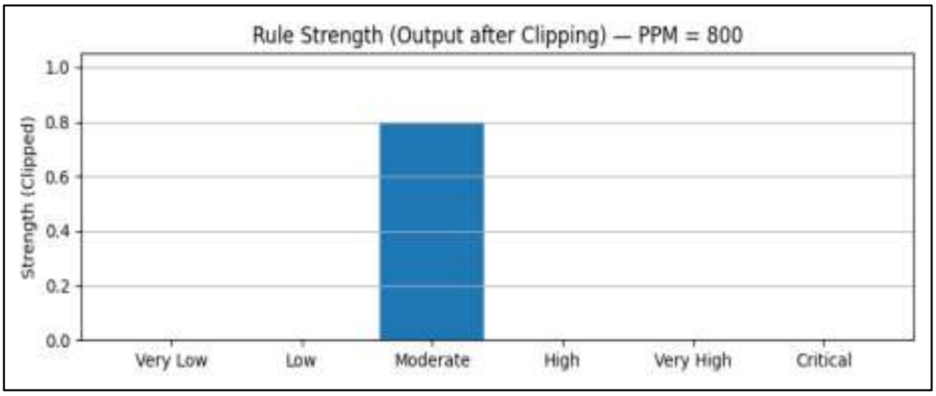

Figure 22: Rule strength for PPP = 800.
Source: Authors, (2026).

In figure 23, the graph shows that the output surface is predominantly shaped by the “Moderate” set. The dashed line indicates the defuzzified value. The system interprets that the process is within expectations, but with clear warning signs.

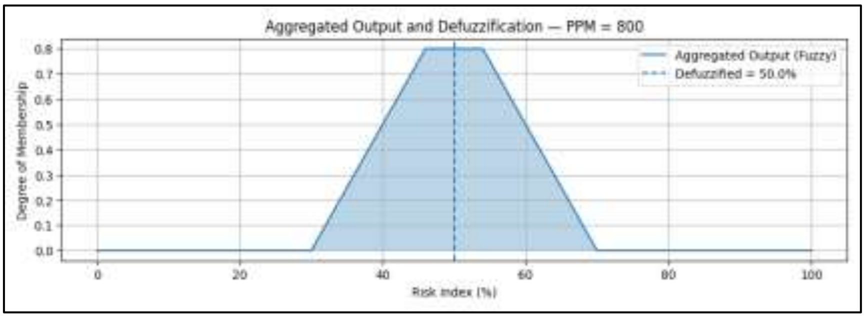

Figure 23: Aggregate output for PPP = 800.
Source: Authors, (2026).

d) For PPM = 2500

In Figure 24, it can be observed that PPM = 2500 belongs mostly to the “Alert” set, with a membership degree of approximately 0.75. The other classes (“Excellent”, “Good”, “Acceptable”, “Bad”, “Critical”) have a membership close to zero.

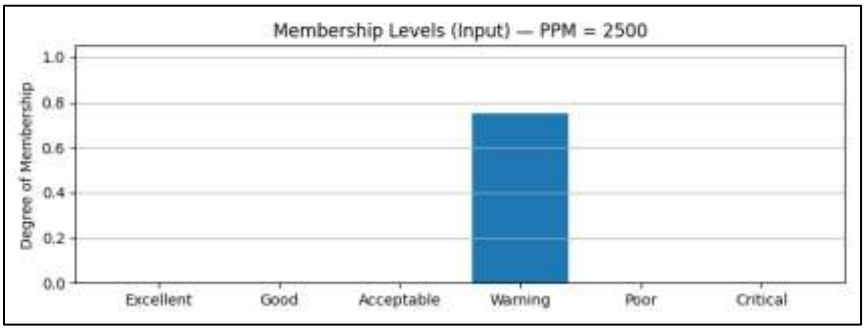

Figure 24: Membership degree for PPM = 2500.
Source: Authors, (2026).

In Figure 25, only the rule associated with the "High" set is activated. The strength of this rule is equivalent to the degree of membership calculated in the input, which demonstrates that the system exclusively uses knowledge related to high-performing processes to generate its output. No other rule contributes to the final calculation, reinforcing the natural classification of the process as High risk.

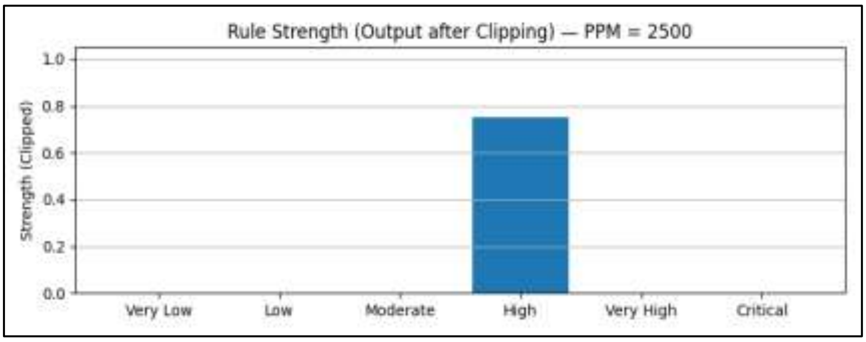

Figure 25: Rule strength for PPP = 2500.
Source: Authors, (2026).

In Figure 26, the graph shows that the output surface is predominantly shaped by the "High" set. The dashed line indicates the defuzzified value. The system interprets this as the process being in a high alert/risk zone.

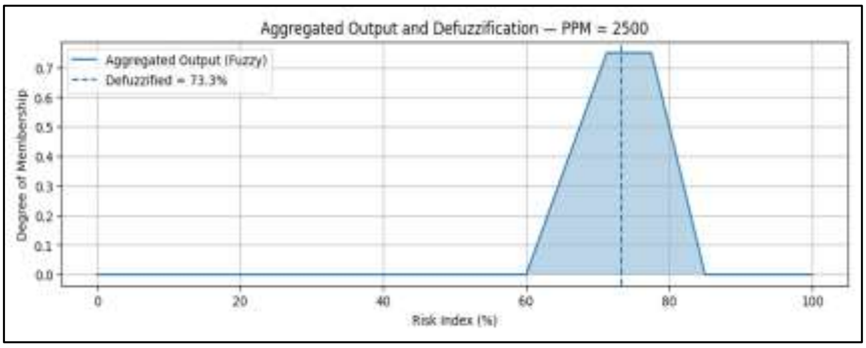

Figure 26: Aggregate output for PPP = 2500.
Source: Authors, (2026).

e) For PPM = 6000

In Figure 27, it can be observed that PPM = 6000 belongs mostly to the "Poor" set, with a membership degree of approximately 0.40. The other classes ("Excellent", "Good", "Acceptable", "Alert", "Critical") have zero membership. The system considers that PPM = 6000 is clearly a value outside the acceptable level, but it is not yet extreme.

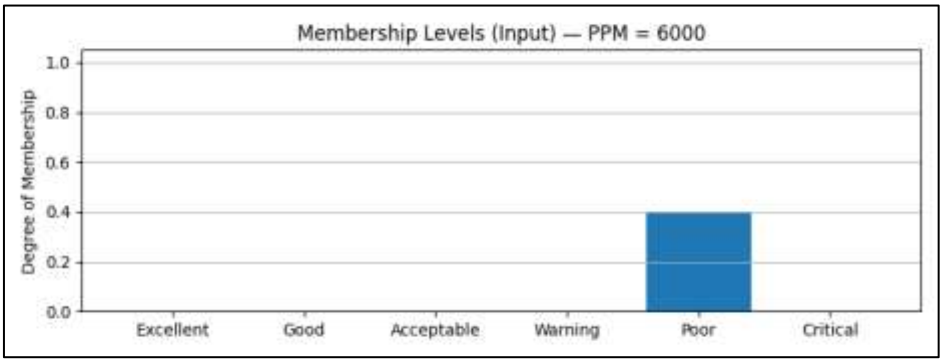

Figure 27: Membership degree for PPM = 6000.
Source: Authors, (2026).

In figure 28, only the rule associated with the "Very High" set is activated. The strength of this rule is equivalent to the degree of relevance calculated in the input, which demonstrates that the system exclusively uses knowledge related to high-performing processes to generate its output. No other rule contributes to the final calculation, reinforcing the natural classification of the process as Very High risk.

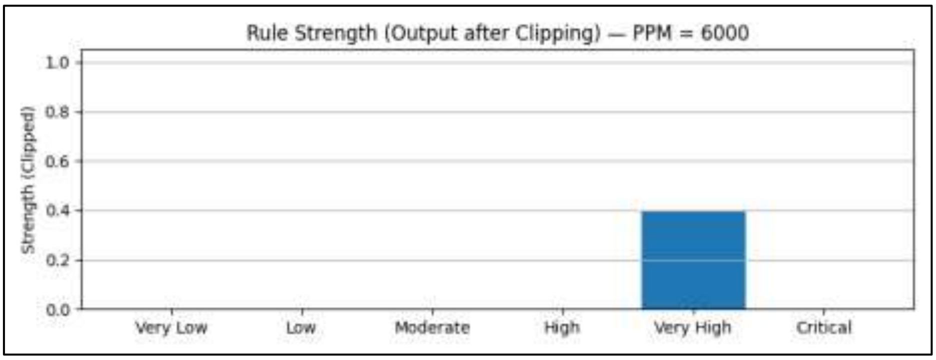

Figure 28: Rule strength for PPP = 6000.
Source: Authors, (2026).

In figure 29, the graph shows that the output surface is predominantly shaped by the "Very High" set. The dashed line indicates the defun zzified value. The system interprets this as the process being in a very high risk zone.

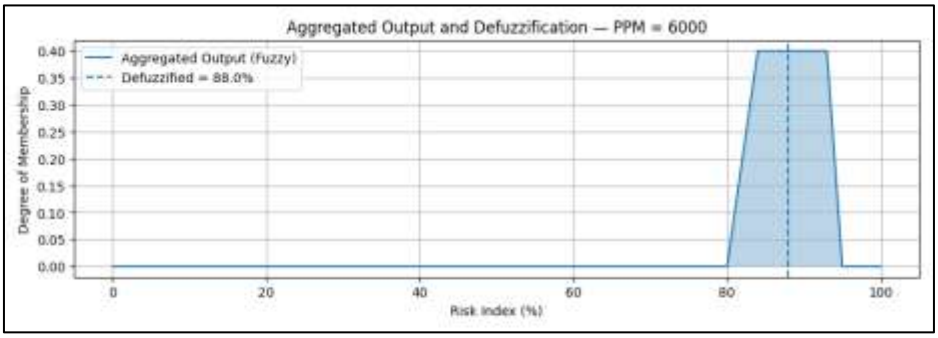

Figure 29: Aggregate output for PPP = 6000.
Source: Authors, (2026).

a) For PPM = 11000

In Figure 30, it can be observed that PPM = 11000 belongs entirely to the "Critical" set, with a membership degree of approximately 1.0. The other classes ("Excellent", "Good", "Acceptable", "Bad", "Critical") have zero membership. There is no ambiguity: the entry is at the maximum plateau of the critical set.

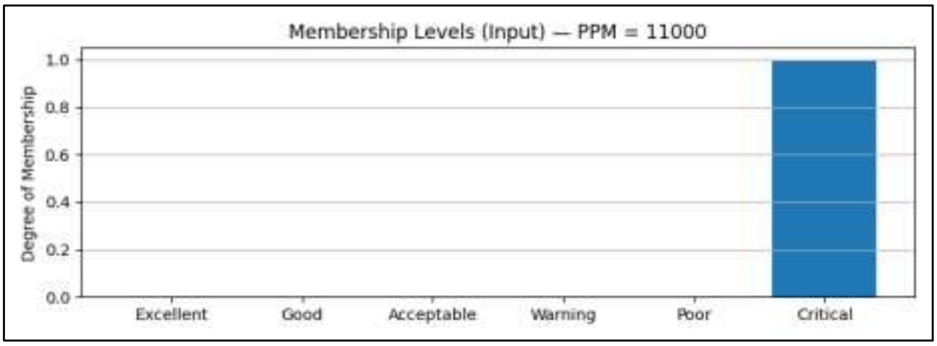

Figure 30: Membership degree for PPM = 11000.
Source: Authors, (2026).

In Figure 31, only the rule associated with the "Critical" set is activated. The strength of this rule is equivalent to the degree of relevance calculated in the input, demonstrating that the system exclusively uses knowledge related to high-performance processes to generate its output. No other rule contributes to the final calculation, reinforcing the natural classification of the process as Critical risk.

Figure 31: Rule strength for PPP = 11000.
Source: Authors, (2026).

In Figure 32, the graph shows that the output surface is predominantly shaped by the "Critical" set. The dashed line indicates the defuzzified value. The system interprets that the process is in the Critical risk zone.

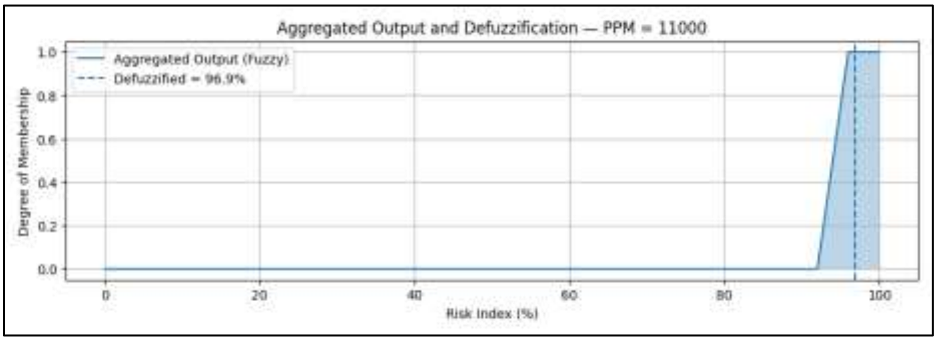

Figure 32: Aggregate output for PPP = 11000.
Source: Authors, (2026).

IV.1.2 Results and discussion

According to the analysis of the results, the developed fuzzy system was able to:

a) Faithfully represent the expected behavior of industrial processes.

– Extremely low values (such as PPM = 20) were correctly classified as a stable situation, aligning with a robust process, with minimal variability and adequate control.For intermediate values, such as 150 and 400 PPM, the
– system does not present binary responses, but rather gradual degrees of risk, which more realistically represent the uncertainty and the transition between stability and attention.

b) Provide sensitivity to the process, even in "gray" regions.
In the real industrial scenario, a process with 400 to 800 PPM may not be considered completely out of control, but it certainly requires monitoring. The fuzzy system managed to capture this, classifying them as:

– 400 PPM → moderate risk
– 800 PPM → high risk

This differentiation is essential to avoid both false alarms and excessive complacency.

c) Handling Severe Scenarios Well

In tests with high values (2500, 6000, and 11000), the system reacted appropriately, raising the belonging function in the maximum risk categories, ensuring that clearly unstable processes were classified as "critical." This behavior reflects industrial logic, in which PPM above 2000 generally indicate:

– process out of control;
– raw material, setup, or calibration problems;
– systemic failures or equipment wear.

In environments where standards such as IATF 16949 or ISO 9001 are applied, processes with very low PPM indicate maturity and stability, while high values require immediate corrective actions. The fuzzy system demonstrated the ability to simulate this logic, but with greater flexibility, because:

a) it does not depend exclusively on fixed limits;
b) it incorporates human knowledge through linguistic rules;
c) it allows smooth transitions between risk ranges.

This means that the fuzzy model can behave like an expert, evaluating real process conditions. The tests performed demonstrated that the fuzzy system is capable of detecting increasing levels of non-conformity in a coherent, continuous manner, aligned with the real needs of industrial manufacturing. The interpretation of each PPM range confirmed that the system:

a) reproduces the behavior of a quality expert,
b) provides gradual and reliable diagnoses,
c) assists in operational and strategic decision-making,
d) can replace or complement traditional SPC systems.

Below is a summary of the tested values, aggregated outputs, and recommended action by the fuzzy logic:

Table 2: Summary of tested values, aggregated outputs, and action recommended by fuzzy logic.

PPM	Active Relevance Set	Fuzzy System Interpretation	Resulting Risk Index	Recommended Action in the Industry
20	Excellent (≈1.0)	Process in excellent condition.	Very Low Risk	No action required.
150	Good (≈0.50), Excellent (≈0.00)	Partially belonging to the "Good" group.	Low Risk	Perform periodic checks.
400	Acceptable (≈1.0)	The process was fully classified as "Acceptable".	Moderate Risk	Monitor trends; initiate corrective actions.
800	Alert (≈1.0)	Process reaches alert level. System identifies high risk.	High Risk	Review machine, process parameters, calibration, and training. Initiate action plan.
2500	Poor (≈1.0)	Process clearly inadequate. Strong activation of the “Poor” category.	Very High Risk	Stop the process for corrections; perform maintenance.
6000	Poor (≈1.0) → near critical	The process is still within the "Bad" category, but close to the "Critical" threshold.	Very High Risk / Trending Towards Critical	Immediate action: Block the batch, conduct root cause analysis, and implement urgent correction.
11.000	Critical (≈1.0)	Full relevance in "Critical". System indicates maximum severity.	Extreme Risk	Complete shutdown; process audit; emergency actions; rework.

Source: Authors, (2026).

Thus, the application of the developed system demonstrates that fuzzy logic is a powerful and suitable tool for implementing intelligent non-conformity detection systems.

V. CONCLUSIONS

This dissertation presented the development and validation of a Non-Conformance Detection System for Industrial Manufacturing Processes based on Fuzzy Logic, capable of analyzing process performance using the PPM (Parts Per Million) indicator and providing intelligent diagnoses of the risk level associated with product quality. The results obtained demonstrated that the fuzzy system is capable of interpreting input values continuously, flexibly, and in line with industrial reality, providing understandable classifications such as low, moderate, high, critical risk, or widespread failure. The fuzzy approach proved particularly useful for processes where binary interpretation (accept/reject) is insufficient, allowing the system to represent uncertainties, gradual transitions, and intermediate scenarios with greater sensitivity. The development of the fuzzy system, with simulation in various scenarios, fulfills the general and specific objectives that comprise this dissertation, as it demonstrated excellent capacity to:

a) Correctly classify all tested PPM ranges (20, 150, 400, 800, 2500, 6000 and 11000), reflecting the expected behavior of an industrial process under different compliance conditions;
b) Provide continuous and realistic responses, avoiding abrupt changes common in traditional deterministic systems;
c) Represent expert knowledge through fuzzy rules and linguistic terms;
d) Assist in industrial decision-making, intuitively identifying situations ranging from full stability to systemic failure.

This behavior confirms that the system is suitable for manufacturing monitoring, internal audits, improvement programs, and operational control.

VI. AUTHOR'S CONTRIBUTION

Conceptualization: Roberto Ferreira de Lima and Helder Kiyoshi Miyagawa.
Methodology: Roberto Ferreira de Lima, Helder Kiyoshi Miyagawa and Rivanildo Duarte Almeida.
Investigation: Roberto Ferreira de Lima and Helder Kiyoshi Miyagawa.
Discussion of results: Roberto Ferreira de Lima and Helder Kiyoshi Miyagawa.
Writing – Roberto Ferreira de Lima.
Writing – Review and Editing: Roberto Ferreira de Lima and Rivanildo Duarte Almeida.
Resources: Roberto Ferreira de Lima.
Supervision: Helder Kiyoshi Miyagawa.
Approval of the final text: Helder Kiyoshi Miyagawa, Roberto Ferreira de Lima and Rivanildo Duarte Almeida.

VII. REFERENCES

[1] Slack, N., Brandon-Jones, A., Burgess, N. (2020). Operations Management. Pearson.

[2] Montgomery, D. C. (2019). Introduction to Statistical Quality Control. Wiley.

[3] Zadeh, L. A. (1996). Fuzzy Logic = Computing with Words. IEEE Transactions on Fuzzy Systems.

[4] Kasabov, N. (2020). Time-Space, Spiking Neural Networks and Brain-Inspired Artificial Intelligence. Springer.

[5] Schumacher, Simon, et al. Conceptualization of a Framework for the Design of Production Systems and Industrial Workplaces. 30th CIRP Design 2020 (CIRP Design 2020). Fraunhofer Institute for Manufacturing Engineering and Automation IPA, Fraunhofer Institute for Industrial Engineering IAO, Institute of Industrial Manufacturing and Management, University of Stuttgart, Allmandring, Stuttgart, Germany. 2020.

[6] Wagner, Tobias, Herrmann, Christoph, Thied, Sebastian. Industry 4.0 impacts on lean production systems. Chair of Sustainable Manufacturing & Life Cycle Engineering, Institute of Machine Tools and Production Technology (IWF), Technische Universität Braunschweig, 2017.

[7] Rahman, A. Azwan Abdul. "Revolution of Production System for the Industry 4.0". IntechOpen, Mar. 11, 2020. doi: 10.5772/intechopen.90772. CAPÍTULO 1, 2020.

[8] Dombrowski, Uwe, Richter, Thomas, Krenkel, Philipp. Interdependencies of industrie 4.0 & Lean Production Systems - a use cases analysis -. Institute for Advanced Industrial Management, Technische Universität Braunschweig, 2017.

[9] Bihi, T., Luwes, N., Kusakana, K. Innovative Quality Management System for Flexible Manufacturing Systems. Department of Electrical, Electronic and Computer Engineering, Central University of Technology Bloemfontein, South Africa, 2018.

[10] Akdogan, Anil, Vanli, Ali Serdar. 'Introductory Chapter: Mass Production and Industry 4.0', Mass Production Processes. IntechOpen, doi: 10.5772/intechopen.90874, 2020.

[11] Zhong, Ray Y., et al. Intelligent Manufacturing in the Context of Industry 4.0: A Review. Department of Mechanical Engineering, The University of Auckland, Auckland 1142, New Zealand, Industry 4.0 Campaign, Festo AG & Co. KG, Esslingen 73726, Germany, Department of Mechanical Engineering, University of Bath, Bath BA2 7AY, UK, 2017.

[12] Kusiak, Andrew. Smart manufacturing. Intelligent Systems Laboratory, Department of Mechanical and Industrial Engineering, The University of Iowa, Iowa City, IA, USA, 2018.

[13] Li, Bo-hu et al. Applications of artificial intelligence in intelligent manufacturing: a review. The Second Academy of China Aerospace Science and Technology Corporation, Beijing 100039, China, Beijing Aerospace Intelligent Manufacturing Technology Development Co., Ltd., Beijing 100039, China, 2017.

[14] Lenz, Juergen et al. Optimizing smart manufacturing systems by extending the smart products paradigm to the beginning of life. Industrial and Management Systems Engineering, Benjamin M. Statler College of Engineering and Mineral Resource, West Virginia University, Morgantown, WV 26506, United States, Advanced Manufacturing Research Center, Youngstown State University, Youngstown, OH 44555, United States, McNair Aerospace Center, University of South Carolina, Columbia, SC 29208, United States, 2020.

[15] Carneiro, Flávio Araújo. *Sistema de gestão da qualidade: uma revisão bibliográfica*. Research, Society and Development, v. 9, n. 10, p. e4309108373, 2020. Disponível em: https://rsdjournal.org/index.php/rsd/article/download/43006/34685/454384. Acesso em: 13 ago. 2025.

[16] Lima, Sávio Araújo; Seleme, Rogério. Qualidade 4.0: uma revisão sobre os impactos da indústria 4.0 na gestão da qualidade. In: Congresso Brasileiro de Engenharia de Produção – CONBREPRO, 10., 2021, Ponta Grossa. Anais [...]. Ponta Grossa: APREPRO, 2021. Disponível em: https://aprepro.org.br/conbrepro/2021/anais/arquivos/09272021_210901_615266f53f133.pdf. Acesso em: 13 ago. 2025.

[17] Hoffmann, Vanderlei. Gestão da qualidade na Indústria 4.0. Ponta Grossa: Universidade Tecnológica Federal do Paraná (UTFPR), 2019. Disponível em: https://repositorio.utfpr.edu.br/jspui/bitstream/1/25908/1/PB_ESEP_IV_2019_21.pdf. Acesso em: 13 ago. 2025.

[18] Moraes, Simone de Sá de. Implementação dos requisitos da ISO 9001:2015 em vidrarias industriais. Universidade do Minho. Dissertação (Mestrado em Engenharia Industrial) – Universidade do Minho, Braga, 2023. Disponível em: https://repositorium.sdum.uminho.pt/handle/1822/84142. Acesso em: 13 ago. 2025.

[19] Peixoto, Rafaela Aparecida Martins. Gestão da qualidade na indústria: estudo de caso. Dissertação (Mestrado em Engenharia de Produção) – Universidade Presidente Antônio Carlos, Barbacena, 2013. Disponível em: https://ri.unipac.br/repositorio/wp-content/uploads/tainacan-items/282/283918/RAFAELA-AP.-Martins-Peixoto-Gestao-da-Qualidade-na-Industria-Engenharia-de-Producao-2013.pdf. Acesso em: 13 ago. 2025.

[20] Wiley, John. Statistical Quality Control: Using Minitab, R, JMP, and Python. Phase I Quality Control Charts for Variables, 2021.

[21] Zinchenko, Timur O. Development of a Quality Control System for Transparent Conductive Oxides, Penza State University, Russia, 2020.

[22] Ciecińska, Barbara (2023). Identification of Defects Causes: Ishikawa Diagram and 5 Whys in Theoretical and Practical Terms. Industrial Engineering and Management. IntechOpen, May 29, 2024. doi: 10.5772/intechopen.113990.

[23] Chaves, M.L., et al. Experimental assessment of quality in injection parts using a fuzzy system with adaptive membership functions. Department of Computer and Systems Engineering, Universidad Católica de Colombia, Caracas, Bogotá - Colombia, Departmento de Ingenierías Mecánica, informática y Aeroespacial, Universidad de León, León, Spain, Departamento Ingeniería Mecánica. Universidad de La Frontera. Temuco, Chile, Departamento de Ingeniería Mecánica. Universidad Politécnica de Madrid, José Gutiérrez Abascal, Madrid, Spain, 2019.

[24] Amin, S. H., Razmi, J., and Zhang, G. Supplier selection and order allocation based on fuzzy SWOT analysis and fuzzy linear programming, Expert Systems with Applications, vol. 38, pp. 334-342, 2011.

[25] Almeida, Rivanildo Duarte. Análise de Impactos Harmônicos em Rede de Distribuição de Energia Elétrica de Média Tensão Utilizando Técnicas de Inteligência Computacional. Universidade Federal do Pará. Instituto de Tecnologia. Programa de Pós-Graduação em Engenharia de Processos – PPGEP, Belém, UFPA, 2018.

[26] Aquino, Dener Jeferson Horta de. Análise de impactos harmônicos em redes elétricas: um estudo comparativo entre as técnicas regressão linear e árvore de decisão. Universidade Federal do Pará – UFPA, 2022.

[27] Khadeer, Ahmed. Brain-Inspired Spiking Neural Networks. DOI: 10.5772/intechopen.93435, 2020.

[28] HERNÁNDEZ-HERNÁNDEZ, Marisol, CRUZ, Luis Alfonso Bonilla e COBIÁN-ROMERO, Lizbeth. Improvement of Validated Manufacturing Processes with Fuzzy Logic. INTECHOPEN, DOI: 10.5772/intechopen.113302, 2023.