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A DECISION-MAKING MODEL FOR QUALITY IMPROVEMENT USING FUZZY LOGIC

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ABSTRACT

The world has been experiencing a fierce competition on all levels lately, especially in the field of industry, which has pushed manufacturing companies to improve their key performance indicators, especially quality indicators such as yield and rejection rate, in order to better satisfy customers and also to reduce financial losses due to non-compliant products.

In order to improve the level of quality and before moving on to solutions, companies aim to first determine the most critical issues in order to prioritize them in the analysis and actions. Among the most used Lean Manufacturing tools in this sense is the Pareto chart which is often used to identify the most critical defects based on a single input indicator which is usually the rejection rate, but this indicator alone is not sufficient to give accurate results to decide which defects are the most critical.

The objective of this research is to develop a decision support model using fuzzy logic capable of accurately determining the most critical defects to prioritize based not only on the rejection rate but also on two indicators that have an impact on the criticality of the defects, namely the recovery rate following rework and the rework cost.

Then to validate the proposed model, a case study was conducted on the defect data of a car windshield manufacturing plant. The results were compared with those of the Pareto tool, which allowed to reveal its limitations and to retain the proposed fuzzy logic model for the estimation of the criticality of defects in industrial companies.

Keywords: *Quality Improvement, Fuzzy Logic, Artificial Intelligence, Decision-Making, Pareto Chart.*

1. INTRODUCTION

Quality management has become a competitive advantage and one of the key elements that allows organizations to distinguish themselves in the market through continuous improvement of product quality and thus customer satisfaction [1], it is currently a necessity in company policies and strategies in view of rising customer expectations and fierce global competition, which means that industrial companies today are obliged to manufacture products with a high quality in order to meet the requirements of their customers and to remain competitive [2], given that the quality of a product is defined from the customer's point of view [3].

A high rate of defects and thus a low level of quality is a major source of financial losses and additional costs that could affect the short and long term performance of companies [4].

A defect means an error or non-conformity in the product due to an anomaly in the manufacturing process, which results in a drop in the value of the product from the customer's point of view, and thus a direct loss of parts or a need for additional processing costs to rework the product and correct the defect [4], which causes a waste of resources and time, as well as a great risk of losing customers [5]. The errors and defects can naturally be generated during the manufacture of products as the production processes are not perfect. The number of defects that can be generated during production can be influenced by several factors, like manpower errors, equipment adjustments, progressive machine degradation and also raw material variability that can all lead to process variations [4].

As a result, defects are a clear source of waste, which has led many companies to make efforts to reduce or even eliminate defects as part of the Lean philosophy [4].

Several methodologies and programs aim at quality improvement, such as Kaizen, six sigma, design for six sigma (DFSS) and others, and are

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based mainly on the collection of data that are becoming more and more available thanks to automation and the progress of computer systems that allow not only to collect data from industrial processes, but also to exploit and analyze them correctly in order to be able to act effectively on each problem [6]. The Pareto tool is one of the most effective Lean tools used in quality improvement projects.

Indeed, improving the quality of products and manufacturing processes and resolving the problems associated with defects that impact on quality indicators requires detailed data collection and thus a correct and complete analysis that will enable effective action to be taken [6].

The fourth industrial revolution continues to dominate all aspects of industry, especially in terms of quality culture and management in industrial enterprises [7], in fact industry 4.0 technologies offer many opportunities for better quality management by improving the quality of products and processes through the use of data and information to facilitate decision making and in a more efficient way [2].

In fact, among the major challenges that managers and engineers face regarding the quality improvement strategy are those related to decision making or, in other words, the evaluation of the criticality of the issues and the definition of those that have more impact financially and on the yield and quality indicators and which require more effective actions and priority. In fact, in this context, quality defects are generally the issues that factories aim to tackle in order to improve quality and reduce financial losses.

The proposed methodology consists of a mathematical model of fuzzy logic that allows to calculate and determine the criticality of defects in order to identify those that cause more losses for companies and require priority improvement actions, and this based on three parameters: the rejection rate, the recovery rate and the cost of rework. The results of this model are compared to those of the Pareto analysis, which is limited when the monitored quality indicator is influenced by more than one factor.

2. LITTERATURE REVIEW

To remedy quality problems, and to prioritize the critical defects that need to be focused on, among the most used techniques is the Pareto analysis which is a quality tool used to identify the major causes having more impact on the problems [8], since quality defects or process problems in general can be caused by different factors with varying proportions [9].

In the 19th century, the economist Vilfredo Pareto developed the concept of the Pareto tool, which is based on the assumption that 80% of effects are results of only 20% of causes. This concept is also known as the 20/80 principle, and subsequently the Pareto tool has become one of the most effective quality tools, and has been recognized by the American Society for Quality (ASQ) as one of the seven basic tools for quality and process improvement [10]. The 80/20 principle remains general and theoretical, but it can be changed practically to 70/30 or 60/40 [8].

Pareto chart is a very powerful statistical tool used to identify and highlight the parameters with the greatest impact on a certain effect [11], it is a bar chart where the frequency is plotted on the y-axis on the left-hand side, the percentage on the z-axis on the right-hand side, and the contributing factors are plotted in decreasing order of frequency on the x-axis. The curve representing the cumulative percentages of the factors is a key element of the 20/80 rule of the Pareto chart, when an accumulation of 80% is reached, it means that all the elements previously added up represent about 20% of the causes. Thus focusing on these causes allows more improvements to be achieved effectively [10].

Establishing the Pareto chart and analyzing it well allows to make correct decisions and to intervene on the most critical causes that need to be prioritized in order to improve quality, as the general principle of the Pareto chart is to concentrate efforts on the factors that have more weight and impact on the indicators to be improved, thus saving time, effort and unnecessary costs [10].

Hence, the Pareto tool is a very powerful tool that allows decision making through the highlighting of the main causes of the low quality indicator in order to prioritize them in the analysis and improvement actions. However, the effectiveness of the Pareto diagram is limited to problems where only one characteristic is used to classify the factors, which means that when the decision must be made by taking into account at least two characteristics, the Pareto tool will not give precise results even if two Pareto diagrams are drawn up for each of the characteristics, because the results may be contradictory without knowing which one is more significant.

In the case of reducing critical quality defects, the Pareto tool is often used to classify the defects according to the rejection rate of each of them, but this characteristic is not sufficient to

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decide which are the critical defects that require action plans, since there are also other important parameters, these are the recovery rate of each defect following rework and automatically a third parameter which is the cost of rework for each of the defects.

3. MATERIAL AND METHODS

3.1 Presentation of Fuzzy Logic

Fuzzy logic is an artificial intelligence logical system developed by Professor Lotfi Zadeh that aims at the formalization of natural human reasoning, as artificial intelligence is mainly aimed at the development of programs and models with intelligent behavior [12].

Fuzzy logic is a very effective technique for facilitating management and decision making, especially for problems that are not very precisely described and are characterized by the interaction of different factors, although it is not widely used in management fields [12].

In fuzzy sets it is possible for elements to belong partially as the boundaries are not clearly defined. The theory of fuzzy sets forms the basis of fuzzy logic modelling and is different from that of ordinary binary sets [13]. The classical sets considers just a limited number of membership degrees which are usually "0" and "1" [14]. Each element of the fuzzy set belongs to the interval between 0 and 1 inclusive, and its value is assigned by the membership function associated with the fuzzy set [13].

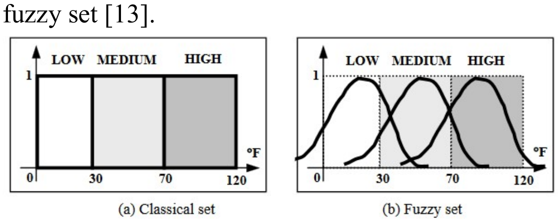

Figure 1: Classical and fuzzy sets examples [14]

Membership functions and fuzzy rules are the two main components of fuzzy logic, which allow linguistic expressions to be translated into mathematical formulas and thus a transition from a qualitative description resulting from the expertise of a man in the field to a quantitative description via the mathematical model [12].

The modeling of a process according to fuzzy logic requires that the variables of the model belong to fuzzy classes and are controlled by rules of the form IF...THEN to allow to establish a result for each combination of the fuzzy classes which contain the variables [13].

3.2 Fuzzification

This first step allows to translate classical or crisp data into fuzzy data [14], by defining the membership functions for both input and output variables, which makes it possible to transform numerical data into linguistic variables by determining the form of the membership functions and the degree of membership in each of the states that must be defined and specified [15]. The most commonly used forms of functions are triangular and trapezoidal:

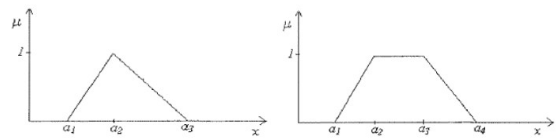

Figure 2: Membership function of a triangular and trapezoidal fuzzy number [13]

The membership functions should be defined by domain experts, and then the model generate the output variable by the center of gravity method [15].

3.3 The Fuzzy Inference engine

This step consists in combining the control rules with the membership functions already defined to obtain the fuzzy output data [14].

In other words, after defining the linguistic variables, it is time to exploit them in the inference engine, and this by determining the rules resulting from the field expertise and by enunciating them in natural language to make it possible to formalize human reasoning, which is one of the objectives of fuzzy logic [15].

3.4 Defuzzification

After the inference is complete, this last phase allows the set of fuzzy outputs to be determined, with the need for a transition from the "fuzzy world" to the "real world" to be able to use the results of the model accurately [15].

The calculation of the "center of gravity" of the fuzzy set is one of the most widely used methods for this purpose [15], in addition to the maximum output method [12]:

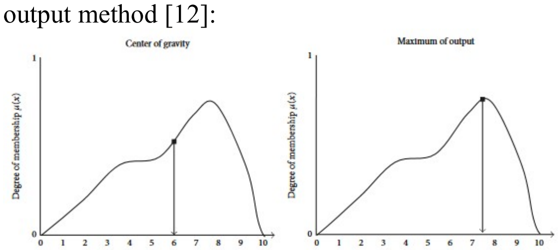

Figure 3: Defuzzification common methods [12]

3.5 Summary of fuzzy logic modelling

Following the explanation of the different stages of fuzzy logic modelling, these can be summarized in the form of the scheme shown in the figure below:

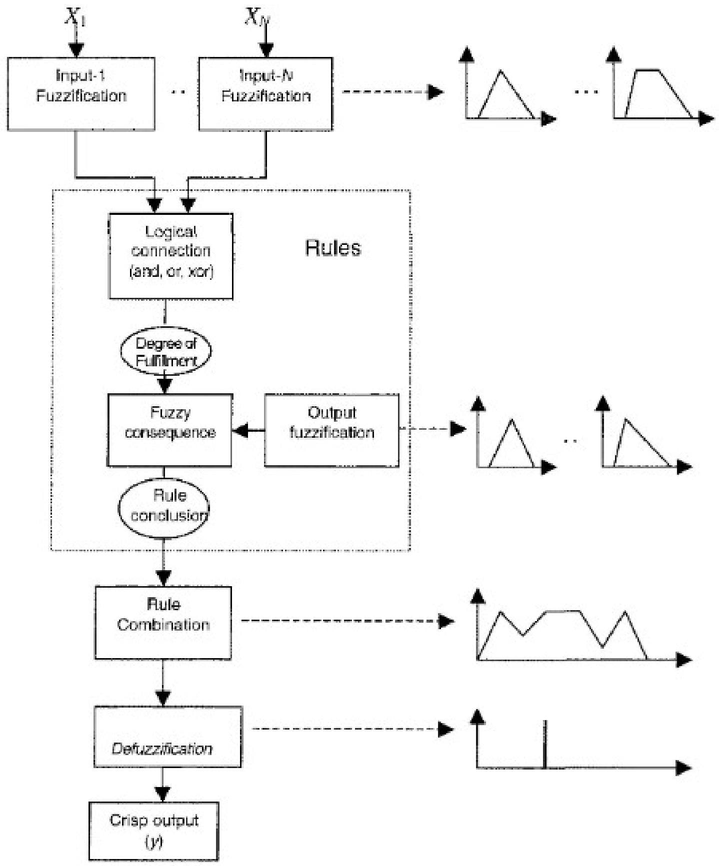

Figure 4: Schematic of a fuzzy logic-based model [13]

4. CASE STUDY

4.1 Proposed method for defect criticality estimation

Generally, the criticality of quality defects is estimated based on a single indicator which is the rejection rate through the Pareto chart. However, what makes a defect critical from the management point of view is the level of financial losses it may cause. Hence, the rejection rate alone is not sufficient to estimate the losses since many defects can be reworked and recovered, while the cost of rework differs from one defect to another.

The interaction between all these parameters makes the decision on the criticality of defects a bit complicated, hence the importance of fuzzy logic.

In this paper, we will present a new method based on a fuzzy logic model for calculating the criticality of quality defects, using the terms "low", "medium" and "high" to describe both the input variables "rejection rate", "recovery rate" and "rework cost" and the output variable "defect criticality".

4.2 Indicators definition

The defect criticality as an output indicator will be evaluated on the basis of the following three indicators:

Rejection rate: which means the total number of rejected pieces containing the relevant defect out of the total number of pieces produced, hence:

Rejection rate = Number of rejected pieces / Number of produced pieces

Recovery rate: which means the number of pieces recovered through rework out of the total number of pieces rejected, hence:

Recovery rate = Number of reworked pieces / Number of rejected pieces

Rework cost: which includes the cost of the resources required to perform the rework in terms

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of manpower, consumables and also processing time.

Hence, the proposed model will be schematized as shown in the following figure:

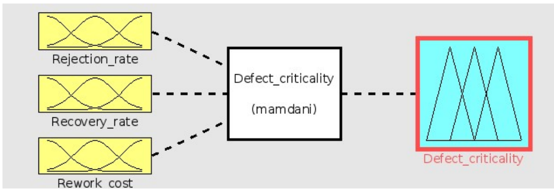

Figure 5: Proposed fuzzy model

4.3 Modeling of indicators

After defining the proposed method and the input and output indicators, it is time to model them by determining the membership functions of each variable as shown in the figures below:

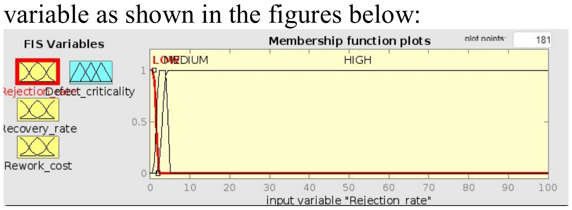

Figure 6: Membership function for "Rejection rate"

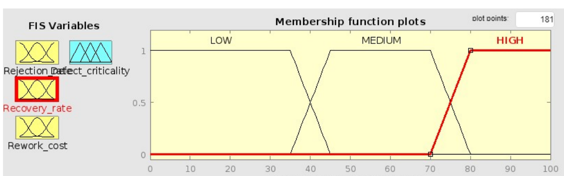

Figure 7: Membership function for "Recovery rate"

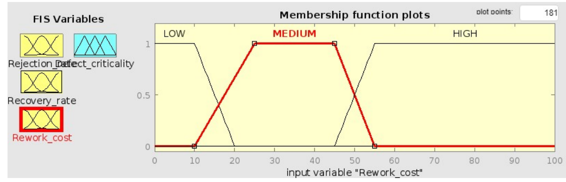

Figure 8: Membership function for "Rework cost"

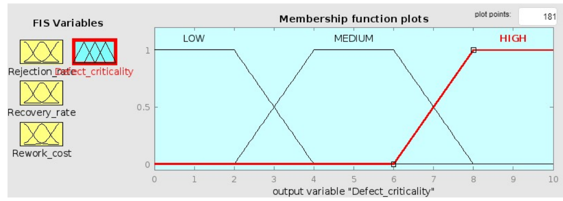

Figure 9: Membership function for "Defect criticality"

4.4 Fuzzy inference

In this step, we will define the fuzzy rules resulting from the field expertise to manage the interaction between the different input variables.
These are 27 fuzzy rules (3*3*3) using the <<AND>> operator:

1. If (Rejection_rate is LOW) and (Recovery_rate is LOW) and (Rework_cost is LOW) then (Defect_criticality is LOW) (1)
2. If (Rejection_rate is LOW) and (Recovery_rate is LOW) and (Rework_cost is MEDIUM) then (Defect_criticality is LOW) (1)
3. If (Rejection_rate is LOW) and (Recovery_rate is LOW) and (Rework_cost is HIGH) then (Defect_criticality is LOW) (1)
4. If (Rejection_rate is LOW) and (Recovery_rate is MEDIUM) and (Rework_cost is LOW) then (Defect_criticality is LOW) (1)
5. If (Rejection_rate is LOW) and (Recovery_rate is MEDIUM) and (Rework_cost is MEDIUM) then (Defect_criticality is LOW) (1)
6. If (Rejection_rate is LOW) and (Recovery_rate is MEDIUM) and (Rework_cost is HIGH) then (Defect_criticality is LOW) (1)
7. If (Rejection_rate is LOW) and (Recovery_rate is HIGH) and (Rework_cost is LOW) then (Defect_criticality is LOW) (1)
8. If (Rejection_rate is LOW) and (Recovery_rate is HIGH) and (Rework_cost is MEDIUM) then (Defect_criticality is LOW) (1)
9. If (Rejection_rate is LOW) and (Recovery_rate is HIGH) and (Rework_cost is HIGH) then (Defect_criticality is LOW) (1)
10. If (Rejection_rate is MEDIUM) and (Recovery_rate is LOW) and (Rework_cost is LOW) then (Defect_criticality is MEDIUM) (1)
11. If (Rejection_rate is MEDIUM) and (Recovery_rate is LOW) and (Rework_cost is MEDIUM) then (Defect_criticality is MEDIUM) (
12. If (Rejection_rate is MEDIUM) and (Recovery_rate is LOW) and (Rework_cost is HIGH) then (Defect_criticality is MEDIUM) (1)
13. If (Rejection_rate is MEDIUM) and (Recovery_rate is MEDIUM) and (Rework_cost is LOW) then (Defect_criticality is LOW) (1)
14. If (Rejection_rate is MEDIUM) and (Recovery_rate is MEDIUM) and (Rework_cost is MEDIUM) then (Defect_criticality is LOW) (
15. If (Rejection_rate is MEDIUM) and (Recovery_rate is MEDIUM) and (Rework_cost is HIGH) then (Defect_criticality is MEDIUM)
16. If (Rejection_rate is MEDIUM) and (Recovery_rate is HIGH) and (Rework_cost is LOW) then (Defect_criticality is LOW) (1)
17. If (Rejection_rate is MEDIUM) and (Recovery_rate is HIGH) and (Rework_cost is MEDIUM) then (Defect_criticality is LOW) (1)
18. If (Rejection_rate is MEDIUM) and (Recovery_rate is HIGH) and (Rework_cost is HIGH) then (Defect_criticality is MEDIUM) (1)
19. If (Rejection_rate is HIGH) and (Recovery_rate is LOW) and (Rework_cost is LOW) then (Defect_criticality is HIGH) (1)
20. If (Rejection_rate is HIGH) and (Recovery_rate is LOW) and (Rework_cost is MEDIUM) then (Defect_criticality is HIGH) (1)
21. If (Rejection_rate is HIGH) and (Recovery_rate is LOW) and (Rework_cost is HIGH) then (Defect_criticality is HIGH) (1)
22. If (Rejection_rate is HIGH) and (Recovery_rate is MEDIUM) and (Rework_cost is LOW) then (Defect_criticality is MEDIUM) (1)
23. If (Rejection_rate is HIGH) and (Recovery_rate is MEDIUM) and (Rework_cost is MEDIUM) then (Defect_criticality is HIGH) (1)
24. If (Rejection_rate is HIGH) and (Recovery_rate is MEDIUM) and (Rework_cost is HIGH) then (Defect_criticality is HIGH) (1)
25. If (Rejection_rate is HIGH) and (Recovery_rate is HIGH) and (Rework_cost is LOW) then (Defect_criticality is LOW) (1)
26. If (Rejection_rate is HIGH) and (Recovery_rate is HIGH) and (Rework_cost is MEDIUM) then (Defect_criticality is MEDIUM) (1)
27. If (Rejection_rate is HIGH) and (Recovery_rate is HIGH) and (Rework_cost is HIGH) then (Defect_criticality is HIGH) (1)

Figure 10: Fuzzy Rules Presentation

4.5 Defuzzification

This defuzzification step as shown in the following figure allows to transform through the center of gravity method the fuzzy set containing: Rejection rate, recovery rate and rework cost into a precise numerical value of the defect criticality:

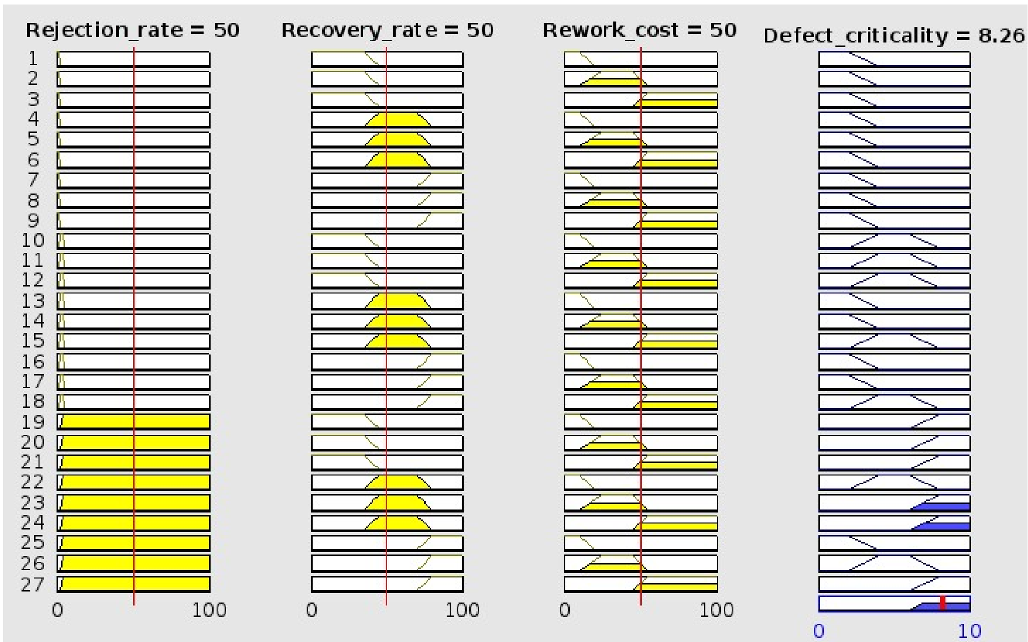

Figure 11: Deffuzification process

5. RESULTS AND DISCUSSION

After the construction of the inference system, it is necessary to interpret and analyze the results of the defuzzification. In fact, the interpretation of the surface viewer graphs will allow us to understand the relationship between the three input indicators and the criticality of the defects. Thus, we will study three possible cases, where we will fix each time one of the input variables on a medium value.

5.1 Use case 1: Medium rejection rate

In this case the rejection rate indicator is set as medium:

Med: Rejection rate.
Y: Recovery rate.
Z: Rework cost.

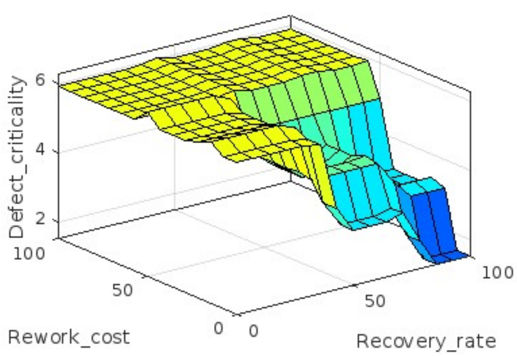

Figure 12: Surface View for Use Case N°1

Based on figure 12, where the surface shows the case where the rejection rate is fixed at a medium value of "3", it can be seen that when the recovery rate is high with a low rework cost, the criticality of the defect is low, however if the rework cost is high, the criticality of the defect is also high whatever the value of the rework rate, which shows that the recovery rate does not have a great impact to compensate the losses linked to the high or medium rejection rate as long as the rework cost is not low. Similarly, a low rework cost is not too significant if the recovery rate is low.

5.2 Use case 2: Medium recovery rate

In this case the recovery rate indicator is set as medium:

X: Rejection rate.
Med: Recovery rate.
Z: Rework cost.

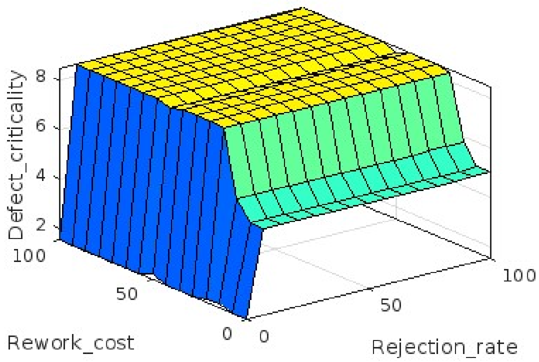

Figure 13: Surface View for Use Case N°2

According to figure 13, where the surface presents the case where the rework rate is fixed at an average value of "55", we notice that when the rejection rate is low the criticality of the defect is also low whatever the value of the rework cost, i.e. the rejection rate is the variable that has more influence in principle, on the other hand if this indicator is high with an average or high rework cost, the defect becomes more critical, or with an average criticality if the rework cost is low. It is deduced that the criticality of defects is automatically low when the rejection rate is low, but with a high rejection rate the rework cost if low can reduce the criticality of the defect moderately.

5.3 Use case 3: Medium rework cost

In this case the rework cost indicator is set as medium:

X: Rejection rate.
Y: Recovery rate.
Med: Rework cost.

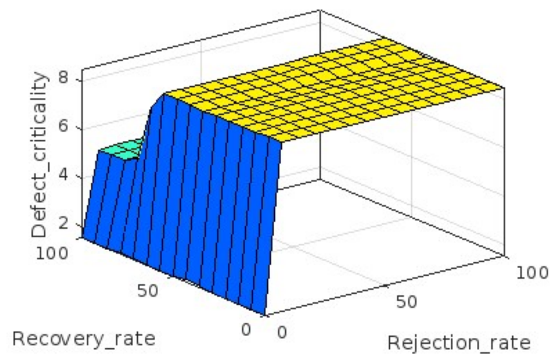

Figure 14: Surface View for Use Case N°3

From figure 14, where the surface shows the case where the rework cost is fixed at an average value of "35", we can see, as in the previous case, that when the rejection rate is low, the criticality of the defect is also low whatever the value of the rework rate, but if the rejection rate is high, the criticality of the defect is also high if the recovery rate is medium or low, and medium if the recovery rate and high. Thus the rejection rate mainly influences the criticality of the defects with an average compensation by a high recovery rate when the rejection rate is high.

5.4 Comparison between the results of Pareto analysis and fuzzy logic

In order to be able to compare the results of the Pareto chart and the fuzzy logic model, we will study the following data extracted from the defect situation of a car windshield manufacturing plant:

Table 1: Rejection rate, recovery rate and rework cost for windshield defects

Defect	Chips	Contamination	Optical defect	Breakage	Scratch	Printing defect	Deformation	PVB withdrawal	Air bubble	Dismantled profile
Rejection rate (%)	4,48	3,17	1,93	4,12	6,02	1,51	0,38	1,02	0,87	2,52
Recovery rate (%)	80	18	22	0,15	93	33	0,61	8	6	100
Rework cost	13	72	51	78	37	46	82	61	56	91

Based on these data, we have constructed the Pareto chart corresponding to the defect rejection rate:

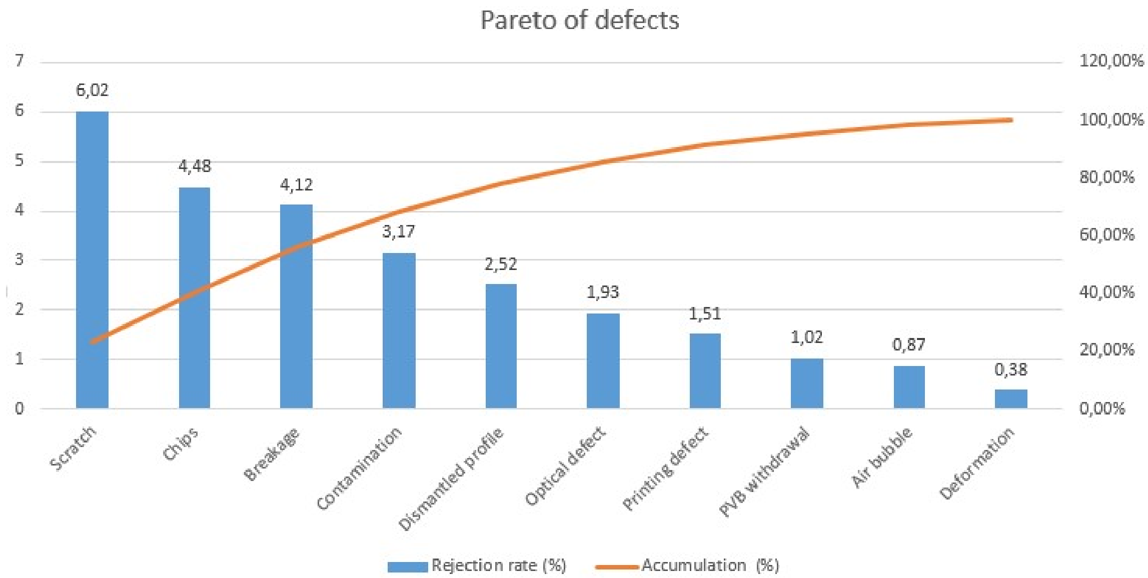

Figure 15: Pareto chart of defects rejection rate

Then, using the proposed fuzzy logic model, we calculated the criticality values of each of the defects based on the rejection rate, the recovery rate and the rework cost of each of them, and we listed them in the following table to compare them with the results of the Pareto analysis:

Table 2: Comparison between Pareto analysis and fuzzy logic model results

Defect	Scratch	Chips	Breakage	Contamination	Dismantled profile	Optical defect	Printing defect	PVB withdrawal	Air bubble	Deformation
Rejection rate (%)	6,02	4,48	4,12	3,17	2,52	1,93	1,51	1,02	0,87	0,38
Recovery rate (%)	93	80	0,15	18	100	22	33	8	6	0,61
Rework cost	37	13	78	72	91	51	46	61	56	82
Defect criticality	5	2,71	6,53	6,03	5,51	4,8	3,76	1,65	1,53	1,53

We deduce that there is a remarkable difference in the results since according to the Pareto analysis, the most critical defects are "Scratch", "Chips" and then "Breakage" whereas according to our fuzzy model the most critical defects are "Breakage" and "Contamination". This is due to the fact that the Pareto chart only takes into account one input indicator which is the rejection rate without having the possibility to consolidate it with the other indicators to decide on the criticality of the defects, on the other hand the fuzzy logic gives this possibility and allowed us to

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calculate the criticality of the defects with precision and thus a noticeable help to the decision making within the context of quality improvement.

Indeed, the added value of the use of fuzzy logic and more precisely of the proposed model can be clearly seen by focusing on its results which take into consideration all the input data that can impact the criticality of the defect with a certain degree of contribution of each one defined thanks to the inference rules, which makes this model capable of acting in a way similar to human reasoning and with great precision, which is one of the strongest uses and applications of artificial intelligence especially in the industrial field, which remarkably facilitates decision making on the part of the industrialists and thus ensures good improvements and efficient problem solving.

6. CONCLUSION

The improvement of quality has become a requirement for industrial companies especially in the context of global co-competition. For this purpose, companies are looking for methods to determine the most critical problems that require urgent and priority actions, in order to use them to identify the defects that cause them more financial losses and thus implement improvement actions to reduce or even eliminate them.

In this article, we have developed an artificial intelligence based decision making model using fuzzy logic, which identifies the most critical defects based on three input indicators which are the rejection rate, the recovery rate after rework and the cost of rework.

Subsequently, we compared the results of the Pareto analysis which is a Lean tool strongly used for problem prioritization with the proposed model results through the case study of defects in a windshield manufacturing plant, which highlighted the effectiveness of the model compared to the Pareto tool in the determination of critical defects, since this tool cannot take into account more than one input indicator which is usually the rejection rate.

This artificial intelligence model has shown a great efficiency in decision support, but other Industry 4.0 technologies are also very powerful and recommended in the quality improvement strategies, especially from the point of view of standardization of the best quality practices or the reinforcement of the control of the produced parts with a facilitation of the analysis of the deviations in the process, which also allows to prevent the quality defects and not only to correct them.

7. LIMITATIONS

The fuzzy logic model we have proposed has proven to be very effective for quality improvement through the identification of the most critical defects on which companies should focus their efforts, thus avoiding many sources of financial losses and providing good quality products to the customer.

This model allows organizations to determine the most critical defects to be solved immediately based on several input parameters, which allows decisions to be made based on complete and very accurate results, which is not achievable based on the Pareto tool that is widely used in companies and which only takes into consideration one input indicator, which is usually the rejection rate. However, it is essential that the membership functions be precisely defined by the experts in the field in order to adapt them to the context of the plant and to obtain more reliable and credible results.

However, this method does not focus mainly on the control of the products, that is to say that it is possible to send non-conforming parts to the customer, so the risk of claims is very high and the results efficiency externally is not quite guaranteed as the internal gain of the company, that is why this issue will be the subject of the next research work.

8. AUTHOR CONTRIBUTIONS

Anass Mortada wrote the paper, developed the fuzzy logic model and carried out the case study. Aziz Soulhi reviewed and commented on the points to be modified in the manuscript and approved the final version for submission.

REFERENCES:

[1] R. Godina, J. C. O. Matias, and S. G. Azevedo, “Quality Improvement With Statistical Process Control in the Automotive Industry”.

[2] H. Foidl and M. Felderer, “Research Challenges of Industry 4.0 for Quality Management,” in *Innovations in Enterprise Information Systems Management and Engineering*, M. Felderer, F. Piazolo, W. Ortner, L. Brehm, and H.-J. Hof, Eds., in Lecture Notes in Business Information Processing, vol. 245. Cham: Springer International Publishing, 2016, pp. 121–137. doi: 10.1007/978-3-319-32799-0_10.

[3] D. Prestiadi, W. Zulkarnain, and R. Bambang Sumarsono, “Visionary Leadership in Total Quality Management: Efforts to Improve the Quality of Education in the Industrial

Revolution 4.0," in *Proceedings of the 4th International Conference on Education and Management (COEMA 2019)*, Malang, East Java, Indonesia: Atlantis Press, 2019. doi: 10.2991/coema-19.2019.40.

[4] P. Arunagiri and A. Gnanavelbabu, "Identification of Major Lean Production Waste in Automobile Industries using Weighted Average Method," *Procedia Eng.*, vol. 97, pp. 2167–2175, 2014, doi: 10.1016/j.proeng.2014.12.460.

[5] D. C. C. Okpala, "TACKLING MUDA – THE INHERENT WASTES IN MANUFACTURING PROCESSES".

[6] G. Köksal, İ. Batmaz, and M. C. Testik, "A review of data mining applications for quality improvement in manufacturing industry," *Expert Syst. Appl.*, vol. 38, no. 10, pp. 13448–13467, Sep. 2011, doi: 10.1016/j.eswa.2011.04.063.

[7] S. Hyun Park, W. Seon Shin, Y. Hyun Park, and Y. Lee, "Building a new culture for quality management in the era of the Fourth Industrial Revolution," *Total Qual. Manag. Bus. Excell.*, vol. 28, no. 9–10, pp. 934–945, Jul. 2017, doi: 10.1080/14783363.2017.1310703.

[8] K. Ali and S. K. Johl, "Critical success factors of total quality management practices using Pareto analysis," *Int. J. Product. Qual. Manag.*, vol. 36, no. 3, p. 353, 2022, doi: 10.1504/IJPQM.2022.124704.

[9] Mechanical Engineering Department, ABES Engineering College, Ghaziabad.(Research Scholar Visvesvaraya Technological University,Belgaum, Mr. R. S. Raman, P. (Dr.) Y. Basavaraj, and Mechanical Engineering Department, Ballari Institute of Technology & Management, Ballari,India., "Quality Improvement of Capacitors through Fishbone and Pareto Techniques," *Int. J. Recent Technol. Eng. IJRTE*, vol. 8, no. 2, pp. 2248–2252, Jul. 2019, doi: 10.35940/ijrte.B2444.078219.

[10] M. Alkiayat, "A Practical Guide to Creating a Pareto Chart as a Quality Improvement Tool," *Glob. J. Qual. Saf. Healthc.*, vol. 4, no. 2, pp. 83–84, May 2021, doi: 10.36401/JQSH-21-X1.

[11] "Transilvania" University of Brasov, Romania, R. Nicolae (Mănescu), A. Nedelcu, "Transilvania" University of Brasov, Romania, A.-E. Dumitraşcu, and "Transilvania" University of Brasov, Romania, "IMPROVEMENT THE QUALITY OF INDUSTRIAL PRODUCTS BY APPLYING THE PARETO CHART," *Rev. Air Force Acad.*, vol. 13, no. 3, pp. 169–172, Dec. 2015, doi: 10.19062/1842-9238.2015.13.3.29.

[12] A. A. Aguilar Lasserre, M. V. Lafarja Solabac, R. Hernandez-Torres, R. Posada-Gomez, U. Juárez-Martínez, and G. Fernández Lambert, "Expert System for Competences Evaluation 360° Feedback Using Fuzzy Logic," *Math. Probl. Eng.*, vol. 2014, pp. 1–18, 2014, doi: 10.1155/2014/789234.

[13] Y. Hundecha, A. Bardossy, and H.-W. Werner, "Development of a fuzzy logic-based rainfall-runoff model," *Hydrol. Sci. J.*, vol. 46, no. 3, pp. 363–376, Jun. 2001, doi: 10.1080/02626660109492832.

[14] Y. Bai and D. Wang, "Fundamentals of Fuzzy Logic Control — Fuzzy Sets, Fuzzy Rules and Defuzzifications," in *Advanced Fuzzy Logic Technologies in Industrial Applications*, Y. Bai, H. Zhuang, and D. Wang, Eds., in Advances in Industrial Control. London: Springer London, 2006, pp. 17–36. doi: 10.1007/978-1-84628-469-4_2.

[15] Y. Chaabi, K. Lekdioui, and M. Boumediane, "Semantic Analysis of Conversations and Fuzzy Logic for the Identification of Behavioral Profiles on Facebook Social Network," *Int. J. Emerg. Technol. Learn. IJET*, vol. 14, no. 07, p. 144, Apr. 2019, doi: 10.3991/ijet.v14i07.8832.