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A DECISION-MAKING MODEL BASED ON FUZZY LOGIC TO SUPPORT MAINTENANCE STRATEGIES AND IMPROVE PRODUCTION LINES PRODUCTIVITY AND AVAILABILITY

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ABSTRACT

One of the bases of competitiveness between organizations is their ability to manage and reduce their costs and ensure their economic gains on a permanent basis. In fact, the maintenance and reliability of machines and equipment are two of the aspects that cause the highest costs for companies. For this reason, plant managers have been aiming in recent years to improve their maintenance policies and adopt the most effective strategies while reducing costs.

In fact, the adoption of effective maintenance strategies plays a critical role in ensuring the availability and productivity of production lines in order to cover customer orders, ensure their satisfaction, and avoid any type of complaint related to the non-fulfillment of deadlines. Companies often resort to two classical types of maintenance, namely corrective maintenance and preventive maintenance, or even a more general philosophy based on total productive maintenance (TPM). However, these strategies lack the tools and decision-support models to be applied effectively.

In this context, this paper aims to develop a decision support model using fuzzy logic to determine the types of maintenance adequate to each type of anomaly in the production lines by estimating the need for preventive action based on the costs of corrective intervention and preventive intervention and also based on the impact of the anomaly on the plant's performance.

Keywords: *Corrective maintenance, Preventive maintenance, Total productive maintenance, Productivity, Availability, Fuzzy logic, Decision-making.*

1. INTRODUCTION

In recent years, maintenance was a traditional activity that all companies applied without realizing its importance. However, after the improvement of production methods and the flexibility of production lines to achieve large volumes of different products, the importance of adopting effective maintenance strategies has increased, especially with the considerable need to ensure the availability of the lines and product quality in accordance with expectations. [1]. Hence, the adoption of effective maintenance policies plays a fundamental role in the economic performance of plants [2].

Indeed, maintenance policies have undergone significant changes in recent years, moving from failure-based maintenance to strategies based on monitoring and tracking the condition of machines, or, in other words, reliability-based preventive maintenance. [2]. In fact, maintenance is generally classified into corrective and preventive maintenance [3].

Corrective maintenance is based on the concept of "run-to-failure" and consists of replacing a degraded piece of equipment or part of a mechanism with the appropriate spare part. The availability of spare parts is a necessity for companies as failures can happen at any time, which is the essence of the corrective maintenance process as an emergency plan to solve unexpected failures. This type of maintenance, although traditional, is still popular in the industrial context. In terms of financial costs, this maintenance strategy often impacts the availability of production lines with a significant number of unplanned downtime hours, which has a negative impact on productivity and customer satisfaction in terms of lead time. On the other hand, given the complexity of machines and installations and the difficulty of predicting failures in a well-located manner, corrective maintenance remains the most economical solution compared to other maintenance strategies [4].

Preventive maintenance is the process of carrying out checks, measurements, adjustments, or replacements of specific parts for the prevention of failures. Effectively, preventive maintenance consists of the planning of regular, periodic replacements of equipment and machinery parts, even if these components are still working properly. However, if these frequencies are not well defined, these preventive actions become useless [4]. Indeed, a high frequency of maintenance interventions, although often recommended by companies, can sometimes represent unnecessary financial costs that do not really improve the reliability of components [5], hence the application of preventive maintenance cannot guarantee the non-occurrence of failures between two periods of preventive interventions [5], but it can make a significant contribution to reducing the probability of breakdowns and unexpected failures on production lines [2]. That is why plant directors and managers are now faced with the importance of making effective decisions regarding the application of preventive maintenance to prevent losses and optimize costs [2].

The estimation of reliability and maintainability values of equipment is necessary to determine adequate maintenance strategies; however, when the history of a certain failure gives different distributions in terms of time, the estimation of these parameters becomes delicate [6]. Likewise, estimating maintenance costs has always been a challenge because of the lack of accurate historical cost data and the uncertainties associated with the use and reliability of equipment [7].

In this context, among the most commonly used maintenance indicators are the mean time between failures (MTBF), which means the time between two successive failures, and the mean time to repair (MTTR), which means the time required to repair the failure [7].

Total Productive Maintenance (TPM) is a new maintenance philosophy developed to meet the new needs of production line reliability [1], it is a system that encompasses and covers the whole life cycle of equipment and machinery in terms of planning, production, and maintainability. This method ensures a synergistic relationship between all organizational functions, especially between production and maintenance, in order to guarantee the continuous improvement of the availability of production lines, product quality, and safety assurance while saving financial costs [8].

In the industrial context, one of the most challenging situations in which plant managers and supervisors find it difficult to make correct decisions is when an anomaly is detected in a certain machine that has not caused a breakdown but may stop production at any time. In these situations, they have to decide whether the anomaly requires urgent preventive action or whether to keep production running until the breakdown has occurred in order to carry out the corrective action. Similarly, when planning the hours or days dedicated to preventive maintenance, managers are confronted with the need to decide and determine the most critical anomalies to be treated in priority, as the duration of preventive interventions is often limited and does not allow them to act on all the failures.

To remedy this problem, in this paper we propose a methodology based on a fuzzy logic model that allows us to calculate a very important indicator, which is the necessity of preventive action, in order to make adequate decisions on which maintenance strategy will be more efficient in terms of financial costs for each type of anomaly. This methodology is based on three input parameters: the cost of preventive action, the cost of corrective action, and a third strategic indicator, which is the impact of the anomaly on the performance of the plant and the manufacturing conditions.

2. LITTERATURE REVIEW

Total Productive Maintenance (TPM) is a philosophy that aims to improve the efficiency and availability of equipment and machinery in order to reduce the high costs of downtime, repairs, and corrective actions, as well as establish a comprehensive management system for the performance of equipment throughout its life and reduce process variation [8]. However, TPM does not only take into consideration the reliability and technical aspects of mechanisms but also the involvement of all employees and the entire organization, from management to those concerned with maintenance and production [9]. In fact, as the name suggests, total means both focusing on all aspects of maintenance that affect production and involving everyone in this methodology, as well as efficiency and economic profitability, while maintenance means keeping equipment in good condition and with maximum reliability, and the word productive means that these actions of maintenance aim to ensure optimal availability and thus a better rate and maximum productivity [10], so we are talking about a philosophy that requires a synergy that must be developed between all the services of the organization, and particularly between the production and maintenance departments, in order to achieve effective results [11].

In order to properly implement the TPM philosophy, it is essential to take into account basic elements such as the 5s activities including cleaning and organization of the different workplaces, and then the autonomous maintenance activities, which must also be carried out on a daily basis by the operators [3]. Subsequently, it is necessary to plan hours and sometimes even days of downtime to be sacrificed in order to effectively carry out preventive maintenance and the various interventions necessary for critical equipment in order to restore it to good condition and prevent any type of breakdown or sudden stoppage, which could result in very high costs, especially with the differences in the quantities produced due to the high rate of unavailability. In fact, several studies have confirmed that the cost of corrective maintenance actions is almost three times higher than the cost of the same repair carried out in preventive mode [8].

To evaluate the effectiveness of TPM, it is necessary to focus on indicators that calculate the availability and performance of equipment in terms of productivity and efficiency. Indeed, overall equipment effectiveness (OEE) is a very powerful key performance indicator that gives an overall idea of the efficiency of the equipment through the multiplication of three main indicators: availability rate, performance rate, and quality rate, which indicate the level of three key elements in the industry, which are production, quality, and maintenance. Thus, the OEE is considered a main indicator to evaluate the effectiveness of TPM [8]:

$$\text{OEE} = \text{Availability rate} * \text{Performance rate} * \text{Quality rate}$$

TPM is based on 8 basic pillars, which are:

a) Autonomous maintenance: which aims to involve the operators by carrying out cleaning, adjustments, and readjustments on the production equipment on a daily basis [12].

b) Focused improvement: through the identification and elimination of waste and the reduction of losses by focusing on the root causes of anomalies and improving the OEE of production lines [12].

c) Planned maintenance: which aims at planning interventions in an efficient way during the life cycle of the equipment and thus improving the MTBF and MTTR [12].

d) Quality control and maintenance: through a quality policy that aims at a good follow-up and treatment of the functioning of the equipment and its anomalies and the causes of non-quality, in order to reach zero defects and increase the useful time at the process level [12].

e) Training and improvement of know-how: through the transfer of knowledge and skills in order to ensure the versatility of employees, and to provide them with continuous training and evaluation to align them with the objectives of the organization [12].

f) Safety, health, and environment: this means ensuring a safe and secure working environment by following procedures and standards to eliminate injuries and safety incidents and to ensure good environmental care [12].

g) Administrative TPM: which aims to establish a synergy between the different departments of the company and a total collaboration for the reduction of the different costs by ensuring their functioning in an efficient way, especially at the level of the offices, to avoid any negative impact on production and productivity [12].

h) Development management: through the capitalization of experiences to carry out new projects and the generalization of good practices on new systems with a continuous improvement of maintenance, especially by improving the conception and design of products and equipment [12].

However, practically, the wrong application of TPM can limit its effectiveness in terms of productivity and availability of the production lines because it is not possible to generalize a maintenance strategy for all situations. This is due to the fact that the anomalies and problems related to machinery and equipment functioning are often different from each other, which requires specific actions and decisions adapted to the types of anomalies.

In recapitulation, TPM is indeed a very effective philosophy for ensuring and improving the productivity and availability of production lines. Nevertheless, in order to apply and execute it correctly, it is necessary to reinforce it with decision support tools, in particular to decide on the appropriate maintenance strategies for each situation and to determine the critical anomalies to be treated as a priority during preventive

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maintenance interventions, which is the subject of this research.

3. MATERIAL AND METHODS

3.1 Presentation of Fuzzy Logic

The concept of fuzzy logic and fuzzy sets was first introduced by Professor Lofti A. Zadeh in 1965, it aims at the formalization of natural human reasoning. Fuzzy logic is an artificial intelligence logical system whose objective is the development of models and programs with intelligent behavior [13].

Fuzzy logic is a very effective tool for management support and decision-making, especially for problems that are characterized by the interaction of different factors and parameters [13].

The concept of fuzzy sets is that it is possible for elements to belong partially as the boundaries are not clearly defined. The theory of fuzzy sets is the basis of fuzzy logic modeling, which is different from that of ordinary binary sets [14]. The classical set considers just a limited number of membership degrees, which are usually "0" and "1" [15]. Each element of the fuzzy set belongs to an inclusive interval, and its value is assigned by the membership function associated with the fuzzy set [14].

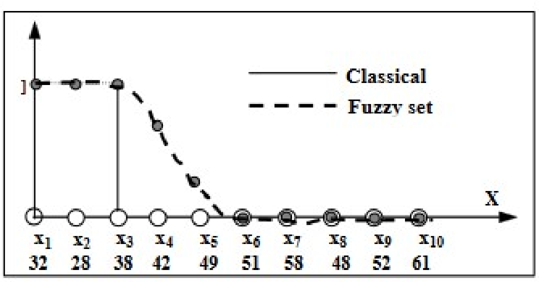

Figure 1: Comparison between classical and fuzzy sets [15]

Membership functions and fuzzy rules are the two main components of fuzzy logic, which allow linguistic expressions to be translated into mathematical formulas, thus allowing a transition from a qualitative description resulting from domain expertise to a quantitative description via the mathematical model [13].

The modeling of a process according to fuzzy logic requires that the variables of the model belong to fuzzy classes and are managed by rules of the form IF...THEN to allow for the establishment of a result for each combination of the fuzzy classes that contain the variables [14].

3.2 Fuzzification

This fuzzification step allows us to translate classical or crisp data into fuzzy data [15], by defining the membership functions for both input and output variables, which makes it possible to translate numerical data into linguistic variables by defining the form of the membership functions and the degree of membership in each of the states that must be defined and specified [16]. The most commonly used forms of functions are triangular and trapezoidal:

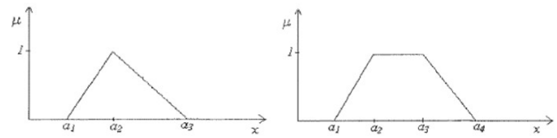

Figure 2: Membership function of a triangular and trapezoidal fuzzy variable [14]

The membership functions should be defined by field experts, and then the model should generate the result of the output variable by the center of gravity method [16].

3.3 The Fuzzy Inference engine

Fuzzy inference engine or fuzzy inference systems are also called fuzzy rule-based systems, fuzzy associative memories, fuzzy models, or fuzzy controllers [17]. The objective of this step is to combine the control rules with the membership functions defined in previous steps to obtain fuzzy output data [15], which means that after defining the linguistic variables, they need to be exploited in the inference engine, and this is done by determining the rules based on field expertise and enunciating them in natural language to formalize human reasoning, which is one of the objectives of artificial intelligence and fuzzy logic [16].

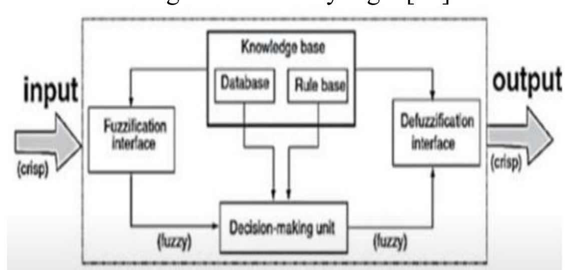

Figure 3: Fuzzy inference system [17]

3.4 Defuzzification

Since the inference is complete, this phase of defuzzification 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 [16].

The calculation of the "center of gravity" of the fuzzy set is one of the most effective methods for this purpose [16], in addition to the method of maximum output [13]:

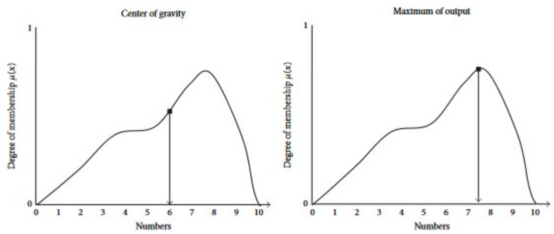

Figure 4: Defuzzification common methods [13]

3.5 Summary of fuzzy logic modelling

After the explanation of fuzzy logic modelling steps, we can summarize them in the form of the schematic shown in the figure below:

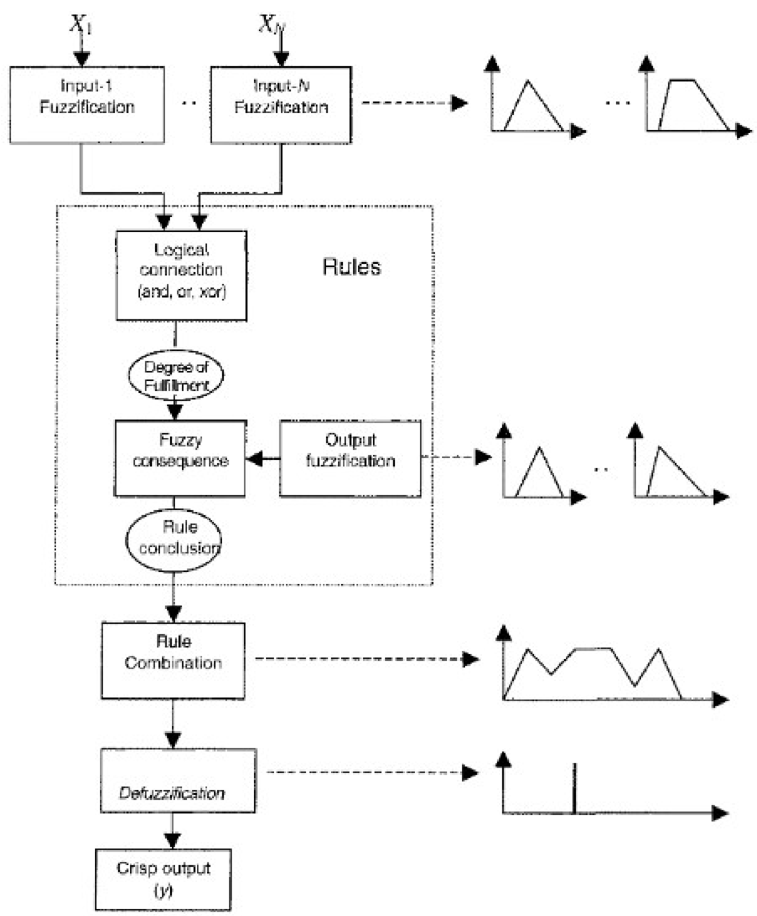

Figure 5: Summary schematic of a model based on fuzzy logic [14]

4. CASE STUDY

4.1 Proposed method for need for preventive action estimation

The decision on the most adequate maintenance strategy is often complicated at the level of plant management since the anomalies and failures under consideration differ from each other mainly in terms of the comparison between the cost of preventive action and the cost of corrective intervention. In some cases, preventive maintenance is less costly when it allows for huge savings in the event of a breakdown or sudden stoppage of production. In other cases, when the reliability of the equipment is not well estimated and the cause of the failure is not clear and well localized, the preventive intervention must concern the whole equipment, which will cost more hours of downtime and more spare parts, while in the case of failure, the cause is well localized, so the preventive intervention will be faster and less expensive.

Apart from the cost comparison, another indicator is very important: the impact of the anomaly in question on the performance of the line in terms of quality, productivity, safety, and others. Some failures require emergency intervention because of their impact, while others have no negative impact other than the reliability of the machine.

In this article, we will introduce a new method in the form of a decision-making model based on fuzzy logic to choose the category of maintenance to apply in each situation. This model allows to estimate the necessity of preventive intervention when a certain anomaly is detected based on three input indicators, which are the cost of preventive action, the cost of corrective action, and the impact of the anomaly on performance, using the terms "low", "medium" and "high" to describe both the input variables "preventive action cost", "corrective action cost" and "impact on performance" and the output variable "need for preventive action".

4.2 Indicators definition

The Need for preventive action as an output indicator will be estimated based on the following three indicators:

Preventive action cost: this includes all the costs necessary to carry out the preventive intervention, in terms of immediate production downtime and its impact on the production planning, spare parts, and manpower.

Corrective action cost: this includes all the costs necessary to carry out the corrective intervention, in terms of unplanned production downtime and the risk of not covering the customer, spare parts, and the necessary manpower.

Impact on performance: this means the impact of the anomaly being investigated on different aspects of production line performance, such as product quality, production speed, 5s and safety.

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

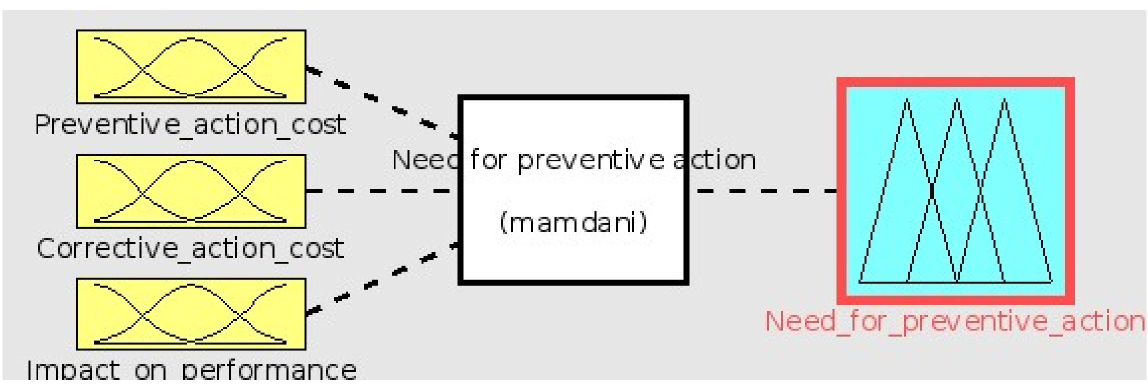

Figure 6: Proposed fuzzy model

4.3 Modeling of indicators

After presenting the proposed model and the input and output indicators, we proceed to determine the membership functions of each variable, as shown in the figures below:

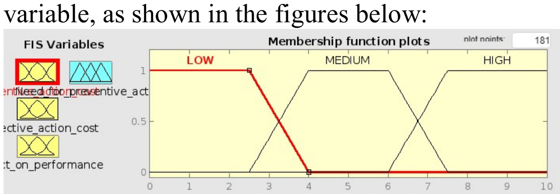

Figure 7: Membership function for "Preventive action cost"

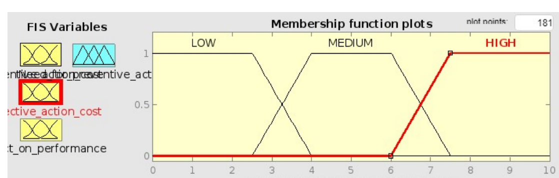

Figure 8: Membership function for "Corrective action cost"

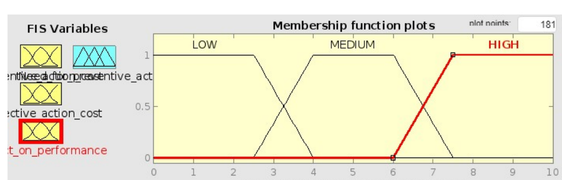

Figure 9: Membership function for "Impact on performance"

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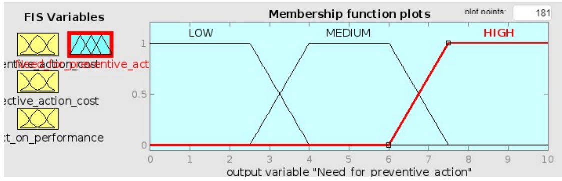

Figure 10: Membership function for "Need for preventive action"

4.4 Fuzzy inference

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

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

Figure 11: Inference Rules Presentation

4.5 Defuzzification

As shown in the following figure, the defuzzification step allows, on the basis of the center of gravity method, to transform the fuzzy set containing preventive action cost, corrective action cost, and impact on performance into an accurate numerical value of the need for preventive action:

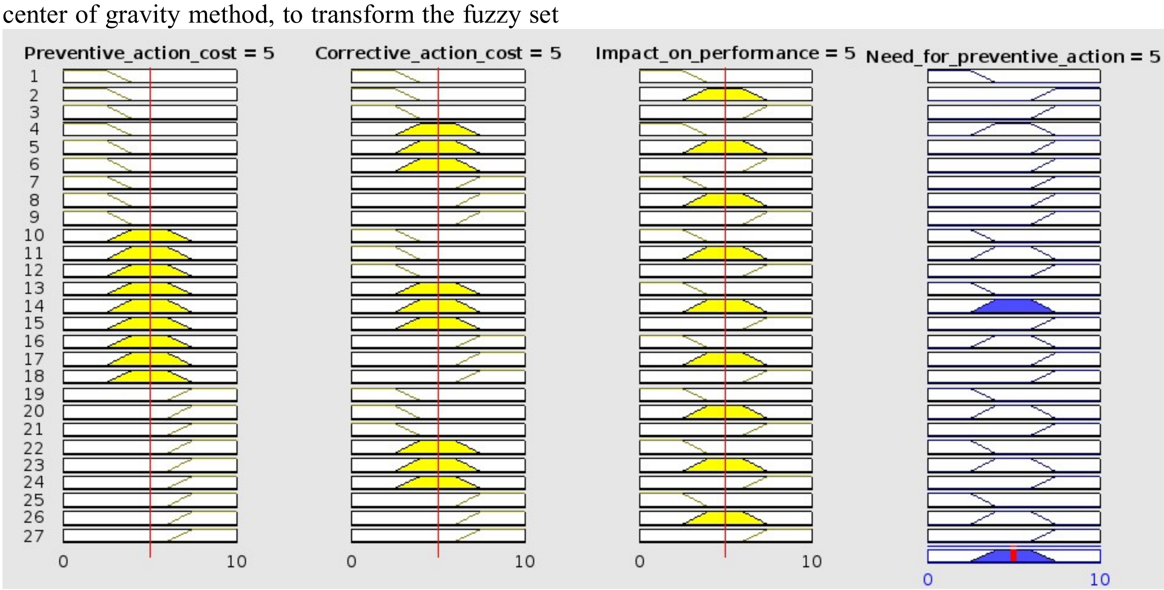

Figure 12: Deffuzification process

5. RESULTS AND DISCUSSION

Following the construction of the inference system, it is time to interpret and analyze the results of the defuzzification based on the graphs of the surface viewer, which will allow us to understand the relationship between the three input indicators

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and the need for preventive action. Thus, we will study three possible cases, where each time we will fix one of the input variables on a mean value.

5.1 Use case 1: Medium preventive action cost

In this case, the preventive action cost indicator is set to medium:

Med: Preventive action cost.
Y: Corrective action cost.
Z: Impact on performance.

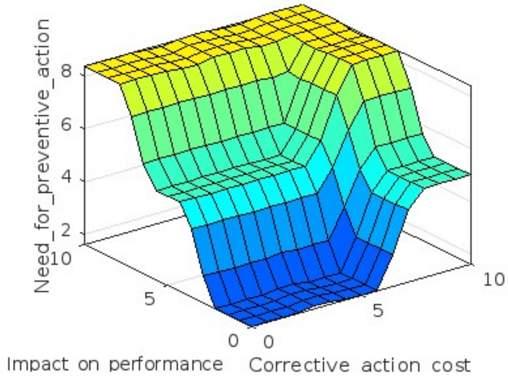

Figure 13: Surface View for Use Case N°1

Figure 13, which illustrates the case where the preventive action cost is set to a medium value, shows that when the impact on performance is high the need for preventive action is also high whatever the value of the corrective action cost, and similarly if the corrective action cost is high unless the impact on performance is low, This means that if the anomaly has a high impact on performance, the preventive action must be implemented urgently and if the cost of the corrective action following the failure caused by the anomaly is high, the need for preventive intervention is only urgent if the impact on performance is not low. On the other hand, if one of the two indicators is low and the other is not high, the need for preventive action is also low to medium. This shows that the output indicator is strongly influenced by the cost of the corrective action and especially by the impact on performance.

5.2 Use case 2: Medium corrective action cost

In this case, the corrective action cost indicator is set to medium:

X: Preventive action cost.
Med: Corrective action cost.
Z: Impact on performance.

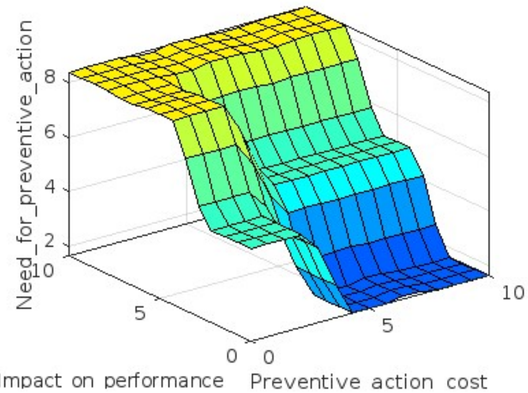

Figure 14: Surface View for Use Case N°2

According to figure 14, where the surface shows the case where corrective action cost is fixed at an average value, we notice, as in the previous case, that if the impact on performance is high, the need for preventive action is high, whatever the value of its cost. Apart from that, as long as the preventive action cost is medium or high, the need for preventive action remains low or medium. Hence, the impact of the anomaly on performance mainly influences the need for preventive action, with some influence of its cost.

5.3 Use case 3: Medium impact on performance

In this case the impact on performance indicator is set as medium:

X: Preventive action cost.
Y: Corrective action cost.
Med: Impact on performance.

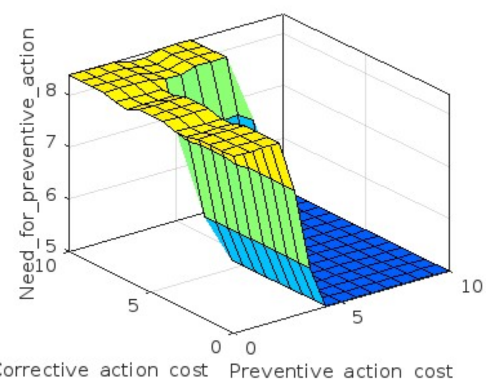

Figure 15: Surface View for Use Case N°3

From figure 15, where the surface shows the case where the impact on performance is fixed at an average value, we can see that if the preventive action cost is strictly lower than the corrective action cost, then the need for preventive action is high or at least medium, but in the opposite case it is generally low.

6. CONCLUSION

Maintenance management has recently become a necessity for companies due to its great impact on the availability and productivity of production lines and also due to the financial losses that can be caused by wrong decisions on the choice of maintenance strategies to be applied to remedy the different failures. Several maintenance strategies have been the subject of previous research, including corrective maintenance, preventive maintenance, and total productive maintenance, which is a Lean manufacturing methodology that aims to improve not only maintenance but all aspects of production related to it. However, these strategies need to be supported by decision-support models that allow manufacturers to correctly choose the appropriate maintenance policies.

In this paper, we have developed a model based on fuzzy logic to determine the maintenance policies that managers should adopt to attack the anomalies that can appear on production lines. This model is based on three input data related to the studied anomaly which are its impact on the different aspects related to the quality and the efficiency of the production and the costs of the preventive action and the corrective action, and on their basis allows to calculate the value of the need for preventive action which allows the companies to define the maintenance policies and to determine the critical anomalies to be prioritized during the planned preventive maintenance work.

Hence, the proposed model considerably supports the TPM philosophy and maintenance strategies by taking into account the different factors that can have an impact on the importance of a certain intervention or another, and thus being able to select the appropriate maintenance strategy for each failure, resulting in a clear improvement in the productivity and availability of the lines and a considerable cost saving.

7. LIMITATIONS

The fuzzy logic model proposed in this research can significantly help companies make decisions on the types of maintenance to be applied to address different faults and defects and determine which ones are more critical.

Yet, the effectiveness of this method and its results depend mainly on the precision and accuracy of the input data of the model, in other words, to find reliable and credible results, managers are expected to accurately estimate and note the cost of corrective and preventive interventions and also the impact of each anomaly on manufacturing performance, and this is done by analyzing deeply the historical data of failures and breakdowns, which is still a great challenge in the industrial environment.

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