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Ken Sammuel I. Camacho
Department of Manufacturing Engineering and Management, De La Salle University

Michael Leander P. Roque
Department of Manufacturing Engineering and Management, De La Salle University

Ryan Rhay P. Vicerra
Department of Manufacturing Engineering and Management, De La Salle University

Nilo T. Bugtai
Evelyn D. Ang - Institute of Biomedical Engineering and Health Technologies, De La Salle University

https://doi.org/10.5109/7395694

出版情報：Proceedings of International Exchange and Innovation Conference on Engineering & Sciences (IEICES). 11, pp.1410-1415, 2025-10-30. International Exchange and Innovation Conference on Engineering & Sciences
バージョン：

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Ken Sammuel I. Camacho[1], Michael Leander P. Roque[2], Ryan Rhay P. Vicerra[3], Nilo T. Bugtai[4]
[1,2,3]Department of Manufacturing Engineering and Management, De La Salle University, [4]Evelyn D. Ang – Institute of Biomedical Engineering and Health Technologies, De La Salle University
ken_sammuel_camacho@dlsu.edu.ph, michael_roque@dlsu.edu.ph, ryan.vicerra@dlsu.edu.ph, nilo.bugtai@dlsu.edu.ph

Abstract: *Predictive maintenance is an increasing trend in research that aims to predict machine failure before it happens. This approach has led to the development of machine learning algorithms to help improve efficiency, reduce maintenance costs, and optimization in production lines. However, machine learning algorithms depend on statistical inferences and historical data to predict failures. The dynamic environment in a manufacturing line makes the maintenance of machines fuzzy, as there are no systematic approaches to developing these algorithms. In this paper, an algorithm is proposed using fuzzy logic techniques to evaluate the probability of machine failure. This model used historical data and knowledge-based algorithms to classify output in nine linguistic defuzzification variables. Results have shown that the developed algorithm correctly classified the probability of failure using only two inputs, rotation speed and torque. This model allows manufacturing companies to implement algorithms for real-time decision-making processes to optimize predictive maintenance procedures.*

Keywords: Decision-Making Algorithm, Fuzzy Logic, Integrated Lean Six Sigma, Machine Failure, Maintenance

1. INTRODUCTION

One of the most important industries in today's world is the manufacturing industry. This is due to its contribution to a country's economy, as it aids in job creation, as well as economic growth [1]. Because of this, there is a necessity for optimizing plants and their various manufacturing lines, both in terms of production and waste elimination. As such, the concepts of "six sigma" and "lean manufacturing" are adapted in the principles of manufacturing companies [2-3]. Although in modern times, a more innovative and effective principle is being implemented, combining both the objectives of six sigma and lean manufacturing. This is called "Integrated Lean Six Sigma" (IL6S), which aims to make continuous improvement a culture, eventually leading to improved quality and processes, as well as reduced costs [4]. It should be noted, however, that IL6S has eight pillars that hold up its ideologies. Two of these pillars directly correspond with the preservation of machine health, also known as maintenance.

In a manufacturing line, it is possible to collect a significant amount of data that contains information about the different facets of industrial systems. Innovative components, like sensors and microprocessors, allow companies to acquire feedback about their physical assets regarding their use and degradation [5]. Processing and analyzing these data can help extract essential information from the manufacturing process and dynamics of systems. Analytical approaches based on the collected data may be used to develop tools for strategic decision-making, including maintenance [6]. This indicates that assessments of physical assets' present and potential future conditions are used to inform maintenance actions (such as repairs, replacements, etc.) [5]. The impact of maintenance accounts for between 15 and 60 percent of all operating expenditures in the industrial sector [7], [8]. Equipment maintenance is essential, as breakdowns can affect equipment efficiency and uptime and lead to employees working overtime to compensate for production schedule delays or losses [9]. Identifying and solving common equipment faults is essential to avoid hindering production processes [10].

A sound maintenance strategy should enhance equipment conditions and minimize maintenance costs while maximizing the life of the equipment [11]. Maintenance strategies cannot be performed anywhere and anytime due to technical and logistical limitations [12]. Maintenance methods are often classified into three main categories: run-to-failure, preventive, and predictive maintenance [13]. In the run-to-failure maintenance method, a new component must run upon installation until an error occurs before maintenance. This method, however, is costly and less efficient due to the additional maintenance overhead and unplanned downtime.

On the other hand, preventive maintenance refers to failures that can be prevented by regularly replacing components, but at the cost of additional operating expenses and increased new life [14]. The third method, predictive maintenance, is often used to repair industrial equipment and restore machinery to its original condition before failure occurs. Predictive maintenance predicts system failures and optimizes maintenance activities using predictive information to plan future maintenance operations [15-17]. The method is also based on the continuous monitoring of machine or process health, so maintenance can be performed when needed [18]. Moreover, predictive maintenance is critical to ensure operational safety [19]. Predictive maintenance aims to minimize maintenance costs, achieve zero waste production, and reduce the number of failures [20]. Moreover, predictive maintenance based on data-driven methods has emerged as the most effective solution for smart manufacturing and industrial big data compared to other strategies [21-22].

Recognition of predictive maintenance as a maintenance strategy that predicts and reduces critical and costly failures, thereby increasing asset reliability, has increased significantly in recent years [23]. Instead of fixing failures, companies try to anticipate failures and minimize the associated risks and costs, and this is now the highest form of maintenance today [24]. According to [25], predictive maintenance also offers many benefits, including extending machine life, reducing environmental impact, reducing maintenance costs, reducing worker injuries, reducing waste in the system, and improving product quality. With the availability of machine sensor data and the intention to use this data in a targeted way, the introduction of predictive maintenance is a logical step toward maintenance optimization in the industry [23]. For instance, the study of [26] explored predictive tool maintenance to predict tool wear.

A general trend in developing predictive maintenance algorithms is to reduce maintenance-related costs or improve production maintenance by predicting required maintenance [27]. Big data analytics, machine learning models, and ontology and reasoning-related concepts are common solutions to predictive maintenance [27]. Prediction tools are also heavily grounded on historical data and statistical inference methods to detect failures [13]. Research has also shown combining historical and relevant domain knowledge and models to predict trends, behavioral patterns, and correlations through statistical or machine learning models [28-29]. There are also studies exploring knowledge-based approaches using expert systems or fuzzy logic [30-31].

Despite the intensive research on predictive maintenance, there is still a need to develop scalable and efficient methods and algorithms for real-time decision-making instead of processing batches of data and developing general decision-making models that represent decision-making processes rather than physical processes [32]. As such, this paper aims to create a predictive maintenance model based on fuzzy logic techniques to predict the probability of failure of machines for real-time decision-making processes. The model will represent the degree of probability of failure to help users estimate whether the device needs maintenance. Moreover, the fuzzy logic algorithm is not integrated with machine learning algorithms to lessen the need for processing batches of data. Lastly, the study aims to implement a fuzzy logic controller for classifying the input parameters of the rotational speed and torque of the machine, due to their correlation to abnormalities and breakdowns. It should be noted that other approaches and models were also considered, including the use of transformers, informers, and even mathematical models [33]. However, fuzzy logic was chosen due to its flexibility, simplicity, as well as its ability to mimic human reasoning. Additionally, other factors were considered, including real-life application and understandability. Due to this, fuzzy logic was chosen as the results would be easier to understand for people who do not understand or are not as adept as others when it comes to mathematical concepts, as well as being appropriate due to maintenance's dynamic nature.

2. FUZZY LOGIC IN MAINTENANCE

Maintenance is considered fuzzy because of the dynamic environment in a production line [34]. The study in [35] also found that defining a general mathematical model for maintenance in production lines is difficult because the data need to provide a direct means to assess the need for preventive care. Moreover, a production line's variables are soft and not crisp because the limits are not defined [35].

Studies related to fuzzy logic have been explored for assessing the health of industrial equipment and maintenance needs, planning, evaluation, improvements, as well as material part strength and capabilities [36-39]. Fuzzy logic has also been used to estimate the number of parts a machine can produce before recalibration [40]. The fuzzy logic technique is also applied in [41] to identify the criticality of failures. There are no known studies that use the fuzzy logic technique to predict the probability of failure of machines.

Faults in machines are known to be segregated into quantitative and qualitative strategies [42]. According to [43], mathematical models for the quantitative approach should be based on domain knowledge, while qualitative methods are based on patterns from historical process data. In [36], a combination of a quantitative approach grounded on historical data is presented. A similar approach is to be performed in this study to define a fuzzy logic system. Most studies also prefer the Mamdani fuzzifier to the Sugeno as it is easier to compute [44-46]. This is because the Mamdani fuzzifier is more intuitive, as well as much better-suited when human input is required. It is also usually used when it comes to applications that deal with control [47]. On the other hand, the Sugeno fuzzifier is more efficient and precise when it comes to computations and is often used when optimization is needed [48]. However, due to this, it is more difficult to understand and interpret. As such, the Mamdani fuzzifier will be employed in the study.

3. METHODOLOGY

3.1 Data Acquisition

This study used a dataset from UC Irvine Machine Learning Repository. The AI41 2020 Predictive Maintenance Dataset is synthetic data that contains 10,000 records of machine measurements [49]. Artificial information is used in the study because real-world data are not published or readily available. The same dataset was used in [50] to reflect a realistic scenario where sensors are connected to a machine for health condition monitoring.

3.2 Data Analysis

According to [51], torque and rotation speed are essential predictors of failure in the machine. Due to their importance in machine design, both torque and rotational speed must be kept within their specific tolerances. Typically, acceptable ranges are kept within ± 1-20% for torque and ±1-10% for rotational speed. Going beyond those ranges will induce faster machine failure. An example of these failures would be if the torque is too high, gear damage and shaft or bearing failure could occur. Another example would be if the rotation speed is too low, it would lead to inefficiencies in the production of the machine, as well as the possibility of breakdowns [52]

As such, these two parameters are necessary for creating the fuzzy logic model. The rotation speed and torque of the dataset are then analyzed using histogram plots. This can be seen in Fig. 1, which represents the histogram for rotation speed.

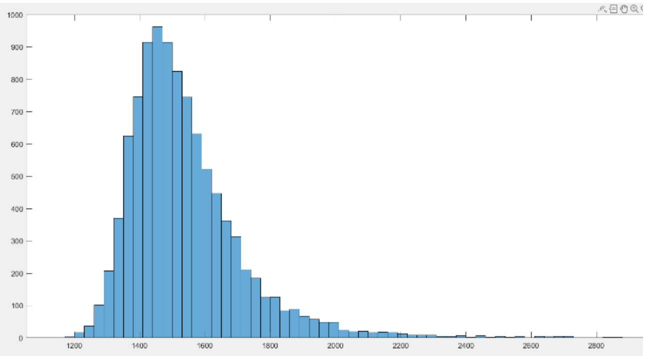

Fig. 1. Histogram for rotation speed.

The rotation speed values are skewed to the right, which signifies that values are clustered closer to the right. The graph also reveals that the lowest rotation speed in the dataset is at 1200 rpm and while the highest exceeds 2800 rpm. As such, the input range should be from 1200 rpm to 2900 rpm.

The histogram for the torque is also acquired and is presented in Fig. 2.

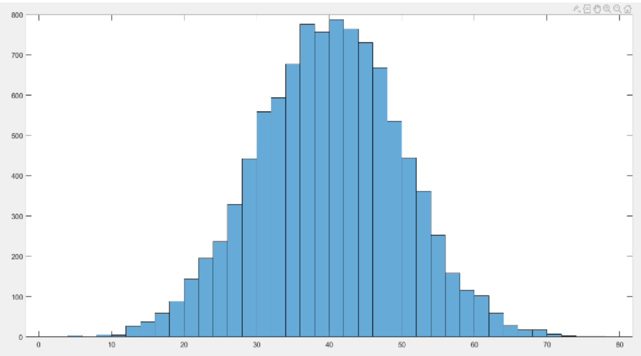

Fig. 2. Histogram for torque.

Data reveals that the torque in the dataset is clustered around the value of 40Nm. Additionally, the range of data is from 0 to 80 Nm with no negative values, which shows that the torque represents only counterclockwise rotations.

3.3 Fuzzy Inference System

The study utilized the MATLAB software to accomplish the study [53]. This is due to its accuracy and efficiency, especially when it comes to computation and modeling. Furthermore, computation and modeling are both needed when it comes to analyzing fuzzy logic systems. Additionally, MATLAB's user-friendly interface and reliability in the fields of engineering greatly supports the results of the study.

The MATLAB fuzzy logic toolbox [54] was used to simulate the probability of failure based on a machine's rotation speed and torque. A Mamdani fuzzifier is employed in the study with two inputs and one output. As stated earlier, this was chosen due to its simplicity, as well as its linguistic rules being easily definable and modifiable, making it more feasible to use. Furthermore, it is already being used in many different real-world systems, including HVAC and automotive systems.

The Mamdani fuzzifier is visualized further in Fig. 3.

Rotation speed is considered a crisp input with four linguistic values: very slow, slow, fast, and very fast rotation speeds. The fuzzification of the inputs into membership functions for rotation speed following a triangular shape is depicted in Fig. 4.

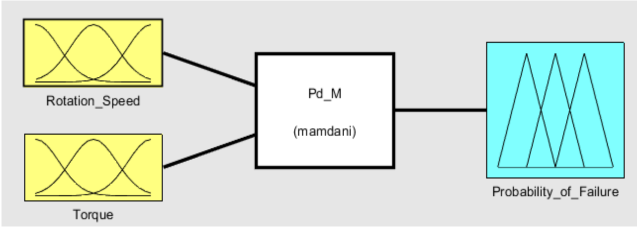

Fig. 3. Fuzzy Inference System of the Fuzzy Logic System.

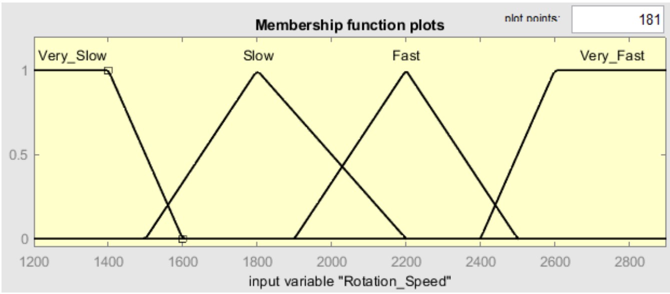

Fig. 4. Membership function for rotation speed input.

The torque input value is also a crisp input with five linguistic variables. The membership function depicting the fuzzification of values into very low, medium, high, and very high torque values is illustrated in Fig. 5.

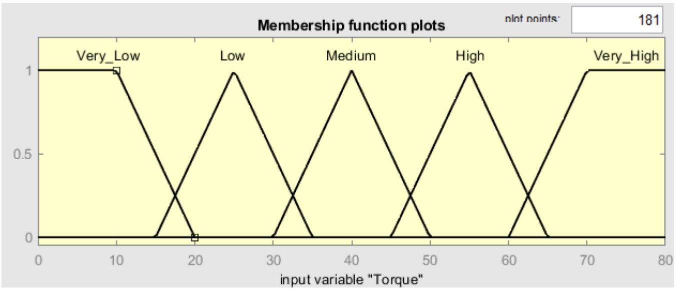

Fig. 5. Membership function for torque input.

The probability of failure output ranges from 0 to 1 to depict the probability values, wherein 0 represents a 0% chance of failure and 1 represents a 100% chance of machine failure. The result also has nine linguistic variables for output defuzzification, namely: extremely low, very low, moderately low, low, neutral, high, moderately high, very high, and extremely high.

The membership function for the probability of failure has a triangular shape, as seen in Fig. 6.

The fuzzy set rules are formulated using IF-THEN statements to derive the appropriate values and conclusions. A rule base is used to tabulate the relationship between rotation speed and torque, as seen in Table 1.

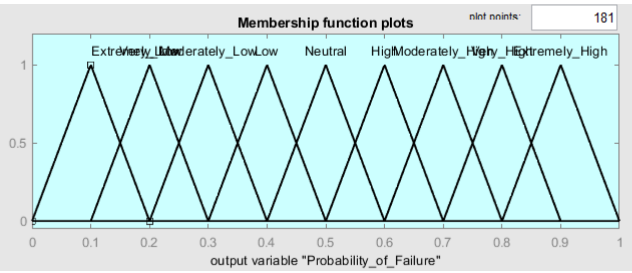

Fig. 6. Membership function for probability of failure output.

Table 1. Rule-based to identify the probability of failure based on rotation speed and torque.

		Torque				
		Very Low	**Low**	**Medium**	**High**	**Very High**
Rotation Speed	**Very Fast**	High	High	Mod. High	Very High	Extremely High
	Fast	Mod. High	Low	Neutral	Mod. High	Very High
	Slow	Very Low	Mod . Low	Low	Neutral	Mod. High
	Very Slow	Extre mely Low	Very Low	Mod. Low	High	High

The fuzzy inference system contains 20 rule combinations due to the input classes for rotation speed and torque being four and five, respectively.

The proposed rules set is implemented in the fuzzy inference system via the rule editor, as shown in Fig. 7.

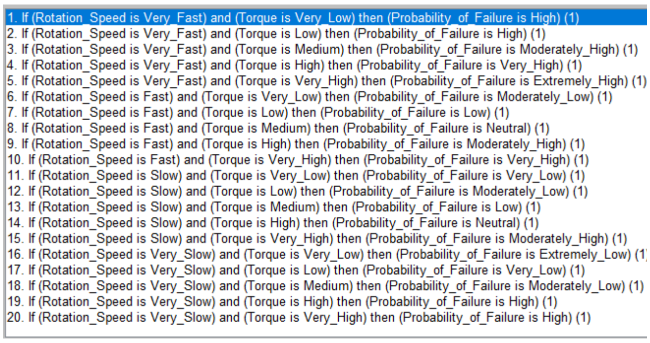
1. If (Rotation_Speed is Very_Fast) and (Torque is Very_Low) then (Probability_of_Failure is High) (1)
2. If (Rotation_Speed is Very_Fast) and (Torque is Low) then (Probability_of_Failure is High) (1)
3. If (Rotation_Speed is Very_Fast) and (Torque is Medium) then (Probability_of_Failure is Moderately_High) (1)
4. If (Rotation_Speed is Very_Fast) and (Torque is High) then (Probability_of_Failure is Very_High) (1)
5. If (Rotation_Speed is Very_Fast) and (Torque is Very_High) then (Probability_of_Failure is Extremely_High) (1)
6. If (Rotation_Speed is Fast) and (Torque is Very_Low) then (Probability_of_Failure is Moderately_Low) (1)
7. If (Rotation_Speed is Fast) and (Torque is Low) then (Probability_of_Failure is Low) (1)
8. If (Rotation_Speed is Fast) and (Torque is Medium) then (Probability_of_Failure is Neutral) (1)
9. If (Rotation_Speed is Fast) and (Torque is High) then (Probability_of_Failure is Moderately_High) (1)
10. If (Rotation_Speed is Fast) and (Torque is Very_High) then (Probability_of_Failure is Very_High) (1)
11. If (Rotation_Speed is Slow) and (Torque is Very_Low) then (Probability_of_Failure is Very_Low) (1)
12. If (Rotation_Speed is Slow) and (Torque is Low) then (Probability_of_Failure is Moderately_Low) (1)
13. If (Rotation_Speed is Slow) and (Torque is Medium) then (Probability_of_Failure is Low) (1)
14. If (Rotation_Speed is Slow) and (Torque is High) then (Probability_of_Failure is Neutral) (1)
15. If (Rotation_Speed is Slow) and (Torque is Very_High) then (Probability_of_Failure is Moderately_High) (1)
16. If (Rotation_Speed is Very_Slow) and (Torque is Very_Low) then (Probability_of_Failure is Extremely_Low) (1
17. If (Rotation_Speed is Very_Slow) and (Torque is Low) then (Probability_of_Failure is Very_Low) (1)
18. If (Rotation_Speed is Very_Slow) and (Torque is Medium) then (Probability_of_Failure is Moderately_Low) (1)
19. If (Rotation_Speed is Very_Slow) and (Torque is High) then (Probability_of_Failure is High) (1)
20. If (Rotation_Speed is Very_Slow) and (Torque is Very_High) then (Probability_of_Failure is High) (1)

Fig. 7. IF-THEN statements for the fuzzy set rules.

The rules viewer in the MATLAB fuzzy toolbox is then used in order to interpret the fuzzy inference system. Using this approach, the user would be able to visualize how specific membership function shapes influence the output values.

The rules viewer is presented in Fig. 8. The surface plot of the fuzzy inference system is also visualized using the MATLAB fuzzy toolbox to determine the dependency of the output on the inputs. The surface plot of the fuzzy inference system is shown in Fig. 9.

4. EVALUATION

The fuzzy inference system was evaluated by getting ten random samples, 5 of which were machine failures and another 5 for non-machine failures, from the dataset to assess the probability of failure of each case. The random sample data are tabulated in Table 2.

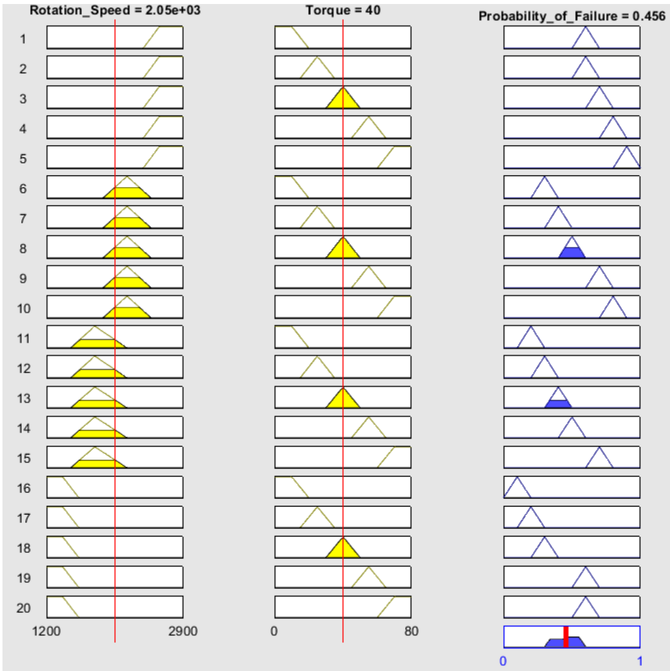

Fig. 8. Membership function relationships based on fuzzy set rules.

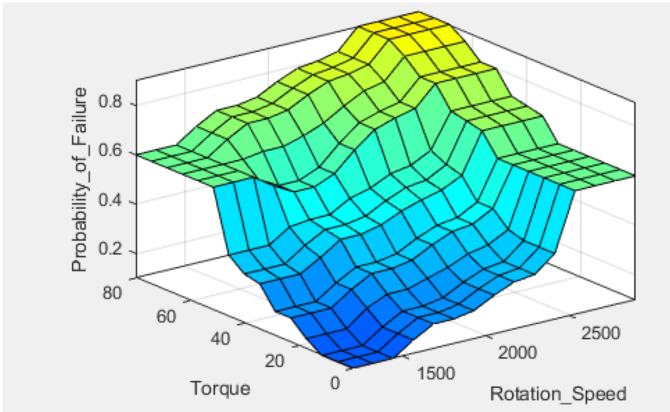

Fig. 9. Surface plot of the fuzzy inference system

Table 2. Random data samples from [49].

UID	Rotational Speed	Torque	Machine Failure
1096	2721	9.3	1
1373	1573	41.8	0
3357	1355	57.8	1
4025	1351	60.3	1
4305	1595	31.4	0
4972	1838	27.8	0
5596	1944	21.4	0
6079	1339	59.1	1
9760	1613	36.7	0
9823	1360	60.9	1

The input values of rotation speed and torque were used to evaluate the fuzzy inference system. The machine failure values are used to identify if the fuzzy inference system can correctly predict the probability of failure. The summary of the fuzzy inference system results is tabularized in Table 3, with its interpretation.

Table 3. Testing results

UID	Machine Failure	Probability of Failure	Interpretation
1096	1	0.6	High
1373	0	0.3657	Low
3357	1	0.6000	High
4025	1	0.6000	High
4305	0	0.3234	Moderately Low
4972	0	0.3000	Moderately Low
5596	0	0.3205	Moderately Low
6079	1	0.6000	High
9760	0	0.4000	Low
9823	1	0.6000	High

Results indicate that the fuzzy inference system correctly classified the probability of failure of the machine with a high value when the device fails. Low and moderately low values are also shown when the machine does not fail, while high values indicate that the machine does indeed fail. This means that the fuzzy inference system was able to successfully predict the probability of machine failure.

5. EVALUATION

Predictive maintenance is often derived from machine learning models, which may require significant computational power and development time. In this paper, a predictive maintenance model is successfully generated using fuzzy logic techniques to predict the probability of machine failure based on historical data. This model allows manufacturing companies to create models for real-time decision-making processes to streamline and optimize predictive maintenance procedures.

However, since a synthetic dataset was used in the study, the results shown in the fuzzy inference system may be too idealistic for real-world applications. It is therefore recommended to research the use of fuzzy logic techniques in developing other failure prediction models using real-world datasets to improve the model further. It is also recommended to apply adaptive fuzzy logic techniques to the system to allow the inference system to adapt to the extreme environmental conditions in the manufacturing line.

ACKNOWLEDGEMENT

The researchers would like to thank the Engineering Research and Development Technology (ERDT) of the Department of Science and Technology (DOST) of the Philippines for allowing the researchers to further continue their education. Additionally, the researchers also appreciate the support of their institution, De La Salle University–Manila (DLSU-M), in advancing their knowledge in research.

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