2022 International Conference on Power, Energy and Innovations (ICPEI 2022)
October 19-21, 2022, Pattaya, THAILAND

Predictive Maintenance Model for Rotating Machinery Using a Fuzzy Logic

Wirunpuch Prommachan
Department of Advanced Manufacturing Technology, Pathumwan Institute of Technology,
Bangkok, Thailand
wiranpatch.b@gmail.com

Manop Pipathattakul
Department of Mechanical Engineering, Pathumwan Institute of Technology,
Bangkok, Thailand
manop@pit.ac.th

Prayoon Surin
Department of Advanced Manufacturing Technology, Pathumwan Institute of Technology,
Bangkok, Thailand
prayoon@pit.ac.th

Pramot Srinoi
Department of Industrial Engineering, Kasem Bundit University,
Bangkok, Thailand
p_srinoi@hotmail.com

***Abstract*—— In the event of an accident, rotating machines has been currently used in multiple methods. Work was disrupted as a result of machine problems. Therefore, routine maintenance was necessary to reduce the likelihood of failure. The objective of this research was to determine the appropriate period for checking the condition of machinery using predictive maintenance by vibration analysis. The following procedure was used for conducting this research: 1) Measure the vibration value, and 2) Determine ISO 10816-3 conformity to predict the appropriate period for inspecting the condition of the machinery. According to ISO 10816-3, the result indicated information on the rotating machinery's performance and vibration level. The fuzzy logic method predicted the life expectancy of equipment in maintenance.**

Keywords— Predictive Maintenance, Vibration, Fuzzy Logic

I. INTRODUCTION

The predictive maintenance technique had been widely applied for vibration, oil, and temperature evaluation of equipment conditions. For example, vibration analysis was a standard method for analyzing moving parts in an electromechanical system and forecasting machinery failures. Abdulrahim Shamayleh applied a predictive maintenance technique to forecast the breakdown of the Vitros-Immunoassay analyzer. The Internet of Things was used to collect real-time vibration data from machines. Machine learning was used to predict and classify the Vitros-Immunoassay analyzer status. According to the findings, the suggested technique might save up to 25% on diagnostic and repair costs with a one-year investment payback period. The approach was scalable: it could be used on many medical devices in major medical institutions [1]. In addition, Marius Baban introduced a condition-based predictive maintenance technique for planning the maintenance tasks of textile machines based on fuzzy logic and vibration monitoring. Vibration monitoring was used to trace the fault progression of the machines. The results showed that such a technique delivered satisfactory results [2].

Data-driven predictive maintenance was based on several monitored variables, namely, vibration, acoustic emission, and temperature. It could be constructed using statistical or artificial intelligence (AI) approach. The artificial intelligence approach was based on soft computing techniques such as fuzzy logic, neural networks, or combinations. Fuzzy logic had been applied to analyze a variety of systems, including rotating machines, printing machines, pumps and gearboxes; to forecast the severity of failure in helical gearboxes [3]; and to construct an early warning system for improving decision-making in condition-based maintenance [4].

Lv Yaqiong introduced an intelligent predictive maintenance solution for multi-granularity defects of manufacturing equipment. In the maintenance solution identification step, fuzzy logic-based decision making was used to discover suitable maintenance options based on the vague practical border of defect severity. Findings demonstrated that the proposed system outperformed Adam-optimized BP neural network, BP neural network with momentum, and extreme learning machine techniques regarding forecast accuracy and performance. According to the advantages of predictive maintenance and fuzzy logic, this study developed a model for predictive maintenance of vibrating machinery using fuzzy logic [5].

II. LITERATURE REVIEW

A. Rotating Machinery

The Rotating System consisted of an AC motor with a nominal rotation of 1,800 rpm driving the axle by a belt. According to Ya'Cubsohn, failures could be divided into two main categories: low-frequency and high-frequency faults. However, it was not enough to measure the frequency of each vibration component to identify a malfunction. The absolute value was required to be known and was related to the rotational speed of the shaft. Therefore, knowledge of shaft rotation speed was essential for fault diagnosis. Some adjustments such as unbalancing, misalignment, excessive gap, insufficient rigidity, flabby or wear strap down, or bent axles would change the vibration amplitude at the rotational frequency of the rotating system [6].

B. Fuzzy inference system

The fuzzy inference system was divided into four major sections: Fuzzification, Knowledge base, Fuzzy Inference, and Defuzzification in the following Fig. 1.

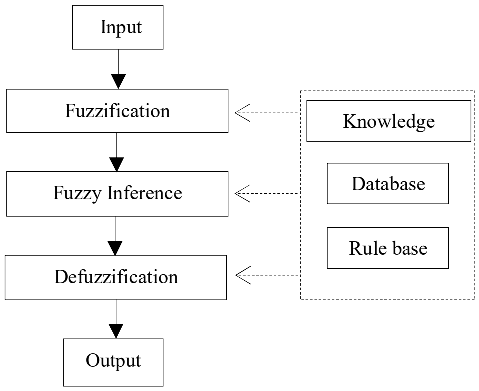

Fig. 1. Fuzzy inference system.

The process started from converting the input to fuzzy input. The initial input's membership value was then calculated using a member function. The resulting values were inferred using rules to obtain ambiguous results. The most common fuzzy rule was the Fuzzy IF-THEN rule based on reasoning. Finally, fuzzy values were rendered more consequential.

C. Standard ISO 10816-3

ISO 10816-3 was mainly applied to vibration measurement of industrial machines similarly to electro motors powering above 15 kW and operating speeds between 120 and 15,000 RPM. This category included common industrial motors, pumps, generators, rotary compressors, blowers and fans, and several types of turbines. Some machines had power requirements or speeds outside the scope of the standard; however, the majority of the machines which most people would be likely to encounter could be evaluated according to these guidelines in the following Fig. 2.

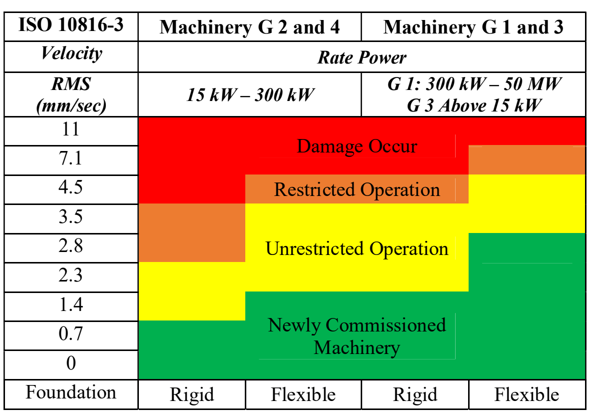

Fig. 2. Fuzzy inference system.

III. METHODOLOGY

This research applied Fuzzy logic in the evaluation process of machine conditions. It was obtained by measuring the vibration value of the motor every 4 days as shown in Table 1.

TABLE I. VIBRATION TESTING IN 1500 – 2000 RPM.

Day	Velocity (mm/sec)	
	1st Sensor	***2nd Sensor***
1	3.3	3.2
4	3.6	3.4
8	3.8	3.6
Maintenance		
12	1.2	1.2
16	1.4	1.5
20	1.4	1.5
24	1.5	1.6
28	1.6	1.6
32	2.4	2.3
36	2.6	2.5
40	2.8	2.5
Maintenance		
44	1.4	1.2
48	1.4	1.3
52	1.5	1.5
56	1.9	1.7
60	2.3	2.4
64	2.6	2.7

The assessment criteria were determined using the vibration standard ISO 10816-3 under conditions arranged in group 2 and rigid foundation in Table 2.

TABLE II. VIBRATION STANDARD ISO 10816-3.

Velocity	**Machinery Group 2**
RMS (mm/sec)	***15 kW – 300 kW***
11	Damage Occur
7.1	
4.5	
3.5	Restricted Operation
2.8	
2.3	Unrestricted Operation
1.4	
0.7	Newly Commissioned Machinery
0	
Foundation	Rigid

TABLE III. FUZZY SET OF INPUT VARIABLES.

Input Variables (Sensor)			
Linguistic Variables	***MF type***	***Interval (1st)***	***Interval (2nd)***
Low	Trimf	0, 0, 1.33	0, 0, 1.33
Medium	Trimf	0, 1.33, 2.67	0, 1.33, 2.67
High	Trimf	1.33, 2.67, 4	1.33, 2.67, 4
Very High	Trimf	2.67, 4, 5.33	2.67, 4, 5.33

TABLE IV. FUZZY SET OF OUTPUT VARIABLES.

Output Variables (ISO 10816-3)		
Linguistic Variables	***MF type***	***Interval***
Newly	Trimf	0, 0.7, 1.4
Unrestricted	Trimf	0.7, 1.4, 2.3
Restricted	Trimf	2.3, 2.8, 3.5
Damage	Trimf	4.5, 7.1, 11

The efficiency of rotating machinery was evaluated using a fuzzy logic system. In the first stage, it was to identify the relevant parts and variables in the system such as the number of input variables, output variables, linguistic variables, membership function, and the number of rules as shown in Table 3 and Table 4.

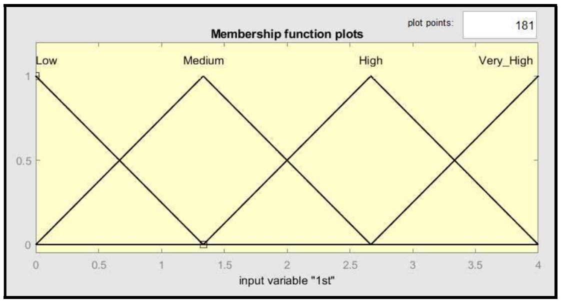

Fig. 3. Triangular membership function of Input (1st Sensor).

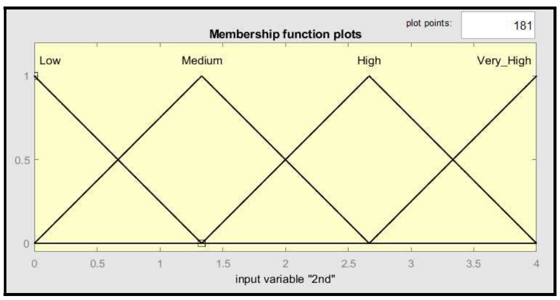

Fig. 4. Triangular membership function of Input (2nd Sensor).

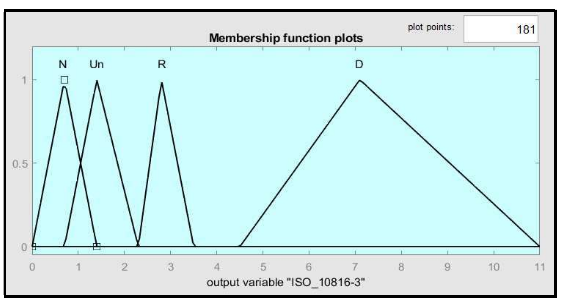

Fig. 5. Triangular membership function of Output (ISO 10816-3)

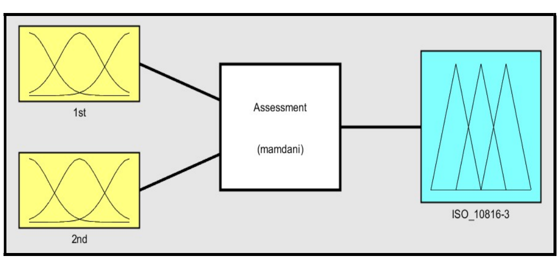

Fig. 6. Assessment system: 2 Inputs, 1 Output, 16 rules.

Fig. 3 and Fig. 4 showed the Triangular membership function of Input whereas Fig. 5 presented Triangular membership function of Output. There were 16 inference rules.

1.(1st =L) & (2nd =L) => (ISO 10816-3=N)
2.(1st =L) & (2nd =M) => (ISO 10816-3=Un)
3.(1st =L) & (2nd =H) => (ISO 10816-3= Un)
4.(1st =L) & (2nd =VH) => (ISO 10816-3=R)
5.(1st =M) & (2nd =L) => (ISO 10816-3= Un)
6.(1st =M) & (2nd =M) => (ISO 10816-3= Un)
7.(1st =M) & (2nd =H) => (ISO 10816-3= R)
8.(1st =M) & (2nd =VH) => (ISO 10816-3= R)
9.(1st =H) & (2nd =L) => (ISO 10816-3= Un)
10.(1st =H) & (2nd =M) => (ISO 10816-3= R)
11.(1st =H) & (2nd =H) => (ISO 10816-3= R)
12.(1st =H) & (2nd =VH) => (ISO 10816-3=D)
13.(1st =VH) & (2nd =L) => (ISO 10816-3=Un)
14.(1st =VH) & (2nd =M) => (ISO 10816-3=R)
15.(1st =VH) & (2nd =H) => (ISO 10816-3=R)
16.(1st =VH) & (2nd =VH) => (ISO 10816-3=D)

It was IF-THEN which consisted of an IF inference, and the default rule was connected by an AND or OR logic. The Mamdani-model fuzzy simulation with system variables was performed on MATLAB tool version R2020b. This model was characterized by the use of semantic rules for inference processing, commonly referred to as the highest-lowest inference. This inference model worked well for this type of problem because it could perform a union and intersection in the following Fig. 6.

IV. ANALYSIS RESULTS

Assessment of performance of rotating machinery using Vibration Standard ISO 10816-3 under conditions were arranged in group 2, and rigid foundation method started with the Fuzzy logic in the following Table 5 and Fig. 7.

TABLE V. ASSESSMENT FUZZY LOGIC.

Day	Velocity (mm/sec)		Assessment	ISO 10816-3
	1st Sensor	*2nd Sensor*		
1	3.3	3.2	6.77	Damage
4	3.6	3.4	6.94	Damage
8	3.8	3.6	7.13	Damage
Maintenance				
12	1.2	1.2	1.38	Unrestricted
16	1.4	1.5	1.69	Unrestricted
20	1.4	1.5	1.69	Unrestricted
24	1.5	1.6	1.78	Unrestricted
28	1.6	1.6	1.78	Unrestricted
32	2.4	2.3	2.40	Restricted
36	2.6	2.5	2.70	Restricted
40	2.8	2.5	2.87	Restricted
Maintenance				
44	1.4	1.2	1.57	Unrestricted
48	1.4	1.3	1.57	Unrestricted
52	1.5	1.5	1.69	Unrestricted
56	1.9	1.7	2.01	Unrestricted
60	2.3	2.4	2.40	Unrestricted
64	2.6	2.7	3.82	Restricted

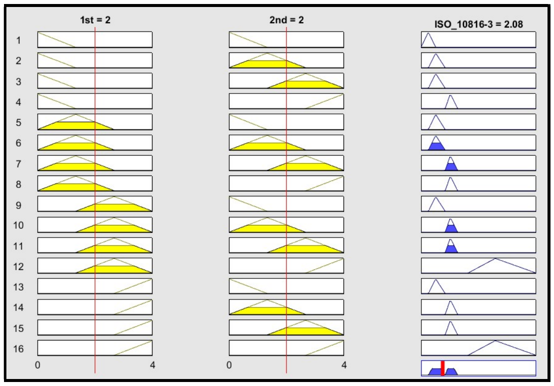

Fig. 7. Rule Viewer of Assessment.

V. DISCUSSION

The experts verified the result of this inference system according to Fig. 8 as shown on the 3D graph. These curves presented all the possible situations for the variables in the simulation. The upper area of the curve was yellow, representing the system's comfort zone when the variable 1st Sensor and 2nd Sensor tended to assume a maximum value. The variable ISO 10816-3 was considered as a maximum value (Damage). The blue area of the curve represented the discomfort zone for the machine or was considered as a not-good area.

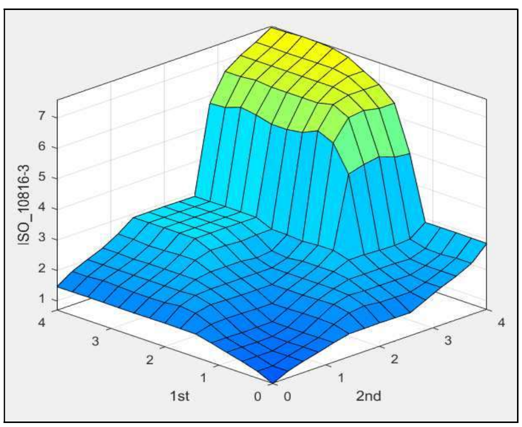

Fig. 8. Resulting Surface ISO 10816-3.

VI. CONCLUSIONS

The goal of the rotating machinery performance assessment was to build a model for predictive maintenance. The result indicated the information pertaining to the rotating machinery's performance and vibration level according to ISO 10816-3. Traditional approaches for forecasting the life expectancy of maintenance equipment in maintenance operations were outperformed by the fuzzy logic method these aids in planning maintenance, service, and replacement of equipment.

ACKNOWLEDGMENT

This research did not receive any specific grant from funding agencies. The authors would like to thank the editor and anonymous reviewers for their comments which helped improve the quality of this work.

REFERENCES

[1] A. Shamayleh, , M. Awad and J. Farhat, "IoT based predictive maintenance management of medical equipment," Journal of Medical Systems, vol. 44 no. 4, 2020, pp. 1-12.

[2] M. Baban, C.F. Baban and M.D. Suteu, "Maintenance decision-making support for textile machines: a knowledge-based approach using fuzzy logic and vibration monitoring," IEEE Access 7, 2019, pp. 83504–83514.

[3] M. Cerrada, C. Li, R.V. Sánchez, F. Pacheco, D. Cabrera and J.V. de Oliveira, "A fuzzy transition-based appr oach for fault severity prediction in helical gearboxes," Fuzzy Sets and Systems, vol. 337, 2018, pp. 52-73.

[4] N. J Vafaei, R.A. Ribeiro and L.M. Camarinha-Matos, "Fuzzy early warning systems for condition-based maintenance," Computers & Industrial Engineering, vol. 128, 2019, pp. 736-746.

[5] R.V. Ya'cubsohn, "Title of the paper," IEEE Transactions on Instrumentation and Measurement, vol.99, no. 33, 2000, pp. 1099-1104.

[6] Y. Lv, Q. Zhou, Y. Li and W. Li, "A predictive maintenance system for multi-granularity faults based on AdaBelief-BP neural network and fuzzy decision making," Advanced Engineering Informatics, vol. 49, 2021, 101318.