Selection Criteria for Evaluating Predictive Maintenance Techniques for Rotating Machinery using the Analytic Hierarchical Process (AHP)

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ABSTRACT

A primary industry objective is to ensure that machinery remains operational through effective management. Predictive maintenance plays a significant role in monitoring the working condition of machinery. The goal of this study is to establish the criteria for evaluating predictive maintenance techniques for rotating machines utilizing the Analytic Hierarchy Process (AHP). To achieve this target, survey data were collected from questionnaires and interviews with 20 experts, which had at least 20 years of professional experience. The Analytic Hierarchy Process (AHP) was utilized for criteria selection. The findings disclosed that predictive maintenance factors for rotating machines were ranked as follows: vibration analysis (45.5%), acoustic analysis (22.7%), oil analysis (22.4%), infrared thermography (5.8%), and wear particle analysis (3.6%). The Consistency Ratio (CR) was determined to be less than 10%, indicating a high level of consensus among the experts. Given the elevated importance attributed to vibration analysis, it can be concluded that the latter is the primary criterion for selecting predictive maintenance techniques for rotating machines.

Keywords-Analytical Hierarchy Process (AHP); criteria; maintenance technique; rotating machinery

I. INTRODUCTION

Machinery is a significant part of the practical manufacturing process, both in quality and quantity. As machinery maintenance is necessary, selecting suitable maintenance techniques is a critical process that cannot be overlooked. Analytical Hierarchy Process (AHP) is an analytical process that assists in making complex decisions by splitting the problem into parts, creating a hierarchy structure. AHP uses information derived from key informants to define criteria, sort the factors by their rating and get the most critical factor for the conclusion. A literature review on maintenance and criteria sorting showed that AHP is the most common approach [1] in machinery condition assessment and intermediate- and long-term maintenance to keep the machine at its highest efficiency [2].

Maintenance is a necessary process that has to be well managed. The first stage of maintenance management in manufacturing facilities is to select the most suitable maintenance strategy for effective machinery maintenance. This stage is unignorable [3]. Maintenance of machinery comes in many forms, such as corrective maintenance, preventive maintenance, predictive maintenance, and proactive maintenance, depending on organizational strategies. Predictive maintenance is most investigated. It is the analysis of deterioration or the intensity of the existing decline. Well-analyzing predictive maintenance indicates whether further maintenance is needed [4, 5]. Predictive maintenance is also defined as a set of activities detecting the changes in the physical condition of equipment to properly conduct the maintenance task and thus maximize the equipment lifespan while reducing the failure risk [6]. The predictive maintenance program helps minimize the unscheduled breakdowns of all mechanical equipment in the plant and ensures that repaired equipment is in acceptable mechanical condition. Moreover, it facilitates the analysis of machine-train issues before they become serious. Predictive maintenance primarily concerns predicting the damages to the system by detecting early damage signs to enable maintenance tasks to be more proactive. It is acknowledged that most mechanical issues can be minimized if they are detected and repaired early. Besides acting before failure, predictive maintenance also intends to manage fault, although the system has no immediate damage, in order to ensure smooth operation and reduce energy consumption [7].

The introduction of advanced manufacturing technologies to increase automation and decline buffering time of inventory has increased the pressure on maintenance management. Maintenance experts require Maintenance Performance Indicators (MPI) to proceed with production activities effectively. For this reason, techniques based on the risk of equipment failure, maintenance cost, AHP, and Goal Programming (GP) have been introduced for MPI strategy selection [8]. AHP has been used for maintenance strategy selection in factories [3, 9] and has been applied along with other methods to solve such problems. The AHP is an effective tool for the decision-making process of sophisticated problems. It helps to structure complex issues hierarchically, causing the decision-making procedure to be simplified and speed up [10, 11]. It solves the problems by classifying them into variables, arranged in a hierarchical order. It assigns numerical values to subjective considerations about the significance of each element. It synthesizes the various considerations to evaluate which element has the highest priority (greatest importance) and impacts the circumstance. There are four steps of solving problems using AHP [12]. AHP has been utilized in decision-making processes of knowledge management implementation [8, 13], selecting data science methodology [14], and maintenance strategy [9]. Authors in [8] proposed the predictive maintenance effectiveness indicator based on AHP to identify the more compelling aspect of the maintenance approach. Authors in [6] investigated the Maintenance Policy Selection (MPS) using AHP. The study tested the practicality of the AHP-based MPS technique by conducting three workshops at three firms. The results demonstrated that AHP was well suited for MPS in this broad setting and provided a structured and detailed technique for MPS. Moreover, AHP facilitated the discussions during and after the sessions, offering a better understanding of the policy selection process. Moreover, authors in [5], applied AHP to obtain a criterion for selecting the applicable spots for building weigh stations. The results demonstrated that engineering factors had the highest importance score among engineering, economic, and environment-social factors (60%). Meanwhile, the economic and environment-social factors had 25% and 15% importance scores, respectively. Considering engineering factors, the truck traffic volume had the highest importance score of 24%. The importance scores of proper constructive area, transport route, and international roughness index were 14%, 13%, and 9%, respectively. Of all the economic factors, lowering highway maintenance showcased the highest importance score of 10%. Regarding the environment-social factors, the highest importance score was that of the effect on community (8%), followed by the area suitability (4%) and pollution reduction (3%).

The literature review showed that AHP has been widely studied and applied as an accurate approach in determining the rating of the criteria and analyzing complex decision-making processes. However, there is no evidence of AHP being employed to establish criteria for selecting assessment techniques concerning predictive maintenance in rotating machines. This study explicitly targets five such primary criteria: vibration analysis, sound emissions analysis, oil analysis, infrared thermography, and wear particle analysis. AHP will be employed to determine the most crucial factors. The identified evaluation criteria will then guide the selection of predictive maintenance techniques.

II. PREDICTIVE MAINTENANCE

Predictive maintenance uses techniques such as vibration analysis, acoustic emission/acoustic analysis, oil analysis, infrared thermography, and wear particle analysis to assess the equipment status. Technique selection depends on equipment, types, impact on the production, and on any other critical for the factor's operations aspects to achieve the predictive maintenance target [15]. The techniques employed by predictive maintenance are described below:

- Oil analysis: analysis of lubricating oil and formation of small particles to learn the status of bearings and gears.
- Vibration analysis: the most effective method for detecting rotating machine defects.
- Acoustic analysis: continuous detection, searching, and checking for cracks in the structure and piping.
- Infrared thermography: used to analyze the working machine and electrical equipment, as it can detect thermal or mechanical defects.
- Wear particle analysis: analyzing worn-out parts, such as pistons, gearboxes, or hydraulic systems. Wear particles that are chipped out will give information about the wear and tear of these parts.

III. METHODOLOGY

The process to get the suitable criteria for predictive maintenance technique assessment can be performed by studying information from related research and experts' feedback to get the connected central and sub-criteria. Then, the questionnaire is constructed for the experts to analyze the importance of each factor before using the AHP. The result is a rating of each criterion that has been collected and screened and can be used for predictive maintenance technique assessment. The analysis result will yield sorted and suitable criteria as shown in Figure. 1.

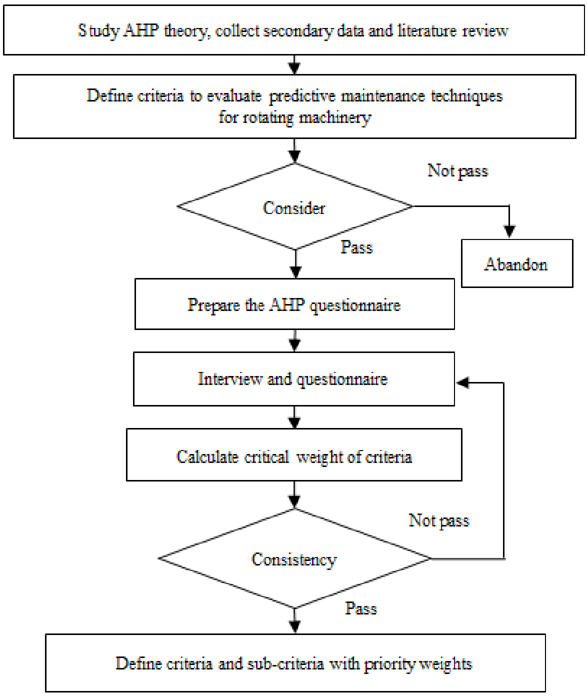

Fig. 1. Assessment procedure for predictive maintenance.

Multiple Criteria Decision Making (MCDM) comprises various methodologies, such as the Analytic Hierarchy Process (AHP), Analytic Network Process (ANP), and TOPSIS (Technique for Order of Preference by Similarity to Ideal Solution), among others. However, AHP stands out due to its superior advantages over other methods. AHP is a decision-making procedure grounded in analysis, involving the subdivision of problems into components and their hierarchical organization based on importance and impact. Essentially, AHP represents a specific method within a broader category in contrast to other MCDM methods. AHP distinctive features include its utilization of a hierarchical structure and pairwise comparisons to establish priorities. These characteristics contribute to AHP's effectiveness in decision-making processes, setting it apart from other methods within the MCDM framework. The AHP process steps are detailed below.

A. Sorting Problems in Hierarchical Structure

Complex problems can be examined thoroughly and in a structured way [16, 17]. In our case, the top level aims to select predictive maintenance techniques. At the bottom level, the decision alternatives can be found [14, 18], as shown in Figure. 2.

B. Making a Questionnaire for Factor Importance Analysis

Factors in criteria assessment for predictive maintenance of the rotating machines can be divided into criteria and sub-criteria. A questionnaire was given to experts to analyze the importance of each criterion [5, 19]. The questionnaire was developed based on requirements and suitability [4]. Twenty experts contributed to this research: 2 managing engineers, 10 maintenance engineers, and 8 repair technicians, each of them with at least 20 years of experience.

C. Prioritization of Problems in Each Component

This part assigns ratings to the components based on objective achievement. The higher rating component will receive higher priority. The first step is the collection of pairwise comparisons in a matrix form. After that, the problem is decomposed, there will be a comparison between the components, i.e. a comparison between the criteria and each criterion will be assigned a rating by cross-comparison [9, 14, 18]. Table I shows the established criteria and their comparison results. Tables II-VI illustrate the pair comparison findings for the sub criteria of each criterion, i.e. oil analysis, vibration analysis, sound emissions analysis, IR thermography, and wear particle analysis.

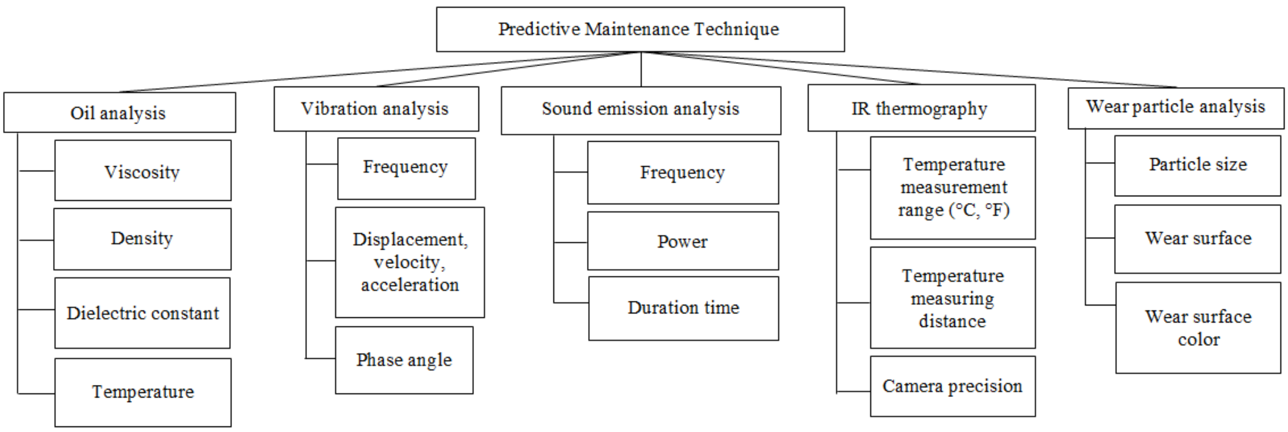

Fig. 2. Predictive maintenance criteria category division.

TABLE I. CRITERIA CALCULATION

Criteria	Oil analysis	Vibration analysis	Sound emission analysis	Infrared thermography	Wear particle analysis
Oil analysis	1	1/4	1/3	5	5
Vibration analysis	4	1	1	8	8
Sound emission analysis	3	1	1	8	8
Infrared thermography	1/5	1/8	1/8	1	2
Wear particle analysis	1/5	1/8	1/8	1/2	

TABLE II. PAIR COMPARISON MATRIX FOR OIL ANALYSIS

Sub-Criteria	Viscosity	Density	Dielectric constant	Temperature
Viscosity	1	2	3	3
Density	1/2	1	2	1/2
Dielectric constant	1/3	1/2	1	1/3
Temperature	1/3	2	3	1

TABLE III. PAIR COMPARISON MATRIX FOR VIBRATION ANALYSIS

Sub-Criteria	Frequency	Displacement, Velocity, Acceleration	Phase angle
Frequency	1	1	2
Displacement, Velocity, Acceleration	1	1	2
Phase angle	1/2	1/2	1

TABLE IV. PAIR COMPARISON MATRIX FOR ACOUSTIC ANALYSIS

Sub-Criteria	Frequency	Power	Duration
Frequency	1	1	2
Power	1	1	2
Duration	1/2	1/2	1

TABLE V. PAIR COMPARISON MATRIX FOR INFRARED THERMOGRAPHY

Sub-Criteria	Temperature measurement range	Temperature measuring distance	Camera precision
Temperature measurement range	1	1/2	1
Temperature measuring distance	2	1	1
Camera precision	1	1	

TABLE VI. PAIR COMPARISON MATRIX FOR WEAR PARTICLE ANALYSIS

Sub-Criteria	Particle size	Wear surface	Wear surface color
Particle size	1	1/2	3
Wear surface	2	1	3
Wear surface color	1/3	1/3	1

D. Geometric Mean Method

The geometric mean calculation is carried out by multiplying the numbers and then taking the root of the result based on several numbers used.

$$V_i = \left(\prod_{j=1}^{n} a_{ij}\right) \quad (1)$$

where a_{ij} is the value of members in the matrix, V_i is the geometric mean, and n is the number of members used to calculate the average.

E. Rating Synthesis

This step synthesizes the total rating from the sub-criteria of each criterion after weighing. Generally, the rating analysis is conducted by:

$$W_i = \frac{V_i}{\sum_{i=1}^{n} V_i} \quad (2)$$

$$\sum_{i=1}^{n} W_i = 1.0 \quad (3)$$

where W_i is the rating of each criterion, V_i is the geometric mean, and n is the number of members utilized to calculate the average.

F. Consistency Ratio

Consistency ratio calculation checks the reasoning consistency of the comparison results. The examination is completed by finding the consistency index. The processing steps are:

1. Calculate by multiplying the sum of the ratings of each criterion in the row with the total mean in the column, and then sum them all together. The result will be the number of all the criteria used for comparison:

$$\lambda_{\max} = \sum_{i=1}^{n}\left[\sum_{j=1}^{n} a_{ij} W_j\right] \quad (4)$$

If the consistency is 100%, then the number of criteria used for comparison is $\lambda_{\max} < (n)$. If the matrix table is not consistent, then $\lambda_{\max} > (n)$.

2. The consistency Index is calculated by:

$$CI = \frac{(\lambda_{\max} - n)}{(n-1)} \quad (5)$$

3. The Random consistency Index (RI) is calculated. The result is shown in Table VII.

4. The Consistency Ratio (CR) is calculated from the ratio between the CI and RI:

$$CR = \frac{CI}{RI} \quad (6)$$

If the CR value is less than or equal to 0.10, it will be accepted.

TABLE VII. RANDOM CONSISTENCY INDEX (RI)

N	1	2	3	4	5	6	7	8	9	10
RI	0.00	0.00	0.58	0.90	1.12	1.24	1.32	1.41	1.45	1.49

IV. A MANUAL AHP CALCULATION EXAMPLE

The presentation is provided in table form for simplicity reasons [12, 20]. This study employs five primary criteria, as depicted in Table VIII, illustrating the prioritization of predictive maintenance techniques by multiplying the rating of each main criterion with its corresponding sub-criteria. The presented table indicates a negligible distinction between the results obtained through manual calculations and table-based calculations of AHP, affirming their suitability for prioritization [8, 21], as illustrated in Table IX. Subsequently, the matrices for each pair are compared and computed, as depicted in Table IX. Cross-assessment between the criteria is demonstrated in Tables IX-XVIII.

TABLE VIII. PAIRED COMPARISON MATRIX FOR PREDICTIVE MAINTENANCE TECHNIQUE

Criteria	Oil analysis	Vibration analysis	Sound emission analysis	Infrared thermography	Wear particle analysis	Priority vector
Oil analysis	1.000	0.250	0.333	5.000	5.000	0.156
Vibration analysis	4.000	1.000	1.000	8.000	8.000	0.391
Sound emission analysis	3.000	1.000	1.000	8.000	8.000	0.367
Infrared thermography	0.200	0.125	0.125	1.000	2.000	0.049
Wear particle analysis	0.200	0.125	0.125	0.500	1.000	0.037

The matrix representing Table VIII is changed to a decimal number form:

$$\begin{bmatrix} 1.000 & 0.250 & 0.333 & 5.000 & 5.000 \\ 4.000 & 1.000 & 1.000 & 8.000 & 8.000 \\ 3.000 & 1.000 & 1.000 & 8.000 & 8.000 \\ 0.200 & 0.125 & 0.125 & 1.000 & 2.000 \\ 0.200 & 0.125 & 0.125 & 0.500 & 1.000 \end{bmatrix}$$

Iteration 1: Squaring the Matrix by (7):

$$A = \begin{array}{c} A_j \\ \cdot \\ \cdot \\ A_n \end{array} \begin{bmatrix} a_{ij} & . & . & . & a_i n_j \\ . & . & . & . & . \\ . & . & . & . & . \\ . & . & . & . & . \\ a_{ij} & . & . & . & a_i n_j \end{bmatrix} = \begin{bmatrix} W_i/W_j & . & . & . & W_n/W_n \\ . & . & . & . & . \\ . & . & . & . & . \\ . & . & . & . & . \\ W_n/W_n & . & . & . & W_n/W_n \end{bmatrix} \quad (7)$$

$$A = \begin{bmatrix} 1.000 & 0.250 & 0.333 & 5.000 & 5.000 \\ 4.000 & 1.000 & 1.000 & 8.000 & 8.000 \\ 3.000 & 1.000 & 1.000 & 8.000 & 8.000 \\ 0.200 & 0.125 & 0.125 & 1.000 & 2.000 \\ 0.200 & 0.125 & 0.125 & 0.500 & 1.000 \end{bmatrix}$$

where $\frac{w_i}{w_j} = a_{ij} => W_i = a_{ij}W_j, (i, j = 1,2,\ldots,n)$, W_i is the input value in row i, and W_j is the input value in column j.

$$A = \begin{bmatrix} 1.000 & 0.250 & 0.333 & 5.000 & 5.000 \\ 4.000 & 1.000 & 1.000 & 8.000 & 8.000 \\ 3.000 & 1.000 & 1.000 & 8.000 & 8.000 \\ 0.200 & 0.125 & 0.125 & 1.000 & 2.000 \\ 0.200 & 0.125 & 0.125 & 0.500 & 1.000 \end{bmatrix}$$

$$\times \begin{bmatrix} 1.000 & 0.250 & 0.333 & 5.000 & 5.000 \\ 4.000 & 1.000 & 1.000 & 8.000 & 8.000 \\ 3.000 & 1.000 & 1.000 & 8.000 & 8.000 \\ 0.200 & 0.125 & 0.125 & 1.000 & 2.000 \\ 0.200 & 0.125 & 0.125 & 0.500 & 1.000 \end{bmatrix}$$

Thus, we get:

$$A = \begin{bmatrix} 4.999 & 2.083 & 2.166 & 17.164 & 24.668 \\ 14.200 & 5.000 & 5.332 & 48.000 & 60.000 \\ 13.200 & 4.750 & 4.999 & 43.000 & 55.000 \\ 1.675 & 0.675 & 0.693 & 5.000 & 7.000 \\ 1.375 & 0.488 & 0.504 & 4.000 & 5.000 \end{bmatrix}$$

The summaries of the geometric mean of consistency and of the criteria are given in Table IX and Table X, respectively.

TABLE IX. GEOMETRIC MEAN OF CONSISTENCY SUMMARY

	CR	Geometric Mean
Predictive technique	< 0.1	0.058
Oil analysis	< 0.1	0.029
Vibration analysis	< 0.1	0.012
Sound emission analysis	< 0.1	0.009
Infrared thermography	< 0.1	0.017
Wear particle analysis	< 0.1	0.026

TABLE X. GEOMETRIC MEAN OF THE CRITERIA SUMMARY

Global priority			
Main criteria	**Sub criteria**	**Priority (%)**	**Rank**
Predictive maintenance technique	Vibration analysis	45.50%	1
	Sound emission analysis	22.70%	2
	Oil analysis	22.40%	3
	Infrared thermography	5.80%	4
	Wear particle analysis	3.60%	5

The Normal Value of the matrix is:

$$\begin{bmatrix} 4.999 & 2.083 & 2.166 & 17.164 & 24.668 \\ 14.200 & 5.000 & 5.332 & 48.000 & 60.000 \\ 13.200 & 4.750 & 4.999 & 43.000 & 55.000 \\ 1.675 & 0.675 & 0.693 & 5.000 & 7.000 \\ 1.375 & 0.488 & 0.504 & 4.000 & 5.000 \end{bmatrix}$$

The sum of the rows is given in Table XI:

TABLE XI. ROW SUMS

	Row sum	Priority vector
	51.074	0.154
	132.532	0.400
	120.949	0.365
	15.043	0.045
	11.367	0.034
Totals	**330.965**	**1.000**

The difference of Table VIII and Iteration I can be seen in Table XII while the deduced criteria ranking is portrayed in Table XIII. The pair comparison matrices are exhibited in Tables XIV-XVIII and the summary in Table XIX.

TABLE XII. DIFFERENCE BETWEEN TABLE VIII AND ITERATION I

Table VIII	Iteration I	Difference
0.156	0.154	0.002
0.391	0.400	0.009
0.367	0.365	0.002
0.049	0.045	0.004
0.037	0.034	0.003

TABLE XIII. CRITERIA RANKING

Criteria	Table VIII	Iteration I	Rank
Oil analysis	0.156	0.156	3
Vibration analysis	0.391	0.391	1
Sound emission analysis	0.367	0.367	2
Infrared thermography	0.049	0.049	4
Wear particle analysis	0.037	0.037	5

TABLE XIV. PAIR COMPARISON FOR OIL ANALYSIS

Sub-Criteria	Viscosity	Density	Dielectric constant	Temperature	Relative priority	Relative priority (%)
Viscosity	1.000	2.000	3.000	3.000	0.445	44.5%
Density	0.500	1.000	2.000	0.500	0.185	18.5%
Dielectric constant	0.333	0.500	1.000	0.333	0.106	10.6%
Temperature	0.333	2.000	3.000	1.000	0.445	4.45%

TABLE XV. PAIR COMPARISON FOR VIBRATION ANALYSIS

Sub-Criteria	Frequency	Displacement, velocity, acceleration	Phase angle	Relative priority	Relative priority (%)
Frequency	1.000	1.000	2.000	0.400	40%
Displacement, velocity, acceleration	1.000	1.000	2.000	0.400	40%
Phase angle	0.500	0.500	1.000	0.200	20%

TABLE XVI. PAIR COMPARISON FOR SOUND EMISSION ANALYSIS

Sub-Criteria	Frequency	Decibel	Duration time	Relative priority	Relative priority (%)
Frequency	1.000	1.000	2.000	0.400	40%
Power	1.000	1.000	2.000	0.400	40%
Duration time	0.500	0.500	1.000	0.200	20%

TABLE XVII. PAIR COMPARISON FOR INFRARED THERMOGRAPHY

Sub-Criteria	Temperature measurement range	Temperature measuring distance	Camera precision	Relative priority	Relative priority (%)
Temperature measurement range	1.000	0.500	1.000	0.261	26.1%
Temperature measuring distance	2.000	1.000	1.000	0.411	41.1%
Camera precision	1.000	1.000	1.000	0.328	32.8%

TABLE XVIII. PAIR COMPARISON FOR WEAR PARTICLE ANALYSIS

Sub-Criteria	Particle size	Wear surface	Wear surface color	Relative priority	Relative priority (%)
Particle size	1.000	0.500	3.000	0.334	33.4%
Wear surface	2.000	1.000	3.000	0.525	52.5%
Wear surface color	0.333	0.333	1.000	0.141	14.1%

TABLE XIX. GEOMETRIC MEAN OF SUB-CRITERIA SUMMARY

Global Priority							
Sub criteria	**Distribution**	**Priority (%)**	**Rank**	**Sub criteria**	**Distribution**	**Priority (%)**	**Rank**
Vibration analysis	Displacement, velocity, acceleration	49.80%	1	**Oil analysis**	Viscosity	40.80%	1
					Temperature	29.40%	2
	Frequency	40.50%	2		Density	21.50%	3
					Dielectric constant	8.20%	4
	Phase angle	9.30%	3	**Infrared thermography**	Temperature measuring distance	45.20%	1
Sound emission analysis	Power	45.50%	1		Camera precision	31.00%	2
	Frequency	40.50%	2		Temperature measurement range	23.80%	3
				Wear particle analysis	Wear surface	42.40%	1
	Duration time	14.00%	3		Particle size	33.90%	2
					Wear surface color	23.80%	3

The prioritization analysis of each criterion, coupled with consistency checks conducted by the 20 experts, indicated that the ratio remained consistent, with a Consistency Ratio (CR) not exceeding 10% (CR < 0.1) [16, 17, 22]. This underscores the robust consistency in the experts' reasoning.

V. RESULTS AND DISCUSSION

This study aimed to specify criteria for selecting predictive maintenance technique assessment for rotating machines based on the AHP. The study analyzed data obtained from questionnaires answered by experts in the field. The results demonstrated that the factors in predictive maintenance techniques for rotating machines, sorted by rating in descending order, were vibration analysis (45.5%, the highest-rated), acoustic analysis (22.7%), oil analysis (22.4%), infrared thermography (5.8%) and wear particle analysis (3.6%). Consequently, vibration analysis is established as the main criterion for the selection and evaluation of predictive maintenance techniques for rotating machinery. An in-depth expert evaluation of the questionnaire focused on vibration analysis revealed that displacement, velocity and acceleration received the highest ratings at 49.8%, followed by frequency at 40.5% and phase angle at 9.3. Regarding sound analysis, the sub-criteria power received the highest rating at 45.5%, followed by frequency at 40.5% and duration time at 14%. In the domain of oil analysis, viscosity emerged as the top-rated sub-criterion at 40.8%, followed by temperature at 29.4%, density at 21.5%, and dielectric constant at 8.2%. Concerning the infrared thermography, the sub-criteria of temperature and distance measuring obtained the highest rating at 45.2%, followed by camera precision at 31% and temperature measurement range at 23.8%. In the sector of wear particle analysis, wear surface was rated the highest at 42.4%, followed by particle size at 33.9% and wear surface color at 23.8%. The consistency ratio, as indicated, remained below 10% (CR < 0.1), emphasizing a high level of consistency in the assessments.

VI. CONCLUSION

AHP-based assessment of predictive maintenance criteria was tested in two factories. The process started with data collection through interviews and surveys. Then, the data were used for model development and identification of the most essential criteria for problem assessment. The hierarchy was developed with participation from the decision-makers, and then the comparison consistent with the requirements and prioritization was performed. This study focused on using multiple-criteria decisions in maintenance, particularly that of rotating machines. To further the study, we suggest utilizing this model for all maintenance types as an efficient tool in the decision-making process.

AHP usage in defining criteria for selecting assessment techniques in predictive maintenance for rotating machinery has gained considerable attention from the research community. The current study's emphasis is clearly delineated across five fundamental criteria: vibration analysis, sound emissions analysis, oil analysis, infrared thermography, and AHP wear particle analysis, all with the overarching goal of identifying the most critical factors. These specified evaluation criteria will play a crucial role as a guiding framework for selecting predictive maintenance techniques, emphasizing simplicity and achieving satisfactory results.

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