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A fuzzy logic modelling of predictive maintenance in rotating machinery

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ABSTRACT

Purpose: The study aims to investigate and assess the application of Fuzzy Logic to construct a predictive maintenance model for rotating machinery.

Design/methodology/approach: The research uses a mixed approach, with both quantitative and qualitative approaches, and are four main steps: 1) surveying and analysing existing predictive maintenance techniques; 2) determining appropriate expert assessment criteria for predictive maintenance techniques; 3) vibration analysis by the experts; 4) evaluate the performance of rotating machinery with fuzzy logic.

Findings: The result of the study will be used to build a rotating machinery predictive maintenance model, which is very similar to the traditional method. The obtained data showed that the efficiency of the rotating machinery and the vibration level were compliant with the standard ISO 10816-3. Thus, such data can be planned for maintenance to maximize benefit.

Research limitations/implications: Future research should optimise the model and add additional modules for automatic data collection. The production monitoring system should help collect data by considering downtime, predicting the functional service life of rotating machinery, etc.

Practical implications: The proposed model can be used in small water pumps in order to perform predictive maintenance. The conceptual framework was tested, particularly with rotating machinery.

Originality/value: The fuzzy logic model is described as the fuzzy of a process with linguistics for greater clarity.

Keywords: Fuzzy logic, Vibration, Predictive maintenance, Rotating machinery

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METHODOLOGY OF RESEARCH, ANALYSIS AND MODELLING

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1. Introduction

A failure in a machine component might cause the machine to malfunction, potentially leading to the failure of the entire production process. More dangerously, the flaws may jeopardize the operators' safety. Therefore, it is vital to establish reliable mechanisms and processes to ensure manufacturing machinery's reliability, maintainability, and safety throughout its lifecycle. Maintenance is a significant part of the manufacturing process. It can be categorised into preventive maintenance, total productivity, and predictive maintenance.

Predictive maintenance has received the most attention from researchers according to its goals to forecast the conditions of the monitored machinery (when and where a defect might happen) and to offer proper maintenance options for defects based on defect kinds and severity degrees [1]. Predictive maintenance is introduced in manufacturing to examine the existence of deterioration as well as the severity of current deterioration. Well-analysed predictive maintenance clearly indicates whether additional maintenance is required at the time [2]. Predictive maintenance is also defined as a series of actions that identify the changes in the physical condition of equipment to effectively undertake maintenance tasks to extend the equipment's lifetime and lower the risk of breakdown [3].

Predictive maintenance is categorized into model-based and data-driven [1]. Model-based predictive maintenance is based on previous knowledge of the machinery deterioration process to forecast its failure. Nevertheless, in practice, it is difficult to construct an accurate model-based predictive maintenance to predict the natural deterioration process of complicated manufacturing equipment as it comprises a variety of operating parameters, and the working conditions are constantly changing. Meanwhile, data-driven predictive maintenance relies on data processes, including signal collection and processing, feature extraction, and status recognition [4]. Data-driven predictive maintenance aims to monitor the condition of machinery using advanced monitoring approaches that can evaluate its condition in real time. The machinery condition monitoring and maintenance decision-making process are the foundations of the data-driven maintenance technique [5].

Data-driven predictive maintenance is based on several monitored variables, e.g., vibration, acoustic emission, and temperature. It can be constructed using a statistical or artificial intelligence (AI) approach. The artificial intelligence approach is based on soft computing techniques, e.g., fuzzy logic, neural networks, or their combination.

Fuzzy logic has been applied to analyze a variety of systems, including rotating machines, printing machines, pumps, and gearboxes [5], to forecast the severity of failure in helical gearboxes [6] and to construct an early warning system for improving decision-making in condition-based maintenance [7].

It has been noticed that predictive maintenance paid more attention to early warnings of the specific failure while ignoring defect severity variations. Further research on defect intensity is essential, as it dramatically influences the subsequent maintenance decision-making process. Due to the practical blurry boundary between defect levels for a given defect type, it is usually difficult to distinguish one from another. Fuzzy decision-making has been introduced to solve this challenge. It is suitable for making decisions in complex and uncertain situations [8].

According to the advantages of predictive maintenance and fuzzy logic, as mentioned above, the study develops a model for predictive maintenance of vibrating machinery using fuzzy logic.

2. Literature review

2.1. Fuzzy logic

The fuzzy logic concept is a valuable technique for constructing a mathematical model to describe the systems by simulating human decision-making processes [9]. Fuzzy logic is often integrated with data-driven approaches such as data-driven predictive maintenance [10]. Baban et al. [11] developed a fuzzy logic-based technique for predictive maintenance of automated grinding lines' wheels. The study demonstrated that predictive maintenance could be utilized to adequately maintain automated grinding lines' grinding wheels before their failure breakdown. Based on a three-axis vibration monitoring technique, the fuzzy decision system determined the number of parts the abrasive wheel could grind until reconditioning. Thoppil et al. [12] applied a fuzzy logic-modified FMECA (failure mode, effects, and criticality analysis) to identify possible faults and prioritize maintenance of CNC lathe subsystems and components for predictive maintenance. Damage severity, fault incidence probability, and defect detection performance of CNC lathe control systems were assessed using various risk factors. S, O, and D scales for the defeat assessment of the CNC lathe were defined using fuzzy linguistic terms and fuzzy ratings. The risk priority number (RPN) was constructed on a fuzzy logic platform. The components and subsystems of a CNC lathe were prioritized using a fuzzy RPN-based criticality ranking. Results demonstrated that fuzzy logic-modified FMECA outperformed conventional FMECA in identifying and prioritizing essential subsystems of a machine for predictive maintenance, and those results matched industrial data and expert elicitation.

Alexandrino et al. [13] introduced a multi-objective genetic algorithm to resolve the challenge of fault identification in structural health monitoring. Results demonstrated that the fuzzy decision-making approach provided a better compromise option for the challenge when the multi-objective genetic algorithm provided numerous options.

Lv et al. [1] introduced an intelligent predictive maintenance solution for multi-granularity defects of manufacturing equipment. Fuzzy logic-based decision-making was used in the maintenance solution identification step to discover suitable maintenance options based on the practical vague border of defect severity. Findings demonstrated that the proposed system outperforms the Adam-optimized BP neural network, BP neural network with momentum, and extreme learning machine techniques regarding forecast accuracy and performance.

2.2. Predictive maintenance

The emergence of artificial intelligence enables predictive maintenance based on data-driven approaches to become more potential than model-based predictive maintenance to address smart manufacturing and industrial big data analytics, particularly for performing health perception [14]. Predictive maintenance involves predicting system failure by recognising early signs of breakdown to make maintenance operations more proactive. In addition to intervening before breakdown, predictive maintenance attempts to address any issue, even if there is no danger of breakdown, in order to ensure smooth operation and lower energy usage. Various manufacturing and service sectors have implemented predictive maintenance to increase dependability, safety, availability, performance, and quality while protecting the environment. A separate sector dedicated to developing predictive maintenance instruments, providing specialized predictive maintenance solutions, and training predictive maintenance professionals has also been established. Predictive maintenance has become more efficient, applicable, and inexpensive due to recent breakthroughs in information, communication, and computing technologies such as the Internet of Things and radio-frequency identifications. Remote and e-maintenance research has aided predictive maintenance tasks, particularly in hazardous working situations and dispersed sites [2].

The increase in industrial data availability has built opportunities for developing and implementing data-driven predictive maintenance [11], which employs cutting-edge computational approaches to offer valuable data on the state of machinery gleaned from the increasing amount of operational information. The data-driven predictive maintenance system comprises two stages. The first stage is model training. This stage requires historical raw sensor signals. In the second stage, the trained model is applied to forecast targets and make decisions. In general, each stage includes three subprocesses: data gathering and preprocessing, which can be single-sensory or multisensory; feature engineering, which contains feature extraction and concatenation, together with selection; and model training as well as forecasting in which a well-trained model will be generated with the optimal variables. The model can then forecast the real-time information stream [15].

The predictive maintenance technique has been widely used for machinery state analyses such as vibration, oil, and temperature analyses [16]. Vibration analysis, for instance, is a typical approach for evaluating moving parts of an electromechanical system and forecasting machinery faults. Baban et al. [5] 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 employed to track the fault progress of the machines. Results demonstrated that such a technique provided satisfactory performance. Shamayleh [16] applied a predictive maintenance technique to forecast the breakdown of the Vitros-Immunoassay analyzer. The Internet of Things was applied to collect real-time data on machinery vibration. Machine learning was introduced to forecast and classify the condition of the Vitros-Immunoassay analyzer. Results revealed that the introduced technique could save up to 25% on diagnostic and repair costs, with a one-year investment payback period. The scalable technique could be applied to various medical devices in extensive facilities.

2.3. Rotating machinery

Rotating machinery or turbomachinery is a machine with a rotating component that transfers energy to a fluid or vice versa. Consequently, there was an energy transfer between the fluid and the rotor through dynamic interaction in a turbomachine. Generally, the energy transfer from the rotor to the fluid is either a pump or fan.

The vibration profile generated by reciprocating and linear motion machines resulted from the mechanical movement and forces generated by the components as the parts of the machine. Constant or intense vibration could damage the machine.

Rotating machinery vibration was a critical issue that must be analysed for further solutions to prevent damage to the machine’s equipment. This could lead to the breakdown of the machine as a consequence. When the vibration occurred, many causes could be detected as follows:

Unbalanced rotating parts could cause the vibration due to having been through incessant use, corrosion, manufacturing-rebuilding (material cavitation), maintenance, etc. Such an imbalance in the rotating components was a significant cause of damage to other devices.

Misalignment of the coupling could cause resistance, damaging and vibrating the rotating components.

Looseness of the components assembled in the rotor could lead to vibration as the components were not stationary during rotating useability.

Bearing defects might be the consequence of the damaged bearing for various reasons, which led to the vibration from the damaged bearing.

Gears mash was regarded as one of the possible causes of the vibration.

The causes mentioned above reflected a correlation with one another. Therefore, it was suggested that annual maintenance and component disassembling for repair should be analyzed regularly for the vibration of the machinery. It was to prevent further severe damages, which could cause a long pause in machinery operation as well as the high cost of maintenance.

2.4. Vibration analysis

Vibration analysis was done by using spectral analysis to get a vibration signal. The idea was that since the signal is a response to the dynamic excitations in the machine's operation, a spectral analysis would reveal the amplitude "peaks" in the frequencies associated with such excitations by observing the spectrum of vibrations and operating frequencies of each component such as the shaft rotation, turbine blade passing, gear coupling, among others. Spectral analysis can be performed by direct visual inspection. Then, each of the machine's key stations was marked and identified through processing techniques like Spectrum Synthetization to determine their standard configuration. The technique drew a spectrum from the vibration profile and selected a small quantity of information for analysis and follow-up. In order to use the vibration meter vibration pen in the measurement, the direction must be measured in all three directions: Axial, Vertical, and horizontal.

3. Background knowledge

Fuzzy logic is a mathematical method that allows decision-making in vague, fuzzy situations, much like a human mind. L.A. Zade invested in it in 1965 and used a fuzzy set to communicate uncertainty. A fuzzy set is a set that has a degree of membership between 0 and 1, in contrast to the classical set that allows only 0 (not a set member) or 1 (is a set member). Setting the membership degree within the set relies on the membership function, an essential part of the fuzzy system mechanism, because the type of membership function is critical to the solution and process in the system.

The selection of membership functions depends on the characteristics of the variables and the experts' needs. Furthermore, the fuzzy set can be used with linguistic variables.

Decision-making in predictive maintenance is determined based on the vibration data on some rotating machinery, which the experts receive. The system is shown in Figure 1.

4. Proposed methodology

The research design was divided into four steps. The first step was surveying and analyzing the existing predictive maintenance techniques. The second step was a determination of appropriate expert assessment criteria for predictive maintenance techniques. In addition to the step, it was found that the vibration of the machinery regarding each axial, horizontal, and vertical spindle significantly affected

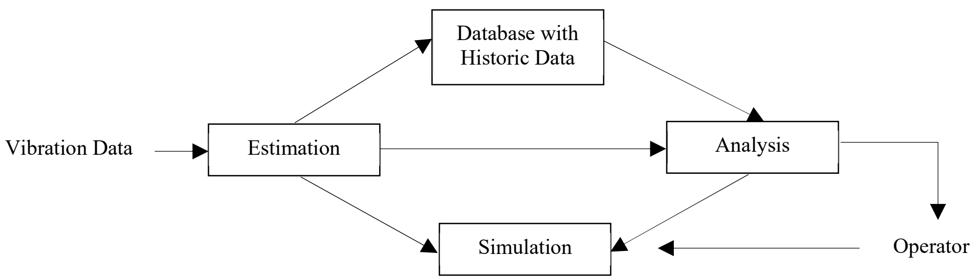

Fig. 1. Decision support system of predictive maintenance

predictive maintenance. The third step was a vibration analysis conducted by the experts. Moreover, the fourth step was a performance evaluation of rotating machinery with fuzzy logic. To specify, the performance evaluation of rotating machinery will be compared between the experts and the fuzzy logic model.

The application of the fuzzy logic system evaluates the efficiency of rotating machinery. In the first step, relevant elements and variables in the system must be defined, such as the number of input variables, output variables, linguistic variables, and the membership function, as shown in Table 1 [17].

The Mamdani-model fuzzy simulation with system variables was performed on MATLAB tool version R2022b, as shown in Figure 2. The Mamdani model was applied to this study because it can define associations using IF-AND-THEN rules. This new FIS contains 64 fuzzy inference rules, as shown in Figure 3. The inferential fuzzy rules were built after editing the pertinence functions of all the variables.

5. Result from analysis

The paper consists of two assessments. The development compared the performance of using the fuzzy logic model in axial, horizontal, and vertical models with the experts until the fuzzy logic system simulations are shown in Table 2. The evaluation results were then calculated for accuracy, precision, recall, and F1-score.

Table 1.
Definition of crisp-fuzzy inputs and output variables of the performance

Ids	Parameters	Linguistic Term	Membership Function-mf	Fuzzy Ratings
I1	Axial	Newly Commissioned Machinery	mf1-Triangular	[0.0, 0.7, 1.3]
		Unrestricted Operation	mf2-Triangular	[1.4, 2.3, 2.7]
		Restricted Operation	mf3-Triangular	[2.8, 3.5, 4.4]
		Damage Occur	mf4-Triangular	[4.5, 7.1, 11.0]
I2	Horizontal	Newly Commissioned Machinery	mf1-Triangular	[0.0, 0.7, 1.3]
		Unrestricted Operation	mf2-Triangular	[1.4, 2.3, 2.7]
		Restricted Operation	mf3-Triangular	[2.8, 3.5, 4.4]
		Damage Occur	mf4-Triangular	[4.5, 7.1, 11.0]
I3	Vertical	Newly Commissioned Machinery	mf1-Triangular	[0.0, 0.7, 1.3]
		Unrestricted Operation	mf2-Triangular	[1.4, 2.3, 2.7]
		Restricted Operation	mf3-Triangular	[2.8, 3.5, 4.4]
		Damage Occur	mf4-Triangular	[4.5, 7.1, 11.0]
P	Performance	Critical	mf1-Triangular	[0, 25, 50]
		Caution	mf2-Triangular	[25, 50, 75]
		Optimum	mf3-Triangular	[50, 75, 100]
		Normal	mf4-Triangular	[75, 100, 100]

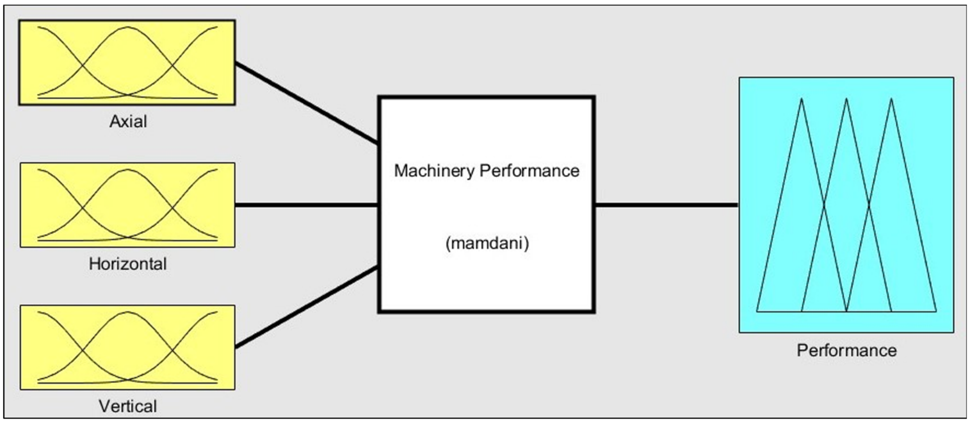

Fig. 2. The hierarchical structure of the performance fuzzy logic model

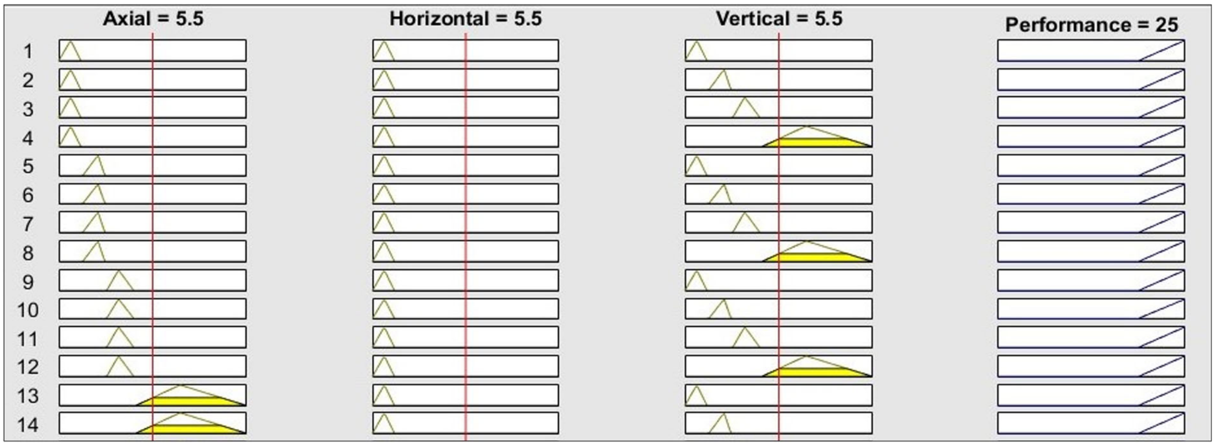

Fig. 3. Fuzzy logic reason mechanism

Table 2.
Fuzzy logic system simulations

No	Axial	Horizontal	Vertical	Expert	Fuzzy	No	Axial	Horizontal	Vertical	Expert	Fuzzy
1	2.5	2.1	1.8	75	75	26	4.2	3.3	3.3	50	50
2	2.5	2.1	1.6	75	75	27	4.4	3.4	3.4	50	50
3	3.1	2.1	1.9	75	75	28	4.3	3.4	3.4	50	50
4	2.9	2.2	1.7	75	75	29	4.5	3.3	3.3	50	50
5	2.9	2.5	1.8	75	75	30	4.7	3.4	3.4	50	50
6	3.1	2.6	1.9	75	75	31	4.3	3.1	4.0	50	50
7	3.1	2.6	1.9	75	75	32	4.4	4.0	4.1	50	50
8	3.2	2.7	2.2	75	75	33	4.5	4.1	4.3	50	50
9	3.2	2.7	2.3	75	50	34	4.4	4.3	4.2	50	50
10	3.5	2.8	2.6	50	50	35	5.8	4.2	4.1	50	50
11	3.6	2.9	2.6	50	50	36	5.9	5.5	4.1	25	25
12	3.8	2.9	2.6	50	50	37	6.1	5.8	4.3	25	25
13	3.9	2.7	2.7	75	50	38	6.3	5.9	4.7	25	25
14	4.2	2.9	2.7	50	50	39	6.4	6.1	5.2	25	25
15	4.4	2.9	2.7	50	50	40	6.6	6.3	5.5	25	25
16	4.2	2.8	2.7	50	50	41	7.0	6.5	5.7	25	25
17	4.4	2.7	2.7	75	50	42	5.5	4.3	5.5	25	25
18	4.3	2.9	2.9	50	50	43	5.8	4.4	5.7	25	25
19	4.5	2.8	2.9	50	50	44	5.9	4.5	5.9	25	25
20	4.7	2.9	3.1	50	50	45	6.1	4.7	6.1	25	25
21	4.6	3.1	3.1	50	50	46	6.3	4.9	6.3	25	25
22	4.5	2.8	3.1	50	50	47	6.4	5.2	6.4	25	25
23	4.3	2.6	3.1	50	50	48	6.6	5.5	6.6	25	25
24	4.2	2.7	3.2	50	50	49	6.8	5.7	7.1	25	25
25	4.4	2.7	3.2	50	50	50	6.8	6.2	7.1	25	25

As shown in Table 3, such assessment was done under vibration standard ISO 10816-3 conditions. 3.

The study shows that the assessment using fuzzy logic was inconsistent with the experts only thrice, including No.9, No.13, and No.17. Calculating the accuracy, precision, recall, and F1-score can be calculated as Equation 1-4. The accuracy, precision, recall, and F1-score were measured using True Positive (TP), True Negative (TN), False Positive (FP), and False Negative (FN).

Table 3.
Machine performance evaluation under ISO 10816-3

RMS, mm/sec	Machinery Group 2 (15 kW – 300 kW)	% Performance
4.5-11.0	Damage Occur	25
2.8-4.4	Restricted Operation	50
1.4-2.7	Unrestricted Operation	75
0.0-1.3	Newly Commissioned Machinery	100

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} = \frac{(47+0)}{(47+0+3+0)} = 0.94 \quad (1)$$

$$Precision = \frac{TP}{TP+FP} = \frac{47}{(47+3)} = 0.94 \quad (2)$$

$$Recall = \frac{TP}{TP+FN} = \frac{47}{(47+0)} = 1 \quad (3)$$

$$F1 - Score = 2 \times \frac{(Precision \times Recall)}{(Precision + Recall)} = 2 \times \frac{(0.94 \times 1)}{(0.94+1)} = 0.97 \quad (4)$$

The research applied the method in the evaluation process of the machine conditions. It was obtained by measuring the motor's vibration with 50 values. After a calculation, the evaluation results of the fuzzy logic system simulations showed an accuracy of 0.94, precision of 0.94, recall of 1, and F1-score of 0.97, with each value approaching 1. It means that the results were very similar to the traditional method (by the experts).

6. Conclusions

The rotating machinery performance assessment aimed to build a model for predictive maintenance [18]. The result indicated information about the rotating machinery's performance and vibration level according to the Standard ISO 10816-3. So, the information could be used for predictive maintenance planning for maximum benefit and to improve maintenance activities to suit the conditions of the rotating machinery better. In applying fuzzy logic for assessment, the assessor has a significant role in defining components within the system, such as the selection of membership functions, number of interpreters, number of rules, etc., to get the assessment system that suits the reality. Applying such sophisticated technology to maintenance complex production facilities can greatly reduce the risk [19]. To use such sophisticated technology. It is essential to understand the interconnected problems and challenges. Some potential benefits of implementing such integrated maintenance management include: 1) Simulate, analyse, and predict system behaviour more realistically. In other words, it eliminates the ambiguity in maintenance planning. 2) Assists in the rapid audit of maintenance schedule checks and equipment life expectancy for planning, maintenance practices/strategies for improving system performance. 3) Improved performance, controlling potential events and events that may lead to failure to function effectively. The fuzzy logic method of predicting the life expectancy of maintenance equipment in maintenance operations provides a better approach than traditional methods. It helps in planning resources for maintenance, service, and equipment replacement.

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Authors contribution

The authors declare no conflict of interest. All authors contributed equally to this study as the co-first authors. All the co-authors have approved the final version of the manuscript.

References

[1] Y. Lv, Q. Zhou, Y. Li, W. Li, A predictive maintenance system for multi-granularity faults based on AdaBelief-BP neural network and fuzzy decision making, Advanced Engineering Informatics 49 (2021) 101318. DOI: https://doi.org/10.1016/j.aei.2021.101318

[2] S. Selcuk, Predictive maintenance, its implementation and latest trends, Proceedings of the Institution of Mechanical Engineers, Part B: Journal of Engineering Manufacture 231/9 (2017) 1670-1679. DOI: https://doi.org/10.1177/0954405415601640

[3] W. Hongxia, Y. Xiaohui, Y. Ming, Study on predictive maintenance strategy, Advanced Science and Technology Letters 137 (2016) 52-56. DOI: https://doi.org/10.14257/astl.2016.137.10

[4] K.T.P. Nguyen, K. Medjaher, A new dynamic predictive maintenance framework using deep learning

for failure prognostics, Reliability Engineering and System Safety 188 (2019) 251-262.
DOI: https://doi.org/10.1016/j.ress.2019.03.018

[5] M. Baban, C.F. Baban, M.D. Suteu, Maintenance decision-making support for textile machines: a knowledge-based approach using fuzzy logic and vibration monitoring, IEEE Access 7 (2019) 83504-83514.
DOI: https://doi.org/10.1109/ACCESS.2019.2923791

[6] M. Cerrada, C. Li, R.V. Sánchez, F. Pacheco, D. Cabrera, J.V. de Oliveira, A fuzzy transition-based approach for fault severity prediction in helical gearboxes, Fuzzy Sets and Systems 337 (2018) 52-73.
DOI: https://doi.org/10.1016/j.fss.2016.12.017

[7] N. Vafaei, R.A. Ribeiro, L.M. Camarinha-Matos, Fuzzy early warning systems for condition-based maintenance, Computers and Industrial Engineering 128 (2019) 736-746. DOI: https://doi.org/10.1016/j.cie.2018.12.056

[8] C.K. Lee, Y. Lv, K.K.H. Ng, W. Ho, K.L. Choy, Design and application of Internet of things-based warehouse management system for smart logistics, International Journal of Production Research 56/8 (2018) 2753-2768.
DOI: https://doi.org/10.1080/00207543.2017.1394592

[9] M. Karakose, O. Yaman, Complex fuzzy system based predictive maintenance approach in railways, IEEE Transactions on Industrial Informatics 16/9 (2020) 6023-6032. DOI: https://doi.org/10.1109/TII.2020.2973231

[10] F. Arena, M. Collotta, L. Luca, M. Ruggieri, F.G. Termine, Predictive maintenance in the automotive sector: a literature review, Mathematical and Computational Applications 27/1 (2022) 2. DOI: https://doi.org/10.3390/mca27010002

[11] M. Baban, C.F. Baban, B. Moisi, A fuzzy logic-based approach for predictive maintenance of grinding wheels of automated grinding lines, Proceedings of the 23rd International Conference on Methods and Models in Automation and Robotics "MMAR", Miedzyzdroje, Poland, 2018, 483-486.
DOI: https://doi.org/10.1109/MMAR.2018.8486144

[12] N.M. Thoppil, V. Vasu, C.S.P. Rao, On the criticality analysis of computer numerical control lathe subsystems for predictive maintenance, Arabian Journal for Science and Engineering 45/7 (2020) 5259-5271.
DOI: https://doi.org/10.1007/s13369-020-04397-7

[13] P.D.S.L. Alexandrino, G.F. Gomes, S.S. Cunha Jr, A robust optimization for damage detection using multi-objective genetic algorithm, neural network and fuzzy decision making, Inverse Problems in Science and Engineering 28/1 (2020) 21-46.
DOI: https://doi.org/10.1080/17415977.2019.1583225

[14] W. Zhang, D. Yang, H. Wang, Data-driven methods for predictive maintenance of industrial equipment: A survey, IEEE Systems Journal 13/3 (2019) 2213-2227.
DOI: https://doi.org/10.1109/JSYST.2019.2905565

[15] J.J. Costello, G.M. West, S.D. McArthur, Machine learning model for event-based prognostics in gas circulator condition monitoring, IEEE Transactions on Reliability 66/4 (2017) 1048-1057.
DOI: https://doi.org/10.1109/TR.2017.2727489

[16] A. Shamayleh, M. Awad, J. Farhat, IoT based predictive maintenance management of medical equipment, Journal of Medical Systems 44/4 (2020) 72.
DOI: https://doi.org/10.1007/s10916-020-1534-8

[17] Aradhana, B. Singh, P. Sihag, Predictive models for estimation of labyrinth weir aeration efficiency, Journal of Achievements in Materials and Manufacturing Engineering 105/1 (2021) 18-32.
DOI: https://doi.org/10.5604/01.3001.0014.8742

[18] L.A. Dobrzański, Role of materials design in maintenance engineering in the context of industry 4.0 idea, Journal of Achievements in Materials and Manufacturing Engineering 96/1 (2019) 12-49. DOI: https://doi.org/10.5604/01.3001.0013.7932

[19] M. Asfar, P. Naveenkumar, V. Naveen Kumar, K. Krishnamurthy, Online vibration suppression in lathe machine, Journal of Achievements in Materials and Manufacturing Engineering 77/2 (2016) 69-74. DOI: https://doi.org/10.5604/17348412.1230100

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