Rule-Based Decision Making in Biologically Inspired Condition Management System

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Abstract: Biomimicry is an approach for solving industrial challenges by taking inspiration from bio-organisms' responses. In an ongoing research project, investigations are being carried out to explore the use of biomimicry approach for a human-centric condition management system. In this system the decision-making process is divided into three types procedural decision-making, deliberative decision-making, and argumentative decision-making. This paper intends to show the experimental verification of rule-based decision making (a type of procedural decision making) in condition monitoring system using an example of rolling element bearing. Rule-based decision-making involves using predefined guidelines to make choices, ensuring structured, consistent, fair, efficient, and unbiased decisions. Vibration sensor data is used from PRONOSTIA datasets to obtain four useful information's and using those information's in fuzzy rules to get decision. The outcomes indicate the viability of the suggested framework for rule-based decision-making using real-time vibration data.

1 INTRODUCTION

Biomimicry, the practice of drawing inspiration from nature to solve human challenges, has found relevance in the realm of decision-making (*The Biomimicry Institute — Nature-Inspired Innovation*, n.d.). The human brain plays a central role in the process of decision making. It's a complex and intricate organ that integrates various cognitive processes and emotions to evaluate options, weigh pros and cons, and arrive at a choice. Old brain and new brain are familiar terms that refer to different parts of the human brain that evolved at different times in human evolution. The old brain is responsible for basic survival functions, while the new brain is responsible for more complex functions such as reasoning, thinking, learning, and problem-solving (Hawkins, 2021). Procedural decision making involves an old brain while the thoughtful decision making involves both old brain and new brain. The old brain carries a cache of "best practices" that is quick and simple.

Effective decision making in condition monitoring system aims to reduce unplanned downtime, extend equipment lifecycles, and optimize maintenance efforts. Condition-based maintenance emerged to minimize expenses associated with overly frequent scheduled maintenance. Within an ongoing research effort, a human-centred condition management system framework has been proposed in (Singh et al., 2024), drawing inspiration from human cognition. Three decision making techniques named procedural decision-making, deliberative decision-making, and argumentative decision-making are presented for equipment maintenance as in Figure 1.

Procedural decision making is the process of making decisions based on a predetermined set of rules, practices, or protocols. It can be modelled either by rule-based approaches (Singh & Pokhrel, 2018) or case-based approaches (Kolodner, 2014). It uses sensory information integration and evaluation to decide a course of action (Van Der Meer et al., 2012). It is important for many everyday tasks, such as recognizing faces, avoiding danger and so on. It involves the brain's ability to process and interpret sensory signal and to use that signal to make decision. It might be useful in ensuring fair and consistent decisions, but not guarantees to accommodate unique or unexpected situations in decision-making like something is better than nothing.

Deliberative decision-making involves a thorough process where individuals thoughtfully analyse

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options, gather information, weight consequences, and assess outcomes before making a choice. It requires conscious thought, reasoning, and differs from procedural decision-making that relies on swift, automatic, and emotional reactions. In deliberative process, the fault finding aims to uncover latent failures, requiring thorough analysis for optimal decision-making, reliability assessment, and streamlined maintenance policy ideal (Junior et al., 2022). An instance of deliberative decision-making, involving reliability assessment and optimization of maintenance policies for the yaw system on a wind turbine, was showcased in (Catelani et al., 2020).

Balancing procedural and deliberative decision-making are key for effective choices, harnessing strengths from both approaches. Argumentative decision-making involves evaluating options using structured arguments and evidence, aiming to enhance decisions by rational and well-justified selection among alternatives. Arguments serve dual roles: aiding alternative selection and justifying adopted choices in both everyday decisions and critical discussions (Amgoud & Prade, 2009). Argumentation enhances AI explain ability by revealing decision steps, offering reasoning amidst uncertainty, and resolving conflicting information (Vassiliades et al., 2021). The performance of decision-making models has been improved by combining the argumentation by providing human supervision for image classification and large-scale real-world semi-autonomous driving in (Fridman et al., 2019).

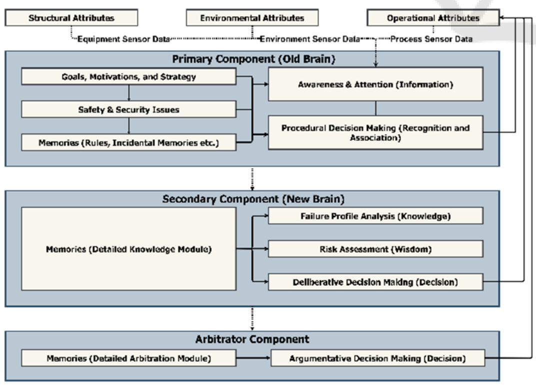


Figure 1: Decision making framework proposed in biologically inspired condition management system.

Immediate maintenance decision is carried by procedural decision making from initial observation, and deliberate or thoughtful maintenance decision is done by using root cause finding, likelihood estimation, continuous learning, and optimization of available resources. The main objective of this work is to show case study of rule-based decision making. This paper thus investigates the usefulness of the framework using in vibration signal in bearing. Some preliminary case study of initial fault identification was carried out in (Singh et al., n.d.). This work shows the complete case of rule-based decision-making using fuzzy rules.

A quick and efficient decision-making system plays a vital role in enhancing maintenance task especially for safety critical equipment's. We argue that the concept of rule-based decision making is at the very basis of the quick decision making and that using limited data through a well-established technique both safety & security as well as goals and motivation of low maintenance cost.

The rest of the paper is structured as follows: Section 2 presents the methodology of rule-based decision making, including fault detection, identification, quantification, and RUL estimation submodules. Section 3 provides the result of each module to obtain corresponding information and how fuzzy rules bind those information into decision and Section 4 draws the concluded remarks.

2 METHODOLOGY

Integral to electromechanical systems, ball bearings play a vital role, but their malfunctions can dramatically impact the operational lifespan of industrial processes. Through continuous monitoring of bearing, potential faults are detected early, leading to prompt rule-based decision. In systems demanding high reliability and safety, timely maintenance decisions are of paramount importance.

The functional flowchart of rule-based decision making consists of five submodules named fault detection, fault identification, fault quantification and fault prognostic and use of fuzzy rule as shown in Figure 2. These submodules are divided into diagnostic and prognostic categories based on timing. The diagnostic aspect includes fault detection, identification, and quantification, while the prognostic aspect estimates remaining useful life (RUL). After fault detection, instantly the three other fault analysis modules make some information's. The fault qualification module notes the degradation index, the fault identification module tries to find out which part of the bearing is showing fault traces and the prognostic module roughly estimate the RUL. After gathering the prerequisites information, the rule module uses fuzzy logic to get decision.

Researchers lack a unanimous agreement on the most suitable vibration-based fault detection, fault identification, damage indicator and fault prognostic method or parameter. While vibration feature-based methods are simple and easily applicable, they are not computationally intensive; Moreover, they provide approximate quantitative damage assessment. We utilize the Naive Bayes classifier for fault detection, relying on time intervals between vibration envelope peaks for fault identification. Additionally, the capability index derived from the kernel density plot of vibration data serves as a degradation indicator for fault quantification. For fault prognostics, we employ polynomial regression to predict RUL.

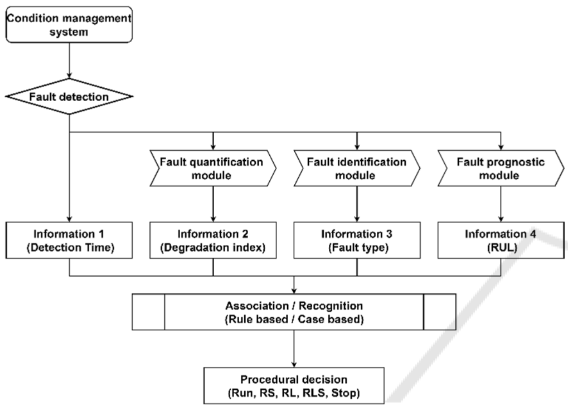


Figure 2: Functional flowchart of procedural decision making in bearing after fault detection.

2.1 Fault Detection

Fault detection aims to spot deviations from normal behavior that might result in errors, failures, or malfunctions. It enables operators to identify mechanical anomalies and determine the underlying problem for subsequent targeted repairs. Common bearing failure modes exhibit distinct characteristics, necessitating varied identification strategies. Single features are insufficient for precise fault detection, prompting the use of machine learning-based fault detection module for intelligent analysis. The fault detection process steps are shown in Figure 3.

Noise is a natural part of vibration data, to minimize effect of noise data we applied sliding window with 5 points. After denoising, thirteen-time domain features (Maximum, Minimum, Average absolute value, Peak to peak, Variance, Standard Deviation, Root mean square, Crest factor, Clearance Factor, Impulse factor, Skewness, Kurtosis, and Shape factor) are extracted from both accelerometer data. Detailed definitions, physical meanings, and statistical equations are described on (Wang et al., 2019). Pearsons's correlation coefficient is used to select useful feature's fault detection (Cai et al., 2018). Maximum value, Variance, Skewness, and Kurtosis features are picked as promising features for fault representation.

Since the datasets contain the measurement until the either of the accelerometer overpassed 20g, there is no pre-defined label. We labelled the fault based on anomalies. Anomalies, unique patterns with distinct attributes from normal instances, hold significance across domains, providing actionable insights. We employ the Isolation Forest algorithm for anomaly finding, leveraging its fast tree-based methodology that assigns anomaly scores via binary search tree paths (Liu et al., 2008). This algorithm accommodates multiple features, enhancing labelling accuracy, and draws insights from diverse monitoring methods (Hayes & Capretz, 2014). Particularly effective for high-dimensional problems with irrelevant attributes or scarce anomalies, Isolation Forest's computational efficiency suits streaming data scenarios.

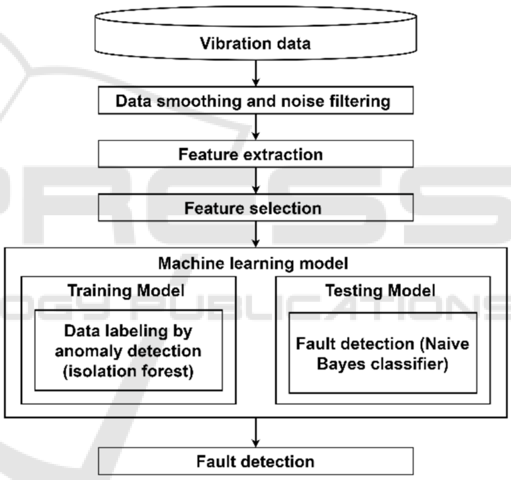


Figure 3: Flowchart of fault detection module.

After labelling, we used the Naive Bayes classifier for fault detection, known for its efficacy in text classification, medical diagnosis, predictive maintenance, and fault detection (Rish, 2001). This classifier simplifies learning by assuming feature independence within classes. It employs Bayesian theory, as shown in equation (1)

$$P(D_k|\, x) = \frac{P(D_k)}{P(x)}\, P(x|\, D_k) = \frac{P(D_k)}{P(x)} \prod_{i=1}^{n} P\,(x_i|D_k) \quad (1)$$

2.2 Fault Identification

Fault identification is the process of specifically pinpointing the component of location underlying causes or mechanism of abnormal behavior in an equipment. Bearing faults can be grouped into two categories single-point defects and generalized roughness. To vibration signature produced by generalized roughness are vague, while the single-point defects can be swiftly and easily identified from the vibration signal envelope. Defects at different components (outer race, inner race, ball, and cage) creates different characteristic frequencies. These defects typically produce periodic vibration signals with repetitive patterns over time (Song et al., 2018). This pattern facilitates frequency measurement, contributing to the detection of periodicity or regularity within the vibration signal. In this context, 'zero crossing time' is synonymous with the time interval that highlights defects on bearing components in time-domain vibration signatures (William & Hoffman, 2011). The comprehensive methodology for extracting vibration signatures from time-domain vibration features is elaborated in our earlier work (Singh et al., n.d.).

2.3 Fault Quantification

Fault Quantification finds the level of abnormality to quantify the degree of degradation and fault (partial or complete) (Kandukuri et al., 2016). As highlighted before, fault quantification significantly influences the informational value for rule-based decision-making, and the choice of degradation indicator features is context-specific, as no single feature proves universally effective for all structures and damage types. The selection of degradation indicators (D_i) involves a compromise between damage sensitivity and alignment with anticipated structural response. To address uncertain parameters, different uncertainty quantification methods have emerged, categorized into Probabilistic and Possibilistic approaches. Probabilistic approaches treat model input parameters as random variables with known probability density functions (Kong et al., 2017).

Capability index have been used in the manufacturing industry to provide quantitative measures on process potential and performance, moreover it can be used as damage index by fault. Here we use kernel density function to measure the uncertainty in the fault model, which is an extension of the histogram. It is coined by statistician and is expressed with different notion as process capability index (Pearn & Chen, 1999), Six Sigma method (Gupta et al., 2018; Kulkarni et al., 2023) Six sigma method was developed to minimize process variance and to improve the quality and performance of the system. The process capability indices reflect the degree of the process variation with respect to the specific limits. As the degree of fault increases the value of degradation index falls.

$$D_i = \frac{d - |\mu - M|}{3\sigma} = \frac{min(USL - \mu, \mu - LSL)}{3\sigma} \quad (2)$$

2.4 Fault Prognostics

Fault prognostics predicts future system behavior using current condition and data history. Due to the uncertainty and nonlinearity of the predictive models when damage accumulates, an alternative goal is to estimate the RUL that the system can perform in a safe status under the future loading before one no longer has confidence in the prognosis model. Here, the fault prognosis module predicts the RUL of the bearing from the time of anomaly detection timeline.

Regression is a powerful statistical method and used widely for RUL prediction in prognosis (Kwon et al., 2019). We've observed a non-linear relationship between vibration feature (maximum vibration value) and failure; therefore, we use polynomial regression. It's important to note that the size and distribution of the dataset used for model building impact the regression performance of the prognostic module. We use the 200 sample measurements for calculation of polynomial coefficients. The mathematical representation of our model follows equation (3), where 'n' represents the polynomial degree and P_0 , $P_1 .. P_n$ are the coefficient of polynomial curve.

$$P(x) = P_0 x^n + P_1 x^{n-1} + \cdots \ldots \ldots + P_n x^0 \quad (3)$$

2.5 Fuzzy Rules

By drawing upon past experiences and knowledge, individuals can make decisions based on the recognition of relevant cues and the associated outcomes associated with them. It relies on the recognition of familiar patterns and the subsequent application of established strategies that have proven successful in similar contexts. The phenomenon of decision making from the viewpoint of computer science and information technology was presented in (Marko Bohanec, 2009). To address uncertainty in FMECA for CNC machine tools' manufacturing stage, fuzzy mathematics and data envelopment analysis are used to determine risk factors, assess failure modes, and calculate a new RPN (Yu et al., 2022).

Here we use Fuzzy rules to obtain decision from the information obtained from diagnostic and prognostic fault analysis submodules. Fuzzy rule emulates human-like reasoning in handling uncertainty and imprecision, making it ideal for ambiguous scenarios. Fuzzy rules, structured as 'IF Antecedent THEN Consequent,' work with linguistic variables and smooth transitions via membership functions. They enable flexible decision-making in imprecise situations, bridging the gap between vague input and actionable output. Fuzzy Rule-Based Systems offer accountability when input data is fuzzified (Trillo et al., 2020). These rules manage uncertainty using degrees of truth, encoding expert knowledge in a human-understandable format.

All input and output membership functions, fuzzy rules and the lookup table are developed prior to the implementation of the fuzzy logic technique to find the rule-based decision, therefore it is less time consuming.

In data science, defining membership functions in fuzzy systems is crucial. Various methods exist to describe membership functions, including horizontal, vertical, pairwise-comparison, problem-specific, fuzzy clustering, artificial neural networks, and genetic algorithms (Klir & Yuan, 1995). In this context, we opt for a simple and quick approach based on the information range obtained from each module.

Decision variables include anomaly detection time, damage index, and RUL. Detection time impacts failure risk: early detection provides time to avoid immediate failure. The damage index quantifies fault severity inversely, with a higher index indicating better performance. RUL guides decisions: a low RUL suggests potential need for immediate action or reduced operating attributes to prolong lifetime. Decision is taken as output membership variables.

The American Roller Bearing Company's catalog, drawing on a century of experience, provides domain knowledge and expert opinions for defining input and output variables as membership functions (American Roller Bearing, n.d.). They emphasize the temperature's influence on bearing life due to reduced hardness at high temperatures, impacting static and dynamic capacities. To compute actual bearing rating life (L), one must account for speed, load, and temperature, all inversely related to rating life (see equation 4). where D is dynamic load rating, P is applied load, e equals 10/3 for rolling element, R is the rotation.

$$Rating\ life\ (L) = \frac{\left(\frac{D}{P}\right)^{e} * 10^{6}}{60 * R} * Temp\ factor \qquad (4)$$

Bearings typically operate under varying loads and speeds, defined by a duty cycle that specifies the load, speed, and percentage of time. In these cases, a full duty cycle occurs within one bearing revolution. Equation 5 provides the formula for calculating the rating life under such variable operating conditions. where T_1, T_2, T_m are percentage of time at different conditions ($T_1 + T_2 + \dots T_m = 1$) and L_1, L_2, L_m are life in hours for each period of constant load and speed.

$$Rating\ life\ (L) = \frac{1}{\frac{T_1}{L_1} + \frac{T_2}{L_2} + \cdots + \frac{T_m}{L_m}} \qquad (5)$$

Our goal isn't to achieve the optimal decision; instead, we aim to demonstrate experimental validation of rule-based decision-making. Our criteria for failure are subjective, prioritizing safe operation. Drawing from equations 4 and 5, we consider five procedural decision alternatives in this work based on criticality. Load's greater quantitative impact than speed determines their order: 'run as is' (decision one), 'reduce speed' (decision two), 'reduce load' (decision three), 'reduce load and speed' (decision four), and 'stop' (decision five). These decisions correspond to five classes: run, reduce speed (RS), reduce load (RL), reduce load & speed (RLS), and stop immediately. The details of membership function, range of information variables, fuzzy sets, and boundary of trapezoid is presented in Table 1.

Table 1: Membership functions and their boundary.

Membership function	Range	Fuzzy sets	Trapezoid
Detection Time	0-25000	Early Awhile Late	[0,0,2000,5000] [2000,5000, 10000, 15000] [10000, 15000, 25000, 25000]
RUL	0-25000	Short Intermediate Long	[0,0,2000,5000] [2000,5000, 10000, 15000] [10000, 15000, 25000, 25000]
Degradation index	0 - 21	Low Medium High	[0,0,1, 3] [1,3,5,10] [5,7, 21, 21]
Decision	1 - 10	Run RS RL RLS Stop	[0,0,1, 2] [1,2,3,4] [3,4,6,7] [6,7,8,9] [8,9,10,10]

Detection time, RUL and degradation indices are taken as Antecedent, and decision is taken as Consequent. Using a 27 linguistic rule base, derived from empirical knowledge, and illustrated in Figure 4, rules are determined for instance:

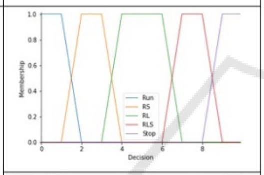
RULE 1: IF early detection time AND short RUL AND low degradation index, THEN decision is 'Stop.'
RULE 27: IF late detection time AND long RUL AND high degradation index, THEN decision is 'Reduce speed.'"

In defuzzification, we convert the output fuzzy set into a single crisp value. In this model, we use the Centre of Gravity (centroid) method to calculate this crisp output value from the accumulated membership functions. This work utilizes the scikit-fuzzy Python package for fuzzy logic operations.

Early	Stop	RLS	RL
Awhile	Stop	Stop	RLS
Late	Stop	Stop	Stop
D_Time / RUL	Short	Inter	Long
Degradation index: Low			

Early	RL	RS	Run
Awhile	RLS	RL	RS
Late	Stop	RLS	RL
D_Time / RUL	Short	Inter	Long
Degradation index: Medium			

Early	RS	Run	Run
Awhile	RL	RS	Run
Late	RLS	RL	RS
D_Time / RUL	Short	Inter	Long
Degradation index: High			



Decision as output membership function

Figure 4: Decision matrices by considering detection time and RUL at three different stages of degradation index. The bottom right graph shows the membership function with five possible categorical.

2.6 Data Sets

We evaluate the model using the PRONOSTIA datasets provided by the FEMTOST Institute, specifically designed for accelerated degradation tests of bearings. Our focus is on vibration data due to its valuable insights for condition management. These datasets include readings from two accelerometers, sampled every 10 seconds at a frequency of 25.6 kHz. Seventeen experiments were conducted under three different operating conditions, as summarized in Table 2. Six experiments (Bearing1_1, Bearing1_2, Bearing2_1, Bearing2_2, Bearing3_1, Bearing3_2) are utilized for training, while the remaining eleven experiments are used for testing. We specifically employ the 'run to failure' experiment from the training and test datasets for verification purposes. Figure 5 illustrates the bearing experimentation platform, and more detailed dataset information can be found in (Nectoux et al., 2012). These datasets are openly available to support prognostics research for condition monitoring, encompassing vibration signals collected throughout the entire lifetime from accelerated degradation tests of rolling element bearings.

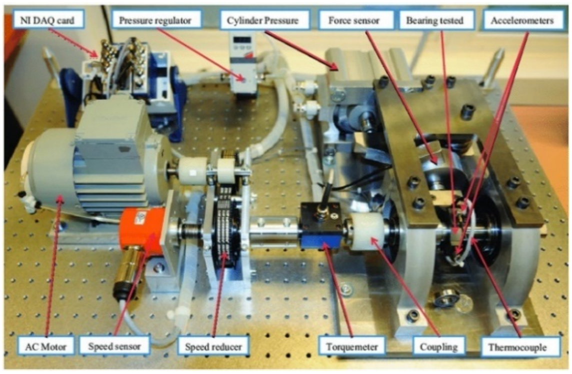


Figure 5: Overview of the experimentation platform (Nectoux et al., 2012).

Table 2: Operating conditions of various experiments.

	Operating Conditions		
	Condition 1	Condition 2	Condition 3
Load (Newton) / Speed (RPM)	4000 / 1800	4200 /1650	5000 / 1500
Training sets	Bearing1_1 Bearing1_2	Bearing2_1 Bearing2_2	Bearing3_1 Bearing3_2
Testing sets	Bearing1_3 Bearing1_4 Bearing1_5 Bearing1_6 Bearing1_7	Bearing2_3 Bearing2_4 Bearing2_5 Bearing2_6 Bearing2_7	Bearing3_3

3 RESULTS

In the older brain, decision-making processes tend to be straightforward and satisfying, enabling quick responses to potential threats or opportunities. To elucidate the implementation process and the practicality of the proposed decision-making framework, we have structured the results steps in a manner consistent with the methodology. We selected the Bearing1_3 experiment as a case study to illustrate the workings of each information-producing module. The subsequent timeline and details are elaborated upon in the methodology section.

3.1 Fault Detection

To establish a clear decision boundary between normal and anomaly, we evaluate two parameters: 'anomaly' and 'decision score' for categorized anomalies. If both parameters meet our criteria, we label it as an anomaly. Furthermore, to enhance confidence and reduce false positives, we consider three consecutive timestamps with anomaly vibration features as the detection time for anomalies. The two top graphs in Figure 6. show the raw vibration data from horizontal and vertical accelerometer and the last graph shows the fault detection time (16430 sec or 4.56 Hours) is the instance to take procedural decision. This module results first information about detection time. The fault detection times for all eleven experiments are documented in the second column of Table 3. After detecting faults, the other three module (fault identification, fault quantification and fault prognostic) begins to find other information.

In Bearing2_5 experiments, we observed initial jerks and heightened vibrations that later stabilized into smooth operation. To eliminate spurious detections, we disregard faults occurring before 10 percent of the useful life. Any faults detected after this point are considered genuine, and we employ analytical methods for rule-based decision-making.

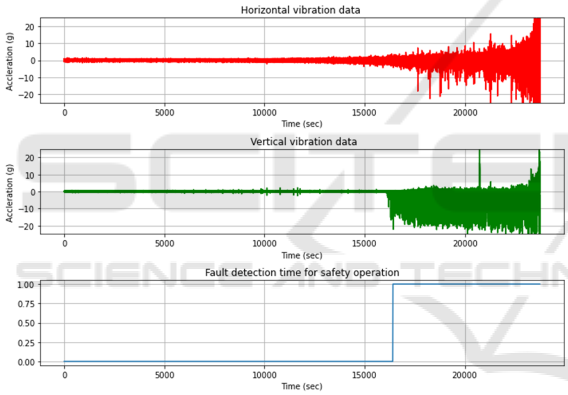


Figure 6: The top two graphs show the temporal vibration signal of horizontal and vertical accelerometers. The last graph shows the fault detection time at 16430 sec.

3.2 Fault Identification

The spacing between the peaks of the vibration envelope serves as an indicator for identifying the failure component. When the peak spacing falls within a ±5% deviation from theoretical values, we classify it as the identified faulty part of the bearing. For an operating condition of 1800 RPM, the theoretical peak spacings are 4.53 ms for inner race defects, 5.91 ms for outer race defects, 9.28 ms for rolling ball defects, and 76.80 ms or 58.89 ms for cage defects. After allowing for a 5% margin of deviation, we consider values within this range as matched cases for fault identification.

However, in the case of Bearing1_3, as shown in Figure 7, we cannot find peak spacings that match the specified fault components. Out of the eleven experiments, we can only identify the faulty part in four experiments, as presented in the third column of Table 3. Additionally, since we lack information about the effects of each part's failure, we do not incorporate this information into the rule for decision-making process. At this moment, advanced signature extraction techniques are essential for improving fault detection, with a focus on future work.

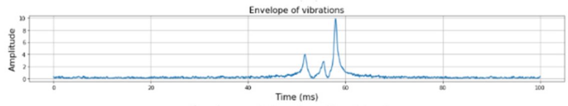


Figure 7: Envelope of vibration data after fault detection (at 16430 sec).

3.3 Fault Quantification

The degradation index is computed based on vibration samples obtained after detecting a fault. The upper and lower specification limits for acceleration values are set at -20g and 20g. To determine the degradation index, we calculate both the lower and upper limits and then select the minimum value between these limits for each sensor. The mean degradation index is subsequently derived by averaging the results from horizontal and vertical accelerometers vibration data. The quantification of fault across all eleven experiments is presented in the fourth column of Table 3. In case of Bearing1_3 experiment, the degradation index value is 3.36, which is marginally acceptable for run of down regulation.

3.4 Fault Prognostics

To expedite RUL estimation, we built a prognostic module using a dataset of 200 samples, with 190 collected before fault detection and 10 after. We employed third-order polynomial regression to estimate RUL. The initial step involves extracting maximum vibration features from both accelerometers. Using these features, polynomial regression models determine coefficients to map the nonlinear relationship between these features and time. RUL is calculated as the time difference between fault detection and the moment the timeline reaches the 20g failure threshold.

Figure 8 displays RUL estimates from the prognostic model. The top graph illustrates two maximum vibration features over time: the red line represents horizontal max values, and the green line represents vertical max values. The black vertical line indicates the fault detection time. Once anomalies are detected, the model uses 200 samples to calculate and fit a regression curve. In the lower graph, the yellow curve represents predictions from the horizontal accelerometer, while the blue curve represents predictions from the vertical accelerometer. The predicted RUL for each experiment is determined by whichever curve first surpasses the 20g amplitude threshold, akin to the failure criteria. The predicted RUL of eleven experiments is presented in the last column of Table 3.

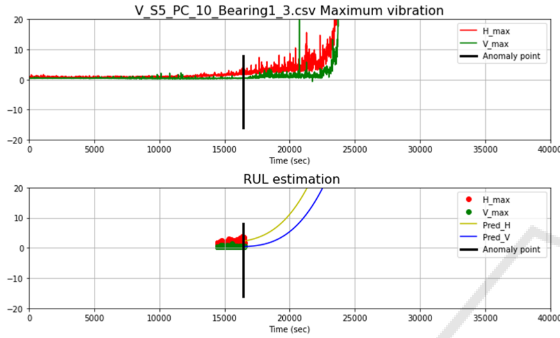


Figure 8: Estimation of RUL by curve fitting after detection of fault by using 200 sample near the fault detection time.

Table 3: Information obtained from different fault analysis submodules for rule-based decision making.

Experiments	Fault analysis			
Experiments	Detection time (sec)	Fault type	Degradation index	RUL (sec)
B1_3	16430	Unidentified	3.36	4920
B1_4	10900	Inner race	5.63	1060
B1_5	24510	Outer race	4.58	580
B1_6	16360	Unidentified	9.48	910
B1_7	22140	Unidentified	6.38	830
B2_3	2580	Unidentified	13.28	1370
B2_4	3440	Unidentified	20.1	6390
B2_5	4030	Unidentified	19.32	2970
B2_6	6890	Outer race	5.5	1150
B2_7	2240	Unidentified	7.68	500
B3_3	4250	Outer race	4.88	1470

3.5 Fuzzy Rules

Decision making can be regarded as the analytical processes of making a choice among several alternatives and committing to a future course of actions or an opinion of choice. After diagnostics and prognostics offer crucial information, it becomes essential to have a decision-making methodology in place. This methodology is necessary to efficiently make use of the available information to produce satisfactory decisions.

We established rules to link procedural decisions with variables, including detection time, predicted RUL, and degradation index, drawing from information as stated in Section 2.5. Figure 9. shows the input and output membership function of Bearing1_3 for decision making. Here fault detection time is 16430 seconds, Predicted RUL from that instance is 4920 seconds and the degradation index is 3.36. By inputting these information's, the defined rule gives 7.52 as defuzzification value. Based on mapping to decision sets, it belongs to reduce load and speed for safety critical system. Similarly, the corresponding defuzzification values for eleven experiments is shown in the last column of Table 4.

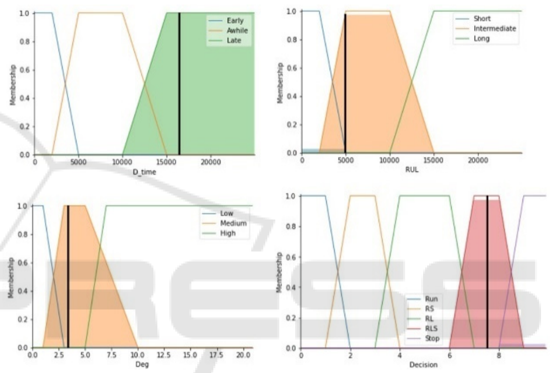


Figure 9: Membership functions of inputs and outputs for the decision making. The top left shows the fault detection time, the bottom left shows the degradation index, the top right shows the RUL and the bottom right graph shows the defuzzification values procedural decisions.

Table 4: Rule-based decision after defuzzification.

Experiment	Input membership function			Output member function
	D_time	RUL	Degrad_index	Decision
B1_3	16430	4920	3.36	7.52
B1_4	10900	1060	5.63	6.69
B1_5	24510	580	4.58	9.17
B1_6	16360	910	9.48	7.59
B1_7	22140	830	6.38	8.13
B2_3	2580	1370	13.28	3.21
B2_4	3440	6390	20.1	1.84
B2_5	4030	2970	19.32	3.93
B2_6	6890	1150	5.5	6.68
B2_7	2240	500	7.68	3.86
B3_3	4250	1470	4.88	6.61

As mentioned previously, our aim is not to identify the best decision but to experimentally validate rule-based decision-making. However, these decisions are subject to the failure criteria outlined by the data provider. The five decision alternatives include: running as is, reducing speed, reducing load, reducing load and speed, and stopping.

In this scenario, we assume the decision membership function ranges from zero to 10 after defuzzification. We divide this range equally into five categories. For instance, decision values from 0-2 are associated with 'run as is,' 2-4 with 'reduce speed,' and so forth.

Out of the eleven experiments conducted, Bearing2_4 aligns with the 'run as is' decision, while Bearing2_3, Bearing2_5, and Bearing2_7 correlate with 'reduce speed.' Similarly, Bearing1_3, Bearing1_4, Bearing1_6, Bearing2_6, and Bearing3_3 fall under 'reduce load and speed,' and Bearing1_5 and Bearing1_7 signify the 'immediate stop' decision. Overall, these decisions seem promising in preventing catastrophic failures in safety-critical systems and in prolonging bearing life through downregulation.

4 CONCLUSION

We apply rapid decision-making techniques inspired by the old brain to enhance timely and effective decision-making for time-sensitive industrial equipment. This approach bridges the gap between cognitive science and condition monitoring, offering a broader perspective on sustainability and inspiring future research in design, modelling, validation, and human-in-the-loop concepts.

In bearing maintenance and fault diagnosis, swift decisions are crucial to avert catastrophic failures and minimize downtime. Our model, utilizing vibration data and extract various information (detection time, RUL and degradation index , and use that information with established rules to make instant decisions.

In scenarios with sparse data and basic algorithms, this rapid decision-making approach proves beneficial for condition management. It's anticipated to assist maintenance engineers in enhancing bearing inspection programs' efficiency. With a specific focus on bearing faults, these findings offer promise for real-world applications.

Future work involves experimental validation of advanced cognitive processes, like root cause analysis, integrated with procedural decision-making for improved maintenance actions. This may also include the incorporation of deep learning and optimization techniques to continuously enhance maintenance strategies.

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