Asuquo, MP, Wang, J, Zhang, L and Phylip-Jones, G

An integrated risk assessment for maintenance prediction of oil wetted gearbox and bearing in marine and offshore industries using a fuzzy rule base method

An Integrated Risk Assessment for Maintenance Prediction of Oil Wetted Gearbox and Bearing in Marine and Offshore Industries Using a Fuzzy Rule Base Method

Maurice Asuquo[1], Jin Wang[1], Lihong Zhang[2], Geraint Phylip-Jones[1]

[1]Liverpool Logistics Offshore and Marine (LOOM) Research Institute, Liverpool John Moores University, Liverpool, UK

[2]School of Mechanical, Aerospace and Civil Engineering, University of Manchester, Manchester, UK

Abstract

This paper presents an integrated risk assessment methodology for maintenance prediction of oil wetted gearbox and bearing in marine and offshore machinery with emphasis on ship cranes. Predictive maintenance uses important parameters measured in the equipment to "feel" when breakdown is eminent. This type of maintenance intends to make interventions on machinery before harmful events may occur. This paper assesses the risk levels of bearing and gearbox, which are the most sensitive components of the ship crane using fuzzy rule based judgement for common elements and their sources. This will provide the ship crane operators with a means to predict possible impending failure without having to dismantle the crane. Furthermore, to monitor the rate of wear in gearbox and bearing of a ship crane, the ship crane reliability (SCR), and a trend to provide an operational baseline of data that will help the engineers to detect abnormal wear rates as they develop, are established. Within the scope of this research, a risk assessment model is developed for determining the risk levels of a crane's components and recommending solutions using all the diagnostic capability obtainable for effective condition monitoring of the gearbox and bearing in ship cranes.

Keywords: Predictive maintenance, rule base, ship crane reliability, risk level, risk assessment, condition monitoring, oil analysis.

1 Introduction

Oil sampling analysis has developed into a mandatory tool. It has not only proven to be an effective condition monitoring tool for equipment failure, but is also a crucial element in a marine crane's condition monitoring. As a predictive maintenance tool, oil analysis can be used to uncover, isolate, and offer solutions for abnormal lubricant and machine conditions. If these abnormalities are left unchecked, they could have detrimental consequences, including health and safety risks.

Apart from monitoring wear metals and oil contamination, oil analysis studies the additives in oils to determine if an extended drain interval is required. In addition, maintenance costs can be reduced using oil analysis to determine the remaining useful life of additives in the oil. By comparing the oil analysis results of fresh and used oil, a tribologist can determine when an oil can be changed. More so, careful analysis might even allow the oil to be "sweetened" to its original additive levels by either adding fresh oil or replenishing additives that were depleted.[1]

The risk of major failures in marine and offshore machinery is an area that is not thoroughly described in academic literature, and it is clear that complexity of the machinery stems from the interaction of their dependencies and the high levels of uncertainty in their operations. Moreover, complexity in the system often results in lack of visibility to monitor the safety performance of operations, as the analysts may have no detailed knowledge about the other part of the system. As a result of this, the analyst is unable to understand the optimisation measures required to enable the machinery to cope with unforeseen extortions and hazards, and maintain functionality of their operations to an acceptable level of performance.

Most of the current methods adopted in monitoring the condition of ship machinery components does provide some levels of confidence. However, they cannot deal with the dependencies of the criteria. It is therefore essential to develop an integrated risk assessment using a Fuzzy Rule Base Method that will account for this shortfall in a systematic manner, and this is provided in this research.

The findings contained in this research are particularly useful for effective condition monitoring of ship crane gearbox and bearing. This risk assessment tool can also be used as an information technology application to monitor the performance of lubricant products, as well as a tool that specifies what the problem/remedy is in the event of failure of a piece of equipment/component.

2 Literature Review

Monitoring machinery condition by lubricant analysis allows the engineer on-board to identify the presence of metallic wear particles carried within the oil stream. These metallic particles are analysed by type to determine which part of the machine is wearing and, by using trending, to find out how fast the wearing may have developed. Often a secondary wear debris analysis is invoked to assess in detail the significance of unusual wear metal results. A secondary function of lubricant analysis is to detect changes in the oil condition that will, if left unchecked, lead to an increased risk of failure. The type of issue that would be highlighted here would relate to increases in foreign substances such as water, dirt, soot, fuel, *etc*., which can degrade the functional properties of the lubricant.[2]

The benefits/savings associated with discovering a potential problem and preventing an unplanned or catastrophic failure of machinery cannot be overemphasised. Effective condition monitoring of marine machineries helps to determine performance, avoid excessive depreciation, ensure accurate production forecast, and guarantee stability in business, increase machinery lifespan, and increase productivity. An effective oil sampling analysis and diagnosis programme requires expert knowledge, and historically, these analyses have been performed by expert analysts who interpret results from oil property and wear metal tests, determine the nature of any abnormality, and make appropriate maintenance recommendations.[3] This increases the reliability and availability of machinery while minimizing maintenance costs associated with oil changes, labour, repairs, and downtime. However, Barrett (2007) believes that accomplishing this task could be time consuming and requires excessive training and experience as well as patience.[4]

2.1 Expert System

The expert system for effective condition monitoring of marine machinery by means of oil sampling analysis is based on an understanding of the equipment, components, physical properties, and additives in the oil, as well as an understanding of the failure modes and mechanically what action needs to be taken to fix a problem.

Expert systems are very beneficial and most valuable to large organisations that have high levels of technical expertise and experience that cannot be easily transferred / shared across the business between people.[5] An expert system is a subject specific knowledge database system that contains analytical skills for knowledge management.

Generally, expert systems are made up of rules that analyse supplied information about a specific class of problems,[6] as well as providing diagnosis of the given problem(s) and suitable recommendations in order to implement corrections. The most important aspect of a knowledge base is the quality of information it contains; it needs to be kept up-to-date. In order to make a business secure and safe, it is ideal to have such knowledge captured in a system that can be accessible when needed, rather than in people.

Highly trained professionals are still generally performing oil analysis in condition monitoring of ship cranes. The use of expert systems would allow a greater diagnostic throughput. For multi-national companies, this will give them the opportunity to monitor performance of their lubricants and help influence their technology strategy around their products. Having a single global database is not only beneficial to achieve global business objectives but also enables the company to benchmark performance of products and applications. This therefore puts them in a very strong position when discussing how good their product is with customers and original equipment manufacturers (OEM). Furthermore, the expert system possesses great potential value for business for both laboratory and on-site maintenance operations.

2.2 Fuzzy Rule Based System

In recent years, there has been a significant increase in the number and variety of applications using fuzzy rule based approaches. Zadeh (1965)[7] first introduced the fuzzy set theory as a classical set for grouping together elements that all have at least one common characteristic[8], as cited by Ramezani and Memariani (2011).[9] A fuzzy rule base provides a coherent and intuitive model for evaluating faults in marine machineries. One realistic way to analyse a fault with incomplete objective data is to employ a fuzzy IF-THEN rule built from human understanding. Such rules have been used because predictive maintenance is considered inadequate to address the needs of complex systems with a high level of uncertainties. For example, IF-THEN rules with a belief structure can be constructed to model a condition-monitoring scenario. An IF-THEN rule example is given below:

IF threat likelihood is “Moderate”, machinery vulnerability is “High”, and impact or consequent severity is “Serious”, THEN machinery failure risk is “High”.

Due to the high degree of uncertainty associated with expert judgement when forming or representing a relationship between premise and conclusion – or, rather, when the evidence available is not adequate to support any viable decision, or when the expert is only partially sure whether to believe in an assumption but only to a certain degree of credibility – it is possible to have fuzzy rules with a belief structure as follows:

IF threat likelihood is “Moderate”, machinery vulnerability is “High”, and impact or consequent severity is “Serious”, THEN the priority for attention would be {(Very Low, 0), (Low, 0), (Moderate, 0.6), (High, 0.4), (Very High, 0)}.

Based on the above, {(Very Low, 0), (Low, 0), (Moderate, 0.6), (High, 0.4), (Very High, 0)} is a belief distribution representing the priority for attention where experts are 60% sure that the machinery failure risk level is Medium, and 40% sure that the machinery failure risk level is High. The rule-base table will be used in the risk assessment model to ascertain the priority for attention to the potential failure modes of vector components identified in the test case.

2.3 Used Oil Sampling Analysis of Marine Crane Bearing and Gearbox

Oil sampling analysis is known to be an effective condition-monitoring tool for marine crane bearing and gearbox diagnosis. This involves a representative sample being taken, which ensures that there is as much information per millimetre of oil as possible. This information relates to such criteria as cleanliness and dryness of the oil, depletion of additives, and the presence of wear particles being generated by the crane. The second goal is to minimize data disturbance. The sample should be extracted so that the concentration of information is uniform, consistent, and representative. The lubricant sample is then assessed by a suitable analytical method to identify signs of increased wear and evidence of unwanted contaminants or lubricant degradation. It is important to ensure that the sample does not become contaminated during the sampling process.[10]

2.3.1 Crane slewing ring bearings

Slewing ring bearings are commonly used in marine cranes for transferring/supporting axial, radial, and moment loads, singularly or in combination. They consist of rings mounted with threaded fasteners, usually with a gear integral with one of the rings. The slew bearing, which is a main structural load-bearing device that attaches the crane to the vessel, is a potential source for catastrophic failure. There are many instances in which cranes have been detached from the vessel because of failure in the slewing bearing.

The lubricants normally recommended by slewing ring bearing manufacturers are greases or oil bath lubrication for slowly rotating continuous operating enclosed bearings, where adequate sealing of the bearing enclosure exists.[11] Grease in itself may be defined as the lubricant that is in a solid or semi-solid state and contains thickener, and some various special additives.

The analysis of used lubricating grease has become a benchmark procedure as part of the UK Health and Safety Executive (HSE) guidelines on managing the safety of pedestal cranes, specifically in offshore operations. A recent independent study found that grease analysis offers the most effective solution.[12]

The issue with grease analysis, however, is the veracity of the sample. The sample must be as representative as possible. A feature of grease analysis, as opposed to oil analysis, is that contaminants and wear debris are not uniformly distributed throughout the lubricant. This can lead to samples with huge variances in debris content. Specific to the application of slewing bearings is the extent to which the loaded surfaces are stressed.

2.3.2 *Crane gearboxes*

Marine crane gearboxes are expected to perform under conditions of high heat and heavy loads. In environments often contaminated with dirt, process debris, and water, without adequate protection, gears will wear prematurely and replacement of parts would need to be done more frequently. Oil change would also need to be done more often, and worst of all, would experience equipment downtime. To combat these difficult conditions, well-formulated lubricants have to be used in marine gearbox applications.[13]

Gear oil consists of two critical components: base oil and additives. Additives impart desirable properties and suppress undesirable ones. The additive package is the backbone of the lubricant's performance, and a strong backbone will provide the performance and protection needed for the gearbox. When selecting gear oil, there are three essential attributes to consider:

1. The gear oil must remain thermally stable and not oxidize at high temperatures, thus avoiding the creation of sludge or varnish. Keeping the oil from oxidizing will lengthen drain and replacement intervals. For example, for every 18 degrees F (10 degrees C) increase in fluid temperature above 140°F (60°C), oxidation will reduce the service life of a lubricant by half.
2. The gear oil must have extreme pressure properties. Gear oil with an extreme pressure (EP) additive will protect the gear surfaces against extreme pressures.
3. Gear oil must fight contamination that enters the system, especially water. The oil must be able to demulsify, which allows for easy removal of the water from the gearbox.

2.4 Performance Thresholds

Using manufacturers' established limits and defining alerts as thresholds for the crane's performance can create effectively monitoring of the condition of the ship crane. This involves the collection and monitoring of data from the crane at each sample interval and comparing the trend against set thresholds. It is worth noting that ignoring limits or trends can have a significant impact on business performance and in some cases may invalidate the crane warranties.

The procedure by which an oil sample is drawn is critical to the success and effective condition monitoring of the crane via oil sampling analysis,[14] and this can only be achieved if every sample contributes to building an accurate history from which trends in wear, contamination, and degradation can be determined. Thus, for effective diagnosis to occur, a threshold has to be established using the upper and lower limits provided by OEM, as well as an accurate statistical trending. The values gathered in this research will be used to generate a diagnostic rule-based tool, which includes possible combination of the plurality of the characteristics monitored. If a threshold is exceeded, a notification is generated and the actions in an alert should be performed.

Crucially, the alert limits should be there to notify the responsible person that values related to precursory failure symptoms have changed in a way that is not normal.[15] This does not necessarily mean that a failure is in progress, nor necessarily imminent, but that there has been unusual change. The person in charge should be able to understand the root cause of the change and then perform a risk analysis.

2.4.1 Fixed limits

A fixed limit evaluates a simple predetermined criterion (pass or fail) for each component. The drawback to this type of technique is that it does not account for different contributing factors. For example, there are many differently sized and shaped gearboxes. Some gearboxes are lightly loaded and at constant speed, which would lend itself to a low wear rate. Such a gearbox might be in serious trouble if the iron (Fe) level were to reach 200 part per million (ppm). On the other side, there may be a low speed, reversing, and heavily loaded gearbox that has not had less than 500 ppm of iron (Fe) in its oil since it was last tested at the assembly plant.

2.4.2 Absolute alarm limit

These are limits based on manufacturers' recommendation. These alarms generally define the working ranges or condemnation limits and are most applicable to lubricant and contamination conditions. Extensive research is normally carried out to arrive at these limits, thus providing a good starting point for any analysis program. An absolute alarms limit is vital when warranties on the new equipment are of greater concern.[16]

2.4.3 Trend (statistical) alarm limit

Manufacturers' guidelines for alarm limits or general standards are often poor and lacking in that they are based on average operational and performance situations, which may not precisely reflect the definite conditions of a specific machine. This is predominantly applicable to machine conditions. Trend alarm limits are based on gathering a small sampling of data from equipment, analysing the distribution of that data, and using this trending characterization to set specific alarm limits.[16] Statistical trend analysis allows the identification of the equipment in greatest need of attention, thus allocating maintenance in an efficient way. With sufficient historical data, reliable alarm limits can be established and maintained by statistical analysis.

2.4.4 Combination of absolute and statistical alarm limits

Effective oil analysis management relies on the combination of both types of alarm limits. For example, the condemnation limit is the absolute alarm. Statistical trending, taking into account variability based on the sampling, contamination, make-up oil *etc.* will develop the standard deviations. Departure from this normal variability signals that real problems are taking place. This is the earliest possible time to take action. Neglecting this, as the trend approaches its warning limit, action such as changing or cleaning the oil, or inspection of the unit is required.[16]

The idealized graph shown in Figure 1 is an example of how absolute and trend line alarms are used together. The test used could be on iron content, viscosity, or other parameters. The normal result variability range takes into account minor variations caused by analytical accuracy, sample homogeneity, *etc*.

Insert Figure 1 here

2.4.5 Upper and lower limits

The upper limit is the value that indicates the highest level of quality acceptable for products or services, while the lower limit is the value that indicates the lowest level of quality acceptable for products or services. Both the upper control limit and the lower control limit are used in conjunction to create the range of variability for quality specifications, thus enabling analysts within an organisation to provide the top level of excellence by adhering to the established guidelines.

3 Methodology

Investing in maintenance prediction in the operations of marine machinery systems requires networks of robust decision making tailored towards improving the capability of the system to exhibit required performance. A major modelling assumption in this paper is that, some overlaps in the description of all risk attributes can be observed, however, the main issue or content is largely independent which allows the use of rule based judgement for their aggregation and synthesis in a systematic method. This study develops a fuzzy set theory (*FST*) and a fuzzy rule based sensitivity analysis method (*FRB-SAM*), to model the risks impacting the smooth operation of the ship crane's components.

The proposed framework is capable of determining the risk levels of the crane's components (bearing and gearbox) in order to predict possible impending failure. The first step of the proposed framework is to identify the critical elements in an oil sample test results for the crane's bearing and the gearbox. The second step is to pre-screen the oil sample test results to identify inconsistency or out of range results. Developing fuzzy membership functions for the test elements of each crane's component that passes the pre-screening process follows this. The fourth step is to develop a FRB diagnosis for risk prediction of the crane's bearing and the gearbox. Lastly, a set of fuzzy conclusions is achieved using the "min-max" method.

Since the study incorporates FST into a FRB method, a set of linguistic priority terms along with the membership functions describing the relationship between elements in each hierarchy of the RB is adopted. Thus, the minimum value comparisons between the elements in each hierarchy using FST are established.

The fuzzy expressions are subsequently converted into a single crisp value using an appropriate defuzzification method. Risk assessment can be carried out from hazardous events for each component. The following three steps are used in determining the risk levels for the proposed framework:

i. Listing the membership function values based on the developed rules.
ii. Determining the minimum value of each combination in terms of comparing the values obtained from each element and the value of weight established.
iii. Determining the maximum value of the minimum values obtained from (ii) that has the same category of linguistic priority terms.

The proposed model in a stepwise regression is presented in the following sections and the framework of this methodology for evaluating the diagnostic process of the used oil sample test results for the crane bearing and gearbox is shown in Figure 2.

Insert Figure 2 here

3.1 Identification of Grease/Oil Sample Test Results (**Step one**)

Under this process, critical elements in the used grease/oil laboratory analysis reports are identified for both port and starboard deck crane slewing bearing/gearbox for the pre-screening process.[17,18]

3.2 Pre-Screening of the Test Results (**Step two**)

The pre-screening process is used to identify inconsistency in the test results, out of range test results, or mistyping during test result entry. The process considers only numeric test results. At pre-screening, the sample test results are initially screened against a specific range (min – max values). The min and max values for an individual test can differ based on the laboratories and lubricant manufacturers. If the test element(s) in a sample fail pre-screening, the sample is sent back for retest. Pre-screening on a sample will then happen again when the re-tested results are entered (*i.e.* if the sample is sent for retesting, it is considered again for the pre-screening until it passes the pre-screening process).

The following steps are followed in the pre-screening process:

1. The pre-screening process fetches all the tests conducted for a sample, the test results, and their min/max values.
2. The sample test results are compared against the predefined min/max values.
3. A test fails pre-screening if the results are outside the min and max values. Failed test samples are sent for retest.
4. Retested samples are then sent through the pre-screening process.

Rules for pre-screening process:

IF (Test Result ≥ Lower Action) & (Test Result ≤ Upper Action)

THEN, *Pre-Screening Passed*

ELSE, *Pre-screening Failed*

Explanation of the Rule:
Each test result is checked to see whether it is within the min and max limits (*i.e.* Lower Action and Upper Action) set for that test; if it falls within that range, the test result passes *pre-screening*; otherwise, the sample fails *pre-screening*.

3.3 Development of Fuzzy Membership Function (**Step three**)

According to Wang (1997),[19] fuzzy membership functions can be used to define the fuzzy input subset from an input variable. The membership functions considered in this study are based on the criteria for oil sample elements and are generated using triangular shapes. A fuzzy membership function is developed for each of the identified critical elements based on their corresponding limits provided. These limits are obtained from a reputable leading oil company. The membership function for each linguistic priority term is evaluated within its limits on an arbitrary scale from 0 to 1.

3.4 Development of Fuzzy Rule-Based Diagnosis for Risk Prediction (**Step four**)

In this step, a fuzzy rule-based diagnosis is produced for predicting the condition of crane bearing and gearbox, utilising the laboratory oil sample test results as the input data. The linguistic terms used in developing the membership functions described in Step 3 are utilized to reflect the priority level of alertness.

3.5 Determining the Risk Levels of each Component (**Step five**)

The priority level (PL) of a specific scenario will be decided based on the fuzzy rule base developed in Step 4. Using a 'min-max' approach, the set of fuzzy conclusions of the scenario will be obtained in terms of membership function values associated with linguistic priority terms. In order to activate the developed rule base, firing rules will be used to obtain the output grade (*i.e.* normal, caution, attention, or critical) based on the results obtained from the *min-max* method. When applying the 'min-max' approach, the following procedure is taken:

- Identify the possible combinations of the test elements in which the membership values associated with the corresponding linguistic priority terms are not zero. The outputs of such combinations can be obtained from the fuzzy rule base developed. Obtaining the output of the test elements combinations from the fuzzy rule base is also known as *firing rules.*
- Determine the minimum value of each combination by comparing the values obtained from each element and the value of the belief degree established in the PL.
- Determine the highest minimum values obtained above with respect to each linguistic priority term.

From the above, each maximum value and its associated linguistic priority term is a fuzzy conclusion. Each set of fuzzy conclusions of each scenario will be defuzzified using the method proposed in next step (Step 6). If there is only one rule that can be applied to the scenario in question, then the minimum value of the membership function and the linguistic priority term associated will be the set of fuzzy conclusions.

3.6 Defuzzification Process (**Step six**)

The defuzzification process is used to create a single crisp ranking from the fuzzy conclusion set (*i.e.* the priority level of scenarios to express the machinery condition). According to Runkler and Glesner (1993),[20,21] several defuzzification algorithms have been developed and used in creating a single crisp ranking. The one selected for use in this research is the weighted arithmetic mean (WAM) of non-empty set of data. This algorithm averages the points of maximum possibility of each priority level of scenarios, weighted by their degree of truth at which the membership functions reach their maximum values.[2,22] The formula used for WAM is as follows:

$$WAM = \frac{\sum_{i=1}^{n} w_i x_i}{\sum_{i=1}^{n} w_i} \tag{1}$$

For normalized weights, the weighted mean is simply:

$$WAM = \sum_{i=1}^{n} w_i x_i \tag{2}$$

where, w_i is the degree of truth of the maximum value of the i^{th} linguistic priority term, and x_i is the risk rank of the maximum value of the i^{th} linguistic priority term. A lower WAM value will indicate that the machinery condition is less risky, while a higher WAM value indicates that the condition of the machinery is at risk, and as such immediate action should be taken.

3.7 Perform Sensitivity Analysis (Final step)

This step employs a sensitivity analysis approach to test how sensitive the model output is to a minor change in the input data. The relative change may be the variation of the parameters of the model or changes in the degrees of belief assigned to the linguistic variables used to describe the parameters of the model. If the methodology is sound and its inference reasoning is logical and robust, then the sensitivity analysis must at least reflect any of the following axioms:

Axiom 1: Slight increment / decrement of degree of belief associated with a risk oriented linguistic variables of the lowest criteria will certainly result in the decrement / increment in the degree of belief of the linguistic variable and the priority preference degrees of the model output.

Axiom 2: If the degrees of belief associated with the highest preference linguistic variable of a lowest level criterion are decreased by *p* and *q* (*i.e.* simultaneously, the degrees of belief associated with its lowest preference linguistic variable are increased by *p* and *q (1 > q > p)*), and accordingly the utility value of the model's output is assessed as U_p and U_q respectively, then U_p should be greater than U_q.

Axiom 3: If x and y criteria, $(y < x)$ from all the lowest level criteria are selected and the degree of belief associated with the highest preference linguistic variables of such x and y criteria is decreased by the same amount (*i.e.* simultaneously, the degrees of belief associated with the lowest preference linguistic variables of such x and y criteria are increased accordingly by the same amount), the utility value of the model's output will be assessed as U_x and U_y; in this case, U_x should be greater than U_y.

4 Test Case

According to Asuquo (2018),[17] the ship crane reliability (SCR) values clearly show that both the bearing and gearbox are the two major crane components susceptible to failure risk over a period of operations. Therefore, based on the given absolute limits and the sample test results, the operating condition of both port and starboard ship crane bearing and gearbox can be evaluated and monitored.

4.1 Identification of Grease/Oil Sample Test Results (**Step one**)

The grease sample test results for the crane bearing and the oil sample test results for the crane gearbox provided are evaluated as follows.

4.1.1 Crane bearing grease sample

Table 1 indicates the laboratory test results of a grease sample obtained for both port and starboard crane bearing. Table 2 indicates the absolute limits for used grease bearing obtained from a reputable lubricant manufacturer based on their experts knowledge. For the purpose of demonstration in this model, four critical elements (Iron, Tin, Nickel, and Sodium) in the crane bearing grease sample are used.

4.1.2 Crane gearbox oil sample

Table 1 indicates the laboratory test results of an oil sample obtained for the port and starboard crane gearbox, respectively. Table 2 indicates the absolute limits for used oil analysis obtained from a reputable lubricant manufacturer based on their experts knowledge. Only four critical elements (Iron, Tin, Aluminium, and Silicon) in the crane gearbox oil sample are used.

Insert Tables 1 and 2 here

4.2 Test Results Pre-Screening (**Step two**)

In order to pre-screen the test results obtained for the samples from both port and starboard cranes, a set of rules is generated based on the absolute limits provided in Table 2.

4.2.1 Pre-screening of port crane bearing grease sample test results

From Table 2, the Lower Action (LA) is set at 140; and Upper Action (UA) is set at 750 for iron (Fe) test element. Also from Table 1, the test result value for iron (Fe) is 43. This test result value is not within the LA and UA limits, thus, based on the pre-screening rule in Section 3.2, the iron (Fe) test result will fail the pre-screening stage, and then will be returned for re-testing.

By applying similar technique for Tin (Sn), Nickel (Ni) and Sodium (Na), they all will pass the pre-screening stage.

4.2.2 Pre-screening of starboard crane bearing grease sample test results

In the similar way, the Iron (Fe) and Tin (Sn) test results in Table 1 will fail the pre-screening stage, and then will be returned for re-testing. Nickel (Ni) and Sodium (Na) test results will pass the pre-screening stage.

4.2.3 Pre-screening of port crane gearbox oil sample test results

From Table 2, the LA is set at 24 and UA is set at 98 for iron (Fe) test element. Also, from Table 1, the test result value for iron (Fe) is 13. This test result value is not within the LA and UA limits, thus, based on the pre-screening rule, the iron (Fe) test result will fail the pre-screening stage, and then will be returned for re-testing.

In a similar way, the Tin (Sn) and the Aluminium (Al) test results will pass the pre-screening stage, and the Silicon (Si) test result will fail the pre-screening stage, and then will be returned for re-testing.

4.2.4 Pre-screening of starboard crane gearbox oil sample test results

Similarly, the Iron (Fe), Tin (Sn) and Silicon (Si) test results for the starboard crane gearbox oil sample elements will fail the pre-screening stage, and then will be returned for re-testing. Whereas, the Aluminium (Al) test result will pass the pre-screening stage.

4.2.5 Summary of the pre-screening results

The pre-screening results obtained for the individual crane bearing and gearbox sample elements are summarised in Table 3.

Insert Table 3 here

The above sample elements test results have either passed or failed the pre-screening process. All the test elements with a failed pre-screening status are returned to the laboratory for a re-test, as indicated in Figure 2, while all of the test elements with a passed pre-screening status are used for determining the risk level of the ship crane's components.

4.3 Development of Fuzzy Membership Function (**Step three**)

Each of the test elements is described using five linguistic terms: *Very Low, Low, Moderate, High and Very High.* The interpretation of the linguistic terms describing each scenario has been defined in Table 4.

Insert Table 4 here

The fuzzy membership functions for the model in this study consist of triangular shapes generated using the linguistic categories identified in the knowledge acquisition stage and applied using the fuzzy Delphi method. [23] The membership functions of each linguistic variable for both crane bearing and gearbox are shown in Figures 3 to 8 and their corresponding belief degrees are shown in Tables 10 to 13.[17]

4.3.1 Port crane bearing grease sample

Tin (Sn) element in bearing grease samples:

Based on expert opinions, the upper limit is found and the rules are written for tin (Sn) with equal distributions, demonstrated as follows:

1. If a crane bearing grease sample laboratory test has a result of 12ppm tin (Sn) or lower, then it can be categorised as 100% very low.
2. If a crane bearing grease sample laboratory test has a result of 24ppm tin (Sn), then it can be categorised as 100% low.
3. If a crane bearing grease sample laboratory test has a result of 36ppm tin (Sn), then it can be categorised as 100% average.
4. If a crane bearing grease sample laboratory test has a result of 48ppm tin (Sn), then it can be categorised as 100% high.
5. If a crane bearing grease sample laboratory test has a result of 60ppm tin (Sn) and above, then it can be categorised as 100% very high.

Based on the stated rules, the membership functions of the tin (Sn) can be constructed as shown in Figure 3.

Insert Figure 3 here

Based on the information in Table 1, the laboratory test result for the grease sample indicates tin (Sn) contents of 15ppm. Based on Figure 3, the belief degrees are calculated as follows:

The Low grade has a rank value of 24ppm

The Very Low grade has a rank value of 12ppm

15ppm is within the range between 12 and 24.

The belief degree associated with the Very Low grade

$= \frac{24-15}{24-12} = \frac{9}{12} = 0.75 = 75\%$

The belief degree associated with the Low grade

$= 1 - 0.75 = 0.25 = 25\%$

Therefore, the tin (Sn) contents in the grease sample test result are assessed as:

$\widetilde{Sn}_3$ = {(0.75, Very Low), (0.25, Low), (0, Moderate), (0, High), (0, Very High)}

Using a similar technique, based on expert opinions, the upper limit is found and the rules for other elements are demonstrated. Based on the given rules, membership functions for Nickel (Ni) and Sodium (Na) elements are constructed as shown in Figures 4 and 5. Based on the information in Table 1, their laboratory test results are assessed and their corresponding belief degrees are calculated and recorded as shown in Table 5.

Insert Figures 4 and 5 here

4.3.2 Starboard crane bearing grease sample

In a similar way the Nickel (Ni) and Sodium (Na) elements from the starboard crane bearing grease sample were modelled and their belief degrees also shown in Table 5.

4.3.3 Port crane gearbox oil sample

Using a similar technique, based on expert opinions, the upper limit is found and the rules for the elements in the crane gearbox are demonstrated.[17] Based on the given rules, membership functions for the elements are constructed as shown in Figures 6 and 7. Based on the information in Table 1, port crane gearbox oil sample's laboratory test results are assessed and their corresponding belief degrees are calculated and recorded as shown in Table 5.

Insert Figures 6 and 7 here

4.3.4 Starboard crane gearbox oil sample

In a similar way the Aluminium (Al) and Silicon (Si) elements from the starboard crane gearbox oil sample were modelled and their belief degrees also shown in Table 5. Based on the given rules, membership functions for the Silicon (Si) element is constructed as shown in Figures 8.

Insert Table 5 here

Insert Figure 8 here

4.4 Development of Fuzzy Rule Base (**Step four**)

To generate a fuzzy rule-base, the evaluated sample elements are grouped into the five linguistic terms that reflect the level of alert priority, namely Very Low, Low, Moderate, High and Very High). To develop the fuzzy rule base, these five linguistic terms are first graded (shown in Table 6) using the four output sample grades (*i.e.* Normal, Caution, Attention, and Critical). These output grades are identified as priority levels of alert for each of the linguistic terms associated with the sample elements.

Insert Table 6 here

In view of the fact that there are three elements (for the port crane bearing) and two elements (for starboard crane bearing, port & starboard crane gearboxes) associated with the five linguistic terms, a total of 125 (5 x 5 x 5) and 25 (5 x 5) rules were developed respectively.[17] Table 7 shows some examples of the 5 x 5 x 5 rules base.

Insert Table 7 here

Moreover, it is worth mentioning that though three test sample elements were used in developing the 125 (5 x 5 x 5) rules, and two test sample elements used in developing the 25 (5 x 5) rules, by using the same technique, a model with fewer or more than three test sample elements can be designed to meet the industrial need.

4.5 Determination of Risk Levels for the Sample Test Elements of each Crane Component and the Acquirement of its Fuzzy Conclusion (**Step five**)

In order to obtain a risk ranking, further calculations are required. Firstly, the linguistic priority terms and the membership values reflecting the risk levels for the sample test element of each crane component should be carefully decided. Secondly, the fuzzy set conclusion of each crane component will be obtained based on the fuzzy rule base using the 'min-max' approach. Since this research only considers three sample test elements for each crane component (Tin, Nickel, Sodium for crane bearing and Tin, Aluminium, Silicon for crane gearbox) for both port and starboard of the ship, the fuzzy sets obtained in Table 5 will be used to determine their fuzzy conclusions.

4.5.1 Risk level for port crane bearing grease sample test elements

By applying the 'min-max' approach, the set of fuzzy conclusions of the port crane bearing grease sample test element in Table 5 is obtained as follows:

i. List the membership function values according to the rules developed.
   (1) If Sn = Very Low 0.75, Ni = Moderate 0.875, and Na = Low 0.9, then based on rule 12 in the fuzzy rule based table (Asuquo, 2018),[17] the priority level is CAUTION.
   (2) If Sn = Very Low 0.75, Ni = Moderate 0.875, and Na = Moderate 0.1, then based on rule 13 in the fuzzy rule based table (Asuquo, 2018),[17] the priority level is CAUTION.
   (3) If Sn = Very Low 0.75, Ni = High 0.125, and Na = Low 0.9, then based on rule 17 in the fuzzy rule based table (Asuquo, 2018),[17] the priority level is ATTENTION.

(4) If Sn = Very Low 0.75, Ni = High 0.125, and Na = Moderate 0.1, then based on rule 18 in the fuzzy rule based table (Asuquo, 2018),[17] the priority level is ATTENTION.

(5) If Sn = Low 0.25, Ni = Moderate 0.875, and Na = Low 0.9, then based on rule 37 in the fuzzy rule based table (Asuquo, 2018),[17] the priority level is CAUTION.

(6) If Sn = Low 0.25, Ni = Moderate 0.875, and Na = Moderate 0.1, then based on rule 38 in the fuzzy rule based table (Asuquo, 2018),[17] the priority level is CAUTION.

(7) If Sn = Low 0.25, Ni = High 0.125, and Na = Low 0.9, then based on rule 42 in the fuzzy rule based table (Asuquo, 2018),[17] the priority level is ATTENTION.

(8) If Sn = Low 0.25, Ni = High 0.125, and Na = Moderate 0.1, then based on rule 43 in the fuzzy rule based table (Asuquo, 2018),[17] the priority level is ATTENTION.

ii. Determine the minimum value of each combination in terms of comparing the values obtained from each element and the value of weight established in the priority level.

In the first combination in (i), Sn = Very Low 0.75, Ni = Moderate 0.875, and Na = Low 0.9. Therefore, the minimum value of Sn, Ni, and Na is 0.75, which is associated with the linguistic priority term CAUTION, according to the fuzzy rule developed. The minimum values of the other seven combinations can be determined in a similar way, as shown in Table 8.

Insert Table 8 here

iii. Determine the maximum value of the minimum values obtained from (ii) with the same category of linguistic priority term.

In the first scenario, there are eight combinations and two different categories of linguistic priority terms, CAUTION and ATTENTION. The membership values in the CAUTION category are 0.75, 0.1, 0.25, and 0.1, respectively. Therefore, the maximum membership value is 0.75, as shown in Table 11. Likewise, the values in the ATTENTION category in the 3rd, 4th, 7th and 8th combinations are 0.125. Thus, the maximum membership value in the ATTENTION category is 0.125, also shown in Table 9.

Insert Table 9 here

4.5.2 Risk level for starboard crane bearing grease sample test elements

By applying a similar technique, the minimum values of each combination for the starboard crane bearing can be determined as shown in Table 8, while the maximum membership value is determined as CRITICAL 0.7.

4.5.3 Risk level for port crane gearbox oil sample test elements

In the same way, the minimum values of each combination for the port crane gearbox can be determined as shown in Table 8, and the maximum membership value is determined as NORMAL 0.667.

4.5.4 Risk level for starboard crane gearbox oil sample test elements

In the same way, the minimum values of each combination for the starboard crane gearbox can be determined as also shown in Table 8, and the maximum membership value is determined as CAUTION 0.875.

The estimates conclusions of the ship's crane are thereby obtained as shown in Table 10.

Insert Table 10 here

4.6 The Defuzzification Process (**Step six**)

By applying Equation (2) in the defuzzification process and the risk ranking for the linguistic term grades given in Table 6, the risk values (RV) for the estimate conclusions can be obtained as shown in Table 10. The crane with higher risk values are considered to be critical. For example, the risk value for the port crane bearing can be determined as follows:

RV = (2 x 0.75) + (3 x 0.125) = **1.875**

In a similar way, the RV for the starboard crane bearing, port and starboard crane gearboxes are obtained as shown in Table 10.

From Table 10, it can be noted that the risk value for the starboard crane bearing is 2.8 (higher risk value). Therefore, the ship starboard crane bearing is considered as being critical. With this information, the maintenance engineer on board the ship can stop the starboard crane (if it is under operation) for investigation, thus preventing any major damage to the crane.

4.7 Sensitivity Analysis (**Final step**)

Sensitivity analysis is performed to assess the robustness and logicality of the delivery of the analysis results obtained in Section 4.6. This is achieved by utilising the three axioms introduced in Section 3.7. The implementation of the axioms will help to identify the most important priority level that should be given attention in order to improve the ship's crane bearing and gearbox operational uncertainties. To perform the analysis, the input data in Table 5 associated with the highest preference linguistic values of all the lower level criteria are decreased by a factor of 10%, 20%, and 30% respectively, whilst simultaneously increasing the input data of the lowest preference linguistic values of each of the criteria at the lower level.

By applying the 'min-max' approach described in Section 4.5, membership function values are listed according to the rules developed for the decrement values obtained in Table 11. The corresponding minimum values of the combinations for each of the scenario are also obtained as described in Asuquo (2018) Appendices 4B, 4C, and 4D.[17] The maximum values associated with the same category of linguistic priority terms for each of the scenarios are determined as shown in Table 9, while Table 12 shows the estimate conclusions of the ship's crane derived as the result of the decrement. It is worth mentioning that all the results obtained remain in harmony with both Axioms 1 and 2.

Insert Tables 11 and 12 here

The risk values for the decremented estimate conclusions are determined using the defuzzification process described in Section 4.6. For example, the risk value from the port crane bearing set of fuzzy conclusions is obtained as follows:

<u>10% decrement</u>

$$Caution\ \frac{0.65}{0.65+0.125+0.1},\ Attention\ \frac{0.125}{0.65+0.125+0.1},\ Critical\ \frac{0.1}{0.65+0.125+0.1}$$

$$RV = 2\times\frac{0.65}{0.65+0.125+0.1} + 3\times\frac{0.125}{0.65+0.125+0.1} + 4\times\frac{0.1}{0.65+0.125+0.1} = 2.366$$

Similarly, the RV for other estimate conclusions from decrement values in Table 12 are obtained as shown in Table 13.

Insert Table 13 here

From Table 13, it can be noted that the starboard crane bearing has the highest risk values (3.4), indicating a similar outcome obtained when the risk value was determined in Section 4.6.

Axiom 3 in Section 3.7 can be examined by comparing the preference degrees of the risk attributes for analysis in a transparent manner. In order to determine if the model aligned with Axiom 3, two elements (*i.e.* Tin and Sodium) out of the three test elements of the analysis from the port crane bearing oil sample (Table 5) are selected and their input data decreased by 30%, as shown in Table 11.

By applying similar technique used in Section 4.5.1 to the two test elements for decreasing port crane bearing grease sample in Table 11, the minimum value of each combination can be determined as shown in Table 8, and the maximum membership values can be determined as shown in Table 9.

The risk value for the decremented estimate conclusions from the two elements of the port crane bearing is obtained as follows:

$$Normal\ \frac{0.45}{0.45+0.1+0.3},\ Caution\ \frac{0.1}{0.45+0.1+0.3},\ Critical\ \frac{0.3}{0.45+0.1+0.3}$$

$$RV = 1 \times \frac{0.45}{0.45+0.1+0.3} + 2 \times \frac{0.1}{0.45+0.1+0.3} + 4 \times \frac{0.3}{0.45+0.1+0.3} = 2.171$$

Note that when the input data associated with the highest preference linguistic values of the ship port crane bearing of the three test elements was decreased by 30%, the risk value of the crane component (*i.e.* failure risk) was evaluated as 2.822, as indicated in Table 13. However, by selecting two elements (*i.e.* Tin and Sodium) out of the three test elements of the analysis from the port crane bearing oil sample (Table 5) and decreasing the input data by the same amount of 30%, the risk value obtained is 2.171. Given that 2.171 is less than 2.822, it can be claimed that the investigation of the model is validated to be sound and aligned with Axiom 3.

5 Discussions

This research has demonstrated how to start with a dynamic reliability model and generate a rule-based diagnostic model. Grease / oil analysis has proven to be a useful tool to evaluate grease and bearing, as well as oil and gearbox condition, respectively. Different situations and influencing factors for wear, contamination, and grease condition have shown complex lucidities between the grease analysis results and their practical meaning. This leads to the deduction that observing and interpreting these factors with expert knowledge can allow proactive maintenance strategies to be applied in a reasonable approach for grease-lubricated components. Understanding the oil sample data and realizing how to properly apply alarm limits can significantly reduce the downtime of marine crane bearing and gearbox failure.

The approach utilised in this research is non-traditional and, according to Ramezani and Memariani (2011),[9] non-traditional modelling approaches may have the following benefits:

1. Rule-based knowledge representation, together with the extraction of rule, offers a means of integrating data-driven modelling with physics-based modelling.
2. A rule-based model is complementary with human investigative reasoning, thereby allowing industrial experts to contribute directly to the model building.
3. A rule-base is transparent to the user. The way the decision is made can be plainly elucidated so that users can quickly gain trust in the system. This is vital in safety-critical machineries like ship cranes where human lives are at risk.

The approach here involves first identifying the key system variables that affect ship cranes, and then developing a set of decision rules relating to these key variables. This provides a powerful tool for knowledge specification and effective condition monitoring of ship cranes.

From the diagnostic risk assessment tool, a NORMAL sample status indicates that the physical properties of the lubricant are within acceptable limits and no signs of excessive contamination/wear are present. ATTENTION indicates that results are outside acceptable ranges but not critical, although caution, re-sampling, and increased monitoring is advised. The CRITICAL status requires immediate corrective action to prevent significant major damage/failure in service.

The effective and quick diagnosis of oil samples is one of the major concerns in the marine industry today. Failure to detect potential lube oil/equipment failure and wear may lead to poor performance and even cause expensive damage and, in some cases, loss of business. On the other hand, inaccurate diagnosis of equipment failure may cause unnecessary interruption to an entire business. Either case can result in significant monetary loss. Oil analysis is an increasingly popular condition-monitoring tool, meaning this developed diagnostic risk assessment tool is needed and, if adopted, will improve operating efficiency and reduce failures of ship cranes.

6 Conclusion

The main aim of this research is to develop an expert system that will diagnose early signs of problems in ship cranes by utilising oil-sampling analysis. This has been achieved by the design concept of a logic rule-based system that provides risk levels diagnosis and comments to enable a large volume of samples test results to be processed for the diagnosis of the ship cranes, using oil-sampling analysis. A fuzzy modelling approach utilizing IF-THEN rules and demonstrations of its usefulness in condition monitoring of applications is illustrated in this chapter. The model showed how to build a bridge between the reliability analysis of the design phase and the diagnosis in the usage phase. The goal of producing a diagnosis model for a ship crane was satisfied. The outcome of this methodology is a rule-based model, which is a diagnosis tool that helps the maintenance crew prevent a ship crane failure with a reduced number of investigations. The tool allows the maintenance crew to make decisions that are more efficient when trying to diagnose fault in a crane, and thus the experience or expertise of the crew becomes less relevant. The generated alert risk levels in the tool helps in addressing some of the concerns raised in the introduction. It provides the maintenance crew with a map that allows recognition of the failing components, and informs them of which ones' need replacing.

This methodology shows how, with several systematic steps, a rule based diagnostic tool can be generated. This leads to the conclusion that this process can be automated and undeniably, that is the goal of this research. The diagnostic tool accuracy can be improved if a comprehensive data is available for a specific crane, as well as all the properties of the lubricant being used by the specified crane, in addition to monitoring trends. Such data can then be incorporated into this rule-based tool. A broader accurate diagnosis can be achieved if a wider range of data is available. These can be achieved if original equipment manufacturers and oil sampling laboratories are willing to supply this information, which is often very difficult to obtain.

The scope of the risk assessment is limited to maintenance and control study. Fuzzy logic and fuzzy systems are a good option for this purpose. However, nowadays maintenance programs seek for: 1) controlling efficiency and safety, 2) managing risks, and 3) optimizing systems performance. Based on the methodology presented in this research, the first two main listed aspects can easily be covered with the approach proposed. Nevertheless, optimization is one of the main limitations of fuzzy systems. Thus, the potential directions to support the aspects of system optimization may be to further adopt the following avenues:

- Integration of diverse but powerful intelligent tools and algorithms such as stochastic maintenance optimization models will open promising new pathways for developing and optimising maintenance systems.
- Application of real-time analysis tools to evaluate the condition of the machinery using the developed models and methodology should enhance the performance and reliability of marine and offshore machinery through early detection of unforeseen events.

Acknowledgements

This research is partially supported by EU H2020 RISE 2016 RESET – 730888. Shell Marine Products is thanked for the provision of test data for the ship cranes.

References

1. FA-ST. UK How clean is you oil? Oil analysis history – Oilcheckuk, http://www.howcleanisyouroil.com/oil-analysis-benefits (n.d. accessed 21 July 2018].
2. Lloyd's Register (LR). Ship right, design and construction: Annexes to machinery planned maintenance and condition monitoring, Southampton, 2013.

3. Toms LA and Toms AM. *Machinery Oil analysis – Methods, automation & benefits - A guide for maintenance managers, supervisors & technician*. 3rd ed., Park Ridge: Society of Tribologists and Lubrication Engineers, 2008, p.29.
4. Barrett M. The new practical guide to oil analysis. *Ezine Articles*. http://ezinearticles.com/?The-Practical-Guide-to-Oil-Analysis&id=516710 (2007, accessed 12 October 2017).
5. Welsh C. Rule-Based/Expert Systems, *CSE 435–IDSS*. https://slideplayer.com/slide/5969435/ (2006, accessed 22 October 2015).
6. Tyler AR. *Expert systems research trends*. New York: Nova Science Publishers, 2007, p.1 – 84.
7. Zadeh LA. Fuzzy sets. *Journal of Information and Control* 1965; 8: 338-353.
8. MIT GMBH. Data Engine Manual. Göttingen, 2006.
9. Ramezani S. and Memariani A. A fuzzy based system for fault diagnosis, using oil analysis results. *International Journal of Industrial Engineering & Productions Research* 2011; 22(2): 91-98.
10. Fitch J. *The basics of used oil sampling - machinery lubrication*, 1st ed. Oklahoma: Noria Publication, 2004.
11. Rezmireş D, Bocăneţ V, Monfardini A, Racocea C and Racocea C. Slewing bearing lubrication & maintenance. Report, Technical University of Iaşi, Romania, 2010.
12. Shorten DC. *Used grease analysis integrated into critical equipment inspection deferral programs - machinery lubrication,* Noria Publication, http://www.machinerylubrication.com/Read/160/used-grease-analysis (2001, accessed 22 October 2015).
13. Lubrication Engineers. Industrial Gear Oils, Asset Reliability Solutions, http://www.lelubricants.com/gear-oils.html [2016, accessed 18 July 2016].
14. Troyer D. *The important of sampling for oil analysis success - machinery lubrication*, Oklahoma: Noria Publication, 2008.
15. Noria Corporation. Fundamental principles in setting alarms and limits in wear debris analysis - *machinery lubrication*, 1st ed. Oklahoma: Noria Publication, 2003.
16. Bots S. A practical approach for evaluating oil analysis results with limit values. *machinery lubrication, Noria publication.* http://www.machinerylubrication.com/Read/29829/a-practical-approach-for-evaluating-oil-analysis-results-with-limit-values- (2014, accessed 23 October 2015).
17. Asuquo MP. *Development of an efficient planned maintenance framework for marine and offshore machinery operating under highly uncertain environment*. PhD Dissertation, Liverpool John Moores University, UK, 2018.

18. Asuquo MP, Wang J, Phylip-Jones G and Riahi R. Condition monitoring of marine and offshore machinery using evidential reasoning techniques. *Journal of Marine Engineering & Technology*, 2019, https://doi.org/10.1080/20464177.2019.1573457.
19. Wang J. A subjective methodology for safety analysis of safety requirements specifications. *IEEE Transactions on Fuzzy Systems* 1997*;* 5(3): 418 – 430.
20. Runkler TA and Glesner M. A set of axioms for defuzzification strategies toward a theory of rational deffuzzification operators. In: *Second IEEE international conference on fuzzy systems/ international conf on neural networks,* San Francisco, USA, 28 March-1 April 1993, 1161-1166.
21. Andrews JD and Moss TR. *Reliability and risk assessment*. 2nd ed. London: *Professional Engineering Publishing Limited*, 2002, p.301-340.
22. Pillay A. and Wang J. Risk assessment of fishing vessels using fuzzy set approach. *International Journal of Reliability, Quality and Safety Engineering* 2002, 9(2): 163-181.
23. Bojadziev G and Bojadziev M. *Fuzzy sets, fuzzy logic, applications*. Singapore: World Scientific, 1995.

Table 1: Critical Wear Elements Test Results for Port & Starboard Crane Bearing Grease and Gearbox Oil Samples

Test Element	Grease Sample Test Result (Port)	Grease Sample Test Result (Starboard)
Crane Bearing		
Iron (Fe) mg/kg	43	69
Tin (Sn) mg/kg	15	7
Nickel (Ni) mg/k	5	8
Sodium (Na) mg/k	84	108
Crane Gearbox		
Iron (Fe) mg/kg	13	13
Tin (Sn) mg/kg	3	1
Aluminium (Al) m	4	6
Silicon (Si) mg/	4	9

Table 2: Absolute Limits for Crane Bearing Used Grease and Gearbox Used Oil

Test	Lower Action	Lower Attention	Upper Attention	Upper Action
Crane Bearing				
Iron (Fe)	140	375	500	750
Tin (Sn)	10	29	40	60
Nickel (Ni)	1	3	5	8
Sodium (Na)	35	80	150	200
Crane Gearbox				
Iron (Fe)	24	49	60	98
Tin (Sn)	1.5	5	7	9
Aluminium (Al)	2.5	4.5	7	10
Silicon (Si)	7	15	30	40

Tables 1 to 2 – Data from a reputable lubricants manufacturer.

Table 3: Pre-screening Results for Port and Starboard Crane Bearing and Gearbox Oil Samples

Test Element	Grease Sample Test Result Value	LA Value	UA Value	Pre-screening Status
Port Crane Bearing				
Iron	43	140	750	Fail
Tin	15	10	60	Pass
Nickel	5	1	8	Pass
Sodium	84	35	200	Pass
Starboard Crane Bearing				
Iron	69	140	750	Fail
Tin	7	10	60	Fail
Nickel	8	1	8	Pass
Sodium	108	35	200	Pass
Port Crane Gearbox				
Iron	13	24	98	Fail
Tin	3	1.5	9	Pass

Aluminium	4	2.5	10	Pass
Silicon	4	7	40	Fail
Starboard Crane Gearbox				
Iron	13	24	98	Fail
Tin	1	1.5	9	Fail
Aluminium	6	2.5	10	Pass
Silicon	9	7	40	Pass

Data Source – Test Data .

Table 4: Description for Test Elements and General Interpretation

Linguistic Term for Test Elements	General Interpretation
Very Low	Wear particles present in small quantities. Acceptable amount of normal wear particles.
Low	Wear particles present in small quantities. Acceptable amount of normal wear particles.
Moderate	Wear particles present in medium quantities. Acceptable amount of normal wear particles.
High	Wear particles present in high quantities. Unacceptable amount of normal wear particles.
Very High	The wear metals content is higher than normal. The crane should be stopped for investigation.

Table 5: Estimates for Port and Starboard Crane Bearing Grease and Gearbox Oil Sample Test Elements

Test Element	Belief Degrees Associated with the Linguistic Terms
Port Crane Bearing	
Tin (Sn)	{(0.75, Very Low), (0.25, Low), (0, Moderate), (0, High), (0, Very High)}
Nickel (Ni)	{(0, Very Low), (0, Low), (0.875, Moderate), (0.125, High), (0, Very High)}
Sodium (Na)	{(0, Very Low), (0.9, Low), (0.1, Moderate), (0, High), (0, Very High)}
Starboard Crane Bearing	
Nickel (Ni)	{(0, Very Low), (0, Low), (0, Moderate), (0, High), (1, Very High)}
Sodium (Na)	{(0, Very Low), (0.3, Low), (0.7, Moderate), (0, High), (0, Very High)}
Port Crane Gearbox	
Tin (Sn)	{(0.333, Very Low), (0.667, Low), (0, Average), (0, High), (0, Very High)}
Aluminium (Al)	{(0, Very Low), (1, Low), (0, Moderate), (0, High), (0, Very High)}
Starboard Crane Gearbox	
Aluminium (Al)	{(0, Very Low), (0, Low), (1, Moderate), (0, High), (0, Very High)}
Silicon (Si)	{(0.875, Very Low), (0.125, Low), (0, Moderate), (0, High), (0, Very High)}

Table 6: Linguistic Term Grades & Risk Ranking

Linguistic Term	Grade	Risk Ranking
Very Low	Normal	1
Low	Normal	1
Moderate	Caution	2
High	Attention	3
Very High	Critical	4

Table 7: Examples of 5 x 5 x Rules Base

Rule No.	Element A Sample Test Result	Element B Sample Test Result	Element C Sample Test Result	Priority Level of Attention
1	Very Low	Very Low	Very Low	NORMAL
2	Very Low	Very Low	Low	NORMAL
3	Very Low	Very Low	Moderate	CAUTION
4	Very Low	Very Low	High	ATTENTION
5	Very Low	Very Low	Very High	CRITICAL
6	Very Low	Low	Very Low	NORMAL
7	Very Low	Low	Low	NORMAL
8	Very Low	Low	Moderate	CAUTION
9	Very Low	Low	High	ATTENTION
10	Very Low	Low	Very High	CRITICAL
11	Very Low	Moderate	Very Low	CAUTION
12	Very Low	Moderate	Low	CAUTION
13	Very Low	Moderate	Moderate	CAUTION
14	Very Low	Moderate	High	ATTENTION
15	Very Low	Moderate	Very High	CRITICAL
16	Very Low	High	Very Low	ATTENTION
17	Very Low	High	Low	ATTENTION
18	Very Low	High	Moderate	ATTENTION
19	Very Low	High	High	ATTENTION
20	Very Low	High	Very High	CRITICAL
21	Very Low	Very High	Very Low	CRITICAL
22	Very Low	Very High	Low	CRITICAL
23	Very Low	Very High	Moderate	CRITICAL
24	Very Low	Very High	High	CRITICAL
25	Very Low	Very High	Very High	CRITICAL

Table 8: The Minimum Value of each Combination

Port Crane Bearing							
1	Caution 0.75	2	Caution 0.1	3	Attention 0.125	4	Attention 0.1
5	Caution 0.25	6	Caution 0.1	7	Attention 0.125	8	Attention 0.1
Starboard Crane Bearing							
1	Critical 0.3	2	Critical 0.7				
Port Crane Gearbox							
1	Normal 0.333	2	Normal 0.667				
Starboard Crane Gearbox							
1	Caution 0.875	2	Caution 0.125				
Port Crane Bearing from Using Two Test Elements for Decrement of Port Crane Bearing by 0.3							
1	Normal 0.45	2	Caution 0.1	3	Critical 0.3	4	Normal 0.25
5	Caution 0.1	6	Critical 0.25	7	Critical 0.3	8	Critical 0.1
9	Critical 0.3						

Table 9: The Maximum Value Associated with the Same Category of Linguistic Priority Terms

For Port Crane Bearing			
Category of linguistic priority terms	**Maximum values**		
Caution	0.75		
Attention	0.125		
For Decrement of Port and Starboard Crane Bearing Grease Sample Elements			
Category of linguistic priority terms	**Maximum values by decrement of 0.1**	**Maximum values by decrement of 0.2**	**Maximum values by decrement of 0.3**
Port Crane Bearing			
Caution	0.65	0.55	0.45
Attention	0.125	0.125	0.125
Critical	0.1	0.2	0.3
Starboard Crane Bearing			
Normal	0.1	0.1	N/A
Caution	0.1	0.2	0.3
Critical	0.7	0.7	0.7
Port Crane Gearbox			
Normal	0.667	0.667	0.667
Critical	0.1	0.2	0.3
Starboard Crane Gearbox			
Caution	0.775	0.675	0.575
Critical	0.1	0.2	0.3
For Port Crane Bearing from Using Two Test Elements for Decrement of Port Crane Bearing by 0.3.			
Category of linguistic priority terms	**Maximum values**		
Normal	0.45		
Caution	0.1		
Critical	0.3		

Table 10: The Estimates Conclusions of the Ship's Crane and Component Risk Values

Ship Crane Components	Estimates Conclusions	Risk Value
Port crane bearing	Caution 0.75, Attention 0.125	1.875
Starboard crane bearing	Critical 0.7	2.8
Port crane gearbox	Normal 0.667	0.667
Starboard crane gearbox	Caution 0.875	1.75

Table 11: Decrement of Port and Starboard Crane Bearing Grease and Gearbox Oil Sample Test Elements

The degree of belief associated with the highest preference linguistic variable is decreased and simultaneously the degree of belief associated with the lowest preference linguistic variable is increased by 0.1	
Test Elements	**Port Crane Bearing**
Tin (Sn)	{(0.65, Very Low), (0.25, Low), (0, Moderate), (0, High), (0.1, Very High)}
Nickel (Ni)	{(0, Very Low), (0, Low), (0.775, Moderate), (0.125, High), (0.1, Very High)}
Sodium (Na)	{(0, Very Low), (0.8, Low), (0.1, Moderate), (0, High), (0.1, Very High)}
Test Elements	**Starboard Crane Bearing**
Nickel (Ni)	{(0.1, Very Low), (0, Low), (0, Moderate), (0, High), (0.9, Very High)}

Sodium (Na)	{(0, Very Low), (0.2, Low), (0.7, Moderate), (0, High), (0.1, Very High)}
Test Elements	**Port Crane Gearbox**
Tin (Sn)	{(0.233, Very Low), (0.667, Low), (0, Moderate), (0, High), (0.1, Very High)}
Aluminium (Al)	{(0, Very Low), (0.9, Low), (0, Moderate), (0, High), (0.1, Very High)}
Test Elements	**Starboard Crane Gearbox**
Aluminium (Al)	{(0, Very Low), (0, Low), (0.9, Moderate), (0, High), (0.1, Very High)}
Silicon (Si)	{(0.775, Very Low), (0.125, Low), (0, Moderate), (0, High), (0.1, Very High)}
The degree of belief associated with the highest preference linguistic variable is decreased and simultaneously the degree of belief associated with the lowest preference linguistic variable is increased by 0.2	
Test Elements	**Port Crane Bearing**
Tin (Sn)	{(0.55, Very Low), (0.25, Low), (0, Moderate), (0, High), (0.2, Very High)}
Nickel (Ni)	{(0, Very Low), (0, Low), (0.675, Moderate), (0.125, High), (0.2, Very High)}
Sodium (Na)	{(0, Very Low), (0.7, Low), (0.1, Moderate), (0, High), (0.2, Very High)}
Test Elements	**Starboard Crane Bearing**
Nickel (Ni)	{(0.2, Very Low), (0, Low), (0, Moderate), (0, High), (0.8, Very High)}
Sodium (Na)	{(0, Very Low), (0.1, Low), (0.7, Moderate), (0, High), (0.2, Very High)}
Test Elements	**Port Crane Gearbox**
Tin (Sn)	{(0.133, Very Low), (0.667, Low), (0, Moderate), (0, High), (0.2, Very High)}
Aluminium (Al)	{(0, Very Low), (0.8, Low), (0, Moderate), (0, High), (0.2, Very High)}
Test Elements	**Starboard Crane Gearbox**
Aluminium (Al)	{(0, Very Low), (0, Low), (0.8, Moderate), (0, High), (0.2, Very High)}
Silicon (Si)	{(0.675, Very Low), (0.125, Low), (0, Moderate), (0, High), (0.2, Very High)}
The degree of belief associated with the highest preference linguistic variable is decreased and simultaneously the degree of belief associated with the lowest preference linguistic variable is increased by 0.3	
Test Elements	**Port Crane Bearing**
Tin (Sn)	{(0.45, Very Low), (0.25, Low), (0, Moderate), (0, High), (0.3, Very High)}
Nickel (Ni)	{(0, Very Low), (0, Low), (0.575, Moderate), (0.125, High), (0.3, Very High)}
Sodium (Na)	{(0, Very Low), (0.6, Low), (0.1, Moderate), (0, High), (0.3, Very High)}
Test Elements	**Starboard Crane Bearing**
Nickel (Ni)	{(0.3, Very Low), (0, Low), (0, Moderate), (0, High), (0.7, Very High)}
Sodium (Na)	{(0, Very Low), (0, Low), (0.7, Moderate), (0, High), (0.3, Very High)}
Test Elements	**Port Crane Gearbox**
Tin (Sn)	{(0.033, Very Low), (0.667, Low), (0, Moderate), (0, High), (0.3, Very High)}
Aluminium (Al)	{(0, Very Low), (0.7, Low), (0, Moderate), (0, High), (0.3, Very High)}
Test Elements	**Starboard Crane Gearbox**
Aluminium (Al)	{(0, Very Low), (0, Low), (0.7, Moderate), (0, High), (0.3, Very High)}
Silicon (Si)	{(0.575, Very Low), (0.125, Low), (0, Moderate), (0, High), (0.3, Very High)}
Using Two Test Elements for Decrement of Port Crane Bearing by 0.3	
Tin (Sn)	{(0.45, Very Low), (0.25, Low), (0, Moderate), (0, High), (0.3, Very High)}
Sodium (Na)	{(0, Very Low), (0.6, Low), (0.1, Moderate), (0, High), (0.3, Very High)}

Table 12: The Estimate Conclusions of the Ship's Crane from Decrement values

Ship Crane	**Estimate Conclusions**		
	Decrement by 0.1	**Decrement by 0.2**	**Decrement by 0.3**
Port crane bearing	Caution 0.65, Attention 0.125, Critical 0.1,	Caution 0.55, Attention 0.125, Critical 0.2,	Caution 0.45, Attention 0.125, Critical 0.3,

Starboard crane bearing	Normal 0.1, Caution 0.1, Critical 0.7,	Normal 0.1, Caution 0.2, Critical 0.7,	Caution 0.3, Critical 0.7,
Port crane gearbox	Normal 0.667, Critical 0.1	Normal 0.667, Critical 0.2	Normal 0.667, Critical 0.3
Starboard crane gearbox	Caution 0.775, Critical 0.1	Caution 0.675, Critical 0.2	Caution 0.575, Critical 0.3

Table 13: Risk Values from the Decremented Estimate Conclusions

Ship Crane Component	Risk Values		
	Decrement by 0.1	**Decrement by 0.2**	**Decrement by 0.3**
Port crane bearing	2.366	2.594	2.822
Starboard crane bearing	3.441	3.3	3.4
Port crane gearbox	1.389	1.689	1.929
Starboard crane gearbox	2.226	2.454	2.682

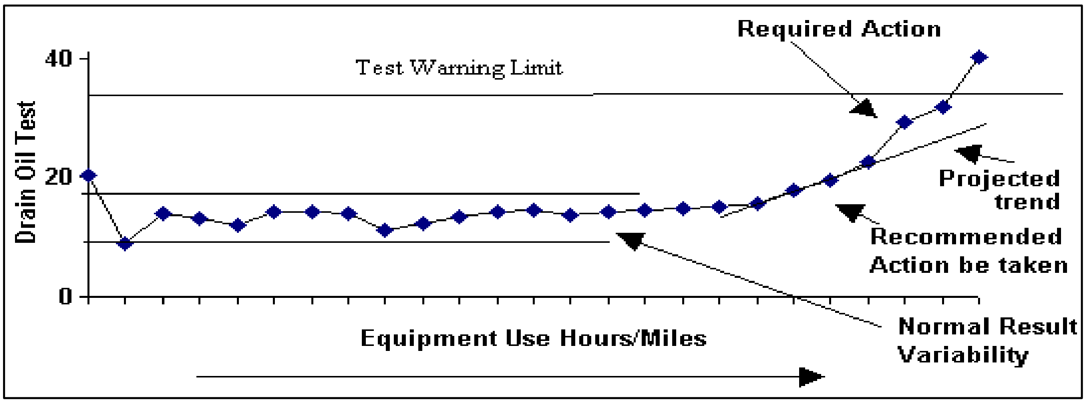

Figure 1: Absolute and statistical alarms *Source: Bently Tribology Services (n.d)*

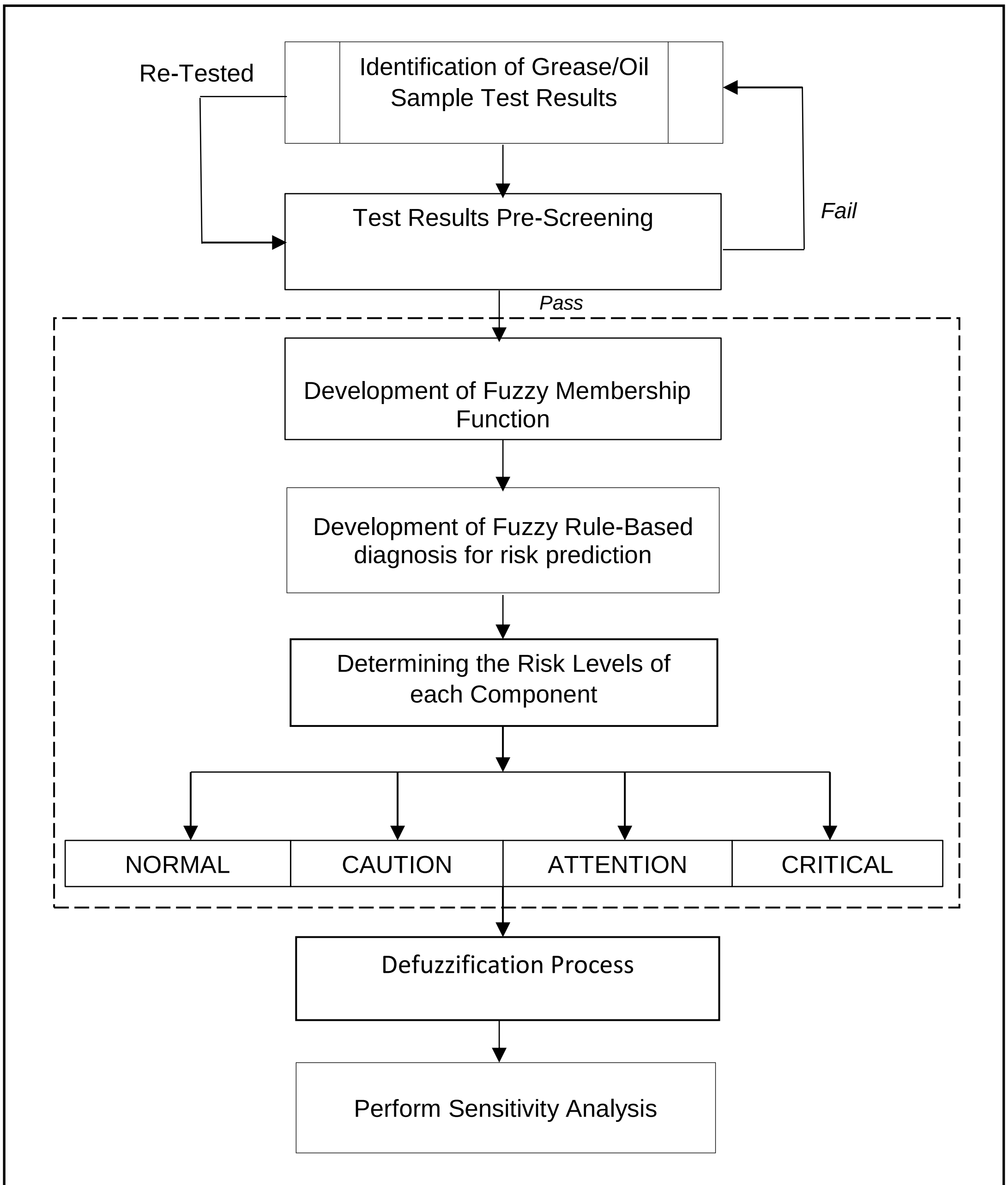

Figure 2: Diagnostic Flow Chart

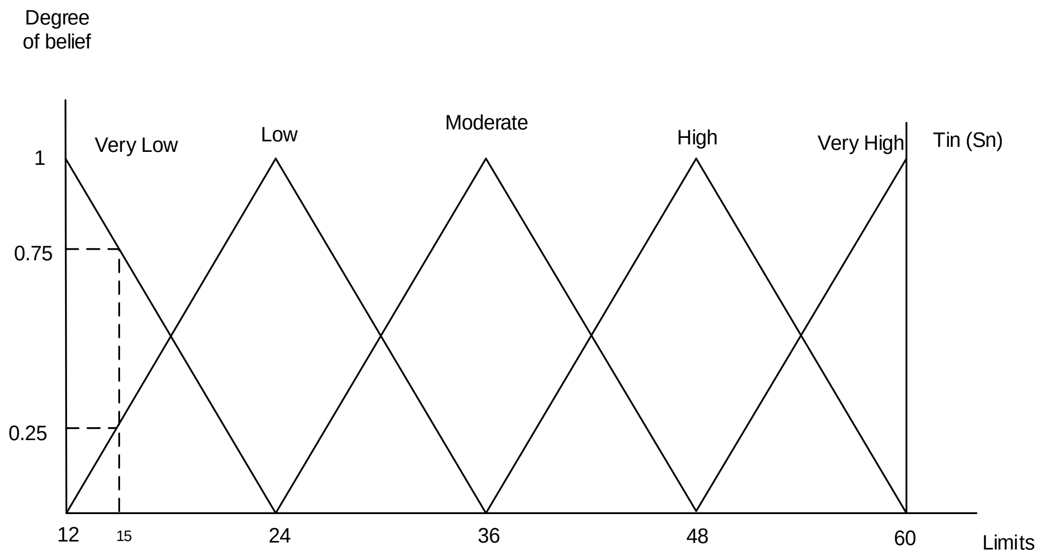

Figure 3: Membership Function of the Tin (Sn) Element

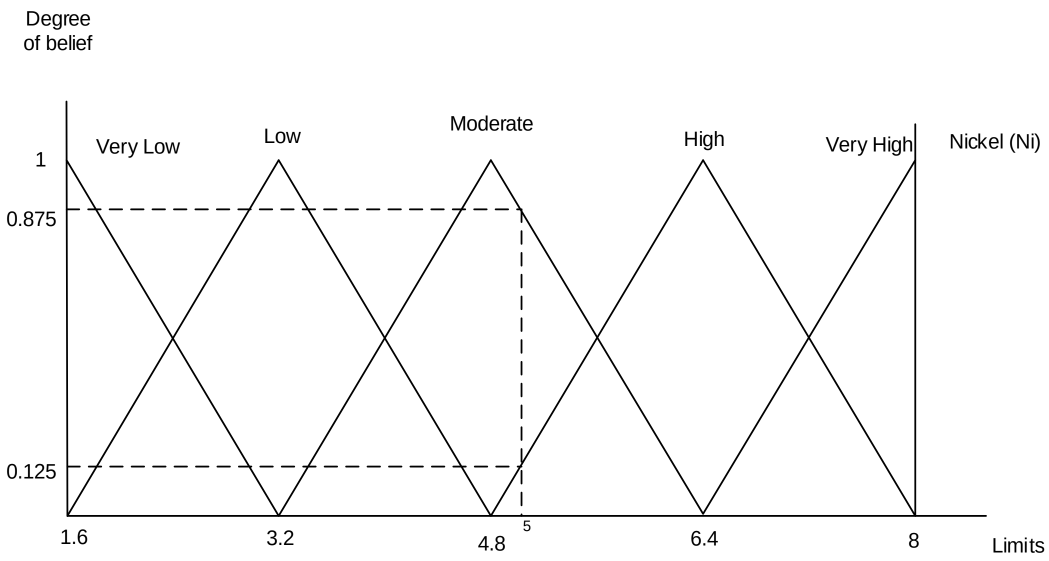

Figure 4: Membership Function of the Nickel (Ni) Element

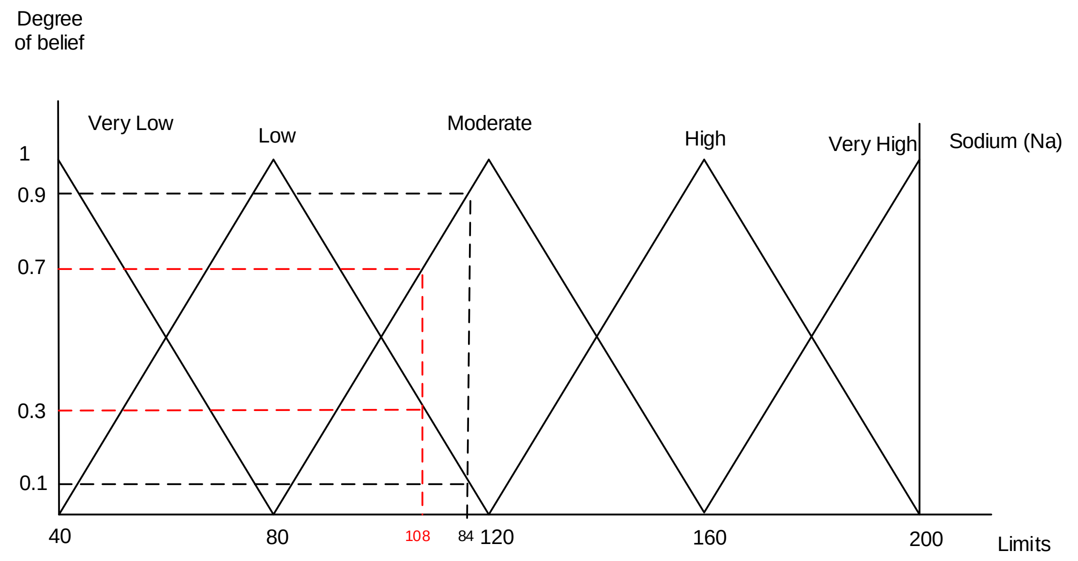

Figure 5: Membership Function of the Sodium (Na) Element

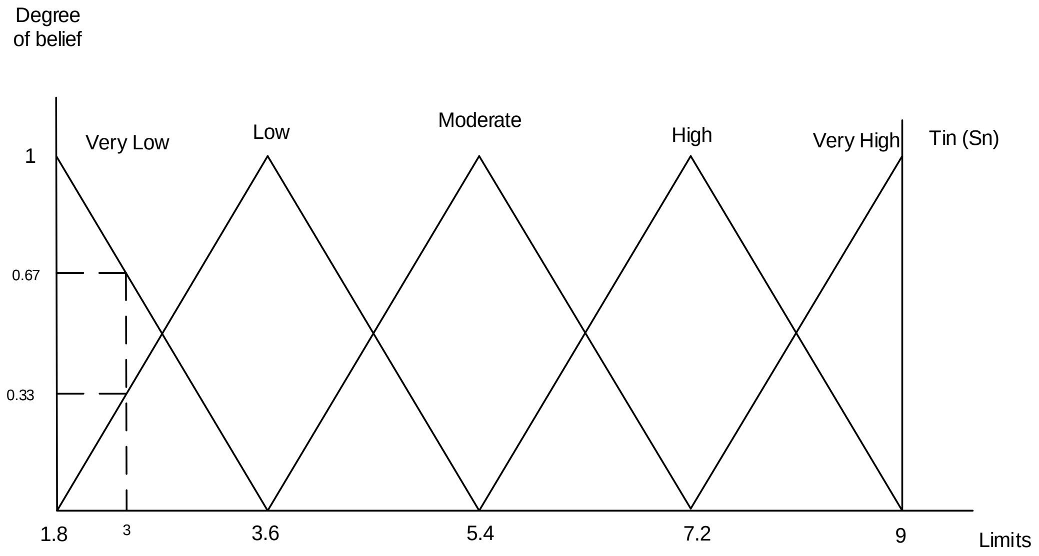

Figure 6: Membership Function of the Tin (Sn) Element

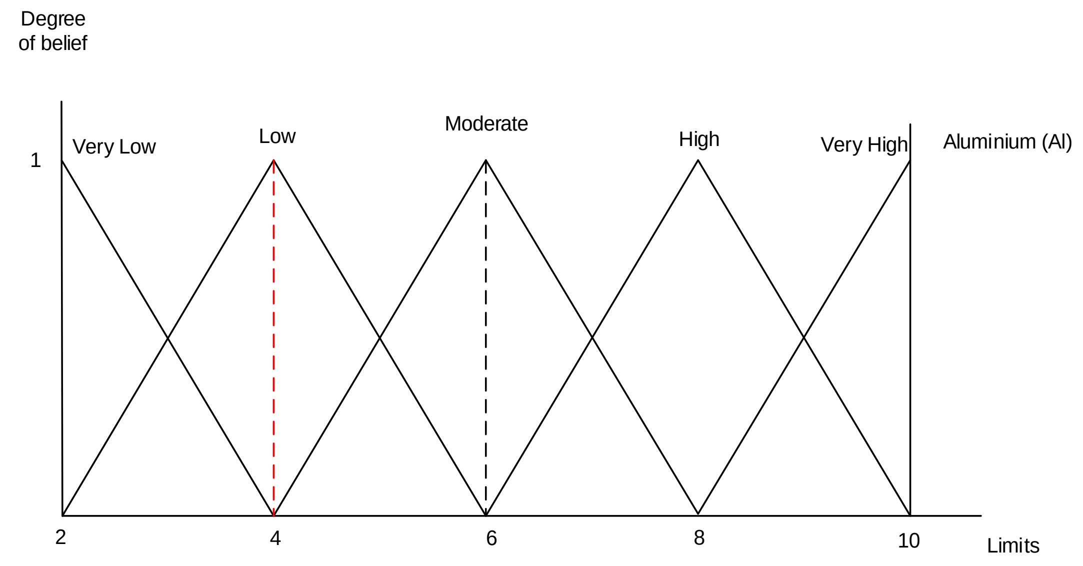

Figure 7: Membership Function of the Aluminium (Al) Element

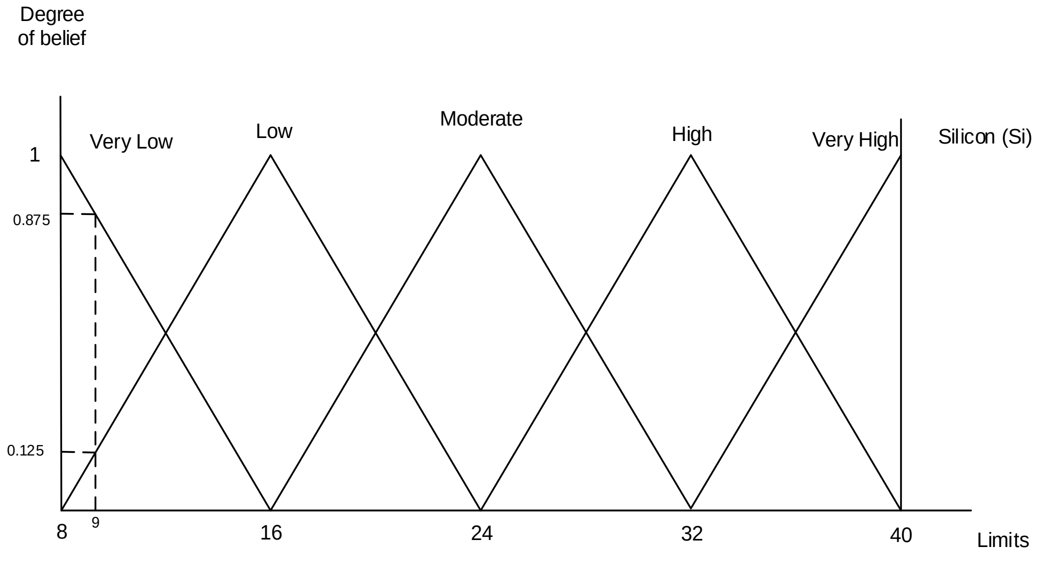

Figure 8: Membership Function of the Silicon (Si) Element