# Investigating Ship System Performance Degradation and Failure Criticality Using FMECA and Artificial Neural Networks

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ABSTRACT: The goal of all maintenance methods is to eliminate failures or reduce their occurrence. Extended downtime on key ships systems such as power generation plants can lead to undesirable consequences beyond economic and operational losses, especially considering naval vessels. One solution to overcome this challenge is through a system-specific analysis that identifies the most critical component and possible causes of delays be it technical or logistics. In this regard, this paper presents a methodology using FMECA approach that adopts the risk priority number differently to identify Mission Critical Components. This was supported with ANN classification using unsupervised learning to identify patterns in the data that signifies the onset of performance degradation and potential failures onboard an OPV. The study has identified some critical components and failure patterns that contribute to extended downtime based on survey and machinery maintenance reports. Recommendations were provided on preventing/mitigating the failures and how to prioritise existing ship systems maintenance.

Keywords
FMECA, ANN, SOM, Mission Critical components, OPV, Power Generation Plant

## 1 INTRODUCTION

Ships of any type are structures that are operated through a network of systems, the majority of which operate interdependently for their correct functioning. The systems onboard ships are connected to enable economic and efficient operations and maintenance of all equipment/systems. However, a challenge lies in failure of equipment that provides utility to other ship systems. Therefore maintenance efforts are directed to ensure these failures do not occur and if they do the impact can be managed efficiently (Lazakis & Ölçer, 2016). More so, when considered against the cost of routine maintenance which accounts for more than 14 % of ships operating cost and increases as the ship age (Stopford, 2010). Therefore, when this cost is considered against the impact of unscheduled maintenance and the associated operational delays, it becomes a major concern for ship operators. Maintenance uncertainties on ships that belong to law enforcement agencies such as the navy and coast guard ships may not be measured in economic terms but could be the difference between life and death (Goossens & Basten, 2015). It then becomes necessary that ships maintenance adopts a flexible maintenance approach that ensures an efficient and cost-effective ships operational availability (Cheliotis et al., 2019). In this regard other maintenance styles were introduced to overcome some of the challenges when using traditional maintenance (Gits, 1992). Similarly (Shafiee, 2015) provides a review on maintenance selection strategies which highlighted the dynamics involve in maintenance selection, especially in a complex environment such as ships.

Planned Maintenance System (PMS) has remained the mainstay of ships maintenance for both civil and defence sectors (Lazakis et al., 2018,New, 2012). Increasing number of research conducted on ship maintenance has shown that the prepared maintenance onboard ships is preventive maintenance system followed by predictive maintenance system (Lazakis et al., 2018,Velasco-Gallego and Lazakis, 2020). Nonetheless, risk and criticality approach to ship system maintenance are increasingly used to overcome critical component failures or emergency failure events underway especially with advent of unmanned ships(Eriksen et.al 2021)

Therefore, based on the foregoing, there is the interest to adopt more efficient maintenance systems, but the challenge is how these technologies can be incorporated by organisations and ship owners/operators. The challenges due to cost of technology can be attributed to installation of new sensors, system upgrades and the cost of training to match new technologies (Mihanović et al 2016). Notwithstanding the need to improve the flexibility of onboard maintenance and the current regulations towards reducing emissions and the strategy by some Original Equipment Manufacturers (OEM) to adopt remanufacturing which offers some discount for operators participating in the scheme would help change the dynamics of maintenance to be more efficient (International Resource Panel, 2017,IACS Rec, 2018).Moreover, it has been established that the cost of maintenance increases while the equipment ages which can be controlled with more optimised maintenance strategy (Lazakis et al., 2019).

In this regard, this paper presents a methodology based on the combination of FMECA and ANN employing engine sensor records, maintenance, and repair data reports for a set of diesel generators. Therefore, the research provides a comprehensive criticality approach to fault and component reliability that can be replicated onboard or shore maintenance organisations to provide an efficient maintenance practice.

The paper is presented in 5 sections as follows: Section 1 provides an introduction to topic in hand; section 2 highlights a critical review of reliability analysis tools. Section 3 presents the paper methodology while section 4 discusses the paper results as applied on a case study navy patrol vessel. Finally, the conclusion and feature work are presented in section 5.

## 2 CRITICAL REVIEW ON RELIABILITY ANALYSIS TOOLS

Reliability analysis has historically aided maintenance planning since the advent of organised maintenance approaches that evolved from breakdown of simple machines to condition monitoring based predictive analysis(*Fred K, et al*, 2006). In this regard, several maintenance methods were advanced to address peculiar problems faced by organisations (Martin et al., 2017). In early maintenance planning, simple methods that can be used to calculate equipment reliability or availability such as mean time to failure (MTTF), mean time between failure (MTBF) failure rates($\lambda$) were used (Lazakis & Ölçer, 2016,Palmer, 2010 and Dhillon, 2006). However, system complexity and the increasing use of electrical components such diodes, valve and software made necessary to adopt other means for system reliability analysis to account for the nature of static failures which are not related to wear and tear. Accordingly, the progressive advance in maintenance has been made possible through the use of reliability analysis tools in various industries such as aerospace and defence (NASA, 2002,Hillier, Price and Austin, 2003,Kimera and Nangolo, 2020). On the other hand, maintenance within the shipping industry is increasingly getting scrutinised due to regulations including climate change concerns; all this push for the adoption of advanced technologies would require ship operators to adopt additional reliability measures (IACS Rec, 2018,ISO 17359:2018, 2018). Likewise Classification Societies require ships to have a standard maintenance documentation and strategy prior to certifying Class qualification (ClassNK, 2017,ABS, 2016).

Research in various fields of maintenance has shown that reliability analysis tools play a vital role in maintenance plaining (Chemweno et al., 2018, Kabir, 2017). The emergence of Reliability Centred Maintenance has brought to the fore the relevance of risk and criticality in equipment maintenance, which focuses maintenance on safety of operations and system reliability (Mokashi, Wang and Vermar, 2002,NASA, 2002). In this regard, authors have provided in depth research on the application of reliability analysis tools in the various industries. A criticality-based maintenance for coal power plant used FMECA to drive Risk Priority Number (RPN) aimed at identifying critical components in the plant in order to avoid unplanned shutdown was presented (Melani et al., 2018). System reliability analysis using tools such as FTA and FMECA have found wide application in the nuclear industry especially in the energy sector (Volkanovski et al., 2009). A great deal of research has been made in the maritime sector on the use of reliability tools to improve safety, risk reduction and achieving reliability for ships and offshore wind turbines(Lazakis et al., 2016,2018, Leimeister & Kolios, 2018).

In the shipping industry and extensive use of Fault Tree Analysis (FTA), Reliability Block Diagrams, (RBD), Event Tree Analysis (ETA), Failure Mode Effect Analysis (FMEA) and other variants of these tools were used to ensure the emplacement of robust maintenance regimes. Therefore, the adoption of method that combines 2 or more reliability tools in order to overcome deficiencies or take advantage of the other tool as shown in (Lazakis et al., 2016,Raptodimos & Lazakis, 2017,Emovon et al., 2018) is increasingly adopted to improve robustness in analysis. Identifying the critical component in system reliability is a dominant area in maintenance research for instance Melani *et al.*( 2018) used FMECA for critical component identification in coal fire power plant, while Cheliotis et al (2022) presented a combination of machine learning fault mapping and Bayesian Networks in order to assess increase ship machinery reliability. A combination of reliability tools and ANN was used to develop a predictive condition monitoring by (Lazakis et al., 2018) which shows the competitive flexibility that can be driven to the use of reliability tools and numerical methods in system reliability analysis. The criticality of system, component or event in FMEA is derived by the use of Risk Priority Number (RPN) (Cicek & Celik, 2013,Sharma & Rai, 2021,Fred & K. Geitner, 2006,Rausand et al., 2021). Reliability analysis tools examine risk of failure by considering quantitative and qualitative aspects. These tools can be grouped into those that are deductive and or inductive based as shown in table 1.

*Table 1 -Deductive and Inductive Reliability analysis tools (adapted from (System Reliability Theory, 2021)*

| Model/Method | Deductive (Backward) | Inductive (forward) |
|---|---|---|
| FMECA | Yes | Yes |
| Fault Tree Analysis | Yes | No |
| Event Tree Analysis | No | Yes |
| Reliability Block Diagram | Yes | No |
| Bayesian Networks | Yes | Yes |

## *2.1 Failure Mode Effects and Criticality Analysis (FMECA)*

FMECA is a reliability evaluation technique to determine the effect of system and equipment failures. FMECA is composed of 2 analyses, FMEA and Criticality Analysis (CA). The FMEA is focused on how equipment and system have failed or may fail to perform their function and the effects of these failures, to identify any required corrective actions for implementation to eliminate or minimize the likelihood of severity of failure. The UK MoD defines Criticality assessment as a means of establishing the risk to platform and personnel arising from the occurrence of a failure mode. It is based on a combination of the worst case consequences of the event coupled with the probability of its occurrence and detection(MoD UK, 2000). Therefore, the Criticality of a failure is determined through a ranking method to obtain RPN which is a product of the risk factors Detectability, Severity and Likelihood.

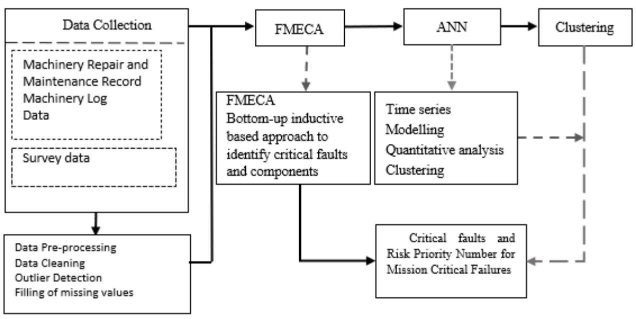



*Figure 1-Methodology Developed*

Stamatis ( 2003)presented a system of ranking of risk factors to obtain the RPN using numerical scale alongside discrete linguistic terms to reduce ambiguity in linear scale ranking between 1-5 or 1-10. The scale is the same irrespective of which one is used however for uniformity, is best not to combine the scales i.e. 1-5 or 1-10 in one study or analysis. Moreover FME(C)A is a team activity, it is important that everyone understand what is required as regards the inputs to provide. On the other hand, a system to account for different experience level in a team is equally important, as skills, competence and knowledge usually comes with training, age in service, and exposure to certain responsibilities. Therefore, Liu *et al.*, (2016) presented a system of RPN ranking integrating linear scale with linguistics meaning to address the subjectiveness of FMEA team members. Similarly (Sharma and Rai, 2021,Ilbahar *et al.*, 2018)provided a methodology of evaluating FMECA using linear scale RPN and provides weights to account for importance for individual inputs. Linear approach alongside discreate linguistic terms for conducting FMECA are widely used especially in risk analysis in various field covering humanities to engineering to help improve the clarity and reduce subjectiveness (Tan *et al.*, 2011, Liu *et al.*, 2016,Mutlu and Altuntas, 2019). Accordingly, the flexibility with which FMECA can be interpreted has made it widely accepted across many disciplines from engineering, humanities to medical sciences.

## *2.2 Artificial Neural Network*

ANN are widely used for statistical analysis and data modelling commonly applied as alternatives to standard nonlinear regression or cluster analysis. Hence, their extensive use in classification, forecasting such as diagnosis, signal processing, speech and image recognition (Gurney, 1997,Mandic & Chambers, 2001). ANN can be defined as interconnected assembly of simple processing elements (units or nodes) whose functionality is loosely based on the animal brain neural. The networks have a processing ability stored in the interunit connection strengths, weights, obtained by a process of adaptation to , or learning from, a set of training patterns (Gurney, 1997). The computational models or nodes are connected through weights that are adapted during use or training to improve performance (Mandic & Chambers, 2001). Therefore the ability of the ANNs to learn, identify patterns and predict them has made their application in the field maintenance very widely, ( Raptodimos & Lazakis, 2018, Vanem & Brandsæter, 2019,Stetco et al., 2019,Lugosch et al., 2020). The process involves the basic node which provides a linear combination of $N$ weights $w_1 \ldots\ldots, w_N$ and $N$ inputs $x_{1,\ldots\ldots} x_N$ and passes the result through a nonlinearity $\Phi$ as show in equation 1.

$$\boldsymbol{y} = \sum_{i=1}^{N} w_i * x_i + w_0 \qquad (1)$$

### 2.2.1 ANN Self Organising Maps

ANN Self Organising Maps (SOM) have been applied in the field of maintenance for machinery health analysis and prediction of machinery condition by various authors. As an unsupervised learning method ANN SOM are effective for data analysis and clustering as presented in (Yu et al., 2015) and used for identifying nonlinear latent features from high dimensional data. Therefore, riding on the existing success and procedures in the use of ANN for machinery data analysis, this research will employ ANN for fault classification and detection, fault/condition prediction and machinery remaining useful life analysis (Wu et al., 2007). ANN approach for fault detection was applied with FTA to identify critical component of a diesel generators in a research presented by (Raptodimos & Lazakis, 2017). In some cases, machinery fault data are recorded without identifying the fault signals, therefore this requires data clustering. Clustering is a form of unclassified machine learning which is applied for machinery diagnostics (Gkerekos et al., 2019). The advantages of using clustering models help identify possible clusters as well as the most influential clusters in the data. SOM consists of competitive layer which can classify a dataset of vectors with any number of dimensions as the number neurons in the layer and are good for dimensionality reduction as presented in (Raptodimos & Lazakis, 2018 ,Ponmalai & Kamath, 2019).

## 3. Methodology

The methodology is provides a holistic maintenance strategy to cover the entire ship system in a manner that enables flexibility in assigning component maintenance priority or scheduling. The combination of systems onboard ships makes it unsuitable to have a single approach to maintenance. This is more so, when additional consideration is given to ship operators in developing countries where access to technology and original equipment manufacturers is limited and, in some cases, restricted; leading to extended downtime for some critical onboard equipment usually ignored in most cases. In this regard, the present methodology provides an efficient approach to component/equipment failure and degradation analysis. This is because the nature of failure and equipment performance degradation varies a lot from component, equipment, or subsystem as such the need to consider multiple analysis tools to enable a more efficient and flexible methodology. Figure 1 shows the overall methodology of the research. In this paper, Failure Mode Effect and Criticality analysis is used to identify Mission Critical component to ship operations.

### 3.1 FMECA

FMECA has been widely adopted in many fields beyond engineering to analyse what can wrong, how it could go, why it goes wrong, and how it can be corrected or addressed. The Criticality Analysis (CA) provides a means of identifying the events, occurrence or components that need more attention to avoid more serious or catastrophic situations. FMECA is a bottom-up approach which provides a systematic methodology to gain deep insight on failures and their course on an equipment or system. Therefore, measuring criticality in FMECA helps to explicitly bring out the most critical component failure which can assist in maintenance actions and planning.

Therefore, the criticality ranking based on risk use a combination of the consequence (severity) of the failure and the anticipated likelihood of the consequence occurring (ABS, 2015). Criticality analysis will highlight failure modes with probability of occurrence and severity of consequence, allowing corrective actions to be implemented where they produce greatest impact. Given the overall lack of reliability data for many marine systems and components, performing an assessment on qualitative level based on experience and knowledge of the system is sometimes the only means by which to achieve a meaningful criticality assessment. Accordingly, research presents the combination of FMECA and ANN for the investigation of mission critical components of a marine diesel generator. For the FMECA a survey was conducted based on presented in the form of common failures that contributes to about 40 per cent in DGs non availability. Therefore, respondents were asked to rank faults/failures based on 3 criteria on a linear scale from one (1) to ten (10). These criteria were Criticality, Severity and Likelihood as define below:

*Table 2- Sample FMECA table*

| Sub system | Component | Function | Description of Failure | | | Effects of Failure | | Effects of Failure | | Safeguards | | Criticality | Severity | Likelihood | RPN |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | Mode | Causes | Detection | Local | Global | Influence | TTR | Prevention | Mitigation | 1-10 | 1-10 | 1-10 | CxSxL |
| | | | | | | | | | | | | | | | |
| | | | | | | | | | | | | | | | |

Criticality: Criticality determines the immediate impact of failure event to the equipment availability and functions. Therefore, a failure mode due to which the ship will not achieve one or more of the mission's targets and /or the safety of whole vessel is at risk until the failure is rectified (NASA, 2008).

Severity: Severity assesses how the failure impacts on the operational availability of the equipment or system regarding normal operation and the duration it takes to be repaired or restored to normal operational levels. Severity is described as the worst potential consequence of the failure determined by the degree of injury, property damage or system damage that could occur (System Reliability Theory, 2021).

Likelihood: This refers to the failure rate of the component including possibility and frequency of the fault occurring over a certain time frame (MIL-STD 1629A, 1980).

### *3.1.1 Estimated RPN*

The RPN was calculated from the obtained population mean by multiplying each criterion based on the assigned weights according to the seniority of the respondents as a percentage of the original value using equation 2 and 3. The linear values used for the criteria was between | 1 – 10 | therefore was 0 ≤RPN ≥ 300. In this regard to obtain the Mission Criticality the RPN was normalised to ≤100 using the min-max normaliser equation 4.

$$Weighted\ average\ w = \frac{\sum_{i=1}^{n} w_i X_i}{\sum_{i=1}^{n} w_i} \qquad (2)$$

$$RPN = \sum_{i=\leq 1} Cw_i \times Sw_i \times Lw_i \qquad (3)$$

$$RPN_{norm} = \frac{X - min\ (X)}{max(X) - min(X)} = Mission\ Criticality \qquad (4)$$

### *3.2 Artificial Neural Network Clustering*

In general, there are 2 types of machine learning namely supervised and unsupervised learning (Mahantesh Nadakatti, 2008, Cipollini *et al.*, 2018). The supervised machine learning is used to train a labelled model using a labelled that, that is the features to be looked out are already know there the input data (Gkerekos et al., 2017). On the other hand, unsupervised learning deals with unlabelled data which means the algorithm will identify the unique features in the data and partition it accordingly (Coraddu *et al.*, 2016,Vanem and Brandsæter, 2019). Unsupervised learning is useful for exploring data in order to understand the natural patten of the data especially when there is no specific information about significant incidents in the data that can easily point to some fault indicators(Cipollini et al., 2018). The data collected included hourly machinery log of the DGs hence with no indication of failure or maintenance periods. Therefore, the best method to get the information was to conduct cluster analysis, consequently ANN SOM was used for dimensionality reduction and clustering in the collected data from the case study ship.

Implementing SOM requires the initial training which composes of three phases namely, competition, cooperation and adaption (Kohonen, 2013). The neurons are trained during the competition by competing with each other, whereby the neuron having weight vector closest to the input signal vector is declared as the winner neuron or the Best Matching Unit (BMU). The process can be demonstrated thus; taken the input signal vector to be represented by $I = [\, I_1, I_2, I_3 \ldots . I_n \,]^T$ and the weight vector is represented by $W = [\, W_1, W_2, W_3 . \ . \ . \ . \ W_n]^T$. The difference between the weight vector and input signal vector is computed as the Euclidean Distance (E) between them given by equation 5.

$$E = \parallel I - W \parallel \sqrt{\sum_{i=1}^{n} (I_i - W_i\,)^2} \qquad (5)$$

The above equation determines the neuron with the smallest E, which is also the BMU. This is followed by the cooperation phase where the direct neighbourhood neurons of the BMU are identified. The third phase is the adaptation process which neurons are selectively tuned to adopt a specific pattern on the lattice that corresponds to a specific feature of the input vector. The tuning function is written as:

$$W(t+1) = W(t) + \alpha(t)\theta(t)[I(t) - W(t)] \qquad (6)$$

Where $\alpha(t)$ is the tuning rate and $\theta(t)$ is the exponential neighbour function; $\alpha(t)$ decrease exponentially with further iteration hence refining the training process, this can be represented in the following equation.

$$\alpha(t) = \alpha_0 e^{\left(-\frac{t}{\lambda}\right)} \quad (7)$$

where $\alpha_0$ is the initial learning rate and $\lambda$ is the time constant given by.

$$\lambda = \frac{N}{\sigma_0} \quad (8)$$

In the above equation N is the total number of training samples and $\sigma_0$ is the radius of the map. The radius is calculated as the Euclidean distance between the coordinates of the outmost neuron and the centre neuron

$$\sigma_0 = \| T_{outmost} - T_{centre} \| \quad (9)$$

In equation 9, $\mathbf{T}_{outmost}$ and $\mathbf{T}_{centre}$ stands for the coordinate of the outmost and central neurons respectively. The overall process is an iterative one to identify the closest neuron to the BMU, thereby fitting the data to required cluster using θ(t) equation 10.

$$\theta(t) = \left(\frac{\|T_j - T_{BMU}\|^2}{2\sigma(t)^2}\right) \quad (10)$$

$$\sigma(t) = \sigma_0 exp\left(\frac{-t}{\lambda}\right) \quad (11)$$

In equation 10 $T_j = [t_j^1 \; t_j^2]$ which denotes the coordinates of each neuron in a 2D map, $T_{BMU}$ is the coordinate of the best matching unit and σ(t) is the radius of the neighbourhood as shown in equation 11. Therefore, the neurons will keep on updating to get the BMU; In this respect, SOM uses unsupervised learning to produce a map of the input thus providing a good solution for interpreting highly dimensional data making it a good candidate in machinery fault diagnosis

## 4. Results and Discussions

A case study to demonstrate the proposed approach was conducted on an OPV power generation plant consisting of 4 diesel generators. All generators are rated at load speed of 1800rpm and maximum output 400KW with an overload capacity of 110% for 1 hr in 12hrs. The DGs are 4-stroke, 12-cylinder, V-type, direct injection, sea water intercooled turbocharge and water cooled. All DGs are capable of independent operation or in parallel and can as well change over automatically in case of failure. Overall machinery health monitoring is achieved via as set of sensors capable of shutting the DG or setting up an alarm at certain threshold as shown in table 3.

*Table 3 – DG Operating parameters*

| Parameter | Abbre viation | Operating Ranges | | Alarm |
|---|---|---|---|---|
| | | Min | Max | |
| Lubricating Oil Pressure | LoP | 0.4 Mpa | 0.55 Mpa | >0.6 |
| Cooling Fresh Water Temperature | FWT(A/B) | 75 $^{O}$C | 80 $^{O}$C | >85 $^{O}$C |
| Lubricating Oil Temperature | LoT | 30 $^{O}$C | 110 $^{O}$C | > 120 $^{O}$C |
| Fresh water pressure | FWP | 0.02 Mpa | 0.25Mpa | >0.3 |
| Exhaust Gas temperature | EGT(A/B) | 220 $^{O}$C | 400 $^{O}$C | >520 |
| Engine Speed | RPM | 1789 RPM | 1850 RPM | 2052 RPM |
| Power Out Put | KW | 0 | 440KVA | 440Kva |
| Generator running hours | HRS | ≥ 2000hours | | |

A survey was conducted to get the opinion of operators and administrators in an organisation with a fleet strength of more about 40 ships of various sizes mainly used for security patrols. The survey consisted of about 20 questions on various types of faults and failure conditions covering DG system including the alternator. Overall, there were 22 respondents of mixed experience and qualification, mainly consisting of 2 specializations; Marine Engineering and Weapon Electrical Engineer. The approach is adopted in order to account for expert knowledge, organisational peculiarities, and challenges to do with access to original equipment manufacturers representatives.

The experience level of respondents varies between 4 to 28 years of service considering position occupied. In this regard appropriate statistical models were used to gain insight to the data. The survey was conducted mainly to quantify the 3 criteria needed for the calculating the RPN which are Criticality ( C ), Severity (S) and Likelihood (L) (MIL-STD 1629A, 1980). Thereafter, the sample and population of mean of the seven groups were taken using equation 12.

$$population\ mean\ \mu = \frac{\sum x}{N} \quad 12$$

Where μ is the population mean, x = data values, N = number of samples

Table 4 shows the ranks and weights applied to the groups. Therefore, to accommodate other operational peculiarities mission critical will be used to replace criticality for evaluating the critical components as compared to the traditional way of measuring criticality by evaluating detectability, severity, and likelihood. In the context of the research criticality is looking at the immediate impact of the failure event on the equipment or platform availability and readiness.

*Table 4 - Rank and Weights method*

| Ranks | Exp. (years) | No. | W* | Positions | W* | Total A | Total B | Applied weight (%) |
|---|---|---|---|---|---|---|---|---|
| **Slt** | 0–5 | 2 | 50 | **WKO/WKD** | Non | 50 | Non | 0.5 |
| **Lt** | 5–11 | 2 | 60 | **WKDWEO/MEO** | 10 | 60 | 70 | 0.6 |
| **Lt Cdr** | 11–15 | 4 | 60 | **WEO/MEO** | 10 | 60 | 70 | 0.7 |
| **Cdr** | 15–20 | 5 | 65 | **FSWEO/ FSMEO** | 15 | 65 | 80 | 0.8 |
| **Capt** | 20–24 | 3 | 70 | **FSMO/FSG CMDR** | 20 | 70 | 90 | 0.9 |
| **Cdre** | 24–28 | 2 | 80 | **FSMO/ FSG CMDR** | 20 | 80 | 100 | 1 |
| **R/Adm** | 28–35 | 2 | 100 | **FSG CMDR** | Non | 100 | 100 | 1 |

*W= Weights

A summary of the FMECA result is presented table 5 Presented are 22 out of about 81 failures analysed due to paper space limitations. The presented failure represents top 50 per cent of the analysed failures on the diesel generator, this ranking provides very important information on how the failure add to the Mission Criticality of the component.

An important case is the cylinder head bolts which has a very short TTR however have very high CA and RPN scores, this underscores the importance of FMECA in maintenance analysis. A further look at the table indicates that failures with longer TTR had higher RPN than those with lower score, again this can provide some guidance to operators on the need to look at skills, type of spare parts holding onboard and procurement prosses. Therefore, the CA score and the RPN provide a strong base for the next aspect of the analysis which is geared towards identifying features in the machinery health parameters.

The next aspect of the case study is the clustering analysis of the unlabelled DG machinery health data with ANN SOM, a summary of the data is presented in table 6. The analysis provides, insight on the main groups and the health parameters that can be used for further diagnostics analysis. The data range used for the SOM analysis is presented in table 7; as can be seen there are 2 abnormal ranges to account for Operator and OEM limits. This disparity was obtained from the operator and shows while the DGs are all rated at 450KW maximum output they were unable to sustain loads beyond 250KW, about 60 percent of the rated output.

*Table 5- Mission Criticality and RPN values*

| Sub system | Component | Failure Mode | Time to repair | C | S | L | RPN | N. RPN |
|---|---|---|---|---|---|---|---|---|
| **Cylinder Block** | Crankcase | 1.Cracking | 1-3months | 7 | 6 | 3 | 224 | 65 |
| | Cylinder liner | 2. Cracks<br>3. Scuffing<br>4. Seizure | 1wk-3months (spare parts availability) | 7 | 7 | 4 | 196 | 56 |
| | Cylinder head bolts | 5. Loose<br>6. Not tight | 1-3hrs | 7 | 6 | 8 | 336 | 100 |
| | Top Cylinder gasket | 7. Burnt<br>8. Material Failure | 10-24hrs | 6 | 5 | 5 | 207 | 60 |
| | Cylinder head O-ring | 9.Deformation | 2 wk-2 months | 7 | 6 | 5 | 207 | 60 |
| **Power Take Off** | Crank Shaft | 10. Surface roughness<br>11. Mis alignment | 1 month | 7 | 7 | 3 | 200 | 58 |
| | Journal Bearing | 12.Friction and seizure | 6hrs-2 days<br>1-2 months (OEM to supply spares) | 7 | 7 | 3 | 222 | 64 |
| **Cooling System** | Heat Exchanger Tubes | 13. Scale build-up<br>14. Leakages | 30min-6hrs | 5 | 5 | 5 | 221 | 64 |
| | FW circulation pump | 15. No water supply<br>16. Drop in pressure | 2hrs-4weeks | 6 | 6 | 4 | 180 | 51 |
| | SW pump assembly | 17. No SW supply<br>18.Drop in pressure | 2-4hrs | 6 | 5 | 4 | 179 | 51 |
| | Fuel Quality | 19. Loss of power<br>20. Erratic operation<br>21.Filter blockage<br>22. Sludge accumulation in tanks | 1-2weeks | 6 | 6 | 7 | 196 | 56 |

Therefore, clustering will provide a hint on how these operating parameters are related to one another and possibly a clue to fault development. Normal data cleaning and filling of missing data was conducted in order to improve model quality. The initial training was conducted with 6 inputs as shown in table 7. The data consist of 1800 timestamp data points out partitioned in to 70/30 for training and validation, training was completed after 200 epochs, due to the size of the data. Consequently, the generated topology presented 5 distinct clusters which are good representation of the input data. A critical look at the table 5 it can be concluded that the DG has never exceeded 60 per cent of its rated output.

*Table 6-Data Summary*

| | RPM | LoP | FWTA | FWTB | LoT | FWP | EGTA | EGTB | HRS | KW |
|---|---|---|---|---|---|---|---|---|---|---|
| count | 150 | 150 | 150 | 150 | 150 | 150 | 150 | 150 | 150 | 150 |
| mean | 1800 | 0.5 | 66.1 | 68.8 | 84.4 | 0.08 | 334.7 | 317.6 | 2527 | 128 |
| std | 2.9 | 0.1 | 3.4 | 3.8 | 4.7 | 0.01 | 39.3 | 38.9 | 2703 | 34.7 |
| min | 1783 | 0.33 | 40.7 | 42.7 | 41.6 | 0.05 | 161.2 | 146.9 | 523 | 65 |
| 25% | 1799 | 0.38 | 65.2 | 67.7 | 82.4 | 0.07 | 310.2 | 287.5 | 603.3 | 100 |
| 50% | 1800 | 0.56 | 66.2 | 68.8 | 84.6 | 0.07 | 339.5 | 325.8 | 636.5 | 130 |
| 75% | 1801 | 0.57 | 67.4 | 70.3 | 86.4 | 0.08 | 352 | 337.5 | 6341 | 140 |
| max | 1812 | 0.86 | 74.1 | 77.1 | 94 | 0.12 | 426.8 | 408.1 | 6379 | 240 |

*Table 7- DG health parameter range*

| DG health parameter | Normal range | Abnormal range | | Alarm |
|---|---|---|---|---|
| | | Operator | OEM | |
| Freshwater Temperature A/ B-Bank | 76-82 | 85 C | 90 C | 90-92 C |
| Exhaust gas Temperatures A/B-Bank | 250-520 | 480 C | 500 C | 520 C |
| Lub Oil Temperature | 40-95 | 90 | 110 | 113 |
| Lub oil Pressures | 0.45-0.6 | 0.8 | 0.1 | 0.12 |
| Engine power output (kilowatt) | 100-350KW | 240KW | 400KW | 440KW |

The weight input in Figure 2a shows an 8-by-8 two-dimensional map of 100 neurons during the training. The colour variation in the map topology indicates the strength of connection between the neurons; lighter colours indicate short and strong connections while darker colours indicate distant and weak connections. Similarity, the difference in pattern colours indicates how correlated the data cluster are to one another. Accordingly, the cluster weights of Exhaust Gas Temperature B-bank (EGTB) and Fresh Water Temperature B-bank (FWTB) showed a strong correlation which is not present in Fresh Water Temperature A-bank (FWTA) and FWTB. There is also a strong correlation between Power Output in Kilo Watts (KW) and Exhaust Gas Temperature A-bank (EGTA) and to an extent Lubricating Oil Temperature (LoT), therefore the 3 parameters provide a good set of health indicators for further analysis. On the other hand, the slight disparity between both EGT-A/B and FWT - A/B could be an indication of a more serious problem that operators may need to further investigate. Moreover, the fact the DGs are not able to generate beyond 60 per cent of the rated capacity could be due to over rating or dynamic in balance in the DGs. Overall, the SOM neighbourhood weight distances in figure 2b, shows relatively high dimensional data with about 5 clusters as can be seen within the lower left centre having distinct clusters compare to the lower right end. In contrast the upper right is equally a different concentration of clusters, hence an indication of varying health parameters in the data that points to normal and abnormal data conditions.

*Figure 2a-Fisrt training set data*

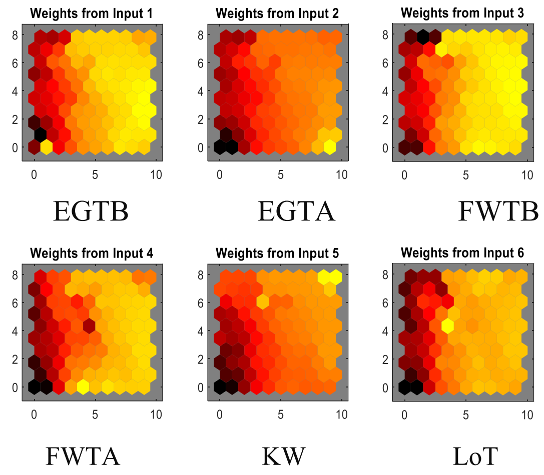
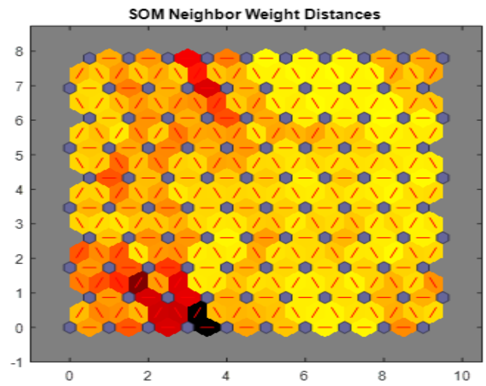



*Figure 2b- SOM Neighbour Weight Distance*




It further points to the variation presented in table 7, in that the OEM values may prove too high above the normal operating range, but could be confused by different operators. Nonetheless, the fact that DG has not been operated beyond 60 percent rated output means that at 50 % output which is about 200KW, the DGs health parameters are already at maximum load capacity. In this regard the darker clusters which indicates weak connections are indication of abnormal readings within the data. Hence this could the reason why, the SOM Neighbour weight distance were heterogeneous and provides a useful indication on degradation in DG performance.

## 5. CONCLUSIONS AND FUTURE WORK

In this paper a methodology combining modified approach of using FMECA RPN and ANN SOM to identify mission critical failure event and related as well as data clustering for anomaly dictation was presented using of Maintenance repair and overhaul data from a set of DGs onboard an OPV. A survey to get expert opinion was conducted to produce the criticality, severity and likelihood scores therefore giving a strong credibility to obtained scores. In this regard a number of mission critical components and failure events were identified. A further analysis to investigate DGs health parameters based on hourly log recordings was conducted using ANN SOM. The clustering analysis was conducted using 6 out of 10 parameters collected from the DGs. The SOM neighbourhood weight distance indicates a heterogenous data distribution showing about 5 distinct clusters that can be useful for future degradation and diagnostics analysis. Therefore, in this research, a method of using expert knowledge was implemented to conduct FMECA that was used to identify mission critical components on a DG. The cluster analysis with ANN SOM provided key insight into machinery health parameters that revealed some sharp contrasts between the exhaust gas temperature of A and B banks. Conversely a strong correlation in the features of KW, LoT and EGTA was identified which can be used for further analysis of the DG health parameters. Accordingly, it can be gleaned from the FMECA results that the mission critical components are those influence by high temperature conditions.

In this regard future research will focus on identifying clusters and clearly mapping out the data point they represent. The outcome of mission criticality analysis will be used as input for a maintenance decision making analysis that can help prioritise spare parts holding onboard and shape future procurement choices. FMECA and ANN-SOM has proven to be a good combination of tools for reliability and machinery health analysis in the context of this research and engineering field in general. Therefore, future research direction will take a look into ANN-SOM application for performance degradation and fault classification, while the FMECA analysis will be used for decisions support analysis using another tool. Moving forward this research has provided the data input for implementing machinery health condition monitoring and reliability analysis platform for onboard system and equipment with a focus on failure events and component criticality.

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