Modeling Maintenance Strategies Based on Dynamic Methodologies

Suzana Lampreia[1[CE1B-1D69-E6FD]], Valter Vairinhos[1[001B-D830-AD91]], Teresa Morgado[1,2,3[3910-F155-79D2]] and Victor Lobo[1,4[3910-F155-79D2]]

[1] CINAV – Portuguese Naval Academy, Base Naval de Lisboa, Alfeite-Almada, Portugal;
[2] Instituto Superior de Engenharia de Lisboa, Lisboa, Portugal;
[3] UNIDEMI, NOVA School of Science and Technology, Universidade NOVA de Lisboa;
[3] NOVA IMS, Universidade NOVA de Lisboa, Portugal;
suzanalampreia@gmail.com

Abstract. Maintenance plays a crucial role in ensuring the availability and high performance of ships. Various techniques have been developed to enhance equipment reliability while minimizing life cycle costs. This study proposes the integration of continuous condition monitoring into Failure Mode, Effects, and Criticality Analysis (FMECA) to optimize maintenance prioritization. Additionally, parallel analyses of other equipment will be conducted to assess the feasibility of performing their maintenance simultaneously, leveraging maintenance opportunities in a dynamic concept. Focusing on an internal combustion engine, the condition monitoring parameters considered include vibration, thermography, temperature, maintenance records, and component wear state. The primary objective is to demonstrate that integrating condition monitoring with FMECA can improve maintenance efficiency, ultimately contributing to a more sustainable ship life cycle.

Keywords: Maintenance, Condition Control, FMECA, Dynamic.

1 Introduction

Dynamic maintenance is an emerging, flexible, and data-driven strategy for maintaining complex systems [1], such as ships. Unlike traditional approaches, this method adapts maintenance priorities over time based on the degradation patterns of components and environmental or operational conditions.

For the result of this study is expected to maximize operational availability while minimizing downtime of ships. This can be achieved through predictive algorithms [2] or by applying Failure Modes, Effects, and Criticality Analysis (FMECA).

To accomplish this aims it will be applied a FMECA to planned maintenance plan to a diesel propulsion engine of a ship, and to test the opportunity of maintenance it will also be applied to an air compressor. Then condition control terms will be allied to

FMECA, and the threat environment. According to the achieved results the risk levels will be defined.

2 Dynamic Maintenance Techniques Concepts

Dynamic maintenance models continuously analyse data streams to estimate probabilistic failure rates and apply these insights via condition-based or predictive maintenance strategies. These models are significantly more efficient than conventional time-based maintenance policies [3][4]. By integrating data from multiple sources, including sensors and logged operational events, it becomes possible to detect correlations and anticipate potential failures earlier. Such data management forms a foundation for implementing a truly dynamic maintenance framework [5].

2.1 Maintenance management with data driven

The development of a FMECA involves two main stages: first, constructing a Failure Modes and Effects Analysis (FMEA), and second, performing a criticality analysis. This methodology was chosen for the present investigation due to its capacity to enhance risk awareness and support failure prevention.

A fuzzy logic system integrated with FMECA has been proposed as an Artificial Intelligent-based (AI-based) approach for risk assessment in ship propulsion systems [6]. In the present study only the traditional FMECA will be applied.

The FMECA methodology aids in identifying potential failure risks in equipment and systems, thereby informing future design improvements [7]. It has also been employed to define maintenance intervals for naval radar systems, using reliability metrics and the cost-benefit ratio to determine optimal replacement periods for critical components [8]. Moreover, FMECA contributes directly to risk-based maintenance management [9].

A standard FMECA process typically includes the following six steps [10]:

a. Transfer relevant data from the FMEA to the FMECA framework;
b. Classify failure effects according to severity;
c. Calculate criticality indexes;
d. Rank failure modes by criticality and identify high-risk items;
e. Define mitigation actions and document residual risks with justification;
f. Monitor the implementation and effectiveness of corrective measures.

The calculus of FMECA can be made with equation nr 1 [10]. Where S is the severity, O the occurrence and D the detection.

$$FMECA=S*O*D \tag{1}$$

The equation nr 1 when integrated with condition control parameters may enhance the results. That will be developed in section nr 3.

2.2 Dynamic Maintenance in Ships

For a maintenance dynamic concept, we suggest the use of FMECA but also Condition control data.

To treat condition control data, such as lubricant oil thermodynamic parameters, and vibration measures of the ship electromechanical equipment's it is suggested the modified short run control charts [11]. For text account, it is suggested the Bayesian method. And if chosen to apply the analysis of thermography artificial neural network may be applied for images processing.

Modified Q Chart

The short run can be used in case of lack of data, which is the case of the equipment's understudy. The Modified Q Chart (QM) is a short run chart adapted to be applicable to equipment's. The variable X is also transformed into the variable Q. The characteristic Q, considering the instant r will be [11]:

$$Q_r\left(X_r\right)=\Phi^{-1}\left(G_{r-2}\left(\sqrt{\frac{r-1}{r}}\left(\frac{X_r-\left(T_L\right)_{r-1}}{S_{r-1}}\right)\right)\right) \qquad r=4,5,\ldots \tag{2}$$

The mean and variance are:

$$\overline{X}_r=\frac{1}{r}\sum_{j=1}^{r}X_j \qquad \text{and} \qquad S_r^2=\frac{1}{r-1}\sum_{j=1}^{r}\left(X_j-\overline{X}_r\right)^2 \tag{3}$$

In this equations (2) and (3), X_r are the observation in instant r and $\left(T_L\right)_{r-1}$ are the vibration limit $\left(T_L\right)_r=\left(T_L\right)_N-3\sigma_{r-1}$, $\left(T_L\right)_N$ is the limit defined by the manufacturer/standard, as applicable to the monitored equipment [12]. S_{r-1} are the observation standard deviation $\left(r-1\right)$, $\Phi^{-1}(\bullet)$is the inverse functioning of Normal Distribution and $G_\nu(\bullet)$is the function *T-student* with ν freedom degree [12].

As the Q variables has Normal distribution, the charts limits, considering de detection of maximum values, are:

$$LSC_Q=3 \qquad LIC_Q=2.5 \qquad LC_Q=0$$

Accounting text

For the accountability and treatment of words occurrence, many statistics procedures may be applied. Bayesian methods may be used as an inference technique, considering that many studies in the maintenance refer these methodologies being applied to monitoring systems associated with condition-based maintenance, for example in military environment, including with the aim of reducing accidents in USA Navy aviation [13].

Bayesian methods can be used to analyse text data considering its classification into categories such as area of study, based on the probability of each category given the text and previous knowledge, can also be used to generate text from data, extract information from text, and compare text. All of these processes depend on the probability of each component, given the text and your knowledge [14].

Bayesian algorithms are statistical methods that use Bayes' theorem to update the probability of a hypothesis as more evidence or information becomes available. These algorithms are widely used in various areas, such as machine learning, statistics, spam analysis and artificial intelligence, due to their ability to deal with uncertainty and make predictions based on historical data [14].

Bayes Theorem Bayes is the basis of Bayesian algorithms and establishes a relationship between the probability of an event and the probability of another related event. It can be expressed in the formula P(H|E) = P(E|H) * P(H) / P(E), where P(H|E) is the probability of hypothesis H being true given event E, P(E|H) is the probability of event E occurring given that H is true, P(H) is the initial probability of the hypothesis, and P(E) is the probability of event E. [14].

Thermography – Images treatment

We also suggest treating the images of thermography to the equipment's, artificial neural network.

Deep learning may be used in thermography data collection analyses and learn images resulting in new techniques of image treatment [15].

A Deep Neural Network (DNN) is a type of artificial neural network (ANN) designed to clone the way the human brain processes information. It consists of various interconnected nodes and can also be linked with other networks, Fig. 1 [16].

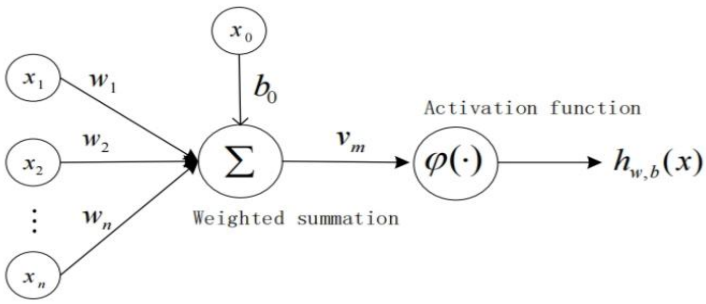

Fig. 1. Neuron structure (Source: adapted from (Song & Chen, 2022).

In the input signals X_i, Fig. 1, "each connection represents an input signal, and each input letter x_i multiplied by the connection weight w_i is a stimulus quantity for the neuron." [16]. For the present study only the account of some words in text were considered.

For reasons of limitation, and facing the existing lack of data this will not be considered in the calculus of the present study or more developed, although it is a parameter of the calculus equation.

3 Methodology

After various simulations and test of the calculus equation for FMECA-CC, considering the state of the art, and the objective of integrate condition control data it was achieved equation nr 4. Where Sm is the mean of a five considered severities (Security Severity, Environment Severity, Equipment Severity, Severity on People and Operational Severity), O is the Occurrence and D the detection. LN if the logarithmical function which is included for reason of dimension results.

$$FMECA\text{-}CC= Sm*O*D* LN[(CCV+CCT+CCP+CCTex)/5*T] \qquad (4)$$

The methodology (Fig. 2) that it is proposed begin with the choice of the equipment's to implement FMECA-CC (nr 1), then apply a FMEA immediately follow by a Critically Analysis (nr2). To validate the responses of the investigate the FMECA calculus should be done by other experts, and to that it is called humanize the responses (nr 3). Then accordingly the existing data the control condition parameters to be integrated are chosen (nr 4). The limits for intervention (nr 5). The limits should be validated with some tests and simulations (nr 6). Analysis of results should be done to appreciate FMECA-CC performance (nr 7), if the performance is not good it should return to step nr 2, if the performance is good, it continuous to step nr 8. Define the dependency of maintenance between equipment's and do some simulations (nr 8). In step nr 9 the performance of the FMECA-CC that integrate various equipment´s are analysed, if the performance it is bad it returns to step 8, if it is good it passes to step nr 10. In step nr 10 the connection and dependency of equipment's are fixed. Then for the others equipment´s the parameters of condition control should be defined (nr 11). On step nr 12 the FMECA-CC are operationalized for a continuous and online monitoring. In step nr 13 the results are evaluated, and if they are not reliable it returns to step nr 8, it it is good the online and continuous monitoring begin (nr 14).

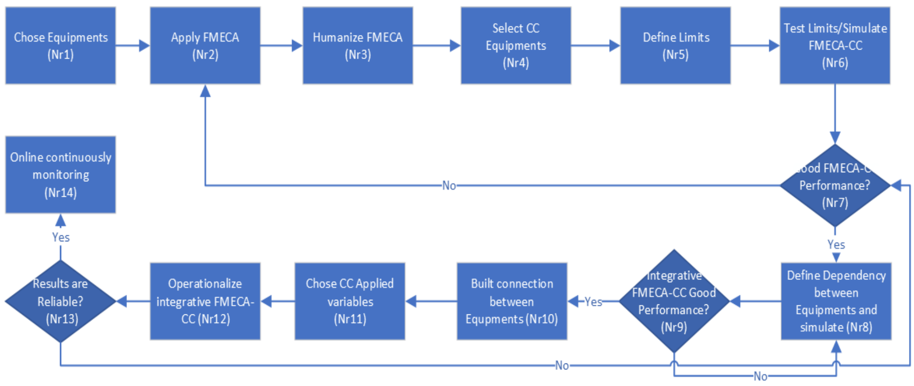

Fig. 2. FMECA-CC Methodology.

To integrate the various data processing methodologies, processing of vibration data and thermodynamic parameters will be with short run control charts, thermography with neural networks, text control in databases with text counting methods, the individual results of each of these methodologies were distributed by valuation in criteria so that they could be combined with the values calculated in FMECA-CC.

In Table nr 1 are present the considerate criteria for severities, occurrence and for detection.

Table 1. Criteria of Severities, Occurrence and Detection. Criteria for Severity, Occurrence and Detection, Security Severity (S_S), Environment Severity (S_E), Equipment Severity (S_{Equ}), Severity on People (S_P), Operational Severity (S_O), Occurrence (O) and Detection (D)

Value Attribution	$S_S/S_E/S_{Equ}/S_P/S_O$	O	D
0,1	Without impact	Occurred more than 10 years ago	Easy detection
1	Low impact	It occurred between 5 and 10 years ago	Detection difficulty medium low
2	Medium impact	Occurred less than 5 years ago	Medium difficulty detection
3	Severe impact	Occurred less than 1 year ago	Detection difficulty medium high
4	Inoperational ship	Occurred less than 6 months ago	Extremely high difficulty detection
5	Impact in the ship platform safety	Permanent	Not detectable (until something goes wrong

In Table nr 2, the criteria for the condition control data are defined.

Table 2. Criteria to condition control data, vibration, thermography, oil pressure or temperature and text detection.

Value Attribution	Vibration (CCV)	Thermography (CCT)	Operating Parameters (Temperatures or Pressures) (CCP)	Text Detection about engine and corrective maintenance (CCText)
1	Low level	Low level (no difference)	Low level	No occurrences in the last 5 years
2	Low medium level (below alert level)	Low medium level (1º - 4ºC difference from normal)	Low medium level	Occurred once in the last 5 years
3	Average level (on the alert level)	Average level (4º - 15ºC difference from normal)	Medium level	Occurred between 2 and 5 times in the last 5 years
4	Medium high level (between alert level and alarm level)	Medium high level (difference 15ºC and maintains)	High medium level	Occurred 5 to 10 times in the last 5 years
5	High level (difference >15ºC from normal)	High level (difference >15ºC from normal)	High level	Occurred more than 10 times in the last 5 years

Other considered parameter in FMECA-CC is the Treat Status (T), considering in the slope that a high treat level increases the value of FMECA-CC, because the equipment's high-performance response is needed in an uncertain security environment.

Table 3. Criteria of Threat

Value Attribution	Treat Status	Treat Occurrence
1	No threat	Without Treat
2	Slight threat	Only Treat and Bluff
3	Medium threat	Cyber Attack
4	High medium threat	Communications and logistic interruption
5	Imminent threat	Physical damage from bombing/Explosion

In Table 4 it can be observed the stablished limits for FMECA-CC.

Table 4. Risk results – FMECA -CC

Linguistic term (Risk level)	Abbreviation	Description	Classification
Not critical	Nc	Risk is totally controlled	[0, 19]
Low criticality	Lc	Risk is controlled	[20, 49]
Semicritical	Sc	There is a little preoccupation about the equipment and system state	[50, 159]
Critical	C	There are some preoccupations about the critic equipment/system situation	[160, 250]

Very critical	Vc	The equipment/system are in a very critical situation	[251, 402.36]

4 Case Study – FMECA-CC in Ships Equipment

Considering the defined methodology, the equipment's for study were chosen. The chosen equipment´s were a diesel propulsion system and an air compressor.

The propulsion engines are the centre of the study, and considering diesel engine state it may influence the air compressor maintenance, on a basis of maintenance opportunity.

Then it was defined a FMEA based on the maintenance plan defined for the diesel propulsion engine (Table 5), and applied the critically analysis (Table 6)

Table 5. FMEA propulsion engine

Nr	Maintenance Activity	Potential Failure Mode	Failure Cause	Failure Effect	How detect/detection
1	Navigating, check the colour of the evacuation gases, condensation, obstructions, etc.	Inappropriate gas color	Inadequate fuel mixture/Valves out of tune	Contamination of lubricating oil, risk of explosion/fire	Method of observing gases outside
2	Change lubrication oil	Non-normal parameters - water > 0.2%	Contaminated oil due to improper operation or lack of replacement	Grip	Physicochemical analysis, presence of filings
3	Lubrication of lubricating grease point	Corrosion	Accelerated material degradation	Material fracture	Visual inspection

For the control condition data from diesel engine the CCT will not be included, because there is no data. To FMECA-CC calculus it was applied equation nr 4. The author applied FMECA, and made available the table for collect opinion of other engineers to validate the data. So FMECA-H, it is considered a Humanized FMECA with integrated responses, i.e. it was used the mean of each response of the activity critical analysis.

In Table 6 are represented the results for FMECA-H without the condition control parameters and the results of FMECA-H_CC.

Table 6. Extract results for diesel propulsion engine FMECA-H_CC (FMEA table 5) (values rounded to the nearest tenth)

Nr	Maintenance Activity	Sméd	O	D	FMECA-H	CCV	CCP	CCTex	Ts	FMECA-H_CC
1	Navigating, check the colour of the evacuation gases, condensation, obstructions, etc.	2,7	3,0	4,2	20	2,0	1,0	3,0	2,0	46,3
2	Change lubrication oil	1,9	3,4	2,8	30,7	2,0	1,0	3,0	2,0	27,8
3	Lubrication of lubricating grease point	2,1	3	2,4	17,6	2,0	1,0	3,0	2,0	24,5

The results in Table 6 shows that the integration of condition control data it made it more sensible. For the CCV, CCP, CCText and Ts the result values are considered the same for all maintenance activity. All the results for diesel engine registered a low criticality.

Table 7. FMEA of air compressor

Nr	Maintenance Activity	Potential Failure Mode	Failure Cause	Failure Effect	How detect/detection
1	Clean air filter - Perform every 1000 hours of operation	Filter with impurities	Lack of intake filter replacement, high number of suspended particles	Entry of impurities into the compressor	Clogged filter, low compression pressure
2	Cleaning the filter between the compressor and the charging reservoir	Impurities in the bottle	Lack of filter replacement, high number of suspended particles	Compressed air bottle degradation	Method of observing the outside of the bottle
3	Oil change	Oil outside normal parameters/contaminated	Failure to replace the filter, high number of suspended particles, clogged filter, malfunction	Air compressor degradation	Compressor takes longer to load compressed air bottles. Lubrication oil analysis.

The considered data from condition control for the air compressor are the account of maintenance occurrence (CCText).

Table 8. Extract of FMECA-CC (FMEA table 7) results for air compressor

Nr	Maintenance Activity	Sméd	O	D	FMECA-H	CCTex	Treat Status	FMECA-H_CC
1	Clean air filter - Perform every 1000 hours of operation	2,7	4,2	3,2	35,9	3,0	2,0	64,2
2	Cleaning the filter between the compressor and the charging reservoir	2,7	3,2	2,8	20,88	3,0	2,0	37,4
3	Oil change	2,3	3,4	3,6	28,5	3,0	2,0	51

The FMECA-H_CC for the air compressor registered in maintenance activity nr 1 and nr 3 are semicritical, and nr 2 have low criticality.

It can be observed that both for the diesel propulsion engine and for air compressor the FMECA-H-CC as more sensitivity than FMECA-H. the control condition may enhance the results of FMECA-H if the monitoring is continuously and online.

According to the results the diesel propulsion engine, can continue operating under supervision but without the need of intervention. For the case of the air compressor, it should be implemented some measures like vibration measure, thermodynamic parameters analysis to eventually detect any anomaly.

If the diesel engine needed intervention as well as the air compressor the intervention of both should be considered.

5 Conclusion

After a FMECA is build it should be validated with responses from other experts.

The diesel propulsion engine chosen for study is probably in a good state. The air compressor needs more accurate monitoring, so its data can be integrated in the FMECA-H-CC concept.

A modified FMECA with an allied condition control parameters may be applied to flexible and integrate information for a dynamic maintenance based on online data.

To integrate data from condition control in FMECA, the results of the various parameters, after apply the appliable techniques (short run control charts, text detection, artificial neural networks), it should be categorized, so that the various forms of approach communicate with the same language.

For future work, the action to take after the risk level is determined should be developed to support and optimize maintenance managers decision.

References

1. Global, I.: *IGI Global - Publisher of Timely Knowledge.* Available at: https://www.igi-global.com/dictionary/dynamic-maintenance-chinagrid-support-platform/8509, last accessed 2025/03/11.
2. Kaiser, K., Gebraeel, N.: Predictive Maintenance Management Using Sensor-Based Degradation Models. *IEEE Transactions on System, Man, and Cybernetics – Part A: Systems and Humans,* 39(4), 840-849 (2009).
3. Diamond, S., Marfatia, A.: *Predictive Maintenance for Dummies.* IBM Limited Edition ed. Hoboken, New Jersey: John Wiley & Sons, Inc (2013).
4. Ben-Daya, M., Duffuaa, S., Knezevic, J., Ait-Kadi, D.: *Handbook of Maintenance Management and Engineering.* Springer-Verlag London Limited 2009 ed. London: Springer (2009).
5. Li, G., Liu, B., Qin, S., Zhou, D.: *Dynamic Latent Variable Modeling for Statistical Process Monitoring.*. s.l., s.n., 12886-12891 (2011).
6. Ahmed, S., Li, T. & Wu, S.: FMECA Study of Cruise Ship Pod Propulsion System Basedon Real-Ship Accident Using Type-2 Fuzzy Expert System. Shanghai, ISOPE (2022).
7. Nadjafi, M., Naseh, H., Koochaki, M.: FMECA-based Risk Assessment in MonoPropellant Hydrazine Propulsion System. *Journal of Space Scioence and Technology* (2023).
8. Suharjo, B., Suharyo, O., Bandono, A.: Failure Mode Effect and Critically Analysis (FMECA) for Determination Time Interval Replacement of Critical Components in Warship Radar. *Journal of Theoretical and Applied Information Tecnology,* 29(10), 2861-2870 (2019).
9. Khan, S., Iwnicki, S., Tucker, G., Louadah, H.: Risk Informed Quantitative Probabilistic FMECA with Monte Carlo Simulation of Human and Organizational Factors for Improved DecisionMaking. [Online] Available at: https://www.researchgate.net/publication/369506911_Risk_Informed_Quantitative_Probabilistic_FMECA_with_Monte_Carlo_Simulation_of_Human_and_Organizational_Factors_for_Improved_Decision_Making?channel=doi&linkId=641ecf6766f8522c38d291a2&showFulltext=true, Last accessed 2023/05/07.
10. Stamatis, D.: Risk management using failure mode and effect analysis. Wisconsin: ASQ - Quality Press (2019).

11. Lampreia, S.: *Manutenção Baseada no Estado de Condição. Uma Aboradgem Utilizando Cartas de Controlo Modificadas.* Monte da Caparica: Faculdade de ciências e Tecnologia da Universidade nova de Lisboa (2013).
12. Pereira, Z., Requeijo, J.: *Qualidade: Planeamento e Controlo Estatístico de Processos* (Quality: Planning and Statistical Process Control), FCT/UNL, Prefácio, Lisboa (2012).
13. Navy, D. o. t., 2021. *Ships´ 3-M Manual.* Navseainst 4790.8D ed. s.l.:Navsea - Naval Sea Systems Command.
14. Youssef, Y.: Bayes theorem and real-life applications. PhD Studies of Cairo University, 2022.
15. Ramesh, V., 2017. A Review on Application of Deep Learning in Thermography. *International Journal of Engineering and Management Research,* 7(3), 489-493.
16. Song, J., Chen, Y.: A Study on the Application and the Advancement of Deep Neural Network Algorithm. *Journal of Physics: Conference Series,* 2146(012001) (2022).