Risk and Reliability Analysis Tool Development for Ship Machinery Maintenance

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Abstract

Concerning the successful business competence, strategic planning should be enhanced considering assets availability by involving maintenance and reliability operational aspects. The INCASS (Inspection Capabilities for Enhanced Ship Safety) FP7 EU funded research project aims to tackle the issue of ship inspection, identification of high-risk ships, providing access to information related to ship surveys and incorporate enhanced and harmonized cooperation of maritime stakeholders in order to avoid ship accidents, promote maritime safety and protect the environment. The current research consists of machinery and equipment specifications and stakeholders' data requirements. Focusing on the methodology perspective, a Machinery Risk Analysis (MRA) model is introduced. All progress and methodology development takes place in Java programming language. Overall, the outcomes of this study demonstrate the reliability performance of marine machinery components. Future development include dynamic failure rate variation through time, probabilistic model's sensitivity analysis and components' and systems' interdependencies in a user-friendly Graphical User Interface (GUI) design.

Keywords

Maintenance; reliability; condition monitoring; probability; machinery, Java programming.

1. Introduction

The business effectiveness and efficiency are influenced by factors such as time, financial restraints, technology and innovation, quality, reliability and information management (Madu, 2000). With the intention of competing successfully, companies should enhance their inspection, maintenance and reliability systems, which need to be considered during the organization's strategic planning. In this respect, several definitions are provided for both maintenance and reliability terms by various authors summarizing the notion that maintenance is a set of technical, administrative and managerial actions targeting to retain or restore the state of a system to function as required (Mobley et al., 2008). Furthermore nowadays, maintenance is encountered as an operational method, which can be employed both as a profit generating process and a cost reduction budget center through an enhanced Operation and Maintenance (O&M) strategy.

Hence, this paper aims to present the Research and Development (R&D) of the Machinery Risk Analysis (MRA) methodology as suggested by INCASS (Inspection Capabilities for Enhanced Ship Safety) FP7 EU funded project. First of all, Section 1 introduces the paper's scope and motivation of research. Section 2 refers to Research Background which involves the exploration of Condition Based Maintenance (CBM) methodology and well known Condition Monitoring (CM) technologies and tools. In Section 3 is presented the suggested Machinery Risk Analysis (MRA) methodology. Section 4 demonstrates the MRA case study, followed by Section 5 that the results of the case study are presented. In Section 6 are discussed the results and future work for the MRA development. Whereas, Section 7 concludes the research findings.

2. Research Background

From business viewpoint in shipping industry, maintenance structure is transformed from budget gain perspective to investment for continuous and reliable asset service. Whereas from operational standpoint, it is restructured from reactive to proactive actions, involving more control and information of the considered machinery and equipment. This section briefly explores the need for automated maintenance control and minimization of human involvement in maintenance actions where operational conditions allow that. Moreover, the latest CBM methodology and CM techniques and tools are presented by introducing the latest notion of multi-component CM. The presented technologies and tools are evaluated and the selected ones will be implemented in the proposed INCASS MRA methodology.

2.1 Human Error and Maintenance Control

Automated inspection and maintenance methodologies are developed aiming to achieve higher level of availability and reliability by reducing operational costs and risk of damage due to human error. A literature review by Dhillon and Liu (2006) focusing on human error impact on applications of maintenance highlights that a large amount of human errors take place during maintenance operations.

Asadzadeh and Azadeh (2014) propose an integrated systemic model for the incorporation of human reliability model with CBM optimization. The functional resonance concept examines human-induced failure scenarios emergent from erroneous functional dependencies. On the other hand, Abbassi et al. (2015) present an integrated method for Human Error Probability (HEP) assessment during the maintenance of offshore facilities. They combined the Success Likelihood Index Methods (SLIM) with the Technique of Human Error Rate Prediction (THERP). Additionally, Noroozi et al. (2013) demonstrate the key role of human error in risk analysis by developing an application to pre-and post-pump maintenance operations. As it can be seen, the most recent research presents the tendency to control human error in inspection and maintenance procedures. Moreover, Probabilistic Risk Assessment (PRA) models are developed by considering human error scenarios for specific occasions. Thus, the need for computerized CM methodologies appears, which will tend to minimize unnecessary human's involvement during acceptable operational machinery conditions.

2.2 Condition Based Maintenance (CBM)

Previous research studies show that proactive maintenance strategies are developed by employing various tools. A predictive maintenance strategy utilizing Failure Modes, Effects and Criticality Analysis (FMECA) and Fault Tree Analysis (FTA) is presented by Lazakis et al. (2010). The model aims to upgrade the existing ship maintenance regime to an overall strategy including technological advances and Decision Support System (DSS) by combining existing ship operational and maintenance tasks with the advances stemming from new applied techniques. CBM is the latest and under continuous development methodology. The scope of CBM, which includes fault diagnosis and prognosis, is related to the detection of upcoming failures before they occur. CBM intends to enhance machine's availability, reliability, efficiency and safety by reducing maintenance costs through controlled spare part inventories (Mechefske, 2005). In an industrial perspective, SKF (2012) supports that CBM aims at the understanding of risks and predetermination of strategic actions, leading to reliability and operational cost reduction. Thus, CBM is maintenance task-centered than failure-centered. Moreover, Tsang et al. (2006) suggest a data structure leading to decision analysis according to machinery condition, proposing a method for data-driven CBM achieving data preparation, model assessment, decision making and sensitivity analysis.

2.3 Condition Monitoring (CM) Technologies/Tools

CBM is the latest maintenance methodology which can be applied through different CM technologies and tools. The most known CM technologies are grouped among vibration, noise, thermography and oil analysis monitoring, which are presented next. This CM tool evaluation stage initiates the INCASS MRA tool investigation by leading to selection.

2.3.1 Vibration Monitoring

Vibration measurement is a key element in any predictive maintenance program. According to Al-Najjar (1996), the implementation of vibration-based maintenance offers early indications of machinery malfunctions involving parameters such as rotational speed, loading frequency, environmental conditions and material state. The most common faults detectable by vibration monitoring are unbalance of rotating machine parts, shaft misalignment, damaged gear teeth, excess sleeve bearing wear, excessive gaps, defects in rolling element bearings and problems in the rotor and stator of electrical engines (Monition, 2014).

2.3.2 Acoustic and Ultrasonic Monitoring

One of the first symptoms of mechanical or electrical fault is the increase of "noise" generated by machinery parts. Most parts emit consistent sound patterns under normal operating conditions. These sonic signatures can be defined and recognized, while changes in these signatures can be also identified as components begin to wear or deteriorate. When a leak is present in a system, an increase of the ultrasound measurement is observed. The ultrasonic detector produces an alarm when there is a deviation from the normal level of background noise (commonly 6dB, even though it will depend on the minimum leak to be detected) (INCASS, 2014a).

Ultrasonic detection is fast and cost efficient compared to temperature, vibration and oil analysis as it does not require sensor installation on the specified components that are monitored (Kim and Lee, 2009). The importance of ultrasonic CM is also suggested by IACS as presented in the Unified Requirements (UR) and Procedural Requirements (PR) for Ultrasonic Thickness Measurements (UTM) (IACS, 2004). In general, acoustic emission technology provides early indication of the onset of degraded strength in metal components. Some of the sources of acoustic emissions in metals are material cracks, plastic deformation development and fracturing.

2.3.3 Thermography

Thermography measures the temperature in any part of machinery and equipment so as to detect any change in the operating temperature thus indicating fault development. Bagavathiappan et al. (2013) support that Infrared Thermography (IRT) is one of the most accepted CM tools. Due to the non-contact function, it is suitable for structural, machinery, electrical and material detection malfunctions. The key advantage of IRT compared to other CM tools is the real-time representation of pseudo-color coded image. It can be generated either by friction, bad contact or excessive wear, thus generating overheating or hot spots.

2.3.4 Oil Analysis/Tribology

Oil analysis is achieved through laboratory concentration analysis in lubricant debris analysis which deals with shape, size, composition of wear particles and lubricant degradation analysis for physical and chemical characteristics (Jiang and Yan, 2008). Lube oil analysis does not only allow to obtain information about the operating conditions, wear and contamination levels and equipment lifespan, but also enables the set-up of a condition-based lubricating program. The parameters measured in order to perform lube oil analysis are summarized as kinematic viscosity, content of water, lube oil acid number, particle count, detection of insoluble and emission spectrometry, absorption spectrometry and ferrography studies.

2.3.5 Data Acquisition Tool Options

This part of research will figure out the necessity and applicability of continuous online monitoring or periodic offline according to the available sensor options. Various sensors and devices are found available in market and their specifications have to be explored. As part of INCASS project, the machinery condition will be assessed on a real-time continuous basis onboard ships. In order to achieve this, sensors will be installed for data collection. The gathered data will be used within the MRA methodology. Hence, it is essential to identify and classify the sensor types for each of the already presented CM technologies. The sensors' characteristics are specified in terms of the output record as well as devices' sensitivity, accuracy on specific operational conditions (i.e. temperature range) and their cost.

The most applicable CM tool is the vibration analysis. Hence, the sensors' range includes a wide variation of equipment. The vibration sensors are categorized among displacement, velocity and acceleration. Each type denotes the output record. However, for particular monitoring conditions, high temperature piezoelectric and triaxial sensors are introduced into the market.

On the other hand, noise monitoring and thermal imaging consist of simpler sensor ranges compared to vibration monitoring. Thermal imaging involves thermal cameras and thermometers. Whereas, acoustic emissions are recorded using ultrasonic hand-held equipment or online installed ultrasonic sensors and portable decibel meters.

3. Suggested MRA Methodology

INCASS Machinery Risk Analysis (MRA) methodology is developed in order to be applied on three different merchant ship types. The three ship types are tanker, bulk carrier and container ship. Hence, the MRA methodology is flexible to be adjusted in order to fulfill all requirements and specifications that each ship type. In this section, the MRA methodology will be presented by demonstrating input data flows and MRA process diagram.

3.1 Machinery Risk Analysis (MRA) Methodology

In this section, the MRA methodology is presented. The data flow is demonstrated as well as the selected data processing and modelling. The graphical demonstration of machinery and equipment modelling and analysis data flow is displayed in Fig. 1. It consists of three stages, the data acquisition and processing, the reliability model and the Decision Support System (DSS). All INCASS MRA and DSS development takes place in Java Object Oriented Programming (OOP) language.

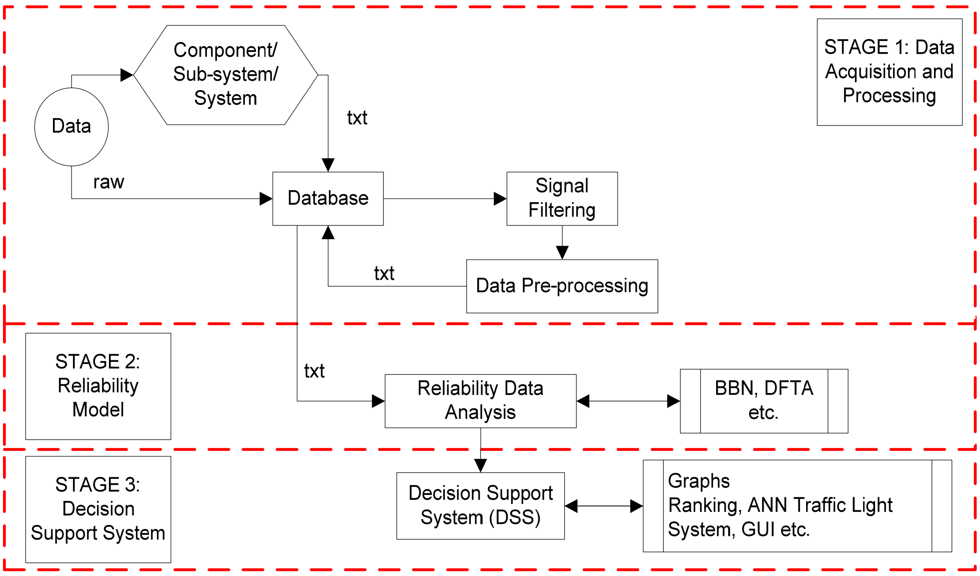

Fig. 1: Machinery & equipment modelling & analysis data flow

The first stage of the MRA methodology gathers data and processes them. Data are categorized among historical, expert and real time monitoring. In Fig. 1 it is shown as raw data (unprocessed information collected from provided source i.e. experts and onboard sensors), that are transformed to data inputs for the MRA methodology. The collected data are classified in component, sub-system and main system levels.

All gained information is stored in the database utilizing 'text' (.txt) files. This format file is selected as files are small in size that can be transferred from onboard to onshore by requiring low amount of data. The following phase involves the real monitoring data/signal processing. At this phase, signals are filtered and unnecessary information gathered from the environment of operation is removed. The following critical phase is the transformation of physical sensorial measurements to reliability inputs.

In Stage 2 'Reliability Model', the processed reliability input data from the database are introduced. The risk and reliability model employs a network arrangement similar to the Bayesian Belief Networks (BBNs). This selection allows the probabilistic and mathematical modelling by considering actual functional relations and system/sub-system/component interdependencies.

The third stage of the INCASS model implements Decision Support System (DSS) aspects. The DSS methodology is divided into two sections. The first one is utilized for local (onboard) and short term decision making, whereas the second one is used onshore (global) for longer term predictions and decision features.

The INCASS methodology so far demonstrates the procedures on the data flow level. Hence, it presents the analysis from an input manipulation perspective. In the following figure (Fig. 2), the analysis takes place on the specific MRA process and modelling level.

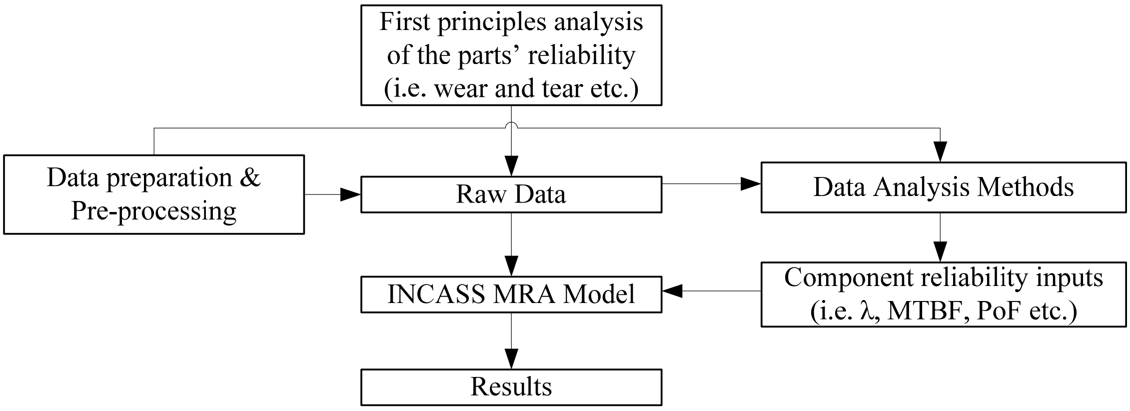

Fig. 2: Machinery Risk Analysis (MRA) process diagram

As it can be seen, INCASS project introduces two main tools the MRA and DSS. On the data flow level, the description incorporates data manipulation from the data gathering phase up to decision making. On the other hand, MRA involves the risk and reliability analysis and processes. At the process level, various methods are employed for the condition and failure diagnostics as well as signal pattern recognition of the received and pre-processed data inputs. The filtered/processed data are transformed into component reliability inputs such as failure rates (λ), Mean Time Between Failures (MTBF) and Probability of Failure (PoF).

Lastly, the INCASS MRA model aims to predict the future condition of the under investigation ship machinery and equipment. This prognostic feature tends to forecast the failure occurrence (failure modes and events), the time that this failure will take place as well as the components, sub-systems and systems that will be affected.

4. Machinery Risk Analysis (MRA) Case Study

After exploring in the previous sections the latest CBM methodology and the most applicable CM technologies, the MRA methodology was presented focusing on aspects that discovered in literature as well as innovations that will be implemented. This section aims to classify and select ship machinery and equipment that MRA methodology will be applied on. Furthermore, the INCASS stakeholders' requirements for the machinery and equipment selection are considered and presented. Additionally, the MRA's input data type classification will be demonstrated. Lastly, a MRA case study is developed for marine diesel engines by applying the risk and reliability model as developed in the MRA methodology.

4.1 Machinery and Equipment Categorization and Selection

First of all, the machinery and equipment classification and selection takes place for three ship types. MRA is developed for tanker, bulk carrier and container ship.

On the initial level of machinery and equipment categorization, they are classified among operational, safety and cargo systems. From this perspective, operational systems include mechanical systems and main equipment, piping and electrical systems. These are followed by onboard safety systems, which consist of electrical emergency systems. In addition, they are considered the cargo systems that refer to the tanker ship's cargo pumps.

Furthermore, additional systems such as the Navigation and the Fire Fighting and safety equipment system were initially examined together with the Operational and Safety systems. However, it was decided to focus on machinery that are essential for the operation of each ship type.

The initial classification of the criticality level of the machinery systems and equipment was based on industry best practices and standards as well as on the operating/ running hours of such systems on board ships. For all three ship types, these critical selected main systems can be classified among the Main Engine (M/E), Turbochargers (T/C), selected critical pumps, heat exchangers, boilers, purifiers, coolers and the steering gear system.

As INCASS MRA methodology is developed, it will be validated on the three already mentioned ship types. Thus, it is important to highlight that the main selected systems are common among the ship types. However, in the case of tanker ship, they are also considered the steam powered cargo pumps.

4.2 INCASS Stakeholders Requirements

INCASS project consortium consists of a number of partners including Universities, Classification Societies as well as ship operators, managers, owners and service providers. Hence, CM requirements vary among the project stakeholders. Due to different CM necessities, the project members' requirements are assessed leading to the final machinery and equipment selection (INCASS, 2014b).

At first, the classification societies' concerns, participating in INCASS project, are examined. The role of Classification Societies is to check that safety standards of ships are met throughout surveys, inspections, tests and controls. On the other hand, ship operators, managers, owners and service providers support that major machinery breakdown leads to major/minor repair cost as well as increasing ship systems downtime. The reasons for monitoring and collecting information on ships from their viewpoint are related to environmental protection, safety of personnel onboard, compliance, class statutory requirements and reduction of business risk and cost.

As it can be summarized from the INCASS stakeholders requirements, the Classification Societies are mostly focused on the ship's functionality ensuring safety. Whereas, ship operators, managers, owners and service providers are focused on ship's operation and availability ensuring business efficiency and safety.

INCASS research intends to consider machinery and equipment for CM that all project stakeholders consider as functionally critical. The final systems that project members agreed on their operational importance ensuring all considered requirements are summarized as the Main Engine (M/E), Turbochargers (T/C), critical selected pumps (including steam powered tanker ship cargo pumps) and steering gear system.

4.3 Data Classification and Collection

MRA methodology tackles the ship machinery and equipment CM by gathering different input data from all three ship types (i.e. tanker, bulk carrier, container ship) that are considered within this research study. Failure inspection and maintenance data will be collected including input from all stakeholders. The data that will be used will originate from historical, experts and real time monitoring data that will be gathered from installed sensors onboard ships.

Firstly, historical data consist of inspection and maintenance intervals, major overhauling and unexpected maintenance actions as well as preventive maintenance data in the form of Plant Maintenance Systems (PMS). On the other hand, expert data collected consist of various types of failures and their consequences, classification societies' reports as well as inspection findings. The expert data will be used in conjunction with the historical and system-gathered data to assess the risk and safety at the machinery component and system level. The historical and expert data can be described as processed data, because they include inputs from professionals and knowledge from past operational conditions.

On the contrast, the third and critical data group is the real time monitoring data type corresponding to the onboard measuring campaign for the three ship types. Hence, in order to gather the appropriate information from the considered machinery and equipment, they are identified the parameters that can be recorded for each system and sub-system independently.

The parameters are identified for the selected machinery and equipment (i.e. Main Engine, Turbochargers, Pumps and Steering Gear System) independently. Furthermore, operational information per trip such as date, time, voyage time, ship sailing time and maneuvering time will be collected. In addition, ship sailing condition parameters will be gathered (i.e. vessel speed, direction, position etc.) as well as environmental parameters per day (i.e. weather, wind speed and direction, sea state and ambient temperature and pressure).

4.4 Machinery Risk Analysis (MRA) Application

The MRA methodology will be applied on various ship main systems. However, as collection of historical, expert and real time monitoring data is still in progress, the current MRA case study is focused on the main engine by employing only processed historical data such as failure rates (λ). This model will be expanded by including all considered main systems.

The ship main engine is widely defined in literature as the 'heart' of the vessel. This statement highlights the criticality of this system and its significance for implementing a CM tool, ensuring cost efficiency, ultimate maintenance planning, ship's performance and human, environmental and asset safety. These reasons enable the case study to be initiated for the diesel main engine.

This section aims to present the current MRA development through a case study. The existing probabilistic model involves various failures modes taken place on different sub-systems and components of a marine diesel engine.

The main engine is divided and assessed among six sub-systems such as Engine Internal and External Components, Starting, Cooling, and Lubrication and Control Monitoring systems. In this section, the case study will present, the Engine Internal and External Components sub-systems and their comprised components. It is decided to be presented these two sub-systems as they figure the component core of the entire M/E.

Data have been provided in the form of failure rates (λ) per component involved. At first, the overall λ is calculated in percentages for each component considered independently for the pre-defined failure scenarios that may occur on these components. In the next stage, the probability of occurrence of the involved failure types on each selected component is calculated. These manually prepared data are stored in notepad (.txt) files and processed via an automated coded procedure in Java programming language.

However, sensorial 'raw' collected data will be considered in future programming stages. Nevertheless, the loading and reading phase of the prepared text (notepad) files pursues to simulate the final process of user and system interaction supplying data collected from online and offline sensors while loaded on the proposed model for initiation of the CM process in a ‘raw’ format.

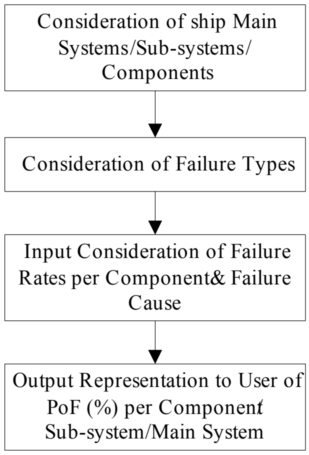

Fig. 3: MRA Study Stages

Fig. 3 presents the stages accomplished into MRA progress from data collection until results are displayed to user. Initially, the main system, sub-systems and components are specified. Data are compiled from OREDA database. Whereas, manual data preparation takes place by developing static failure rates on component level out of the provided overall failure mode occurrence. Automated computation calculations are managed for individual components, overall sub-system and final the entire marine diesel engine. The results present Probability of Working and Failing (PoW and PoF respectively) states for component, sub-system and main system levels.

For the ‘Risk & Reliability Analysis’ stage the Bayes’ Theorem is implemented (Kumamoto and Henley, 1996). The various probabilities are represented by employing Directed Acyclic Graphs (DAG), where each considered probability is presented with a node and its functional relation with any other node using directed arrows (Taheri et al., 2014). This type of DAG in the case of Bayes’ Theorem is defined as Bayesian Belief Network (BBN). A typical example of a BBN display is shown in Fig. 4, where the main diesel engine system and related components are linked with the considered events (failure types) (Dikis et al., 2014).

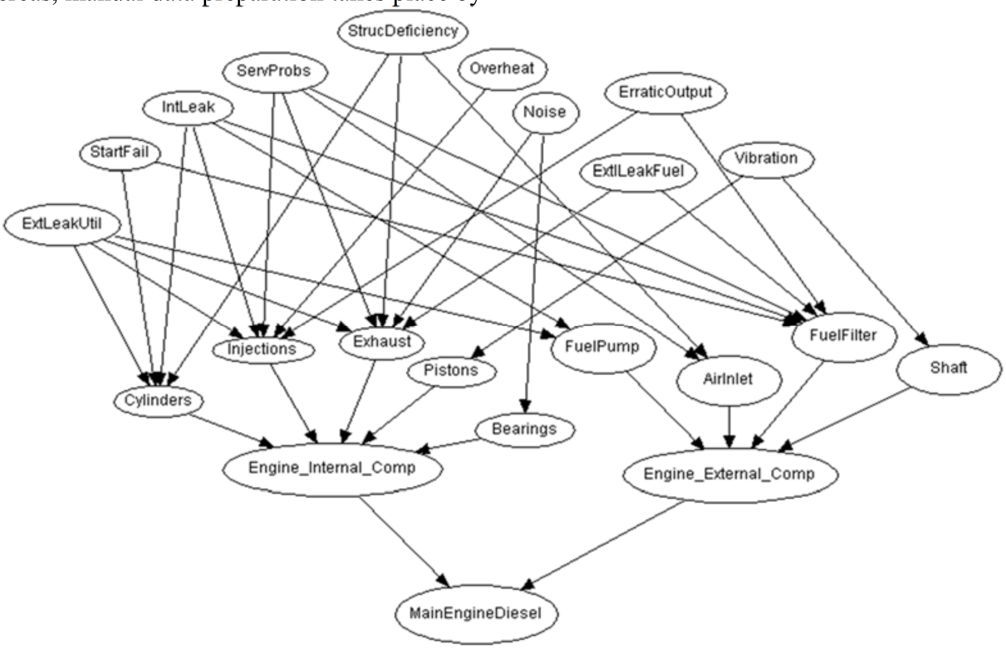

Fig. 4: Main Diesel Engine Components MRA Model

The Bayes’ Theorem can be defined as probabilistic graphical model involving conditional dependencies arranged into DAG and it is expressed in Equation 1 (Bedford and Cooke, 2001):

$$\boldsymbol{P(A|B) = \frac{P(B|A) * P(A)}{P(B)}} \tag{1}$$

Where P(A) and P(B) are the probabilities of events A and B, while A given B and B given A are conditional probabilities.

A part of the M/E system arrangement is presented in Fig. 4. Firstly, two of the major M/E sub-systems, the Engine Internal Components and Engine External, are demonstrated with nodes. The next level of nodes includes the Engine Internal Components involving items attached to the M/E block as radial bearings, cylinders, injections, exhaust and pistons. Whereas the Engine External Components consists of components such as fuel pump, fuel filter, air inlet and shaft.

The highest level of nodes in Fig. 4 presents failure types for the components as defined for the Engine Internal and External sub-systems. These failure breakdowns are listed among External Leakage Utility, Failure to Start, Internal Leakage, Minor In-Service Problems (non-specified from source), Structural Deficiency, Overhearing, Noise, Erratic Output, External Leakage of Fuel and Vibration. This model/node arrangement has been validated through experts (INCASS partners and Advisory Board members) and by utilizing the connections of the failure modes with the components from the observed input failure rates’ records as received from the data source.

$$P_1 = \begin{cases} w: 100 \\ f: \quad 0 \end{cases};$$
$$P_2 = \begin{cases} w: 100 - ft_{f1} \\ f: \quad ft_{f1} \end{cases};$$
$$P_3 = \begin{cases} w: 100 - ft_{f2} \\ f: \quad ft_{f2} \end{cases};$$
$$P_4 = \begin{cases} w: 100 - (ft_{f1} * ft_{f2}) \\ f: \quad (ft_{f1} * ft_{f2}) \end{cases};$$
$$P_5 = \begin{cases} w: 100 - ft_{f4} \\ f: \quad ft_{f4} \end{cases};$$
$$P_6 = \begin{cases} w: 100 - (ft_{f1} * ft_{f3}) \\ f: \quad (ft_{f1} * ft_{f3}) \end{cases};$$
$$P_7 = \begin{cases} w: 100 - (ft_{f2} * ft_{f3}) \\ f: \quad (ft_{f2} * ft_{f3}) \end{cases};$$
$$P_8 = \begin{cases} w: 100 - (ft_{f1} * ft_{f2} * ft_{f3}) \\ f: \quad (ft_{f1} * ft_{f2} * ft_{f3}) \end{cases};$$
$$\ldots$$
$$P_m = (ft_{f1} * ft_{f2} * ft_{f3} * \ldots * ft_{fk}) \qquad (2)$$

While, each component of the main engine is linked with a certain number of failure types (observed input data) that varies among components, a generic form expressing the failure case scenarios is presented in Equation 2. In this expression, *P* denotes the probability of survival for different failure case scenarios, where *w* shows the percentage of working probability, while *f* the remaining percentage of failing. As *ft* is indicated the failure type (i.e. noise, vibration, overheating etc.) and its subscript *f* is the probability of failure of break down scenarios. Hence, *P1* denotes the probability of working (*w*) and failing (*f*) while no failures take place. *P2* denotes the probability of working and failing while one failure type takes place (ft_{f1}) and *P3* for a different failure type (ft_{f2}). Whereas, *P4* demonstrates the probability of a component to work or fail while both failure types (ft_{f1} and ft_{f2}) occur. Equation 2 provides a generic form of this pattern by involving more failure modes for the components that require utilization of more than two failure types.

$$P(comp) = \sum_{j=1}^{m} \left(\sum_{i=1}^{k} P(ft_{f(i)}, ft_{f(j)}) \right) \qquad (3)$$

$$m = 2^k \qquad (4)$$

Equation 3 presents the generic expression of the overall probability of component, including the summation of all possible break down scenarios (*m*: total amount of failure scenarios) and the summation of all considered failure types (*k*: total amount of failure types) as the latter presented in Figure 2. In addition the relation of *m* and *k* is presented in Equation 4.

5. Machinery Risk Analysis (MRA) Results

The demonstrated results are performed through static probabilistic risk assessment modelling. The entire undertaken case study examines the probability of survival of the main engine and specified sub-systems and components. This case study presented that the Engine Internal and External Components are the most critical sub-systems involved in this system as they performed the highest PoF. Furthermore, the generic formulation of the failure case scenarios for the defined failure types per involved component is presented as shown in Equations 2 and 3. Table 1 presents the M/E and overall sub-system PoW and PoF states.

In Table 1, ‘PoW (%)’ demonstrates the probability of working state, while ‘PoF (%)’ denotes the probability of failing state. Overall the presented results show the PoW percentages of all considered sub-systems such as Lubrication, Engine Internal and External, Starting, Control and Monitoring and Cooling systems as well as the entire performance of the M/E.

Table 1: Main Engine and Sub-System PoW and PoF

System	PoW (%)	PoF (%)
Overall Main Engine	99.4126	0.5874
Lubrication System	99.9437	0.0563
Engine Internal Comp.	98.2491	1.7509
Engine External Comp.	99.4081	0.5919
Starting System	99.7152	0.2848
Control & Monitoring	99.8119	0.1881
Cooling System	99.4361	0.5639

Table 1 shows that the overall system has probability to work approximately 99.41% (Overall Main Engine). Hence, the probability the M/E to fail is approximately 0.59%. This failure rate presents the likelihood of failing in case the M/E is considered as one system. Furthermore, this presented reliability performance incorporates inputs from all considered sub-systems, components, failure modes and any mathematically probable failure case scenario.

However, in order to expand system’s PRA, the M/E is separated in six sub-systems and each of these is assessed independently as well. The PoF for these sub-systems is shown as 0.0563% for the Lubrication, 1.7509% and 0.5919% for the Engine Internal and External Components respectively, 0.2848% for the Starting, 0.1881% for the Control and Monitoring and 0.5639% for the Cooling system. Summarizing, the highest failure probability is associated with sub-systems such as the Engine and Internal and External Components. In other words, the calculated outcome provides indication for specific sub-systems that present the highest risk for failure. From practical viewpoint, the need for operational efficiency is highlighted for the sub-systems with lowest reliability performance (or highest likelihood to fail).

Moreover, the MRA development involves the reliability analysis on component level. This assessment will allow to figure out the reliability performance within each sub-system for the involved components. Hence, Table 2 provides the reliability performance of the M/E components. Table 2 demonstrates *PoW* and *PoF* on component level. The results show that the most unreliable components are the Piping performing PoF=4.29%, Valves (4.28%), Injections (3.9%) and the Start Control (3.31%).

Table 2: Component Level Failure Probabilities

Component	PoW (%)	PoF (%)
Air Inlet	97.8249	2.1751
Control Unit	99.5848	0.4152
Cooler	99.4318	0.5682
Cylinders	99.6161	0.3839
Exhaust	98.6634	1.3366
Fuel Filter	98.7409	1.2591
Fuel Pump	98.4747	1.5253
Injections	96.1086	3.8914
Level Instrument	98.1840	1.8160
Oil	98.7636	1.2364
Piping	95.7051	4.2949
Pistons	99.8408	0.1592
Pressure Instrument	98.8819	1.1181
Radial Bearings	99.9587	0.0413
Shaft	99.8408	0.1592
Speed Instrument	99.4481	0.5519
Start Control	96.6883	3.3117
Start Energy	98.7920	1.2080
Starting Unit	98.2604	1.7396
Temperature Instrument	98.5041	1.4959
Valves	95.7246	4.2754

6. MRA Discussion

In the previous section, the MRA case study results are presented. The performance of the M/E is in good overall working condition (99.41%). Whereas, a detailed Probabilistic Risk Assessment (PRA) on sub-system level indicates the Engine Internal and External Component sub-systems as the least reliable, performing 1.75% and 0.59% likelihood of failure respectively. However, the Probability of Failure (PoF) for these sub-systems is low, indicating reliable operation. On the other hand, it is demonstrated the Probability of Working (PoW) and failing on component level. The outcomes show that the most unreliable components are the Piping performing PoF=4.29%, Valves (4.28%), Injections (3.9%) and the Start Control (3.31%). According to the existing reliability performance, all sub-systems and components function on acceptable (reliable) levels. However, the lowest reliability is performed by the Engine Internal and External Component sub-systems. Whereas, in component level, the valves, injection and start control presented the most unreliable outcomes. In other words, these sub-systems and components are the most critical as they may cause failure to sub-systems or main engine system. Hence, an important parameter to be investigated is the degradation pattern and speed of deterioration.

Comparing the overall system's performance as one system and the overall system's in sub-system level analysis, it can be seen that the detailed assessment of sub-systems provides in depth and analytical performance results for the main system (i.e. main engine). In this respect, further detailed probabilistic risk assessment can be developed on component level (i.e. cylinders, pistons, bearing etc.) by comparing accuracy of results on sub-system level with component. This detailed analysis will lead to investigate the source (i.e. component) of failure, hence the initiation of sub-systems' degradation by specifying the faulty component.

The demonstrated outcomes determine the static reliability performance assessment on system, sub-system and component level for various failure modes and all mathematically probable failure case scenarios. This analysis achieves the reliability evaluation through a top-down modelling approach.

In other words, a reliability model is developed that presents the main engine's reliability performance by focusing on the source of failure existence (component level). By knowing the critical and unreliability components, a prioritization study can be developed through which suitable maintenance actions can be suggested through a bottom-up approach. This approach can deliver maintenance suggestions from component to sub-system and then to system level.

Hence, by facing issues and malfunctions on the component level and knowing the overall reliability of the main system, the enhancement of system availability, safety and reliability in operation can be achieved.

6.1 Dynamic Machinery Risk Analysis Model

This section aims to present the future plans for the progress of the probabilistic risk assessment model. The following stage of the MRA development will involve the creation of a dynamic probabilistic model. The notion of this research development is based on the concept that a system that functions will degrade through time. Therefore, a dynamic CM model can capture more successfully than a static one the degradation behavior through time and set the grounds for a fully automated methodology/tool that will monitor the system's reliability levels. At the same time, the system's condition depends on the past operational levels as well as the functional environment. Hence, inputs from historical and expert data will be combined with the dynamic Machinery Risk Analysis. Latest research demonstrates that dynamic probabilistic modelling is under development. For instance, Turan et al. (2011) propose a maintenance strategy based on criticality and reliability assessment using dynamic Fault Tree Analysis (DFTA).

Through research, it was found that dynamic probabilistic models are categorized among discrete and continuous (Fiondella and Xing, 2015). The major difference is focused on the detail of analysis with the observation time and the result density of the gained output. In the discrete modeling, CM measurements are collected in specified time intervals. The main limitation of discrete dynamic probabilistic modeling is the assumption that between two observation points the system's state remains constant/unchanged. On the other hand, continuous dynamic probabilistic modelling tries to achieve a state density under a reliability measure curve (i.e. λ, MTBF, etc.) on which every required observation is measurable. In other words, continuous MRA modelling will achieve analysis and results extraction between two discrete measurements. Another research work consideration is focused towards the component/sub-system and system interdependencies. Hence, the functional interconnectivities will be considered by modelling the idea that each functioning component affects others. Systems will be treated in a holistic way and enable the prediction of failures or malfunctions while different systems are monitored.

7. Conclusions

This paper aimed to demonstrate the development of the Machinery Risk Analysis (MRA) tool. MRA is a probabilistic reliability and risk analysis model established through the work performed in INCASS (Inspection Capabilities for Enhanced Ship Safety) project.

In this paper, the research background is presented first. It consists of the Condition Based Maintenance (CBM) methodology, well-known Condition Monitoring (CM) technologies/tools as well as data acquisition tools and sensor installation options. The MRA demonstration continued with the model's methodology presentation as well as the input data flow and process diagrams.

In the following section, the MRA application is presented through a marine diesel engine case study. The investigation and categorization of ship machinery and equipment for CM is demonstrated and the identification of required data gathering tools and methods. This section initiated with the machinery and equipment classification for the three under investigation ship types (i.e. tanker, bulk carrier, container ship). The research continued by considering the Stakeholders Requirements. Different industrial viewpoints and CM needs were met as INCASS consortium consists of different Universities, Classification Societies and ship operators, managers, owners and service providers. The main systems that MRA model will be applied on are decided to be the Main Engine (M/E), Turbocharger (T/C), critical selected pumps and the Steering Gear system.

The current Machinery Risk Analysis (MRA) model employs the Bayes' Theorem in the application for diesel engines. It incorporates different sub-systems such as the Lubrication, Engine Internal and External Components, Starting, Control & Monitoring and Cooling systems as well as relevant components. Java programming with regularly occurred failure types is used, providing the overall reliability performance of the pre-defined sub-systems as well as the entire Main Engine (M/E) system.

In conclusion, it is essential to highlight that research future considerations include dynamic Machinery Risk Analysis (MRA) modelling. In this case, dynamic failure rate variation will be considered through time aiming to assess the systems' reliability performance into a continuous manner. Furthermore, it is also considered the assessment of systems, sub-systems and components from a holistic viewpoint. Thus, functional interdependencies will be taken into account, involving chain degradation reaction behavior through time from the various units that the MRA model consists.

In addition to dynamic probabilistic modelling, a sensitivity analysis will be taken place through which the network probabilistic parameters will be tested under various adjustments and functional conditions. The sensitivity analysis will provide valuable inputs especially in INCASS MRA methodology where de-noising and signal recognition tools will be introduced. Lastly, an important implementation is the consideration of more systems in the MRA application than only the main engine which will allow to outline a wider and in depth reliability performance outcome.

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