Probabilistic Risk Assessment of Condition Monitoring of Marine Diesel Engines

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Abstract: This paper scopes to provide a suggestion on the maintenance outline as perceived from the evaluation of an extended literature review on marine engineering systems and applications sourced from research and industrial studies. The present research contributes in the creation and initial implementation of a probabilistic multi-component prognostic Condition Monitoring model for ship machinery and equipment maintenance scheduling. Systems involved include engine internal and external components, starting, cooling, and lubrication and control monitoring systems. The overall reliability performance of these sub-systems and the entire Main Engine's is suggested. Moreover, this paper will present the components and failure types' layout arrangement of engine internal and external sub-systems as well as the overall reliability performance of the sub-systems.

Keywords: maintenance, reliability, condition monitoring, probability, failure, main engine, components

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1 Introduction

The operational environment of the day-to-day industrial applications has more complex and pretentious structure, while their business effectiveness and efficiency is influenced by factors such as time, financial constraints, technology, innovation, quality, reliability, and information management (Madu, 2000). Scoping the organization to compete successfully, the enhancement of system maintenance and reliability are necessary operational attributes while sufficient attention has to be paid 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. In further 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. In this respect, a broad exploration of maintenance methodologies takes place, concerned with the most known methods and techniques scoping to motivate the development of an optimized, innovative and applicable maintenance strategy for marine engineering systems.

This paper's initial scope is to recommend a maintenance field arrangement method for practices' classification, demonstrating research and presenting a probabilistic risk evaluation case study on diesel engines, inspiring further research and application development. The paper's sections are distributed between Maintenance Literature Review, Condition Monitoring Technologies/Tools, Condition Monitoring Optimization Tools, Multi-component Condition Monitoring, Case Study as well as Conclusions and Recommendation for inspiration and in further exploration.

2 Maintenance Literature Review

From business perspective in shipping industry, maintenance structure is transformed from budget gain perspective to investment for continuous and reliable asset service. Whereas from operational viewpoint, it is restructured from reactive to proactive actions, involving more control and information of the considered machinery or system. This section classifies maintenance between strategies, methodologies, well-known and applied monitoring technologies and tools by proving the importance of maintenance presenting guidelines from international safety agents.

2.1 Maintenance Strategies

An investigation on various sources indicates that maintenance strategies are classified differently from researchers. For instance, Ahuja and Khamba (2008), Garg and Deshmukh (2006) and Dowlatshahi (2008) combine maintenance strategies and techniques; conversely Shreve (2003) and Arunraj and Maiti (2007) separate them presenting maintenance in a timeline form. In contrast, Wang (2002) approaches maintenance in the common cited types of corrective and preventive strategies. Investigating various applications and research methodologies, this paper identifies the core of strategies between corrective, preventive, predictive and proactive.

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2.1.1 Corrective Maintenance

This type of strategy is implemented in plants at the beginning of 1940s (Shreve, 2003), and it is described from the statement “fix it when it breaks” expressing its reactive side (Kobbacy and Murthy, 2008). It is a routine maintenance approach focused on component’s replacement after failure. Recent research presents a lack of applicability of this maintenance strategy due to its inefficient economic and performance nature. According to Mobley et al. (2008), the main weakness of this strategy is the poor planning and incomplete repair, resulting the repair of obvious failures by ignoring the root that cause them. Nevertheless, it has to be highlighted that this approach is suitable for low in criticality equipment that replacement involves easy and inexpensive actions and parts, where their failure will not affect the performance of operation.

2.1.2 Preventive Maintenance

The next generation of maintenance strategies identified as Preventive Maintenance (PM) is introduced at the beginning of 1950s (Shreve, 2003). It is classified as the first time-driven management program arranged in predefined periods scoping to satisfy particular criteria. Hence as stated by Márquez (2007), it scopes to reduce the possibility of failure due to equipment degradation.

2.1.3 Predictive Maintenance

The third and most modern generation of maintenance strategies introduced into the market by the end of 1960s according to Shreve (2003) and middle of 1970s by Arunraj and Maiti (2007). The notion of this maintenance strategy is the non-destructive testing of a system, determining the condition of equipment and subsequently considering the maintenance plan. A characteristic definition is given by Fedele (2011) supporting that Predictive Maintenance (PdM) is on-condition assessment of assets, employing real time programming by avoiding unnecessary downtime, inspections and reactive failures due to human mistakes.

2.1.4 Proactive Maintenance

The majority of researchers classify maintenance strategies between, corrective, preventive and predictive, presenting the timeline of maintenance concepts from a reactive to a more proactive case. According to Fedele (2011), PdM is oriented on the on-condition-driven concept of maintenance providing alert signals through data collection aiming to schedule actions. In the meanwhile, he extends PdM by presenting proactive maintenance (also known productive), considering the pre-alert actions discovered from system’s performance malfunctions that may lead to machinery deterioration. In further, it analyses the root causes of breakdown events, setting the acceptable operational limits of the predetermined factors.

2.2 Maintenance Methodologies

These are identified by Fedele (2011) as maintenance policies indicating the entire business attitude. Through research, it is discovered that the clustering of them is uniform compared to maintenance strategies that researchers approach them in various ways.

2.2.1 Reliability Centered Maintenance

Reliability Centered Maintenance (RCM) is a methodology applied at the beginning of 1970s and it has wide applicability until nowadays. This maintenance methodology is implemented by a commercial airline company pursuing reduction of maintenance downtime, expenditures and enhancement of flight safety and equipment reliability (Deshpande and Modak, 2002). Including the consequences factor, Nowlan and Heap (1978) state that RCM employs function and risk analysis for prioritization of maintenance actions evaluating the corrective maintenance costing against the preventive costs considering also the loss of potential life.

2.2.2 Total Productive Maintenance

The president of the center for Total Productive Maintenance (TPM) in Australasia (Kennedy, 2006) presents that it is introduced in Japanese car industry in 1970s integrating Total Quality Control (TQC), Just-In-Time (JIT) and Total Employee Involvement (TEI). Comparing the already introduced RCM with TPM, he supports that RCM is maintenance improvement strategy, while TPM independently implemented cannot improve reliability. Describing TPM according to Nakajima (1988) is developed concept of Total Quality Management (TQM) oriented on zero production defects applied on critical equipment, involving highly top management support, sense of ownership and responsibility of operators and maintenance workers.

2.2.3 Total Quality Management

This approach has managerial aspects, integrating values, techniques and tools for accomplishment of customer satisfaction and minimization of resources (where possible), scoping continuous improvement of operational processes sustaining quality involving management, workforce and suppliers (Hellsten and Klefsjö, 2000) and (Powell, 1995). As stated by Hipkin and De Cock (2000) the most reported interventions are TQM and Business Process Reengineering (BPR) due to difficulties of implementation, lack of guidance on procedures, inadequate training, difficult measures of performance and lack of top management support.

2.2.4 Maintenance Risk Based Methodologies

First of all, it is necessary to declare risk as the multiplication of the probability of failure and its consequence (Hecht and An, 2004). This category of methodologies encompasses both inspection and maintenance approaches. Thus, the first one is defined as Risk Based Inspection (RBI) and identified from Classification Societies (DNV, 2002) as assessment between qualitative and quantitative features, employing numerical values, assessment scales and unit measurement of probability failure and consequence respectively. While, the later one according to Arunraj and Maiti (2007) is study of all failure modes, considering the risk of those by developing maintenance strategy for minimization of occurrence of critical incidences.

2.2.5 Asset Management

Through a literature review directed on the cost benefits of maintenance strategies and methodologies, Eti et al. (2006) summarizes that maintenance and Asset Management (AM) can achieve growth of profile by decreasing running costs and increasing capability and availability. Industrial contribution on specifying AM (ABB, 2010) proposes the basis of an ultimate AM tool, integrating Computerized Maintenance Management Systems (CMMS) with real-time Condition Monitoring (CM) collecting data from various sources achieving alerts on failure detection.

It is essential to highlight that AM is notion of viewing business plan and production from a holistic perspective aiming the ultimate performance by controlling every available asset that may affect this.

2.2.6 Computerized Maintenance Management System

The need for implementation of automated maintenance management systems enhanced by computerized, flexible tools for managing critical assets is presented, as equipment onboard the ships become more complex and market more competitive.

These systems according to Shreve (2003) suggest maintenance planning as they assist critical data for equipment, workforce and recorded conditions. In addition, Fernandez et al. (2003) present the functionality of CMMS as gaining information from raw data and enhancing decision making by automating existing processes. Various proposed CMMS models are presented in literature trying to enhance serviceability, accuracy of decision and functionality in complex systems.

2.2.7 Condition Based Maintenance

This is the latest and under continuous development methodology. A literature review by Dhillon and Liu (2006) focusing on humans' error impact in applications of maintenance highlights that a large amount of human errors take place during maintenance operations. Thus, the need for computerized condition maintenance methodology appears, which will tend to minimize unnecessary human's involvement during acceptable operational machinery conditions.

The scope of CBM, fault diagnosis and in extend of prognosis is to detect the upcoming failures before even taking place aiming to enhance machine's availability, reliability, efficiency and safety, by reducing maintenance costs through controlled spare part inventories (Mechefske, 2005). From the industrial direction, SKF (2012a) supports that CBM aims understanding of risks and predetermination of strategic actions, leading to reliability and operational cost reduction.

2.3 Maintenance Guidelines and Regulations

The main international safety agents lay the foundation for uniform standardization of maintenance process are summarized between British Standards (BS) and International Standards Organization (ISO), International Maritime Organization (IMO) and International Association of Classification Societies (IACS).

BS and ISO can be defined as agreed frameworks of specified activities accomplishing actions that will lead on delivery of products and services to customers. A research on recent standards especially related to the latest maintenance strategies and technologies provides a series of standards that classify CM parameters for signal measurement collection and analysis.

On the other hand, the crucial role of IMO is to set a framework controlling safety issues and specifying conditions of security, fire safety, lifesaving appliances, navigation lights and radio communication. A comparative study by Han (2004) presents the key role of Classification Societies with this from IMO, defining that each class is member of IACS leading a global network of well qualified surveyors' feedback of technical data and an internationally suitable management system.

Concluding the importance of international standards, the concept of integrated and unified regulatory framework is confirmed in maritime industry and specifically in maintenance aspects, while IMO and IACS proposed an advanced and specific structured risk analysis process named Formal Safety Assessment (FSA) assessing the risk of failure in occasions that may lead to catastrophic consequences.

3 Condition Monitoring Technologies/Tools

As it is already defined, CBM is the latest maintenance methodology, which assesses equipment and machinery, while they operate. In this extend, Condition Monitoring (CM) technology is applied through various tools recording, and evaluating measurable parameters, that will be reviewed in this section. These measured parameters comprise the signal gathering, from which several data processes can be considered with respect to equipment functionality. This section aims to review the most known CM technologies through research applications expanding the notion of CM into diagnostics and in further prognostics.

3.1 Vibration Monitoring

This is the most known and well applied common technique as Vibration-Based Maintenance (VBM) offers early indication of machinery malfunctions involving parameters as rotational speed, loading frequency, environmental conditions and material state (Al-Najjar, 1996).

Typical examples with extended literature of CM involving vibration measurements are rotating components such as bearings and gears. In system and component levels, VBM provides potential in fault detection of electric motors combined with electric current; monitoring bearing failures as the major cause of malfunctions (Lamim et al., 2007). An alternative view on rotating machinery is presented by Sassi et al. (2007) simulating the dynamic performance of ball bearings in terms of localized surface defects considering bearing rotation, load distribution, structure elasticity and oil film characteristics.

3.2 Thermography

Thermography or thermal imaging is CM tool applicable for both electrical and mechanical equipment, aiming the identification of hot and cold spots providing early signs of equipment failure. As claimed by Bagavathiappan et al. (2013), Infrared Thermography (IRT) is one of the most accepted CM tools. Due to the non-contact function 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. Presenting machinery defects, Budweg (2012) analyses that uncontrolled heat can be generated due to reasons as overloading, phase imbalance, power factors, corrosion and poor electrical connections and this is a warning of loss of energy. Moreover, heat is a parameter that can shorten machinery's lifecycle up to 85%.

3.3 Oil Analysis Monitoring

Defining oil analysis, Jiang and Yan (2008) state that it is achieved through laboratory concentration analysis in lubricant, debris analysis, dealing with shape, size, composition of wear particles and lubricant degradation analysis for physical and chemical characteristics. Integrating oil analysis and computerized technologies. According to Casale et al. (1993), lubricants' monitoring is the most efficient diagnostic tool as from a small amount of fluids is considered the condition of the entire lubricant in each machinery. However, the required laboratory analysis and specific expertise set this monitoring technique one of the most time consuming process. Setting the ground for further analysis and presenting the lack on publications in performance analysis of steam turbine generators, Beebe (2003) promotes the integration of vibration and oil debris analysis supporting the enhancement of efficiency and output reduction such as deposits on blades and erosion of internal clearances.

3.4 Acoustic and Ultrasonic Monitoring

Temperature, vibration and cylinder drain oil monitoring are time and cost consuming techniques due to the installation needs on marine diesel engines (Kim and Lee, 2009). The applicability and utilization of ultrasonic CM is proved by IACS (2004) and IACS (2006) as it is introduced the Unified Requirements (UR) and Procedural Requirements (PR) for Ultrasonic Thickness Measurements (UTM) execution joined part of classification survey procedures.

In practice, Kim and Lee (2009) propose a real-time diagnostic system for high speed Acoustic Emission (AE) signal analysis assessing wear condition of cylinder lines in marine large two-stroke diesel engines. Expanding AE applicability, Vervloesem (2013) explores the user-friendliness and accessibility of ultrasounds on non-rotational equipment breakdowns that exist onboard of ships advancing the ease of manual data collection and the direct sourced result. An unknown aspect of this CM tool compared to traditional vibration analysis is the ability of performing on high and slow speed rotating equipment as low as 0.25 RPM.

3.5 Monitoring Diagnostics

Presenting the CM layout, it consists of phases as data gathering from the installed sensors (on-line) or off-line devices, signal analysis, while leading to decision making. The market need for further systematic automation enforced the implementation of monitoring diagnostics, a methodology which aims to determine and specify the fault type. In line with Delvecchio (2012), fault diagnosis is severe requiring the determination of type, size, location and time of detected faults.

Supporting the importance of fault diagnosis Becker and Poste (2006) state that a specific maintenance issue can be the replacement of a $5,000 bearing turning into a $250,000 project concerning cranes, service crew and power loss. A typical example (Mortada et al., 2011) of diagnostics, hence feature extraction from frequency and time-based signals, assesses the performance of a supervised method called Logical Analysis of Data (LAD) identifying malfunctions in rotating machinery using VBM targeting decision function enhancement. An important factor of managing marine online data for diagnostics SKF (2012b) is the signal categorization to be arranged in load groups for similar trend comparison.

3.6 Monitoring Prognostics

An innovative and newly introduced maintenance concept on CM extending diagnostics is this of prognostics. This scopes to predict whether a failure will occur and the systems' Remaining Useful Life (RUL). Prognostics have limited literature in research, as they are recently established. However, different forecasting techniques are already developed.

An importance CM maintenance concept is developed, this of multi-component modelling. For instance, Niu and Yang (2010) propose an intelligent CM prognostics method based on data-fusion strategy. The algorithm consists of stages such as vibration signal collection and trend feature extraction, feature normalization and use in Neural Networks (NN) for feature-level fusion, data de-noising and wavelet decomposition for reduction of fluctuation and selection of trend information.

4 Condition Monitoring Optimization Tools

In this section, a brief description will follow including maintenance optimization tools, signal processing, and failure and risk analysis methods, setting the grounds by motivating for further enhancement of efficiency and precision of the already published ones.

4.1 Artificial Intelligent Approaches

According to Fiippetti and Vas (1998), Artificial Intelligence (AI) assists equipment degradation assessment, statistic failure analysis, prognostics and intelligent diagnosis for CM tasks and fault detection. Through research, it is found that AI is classified among Artificial Neural Networks (ANNs), Expert Systems (ESs), Fuzzy Logic Systems and Evolutionary Algorithms (EAs). In further, it is identified the need for integration of these, aiming at the improvement of performance and failure diagnostic accuracy. An instance of integration is presented by Wang and Chen (2011) employing for a diagnostic model fuzzy Neural Network and applying Wavelet Transform (WT) and Rough Set (RS).

4.2 Signal Processing and Optimization Methods

One of the most critical phases within the CM algorithm is signal processing. This stage assesses the accuracy of the failure detection as it consists of signal de-noising processes, through which collected data are analyzed and unnecessary information is removed, rendering the signal filtering and preparation for the upcoming feature extraction (i.e. pattern recognition form of dimensionality reduction) process easier and more accurate. Wu and Chen (2006) summarize Short-Time Fourier Transforms (STFT), Wigner-Ville Distributions (WVD) and Continuous Wavelet Transforms (CWT) in their effort to categorize widely used methods for detection of fault conditions and practical fault diagnosis of rotational machineries.

4.3 Failure and Risk Analysis Methods

Deteriorating systems developed for the maritime industry consider internal and external to system failures as interdependencies occur during operation (Delia and Rafael, 2008). Literature presents various failure and risk analysis methods, where the majority of approaches visualize failure occurrence as independent event for each considered component of a system. These can be summarized as Fault Tree Analysis (FTA), Dynamic FTA (DFTA) taking into account time variation, Failure Mode and Effect Analysis (FMEA) and Failure Mode Effect and Criticality Analysis (FMECA), Markov Analysis (MA) and Bayes' Theorem presenting the Bayesian Belief Networks (BBNs).

The latter one can be defined as probabilistic graphical model involving conditional dependencies arranged into Directed Acyclic Graphs (DAG) and it is expressed as presented in Equation 1 (Bedford and Cooke, 2001):

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

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.

5 Multi-component Condition Monitoring

In this section, a Condition Monitoring (CM) methodology will be briefly presented aiming to be applied on critical ship machinery and equipment, as developed after the evaluation of a literature review on the latest published maintenance strategies, methodologies, guidelines and regulations as well as CM technologies and tools.

Furthermore, the researchers' and market's tendency for consideration of operational and failure interdependencies among multiple components within the same system is highlighted. Hence in this manner, the requirement for examining various systems into an integrated CM maintenance scheme appear. The existing methodologies lack on multiple critical component monitoring consideration involving degradation analysis (Heng et al., 2009).

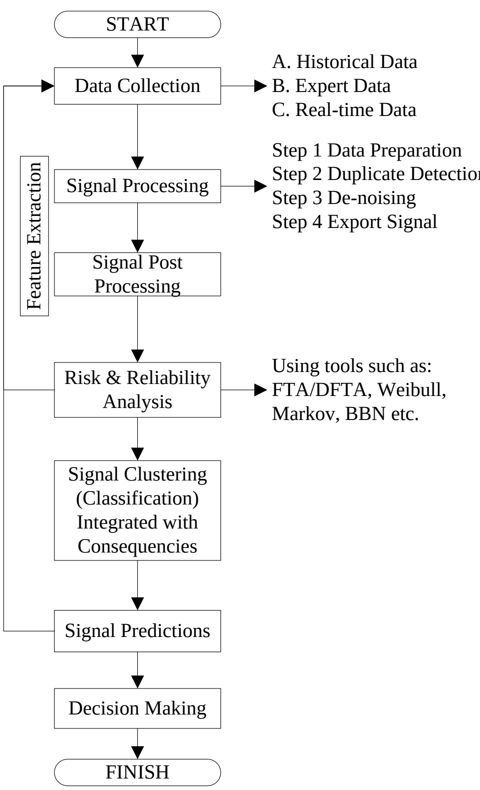

Fig. 1 Multi-component Prognostic Condition Monitoring Model

Figure 1 proposes the arrangement of a flexible prognostic CM strategy taking into account multiple components of a system or multiple systems. Initially, data collection involves multiple historical recorded data, expert and/or real-time data. The following phase is twin level feature extraction arrangement preparing the considered data by filtering and de-noising unnecessary information gathered from the environment that the machinery operates. The exported signal is introduced into the second level of feature extraction from which accurate diagnostics will be sourced (feature identification). The use of risk and reliability analysis is implemented in order to identify critical components for the operation and safety as well as risk levels. Feedback is sent from the 'Risk & Reliability Analysis' phase back to 'Data Collection' aiming to store and monitor the reliability performance of the system. In further, signals are classified under operational conditions and consequences are taken into account. In the next stage, prediction tool is planned to be introduced for signal/condition forecasting, which will lead to decision making for maintenance action hierarchy and determination. Moreover at prediction level, feedback is considered scoping the system's performance monitoring and accuracy of estimation. As it can be seen from Figure 1, *'Risk & Reliability Analysis'* stage is the core of the proposed model structured among predecessor signal preparation phases and successor forecasting and decision making processes. The following section implements a failure and risk analysis tool in first principle design arrangement.

6 Case Study

The ship Main Engine (M/E) 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.

In this respect, the following six diesel M/E sub-systems are identified: Engine Internal and External Components, Starting, Cooling, and Lubrication and Control Monitoring systems are considered. In this section, a case study will be briefly presented, involving the Engine Internal and External Components sub-systems and its comprised components. It is decided to be presented these two sub-systems as they layout the component core of the entire M/E.

6.1 Data Collection

Data have been provided in the form of failure rates per component involved. At first, the overall failure rate is calculated in percentages for each component considered independently for the pre-defined failure scenarios that may occur on these components. In the next phase 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 Object-Oriented Programming (OOP) 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.

6.2 Engine Components Probabilistic Modelling

This section aims to present a probabilistic model produced in Java programming language. For the '*Risk & Reliability Analysis'* stage the Bayes' Theorem is implemented The various probabilities are typically represented employing Directed Acyclic Graphs (DAG), where each considered probability is presented with a node and its relation with any other node using directed arrow. This type of DAG diagram in the case of Bayes' Theorem is defined as Bayesian Belief Network (BBN). A typical example of a BBN display is shown in Figure 2, where the Main Diesel Engine system and related components are linked with the considered events (failure types).

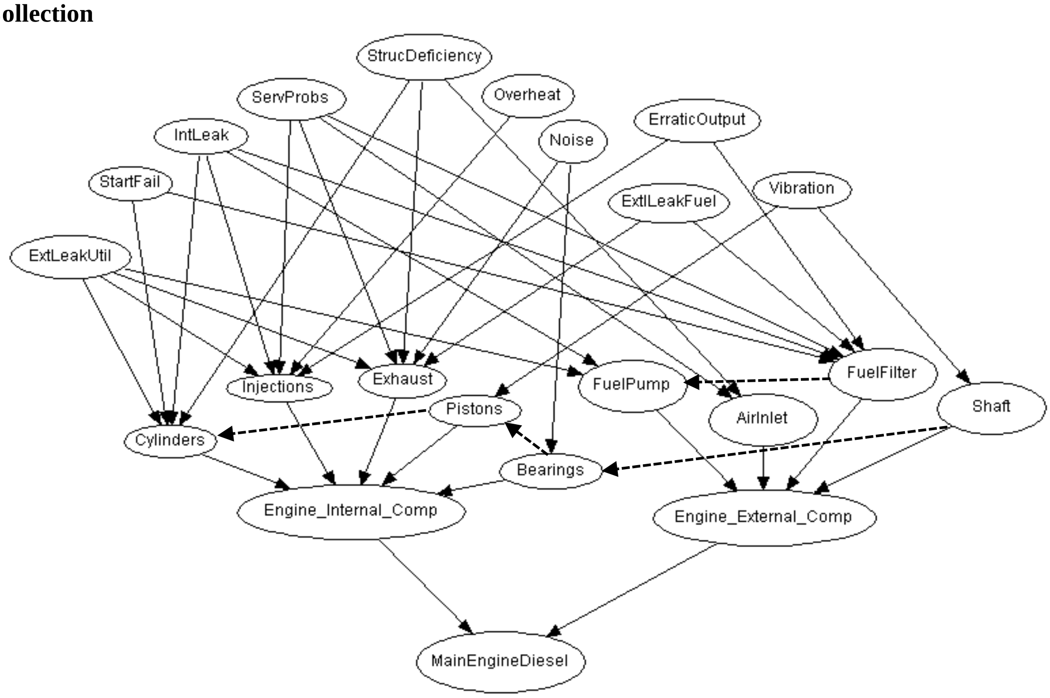

Fig. 2 Main Diesel Engine Components Probabilistic Case Study Model

In Figure 2 is presented a part of the M/E system arrangement. Firstly, they are demonstrated with nodes two of the major M/E sub-systems, the Engine Internal Components and Engine External. The next level of nodes includes the Engine Internal Components involving items attached to the main engine 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 Figure 2 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.

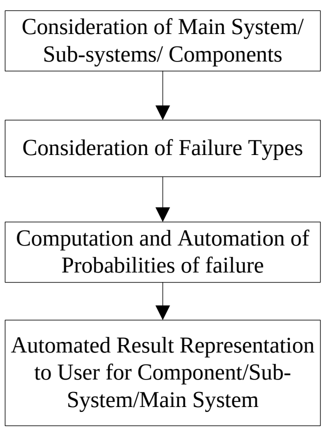

Fig. 3 Probabilistic Case Study Programming Stages

Figure 3 presents the phases accomplished into this case study from data collection until results are displayed to user. Initially, the main system, sub-systems and components are specified. Data are compiled from the OREDA database. Automated computation calculations are managed through Java coding for individual components, overall sub-system and final the entire marine diesel engine. Automated results display presents failure rates in percentages for component, sub-system and main system levels.

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

While, each component of the Main Engine system is linked with a certain number of failure types 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 occurrence of the different failure 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.

$$\boldsymbol{P(comp)} = \sum_{j=1}^{m} \Big(\sum_{i=1}^{k} \boldsymbol{P}(\boldsymbol{ft_{f(i)}}, \boldsymbol{ft_{f(j)}})\Big) \tag{3}$$
$$\boldsymbol{m} = \mathbf{2}^{\boldsymbol{k}} \tag{4}$$

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 later presented in Figure 2. In addition the relation of m and k is presented in Equation 4.

6.4 Results and Discussion

The entire undertaken study examined the probability of failure of Main Engine (M/E) 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 study as they performed the highest probability of failure. In further, it is presented the methodology of the structured model as well as a generic formulation of the failure case scenarios for the defined failure types per involved component. Table 1 presents the overall sub-system and M/E failure probabilities.

Table 1 Sub-System and Main Engine Failure Probabilities

System	Works (%)	Fails (%)
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
Overall Main Engine	**99.4126**	**0.5874**

Overall the presented results show the failure 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. The outcomes are attributed from failure rates sourced from OREDA database. From Table 1 it can be observed that the overall system has probability to fail approximately 0.59%. This failure rate presents the likelihood of break down in case the M/E is considered as one system.

However, in order to increase system's probabilistic risk assessment accuracy, the M/E is separated in six sub-systems. The probability of failure 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 (Fig. 2), 0.2848% for the Starting, 0.1881% for the Control and Monitoring and 0.5639% for the Cooling system. Hence 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 during operation. From practical viewpoint, the need for operational efficiency is highlighted for the sub-systems with lowest reliability performance (or highest likelihood to fail).

7 Conclusions and Recommendations

This paper aimed to initially suggest a maintenance classification based on an extended literature review on marine engineering systems and applications. This review consists of the assessment of under development research as well as industrial applications. The maintenance classification is structured among strategies, methodologies and latest implementation of Condition Monitoring (CM) technologies and tools. The importance of maintenance introduction into the main business plan is verified from the continuous development of unified guidelines and regulatory frameworks from international agents and associations. Following the above, a key contribution of this paper led to the development and initial application of a multi-component prognostic CM model. The novel CM model employs the BBN tool, while the application for diesel engines, incorporating different critical sub-systems such as Lubrication, Engine Internal and External Components, Starting, Control & Monitoring and Cooling systems as well as components is also demonstrated. 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. This performance of the main system layouts an overall working percentage of 99.4126%. 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 1.7509% and 0.5919% likelihood of failure respectively. However, the probability of failure for these sub-systems is low, indicating reliable operation.

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 (M/E). In this respect, further detailed probabilistic risk assessment can be researched 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.

Concluding, it is essential to propose a motivational view of this study by presenting recommendations for further research. The already proposed case study examines the probabilistic modelling of Main Diesel Engine critical sub-systems involving a defined number of components and failure types. One of the upcoming research plans is to develop this model by identifying interconnectivities of components as shown in Figure 2 with the 'dashed' arrows, providing the relation among bearings to pistons, pistons to cylinders, fuel filter to fuel pump and shaft to bearings (i.e. affecting different sub-systems). This stage aims to simulate the relation and effect of failure event leading to chained fails of multiple components. In further, this addition scopes to enhance the final stage of 'Decision Making' by providing information and suggestions for maintenance actions on detailed component level, as it is planned to take place from Figure 1.

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