INCREASING SHIP MACHINERY ENERGY EFFICIENCY BY DYNAMIC CONDITION MONITORING MAINTENANCE

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ABSTRACT

Competition in maritime market in relation to ship energy efficiency and monitoring ship emission develops more compound and pretentious structure affected by parameters such as time, economical restraints, technology and innovation, quality, reliability and information management. The latest technology controlling these parametres is focused on monitoring the condition of main and auxiliary machinery. This paper aims to present the development of a Probabilistic Risk Analysis (PRA) methodology named Machinery Risk Analysis (MRA) for ship machinery and equipment. In a case study, multiple components and sub-systems are considered as well as various failure modes. The innovation of this model is the consideration of components' failure and state interdependencies providing a holistic view of systems' working state reliability performance. Likewise, the PRA model takes into account the system's dynamic state change, involving failure rate variation within time. In order to approach and simulate realistically this dynamic condition monitoring control, a continuous dynamic monitoring model is implemented. The presented methodology involves the generation of Markov Chain arrangement integrated with the advantages of Dynamic Bayesian Belief Networks (DBBNs). All progress and methodology development takes place using Object Oriented Programming (OOP) environment in Java language. The following stage of this methodology is to consider components and systems interdependencies and feed the continuous dynamic probabilistic condition monitoring algorithm. Moreover, user friendly Graphical User Interface (GUI) will be developed by involving Decision Support System (DSS) aspects.

Keywords: energy efficiency maintenance, reliability, dynamic condition monitoring, probability, DBBN, java programming

1. INTRODUCTION

Continuous increase in production demand led to gradual growth of market competition. The industrial and market competence results in the implementation of mechanized and automated systems, which enhance targeted delivery time, quality and quantity of supply. The automation of operational processes and equipment mechanization force the development of maintenance functions and control in order to manage system failure uncertainty. On the other hand, Madu (2000) states that the business effectiveness and efficiency are influenced by factors such as time, financial restraints, technology and innovation, quality, reliability and information management. Hence competing successfully, companies have to introduce inspection, maintenance and reliability systems, which need to be integrated within the business strategic planning. Various definitions are provided for both maintenance and reliability terms by different 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 centre through an enhanced Operation and Maintenance (O&M) strategy. On the other hand, maintenance strategies consider energy efficiency aspects, in order to maximise safety, system reliability and availability, and minimise expenses.

Hence, this paper aims to present the development 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 the research background that consists of the exploration of human error, inspection and maintenance automated control and Condition

Based Maintenance (CBM). Furthermore, research background introduces the latest Condition Monitoring (CM) technologies and up-to-date CM standardisation guidelines. In Section 3 the suggested Machinery Risk Analysis (MRA) methodology is presented. Section 4 demonstrates the MRA case study utilising a ballast pump, two subsystems and multiple components and failure modes, followed by Section 5 in which the results of the case study are presented. In Section 6, the research findings and future work stages for the MRA development are discussed.

2. RESEARCH BACKGROUND

This section demonstrates the latest research background with regards to maintenance control and human error and Condition Based Maintenance (CBM) methodology. Moreover, this section presents the latest Condition Monitoring (CM) technologies and the most known inspection and maintenance guidelines and regulations.

2.1 HUMAN ERROR AND MAINTENANCE OPERATION 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 inspection and maintenance operations. In shipping industry, maintenance structure is transformed from budget gain perspective to investment for continuous and reliable asset service. Whereas, from operational viewpoint, maintenance is restructured from reactive to proactive actions, involving more control and information of the considered machinery or system (Dikis et al., 2014).

In this respect, an integrated systemic model incorporating human reliability model with CBM optimization is presented by Asadzadeh and Azadeh (2014). On the other hand, 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. The most recent research presents the tendency to control human error in inspection and maintenance procedures. Moreover, considering human error scenarios for specific occasions develops Probabilistic Risk Assessment (PRA) models. 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) METHODOLOG

Maintenance methodologies can be identified as maintenance policies indicating the entire business's attitude. Different methodologies are introduced into literature such as Total Productive Maintenance (TPM), Risk Based Inspection and Maintenance (RBI and RBM respectively) and Reliability Centred Maintenance (RCM) (Mobley et al., 2008). However, CBM is the latest and under continuous development methodology. The scope of CBM 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 and industrial aspect, SKF (2012) states that CBM aims understanding of risks and predetermination of strategic actions, leading to reliability and operational cost reduction.

On the other hand, Lazakis et al. (2010) present a predictive maintenance strategy utilizing Failure Modes, Effects and Criticality Analysis (FMECA) and Fault Tree Analysis (FTA). 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. On the other hand, Lazakis and Olcer (2015) introduce a novel Reliability and Criticality Based Maintenance (RCBM) strategy by utilizing a fuzzy multiple attributive group decision-making technique, which is further enhanced with the employment of Analytical Hierarchy Process (AHP). The outcome of this study indicates that preventive maintenance is still the preferred maintenance approach by ship operators, closely followed by predictive maintenance; hence, avoiding the ship corrective maintenance framework and increasing overall ship reliability and availability. In order to layout CBM and the processes that consists of; Tsang et al. (2006) suggest a data structure leading to decision analysis according to machinery's condition, proposing a method for data-driven CBM achieving data preparation, model assessment, decision-making and sensitivity analysis.

2.3 CONDITION MONITORING TECHNOLOGIES AND TOOLS

Condition Monitoring (CM) technology is applied through various tools. These tools record and evaluate measurable parameters that will be reviewed in this section. Hence, well-applied CM technologies are vibration monitoring, acoustic and ultrasonic monitoring, thermography and oil analysis. CM is identified by Delvecchio (2012) in phases between data acquisition, signal pre-processing and feature extraction, signal analysis and fault detection, leading to decision-making and failure prognostics. This section is focused on the first phase of data acquisition. This phase involves the input data record such as displacement, velocity, acceleration, temperature, sound signal and oil analysis parameters.

Vibration monitoring is the most known technique. It offers early indication of machinery malfunctions by involving rotational speed, loading frequency, environmental conditions and material state parameters. These parameters are measured by employing different types of sensors such as; noncontact displacement transducers; velocity transducers and accelerometers (Dikis et al., 2015). On the other hand, thermography is a tool, which is applicable to both electrical and mechanical equipment, and is deployed to identify 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 detecting structural, machinery, electrical and material malfunctions. Thermography requires thermal cameras and thermocouples for recording temperature of machinery, electrical and electronic installations.

2.4 INSPECTION AND MAINTENANCE GUIDELINES AND REGULATIONS

The significance of inspection and maintenance processes, due to their influence on technical, economic, managerial and business aspects, leads to the implementation of guidelines and regulations. The major international safety agents lay to the foundation for uniform standardization of maintenance processes. These safety agents are summarised between British Standards (BS) and International Standards Organisation (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 parametres for signal measurement collection and analysis (BS/ISO 7919-4, 2009), (BS/ISO 17359, 2011) and (BS/ISO 13379-1, 2012). Moreover, International Safety Management (ISM) code ensures safety at sea, prevention of human injury or loss of life, and avoidance of damage to the environment, in particular to the marine environment and to property (Maritime, 2015).

On the other hand, the crucial role of IMO is to set a framework controlling safety issues and specifying conditions of security. 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 (LR, 2014) and (DNV-GL, 2014).

2.5 RISK AND RELIABILITY ANALYSIS METHODS

Risk and reliability analysis methods assess various failure case scenarios of deteriorating systems and their contributing subsystems and components. 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. The analysis tools examine risk of failure by taking into account quantitative and qualitative aspects. These tools can be summarized as Event Tree Analysis (ETA), Fault Tree Analysis (FTA), Dynamic FTA (DFTA) taking into account time dependence, 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 examines the reliability performance on system, subsystem and components levels by considering functional interdependencies among them. This key feature of BBN is significant and innovative, compared to the remaining methods, as it allows the simulation of functions and operations on actual modelling environment. The BBN is defined as probabilistic graphical model involving conditional dependencies arranged into Directed Acyclic Graphs (DAG) and it is expressed as presented in Equation 1 (Dikis et al., 2014).

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

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. Furthermore, innovative features of BBNs involve the utilisation of decision making and cost functions.

3. SUGGESTED MACHINERY RISK ANALYSIS (MRA) METHODOLOGY

In this section, the Machinery Risk Analysis (MRA) methodology will be demonstrated targeting to be applied on critical ship machinery and equipment of three different ship types such as tanker, bulk carrier and container ship (INCASS, 2014a). Hence, the MRA methodology is flexible in order to fulfil all requirements and specifications for each of these three ship types (INCASS, 2014b). Motivation is based on the fact that researchers' and market's tendency involves the holistic consideration of operational and failure interdependencies among multiple components within the same or different system.

The graphical demonstration of machinery and equipment risk and reliability analysis data flow is displayed in

Figure 1. This data flow represents the input data flow among the different functionalities and process levels. The data flow consists of three stages, the data acquisition and processing, the reliability model and the Decision Support System (DSS). All processing, MRA functions and DSS features are developed in Java Object Oriented Programming (OOP) language. This programming language is chosen due to the fact it is cross platform and allows ease of use and compatibility among different Operating Systems (OS) such as Windows, Macintosh or Linux distributors. Furthermore, Java programming language is flexible allowing development of portable device applications, compatible for Android and iOS as well.

On the first stage 'Data acquisition and processing', the input data is classified into the database on system, subsystem and component levels. The input data types are considered as historical, expert and real time monitoring data (sensor raw input). Historical input data involves past failures and records. On the other hand, expert input/judgement takes into account comments, reports and knowledge from ship crew. Real time sensor input consists of raw (unprocessed) physical measurements such as temperature, pressure and vibration recorded by utilising various devices and data acquisition tools. All gained information is stored in the database utilizing 'text' (.txt) files. This format file is selected as files are small in size and can be easily and inexpensively transferred from the onboard to the onshore environment (INCASS, 2015a).

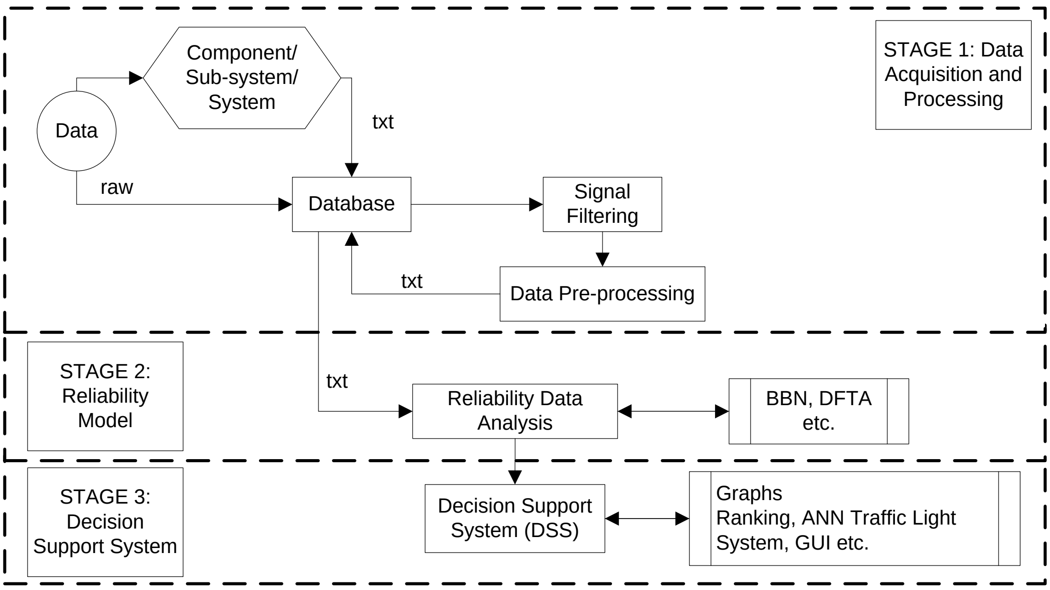

Figure 1: Machinery risk and reliability analysis (MRA) data flow

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 the second stage 'Reliability Model', the processed reliability input data from the database is introduced. The risk and reliability model employs a network arrangement similar to the Bayesian Belief Networks (BBNs). This selection allows the probabilistic modelling by considering functional relations and system, subsystem and component interdependencies. The third stage of the implements the Decision Support System (DSS) aspects. The DSS methodology is divided into two sections. The first one utilises local (onboard) and short term decision making suggestions, whereas the second one is used onshore (global) for longer term predictions and decision features. The DSS demonstrates the considered systems, subsystems and components into a tree structure form. The operator has the option of choosing each of these and getting information related to past, current and predicted reliability performance.

The MRA and DSS methodologies so far demonstrate the procedures on the data flow level. Hence, they present the analysis from an input manipulation perspective. Figure 2 presents MRA and DSS tools and methodologies on the specific process and modelling level. As can be seen, INCASS project introduces two main tools the MRA and DSS. On the data flow level, the description incorporates data handling from the data gathering phase up to decision making (INCASS, 2015b).

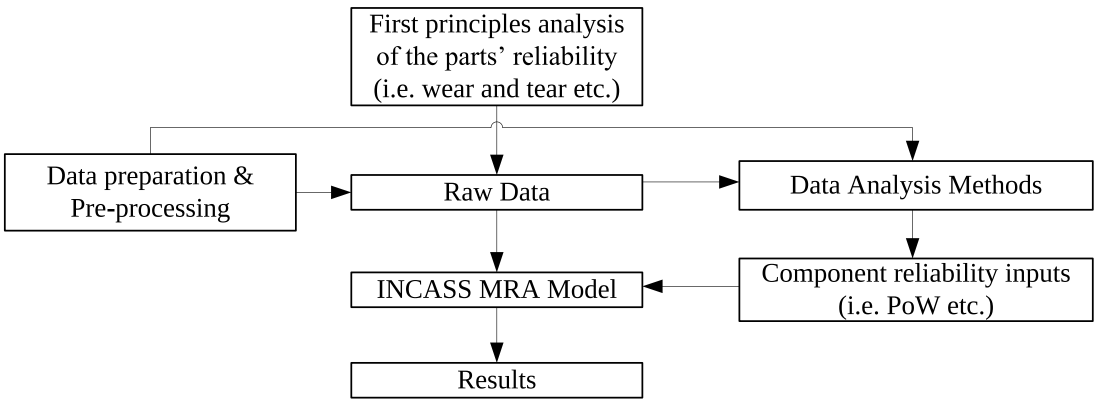

Figure 2: Machinery risk and reliability analysis (MRA) process diagram

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 input. The filtered/processed data is transformed into working state reliability performance at component, subsystem and system level in the format of Probability of Working (PoW). Furthermore, MRA model predicts 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. MRA tool involves for the predictive feature the reliability analysis tool of Bayesian Belief Networks (BBNs), whereas the time domain progress is handled by Markov Chains (MC).

3.1 MRA RELIABILITY MODELLING

In the case of dynamic modelling, the time dependencies and state division of the reliability input are developed in parallel with the network model. The MRA application employs the mathematical tool of Markov Chains (MC). MC is mathematical system that undergoes transitions from one state to another on a state space. Moreover, MC is selected as it is flexible to set up by allowing different levels of state sequence complexity. In order to understand the dynamic probabilistic modelling, a schematic diagram is presented in Figure 3. The presented subsystem sample includes in total three states within the timeline. Firstly, historical processed data from the previous time slice are provided shown as *t-1*. The current state (*t*) is calculated, whereas the predictive state is shown as future state *t+1*. As it can be seen in Figure 3, each time slice (*t-1*, *t*, *t+1*) is based on the previous state. This single state transition from past to present and then to forecasted future is known as Markov Chain (MC). The generic probabilistic expression is shown in Equation 2. On the other hand, Equation 3 presents the PoW per expressed component and subsystem in the future *t+1* time slice. $P(w_{t+1})$ denotes the PoW in future state *(t+1)* by taking into account previous working and failing states $P(w_t)$ and $P(f_t)$ respectively.

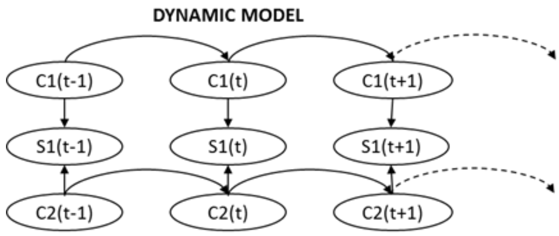

Figure 3: Dynamic probabilistic network arrangement

$$\boldsymbol{P_{X(n-1),X(n)} = P\{X_{t_n} = X_n | X_{t_{n-1}} = X_{n-1}\}} \quad (2)$$
$$\boldsymbol{P(w_{t+1}) = P(w|w_t)P(w_t) + P(w|f_t)P(f_t)} \quad (3)$$

Each component of a subsystem is linked with a certain number of failure modes, at least one, that varies between components. A generic form expressing the failure case scenarios is presented in Equation 7. In this expression, *P* denotes the Probability of Survival (PoS) for different failure scenarios, where *w* indicates the PoW state while *f* shows the Probability of Failing (PoF). The relation of *w* and *f* is shown in Equation 8. Additionally, ft_{fn} indicates the failure mode (i.e. noise, vibration, overheating etc.). Specifically, P_1 denotes the PoW and PoF states while one failure mode takes place (ft_{f1}) (Equation 4). Accordingly, P_2 denotes the PoW state for a different failure mode (ft_{f2}) (Equation 5). P_3 represents the PoW and PoF states while ft_{f1} and ft_{f2} take place at the same time (Equation 6).

$$P_1 = \begin{cases} w: 100 - & ft_{f1} \\ f: & ft_{f1} \end{cases}; \quad (4)$$
$$P_2 = \begin{cases} w: 100 - & ft_{f2} \\ f: & ft_{f2} \end{cases}; \quad (5)$$
$$P_3 = \begin{cases} w: 100 - & (ft_{f1} * ft_{f2}) \\ f: & (ft_{f1} * ft_{f2}) \end{cases}; \quad (6)$$
$$P_m = (ft_{f1} * ft_{f2} * ft_{f3} * \dots * ft_{fk}) \quad (7)$$
$$f = 100 - w \quad (8)$$

Equation 9 presents the generic expression of the overall PoS per 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). In addition the relation of *m* and *k* is presented in Equation 10.

$$\boldsymbol{P(comp) = \sum_{j=1}^{m} (\sum_{i=1}^{k} P(ft_{f(i)}, ft_{f(j)}))} \quad (9)$$
$$\boldsymbol{m = 2^k} \quad (10)$$

4. MRA APPLICATION

In this section, a Machinery Risk Analysis (MRA) case study is presented by involving the ballast pump, different subsystems and multiple components and failure modes. The case study assesses the working state reliability performance on system, subsystem and component levels by analysing various probable failure case scenarios. The case study employs pre-processed data in the form of failure rates (λ) per component. The input data is sourced from Offshore Reliability Database (OREDA) and the entire developed algorithm is performed in Java Object Oriented Programming (OOP) language.

The case study involves the reliability of the ballast pump. This case study demonstrates a sample of results for the shell and mechanical power subsystems. Each of these subsystems consists of multiple, related in function, components. An extract of these subsystems is shown in Figure 4, where the shell and the mechanical power subsystems are demonstrated as well as the relevant components and involved failure modes.

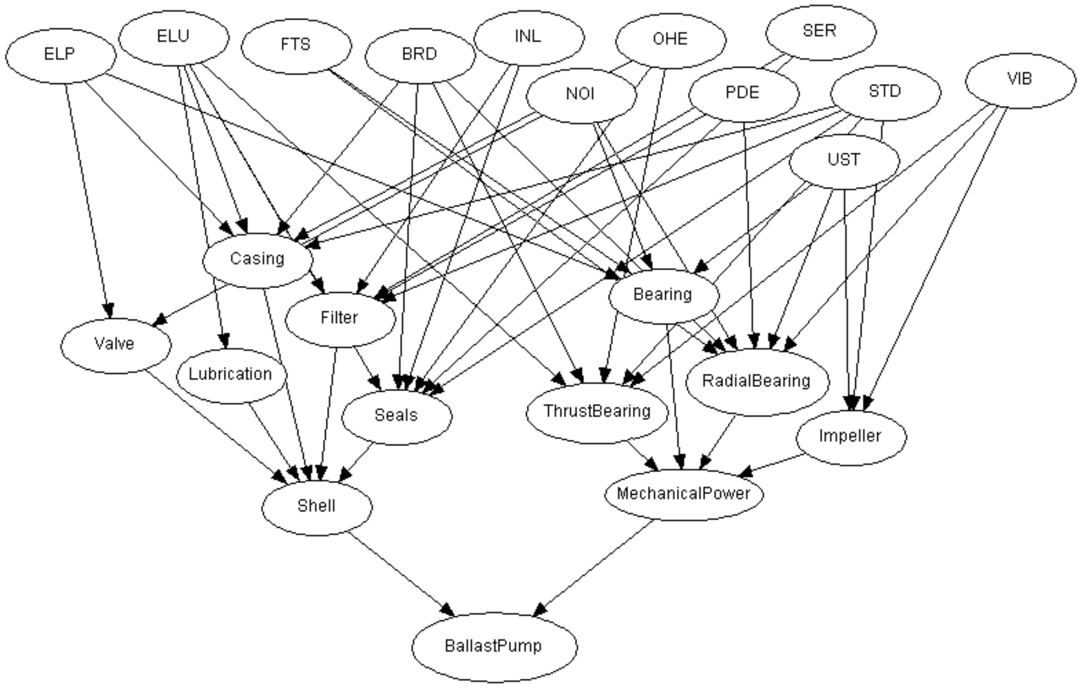

Figure 4: Ballast pump MRA network case study

Each of the subsystems is linked with multiple components. The shell subsystem includes the casing, filter, lubrication, seals and valve. On the other hand, the mechanical power subsystem consists of the bearing, impeller, radial and thrust bearings. Additionally, Table 1 presents the failure mode selection for the MRA ballast pump case study.

Table 1: Failure mode selection for MRA ballast pump case study

Failure Mode	Abbreviation Meaning
BRD	Breakdown
ELP	External Leakage of Process Medium (i.e. oil, gas, condensate, water)
ELU	External Leakage of Utility Medium (i.e. lubricant, cooling water)
FTS	Fail To Start on demand
INL	Internal Leakage
NOI	Noise
OHE	Overheating
PDE	Parametre Deviation (unspecified from source)
SER	Minor in-service problems (unspecified from source)
STD	Structural Deficiency
UST	Spurious Stop (unspecified from source)
VIB	Vibration

Hence, the ballast pump case study examines the working state reliability performance of one main system, two subsystems and nine components by taking into consideration twelve failure modes.

5. MRA CASE STUDY RESULTS

This section presents the results of the MRA ballast pump case study. The outcomes are demonstrated on component, subsystem and system level while different failure modes are considered. At present, the MRA methodology's application utilises pre-processed data from external sources (e.g. OREDA) in which the recorded time and input data process are unknown. Due to the fact that the provided input data is observed in failure rates per 10^6 operational hours, the time intervals of the predicted states cannot be specified, hence the results are demonstrated as unitless. On the other hand, the final MRA application performs by employing real time monitored input data that their record interval will be specified. Hence, when real time monitored data is applied within the MRA, the time slices will gain actual unit in time as required (i.e. record per second, minute, week, month etc.).

An extract of the MRA ballast pump case study results is demonstrated in Figure 5. The results provide the working state reliability performance on subsystem and component level. The shell's subsystem reliability performance is examined as well as the components that this consists of, such as the casing, filter, lubrication, seals and valve. Hence, Figure 5 demonstrates the reliability performance of an entire subsystem and its associated components.

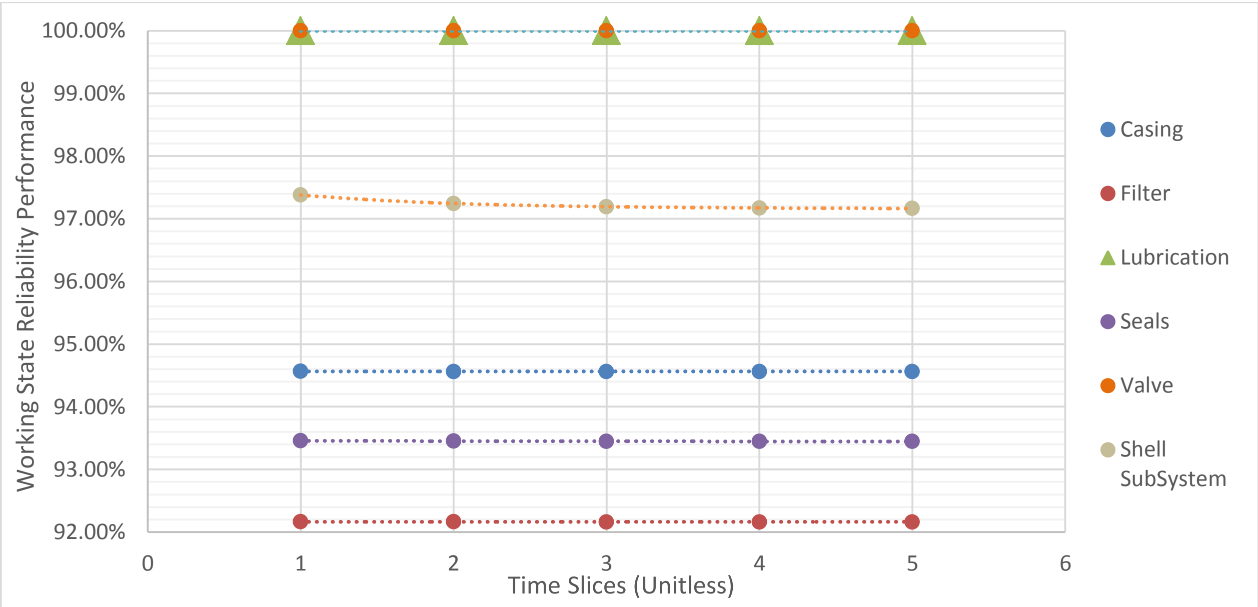

Figure 5: Ballast pump reliability performance of shell subsystem

As Figure 5 shows, the assessed reliability performance on subsystem and component levels ranges from 92% up to 100%. The reliability degradation through time is almost steady without performing rapid reliability drops. The minimum reliability performance is predicted for the filter at 92%. The following more reliable component is the seals at 93.5% and the casing at 94.6%. Lubrication's reliability forecast is expected at the ideal level of 100%, similar as the valve component case. On the other hand, the predicted reliability performance for the entire subsystem is projected at 97.5%. The case study results, on the current research development, are validated by ship owners, operators and service providers. According to their expert judgment, the assessed subsystem and components perform within acceptable reliability levels of ship owners', operators', service providers' and Classification Societies' requirements.

In a similar manner, Figure 6 presents the working state reliability performance on subsystem and component levels as well. It displays the predicted reliability performance of mechanical power subsystem and the interrelated components such as bearing, impeller, radial and thrust bearings. The results present a stable and reliable subsystem and components' profile by performing from 97.6% up to 99.7%. Therefore, the bearing achieves performance at 97.5%, radial and thrust bearings at 97.8%, whereas the impeller at 99.6%. The overall working state reliability performance of mechanical power subsystem is forecast at 99.7%. The demonstrated results are validated as well by maritime industry experts such as ship owners, operators, service providers and Classification Societies, stating that the reliability levels are acceptable and safe for ship's operations and functions.

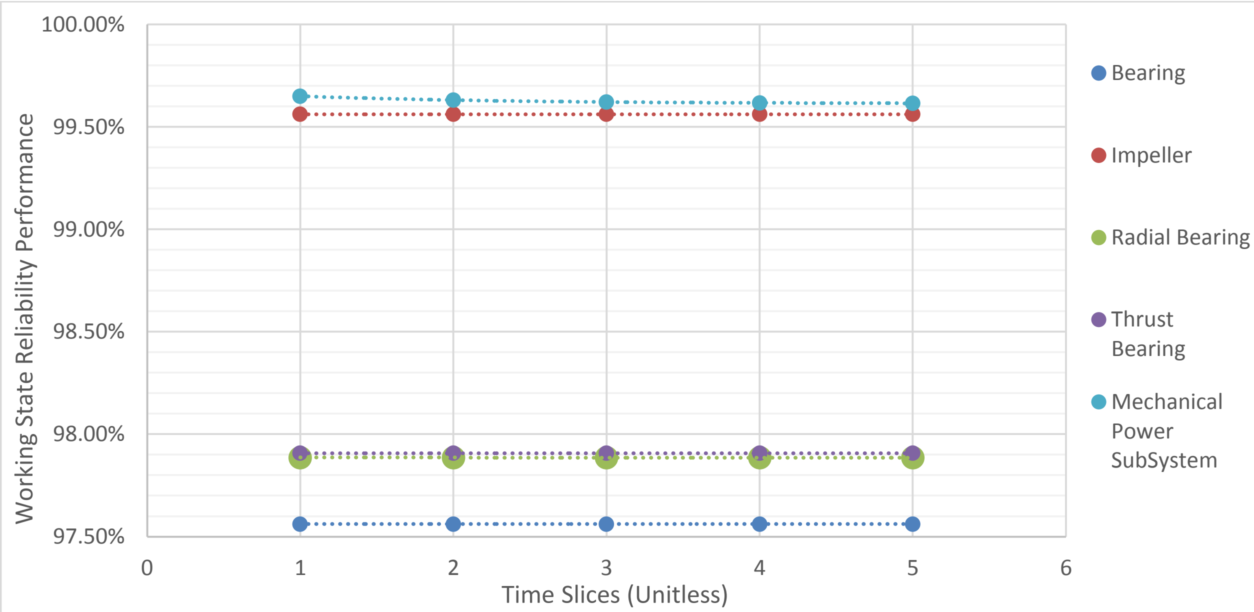

Figure 6: Ballast pump reliability performance of mechanical power subsystem

On the other hand, Figure 7 provides the working state reliability performance results on component level with respect to the failure mode that can be affected. According to historical source records, lubrication was affected by External Leakage of Utility Medium (ELU) such as lubricant or cooling water. The forecasted reliability performance reaches almost 100%. As can be seen, all the predicted results for both lubrication and impeller perform reliability over 99.98%, hence ideal and reliable function. Moreover, the outcomes demonstrate the expected degradation pattern of impeller component with respect to Structural Deficiency (STD), Spurious Stop (UST) and vibration (VIB) failure modes.

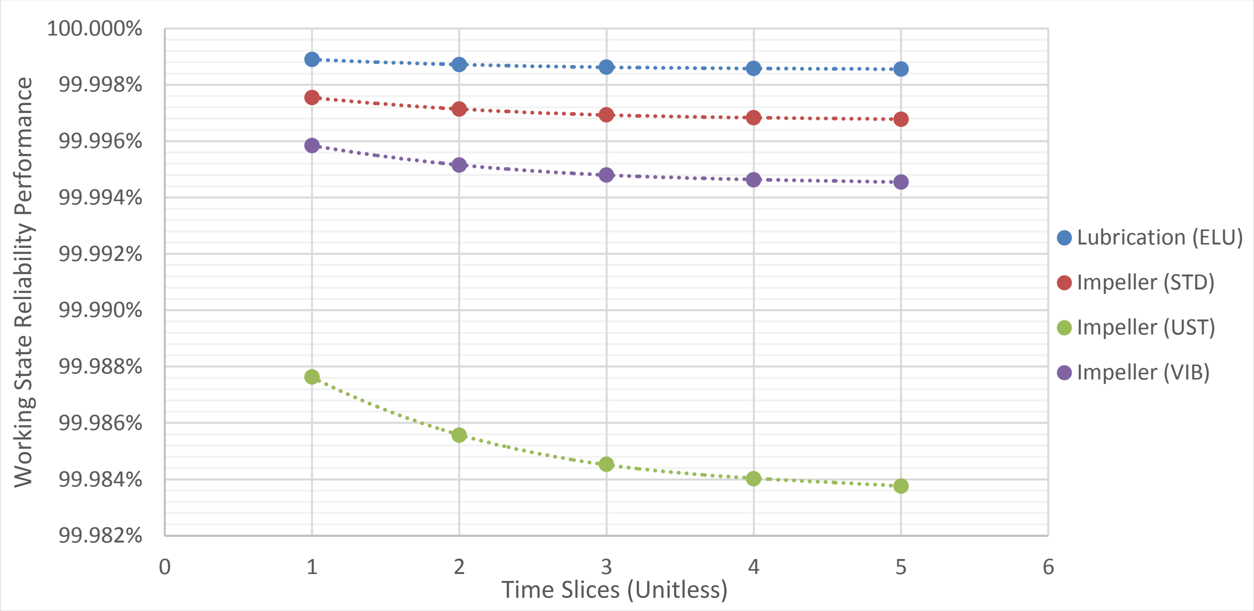

Figure 7: Ballast pump reliability performance of impeller

In the same way, Figure 8 demonstrates the reliability performance on component level for the thrust bearing by taking into consideration multiple failure modes as recorded in the historical pre-processed data. The thrust bearing is recorded to be affected by vibration (VIB), External Leakage of Utility Medium (ELU) such as lubricant or cooling water, Structural Deficiency (STD), breakdown (BRD) that its state and reasoning is unspecified by the input data source and overheating (OHE). The reliability performance shows acceptable, reliable and safe operational levels above 99.99%.

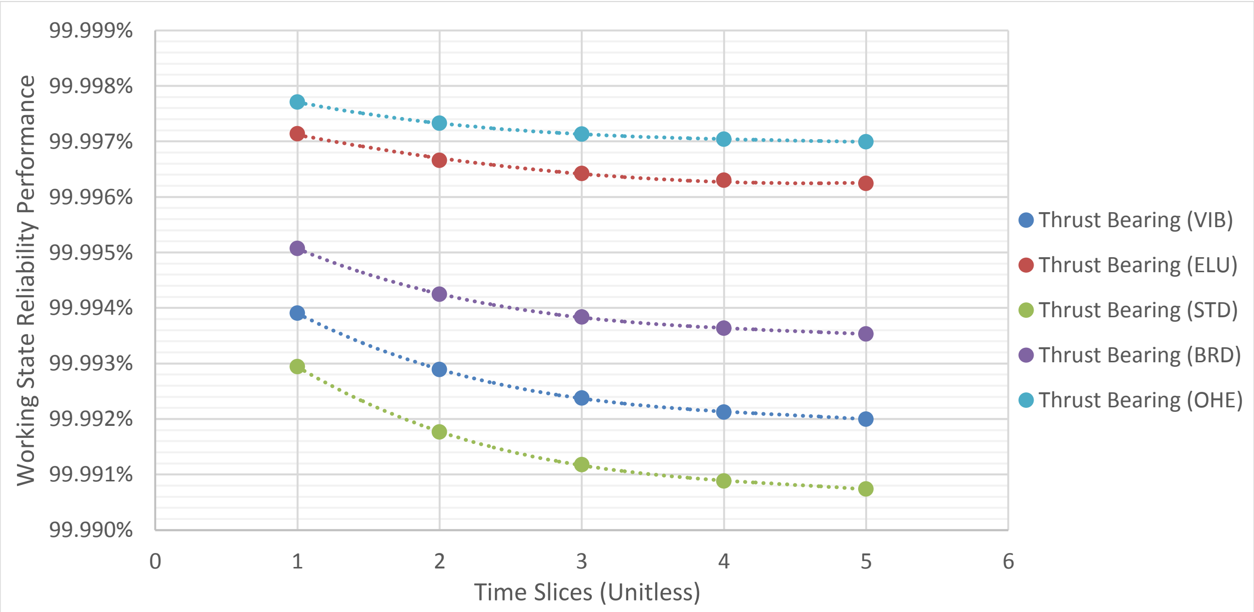

Figure 8: Ballast pump reliability performance of thrust bearing

6. DISCUSSION & CONCLUSIONS

This paper demonstrates 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. The investigation of literature takes into account the human error issues and maintenance operation control that motivated this research study. Moreover, the literature review presented in this paper consists of the latest Condition Based Maintenance (CBM) methodology, the most applied and developed Condition Monitoring (CM) technologies and tools. The research establishes the importance of inspection and maintenance by presenting the latest maintenance and CM guidelines and regulations. The research is introduced by assessing the state-of-the-art of risk and reliability analysis methods.

Once the literature review is presented, the suggested Machinery Risk Analysis (MRA) methodology is proposed as well as the MRA reliability modelling approach. The later consists of the risk and reliability input data flow diagram and the developed analysis processes. The dynamic probabilistic network arrangement is proposed by considering flexible Markov Chains (MC) and the reliability tool based on Bayesian Belief Networks (BBNs). The proposed methodology is applied on a case study utilising a ballast pump, two subsystems (i.e. shell and mechanical power), nine components and twelve failure modes that these can be affected. The following section examines the performed results out of the presented MRA application. The working state reliability performance on subsystem and component level is presented. The outcomes predict acceptable reliability performance levels above 92% and steady degradation pattern without performing fast reliability drops or changes in functioning. The results present the working state reliability performance of shell subsystem at 97.5%, filter at 92%, seals at 93.5% casing at 94.6% and lubrication and valve at the ideal level of 100%. Furthermore, the results demonstrate the reliability performance of mechanical power subsystem at 99.7%, whereas the bearing achieves performance at 97.5%, radial and thrust bearings at 97.8% and the impeller at 99.6%. Additionally, the reliability performance of the impeller and the thrust bearing at failure mode level demonstrates ideal reliability performance prediction at almost 100%.

Future research involves the specification of failure and warning levels and identification of the lowest acceptable reliability results. These warning levels aim to specify alert thresholds that the MRA system operator will be informed before a failure comes up. The thresholds will be specified on component, subsystem and main system levels. Furthermore, different maritime stakeholders' judgment will be considered such as ship owners, operators, service providers and Classification Societies. Additionally, the implementation of a methodology is considered that will allow the utilisation of real time monitoring raw sensor data. Concluding, the results' demonstration to system operators will involve a user friendly Graphical User Interface (GUI) which will be integrated with a Decision Support System (DSS). This tool aims to suggest useful decision making maintenance actions.

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