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Condition Monitoring for Enhanced Inspection, Maintenance and Decision Making in Ship Operations

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Abstract

This paper presents the INCASS (Inspection Capabilities for Enhanced Ship Safety) project which brings innovative solutions to the ship inspection regime by integrating robotic-automated platforms for on-line or on-demand ship inspection activities and selecting the software and hardware tools that can implement or facilitate specific inspection tasks, to provide input to the Decision Support System (DSS). Enhanced inspection of ships includes ship structures and machinery monitoring with real time information using 'intelligent' sensors and incorporating structural and machinery risk analysis, using in-house structural/hydrodynamics and machinery computational tools. Condition based inspection tools and methodologies, reliability and criticality based maintenance are introduced. An enhanced central database handles ship structures and machinery data. The development and implementation of the INCASS system is shown in the case of ship machinery systems. In this way the validation and testing of the INCASS framework will be achieved in realistic operational conditions.

Keywords

Ship safety; structures; machinery; condition monitoring; real-time data; decision making.

Introduction

Recent research shows that competition in maritime market develops more compound and pretentious structure affected by parameters as time, economical restraints, technology and innovation, quality, reliability and information management. In relation to successful business competence, strategic planning should be enhanced considering assets availability, involving maintenance and reliability operational aspects. The latest technology controlling these parameters is focused on monitoring the condition of main and auxiliary machinery.

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.

This paper aims to present the development of a Machinery Risk and Reliability Assessment (MRA) methodology for ship machinery and equipment as well as the MRA Decision Support System (DSS). The innovation of MRA methodology is oriented towards the components' failure and state interdependencies providing a holistic view of systems' reliability performance. Furthermore, MRA 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 dynamic monitoring model is introduced. The presented methodology involves the generation of Markov Chain arrangement integrated with the advantages of Bayesian Belief Networks (BBNs).

All progress and methodology development takes place using Object Oriented Programming (OOP) environment in Java language. Additionally, the MRA DSS tool is developed and introduced. This tool utilizes the MRA results by integrating historical data and expert judgment in order to assist the ship machinery inspection and maintenance. Moreover, user-friendly Graphical User Interface (GUI) is developed by involving useful DSS aspects for onboard risk and reliability control. Lastly, INCASS project developed a measurement campaign, where real time sensor data is recorded onboard a tanker, bulk carrier and container ship. The gathered data will be utilized for MRA DSS tool validation. The entire MRA DSS tool is demonstrated in this paper through a case study by employing currently simulated input data.

Hence, this paper is structured in 4 sections. First of all, Section 1 introduces the paper's scope and motivation of research. Section 2 refers to the research background which involves the exploration of Condition Based Maintenance (CBM) methodology and well known Condition Monitoring (CM) technologies and tools. In Section 3 the suggested Machinery Risk Assessment (MRA) methodology is presented by demonstrating a case study, the performed results, the MRA DSS and. Section 4 concludes with the discussions and future work for the MRA development.

Literature Review

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 tools.

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 inspection and maintenance operations. In shipping industry, maintenance structure is transformed from budget gain perspective to investment for continuous and reliable asset service. However, 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., 2015b).

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.

Condition Based Maintenance (CBM)

Maintenance methodologies can be identified as maintenance policies indicating the entire business's profile. These methodologies set the corporate orientation with respect to the applied maintenance strategy and operations. Different methodologies are introduced in the literature (Mobley et al., 2008). Research presents integration of methodologies and policies, allowing the utilization of flexible frameworks. 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). On the industrial aspect, SKF (2012) states that CBM aims at 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 upgrades 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.

Condition Monitoring (CM) Technologies

CM technology is applied through various tools. These tools record and evaluate measurable parameters such as vibration monitoring, acoustic and ultrasonic monitoring, thermography and oil analysis. CM is identified in phases between data acquisition, signal preprocessing and feature extraction, signal analysis and fault detection, leading to decision-making and failure prognostics (Delvecchio, 2012). 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; non-contact displacement transducers; velocity transducers and accelerometers (Dikis et al., 2015a). 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.

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).

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

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 (* stands for multiplication). Furthermore, innovative features of BBNs involve the utilization of decision making and cost functions.

Suggested MRA Methodology

In this section, the MRA methodology is 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 MRA input data flow consists of three stages, the data acquisition and processing, the reliability model and the Decision Support System (DSS).

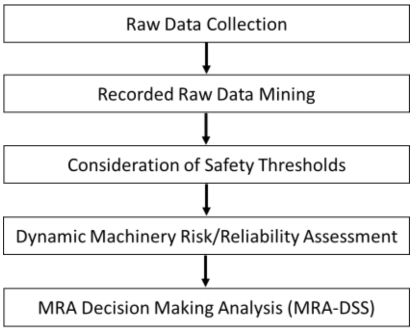

Fig. 1: Machinery Risk Analysis (MRA) Process Flow

All processing, MRA functions and DSS features are developed in Java Object Oriented Programming (OOP) language. Java is chosen as it is cross platform and allows ease of use and compatibility among different Operating Systems (OS) such as Windows, Macintosh or Linux distributors. Fig. 1 demonstrates the Machinery Risk/Reliability Assessment (MRA) methodology with respect to the process flow. On the first stage, the data acquisition and processing is considered by involving the raw data collection, mining and the safety thresholds. 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 utilizing various measurements from the control room of the Engine Room (E/R) and multiple data acquisition tools. All gained information is stored in a database and transmitted in the various methodology stages 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, 2015).

The following phase involves the real monitoring data/signal processing (i.e. recorded raw data mining). This is a critical and innovative phase, where real time input data such as physical measurements are transformed to reliability input. This input data type transformation from physical measurements to probabilistic indices is achieved by employing data clustering analysis and approaches such as k-means, c-means and hierarchical clustering (Jain and Dubes, 1988), (Jain et al., 1999), (Hand et al., 2001). On the other hand, literature demonstrates alternative probabilistic model approaches by utilizing mixture models such as Gaussian Mixture Model (GMM) (Theodoridis, 2015). The selection of data clustering analysis and mixture model is identified with the respect to the features and form of the collected datasets. The following process of the MRA methodology employs the physical measurements' thresholds. In other words, the safety indices are considered by setting the acceptable operational levels. These safety levels identify the acceptable and warning limits of the physical measurements that the system should function. The safety indices are classified according to manufacturers' manuals, Classification Societies' standards or ship owners' and operators' requirements. Furthermore, the integration of the data clustering analysis with the identification of the safety thresholds introduces the probability of occurrence the observed (recorded) input data to perform within the acceptable functional levels. This probabilistic measure in percentage generates the input for the following risk and reliability tool.

The data clustering approach of k-means aims to partition the n observations into $k(\leq n)$ sets $S = \{S_1, S_2, \ldots, S_k\}$ so as to minimize the Within-Cluster Sum of Squares (WCSS) (sum of distance functions of each point in the cluster to the K center). A recorded dataset (raw data collection) $(x_1, x_2, \ldots, x_n)$ is observed, where each observation is a d-dimensional real vector. Hence, k-means data clustering model scope is to find (Theodoridis, 2015):

$$\underset{\mathbf{S}}{\operatorname{argmin}} \sum_{i=1}^{k} \sum_{x \epsilon S_i} \|x - \mu_i\|^2 \qquad (2)$$

where μ_i is the mean of points in S_i (Equation 2).

K-means data clustering approach is selected as it is suitable for large number of variables. K-means is one of the simplest algorithms which uses unsupervised learning method to solve known clustering issues. Moreover, k-means can be computationally faster than hierarchical clustering methods. On the other hand, k-means can produce tighter clusters than hierarchical clustering. Additionally, k-means enables high flexibility in data analysis as it becomes a great solution for pre-clustering, reducing the space of each cluster and allowing the integration with other algorithms for further processing.

In the second stage 'Reliability Model', the processed reliability input data 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. 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) (Fort et al., 2015). MC is mathematical system that undergoes transitions from one state to another on a state space.

Furthermore, 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 Fig. 2. 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 can be seen in Fig. 2 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 3. On the other hand, Equation 4 presents the PoW per expressed component/subsystem in the future *t+1* time slice. Where, $P(w_{t+1})$ 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.

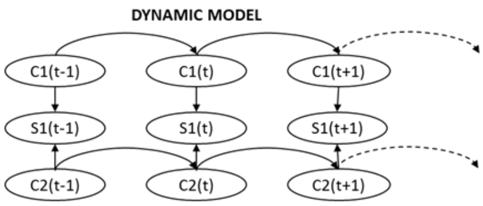

Fig. 2: Dynamic Probabilistic Network Arrangement

$$P_{X(n-1),X(n)} = P\{X_{t_n} = X_n | X_{t_{n-1}} = X_{n-1}\} \quad (3)$$

$$(w_{t+1}) = P(w|w_t)P(w_t) + P(w|f_t)P(f_t) \quad (4)$$

While, each component of a sub-system is linked with a certain number of failure modes 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* shows the PoW state while *f* shows the PoF. The relation of *w* and *f* is shown in in Equation 8. Whereas, 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). Whereas, P_3 represents the PoW and PoF states while ft_{f1} and ft_{f2} take place at the same time (Equation 6).

$$P_1 = \begin{cases} w: 100 - ft_{f1} \\ f: \quad ft_{f1} \end{cases}; \quad (5)$$

$$P_2 = \begin{cases} w: 100 - ft_{f2} \\ f: \quad ft_{f2} \end{cases}; \quad (6)$$

$$P_3 = \begin{cases} w: 100 - (ft_{f1} * ft_{f2}) \\ f: \quad (ft_{f1} * ft_{f2}) \end{cases}; \quad (7)$$

$$P_m = (ft_{f1} * ft_{f2} * ft_{f3} * \ldots * ft_{fk}) \quad (8)$$

$$f = 100 - w \quad (9)$$

Equation 10 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 11.

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

$$m = 2^k \quad (11)$$

The third stage of the MRA tool implements the Decision Support System (DSS) aspects. The MRA DSS methodology is divided into two sections. The first one utilizes local (onboard) and short term decision making suggestions, whereas the second one is used onshore (global) for longer term predictions and decision features. The MRA 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. This research paper is focused on the Machinery Risk and Reliability Assessment (MRA) tool. Hence, the introduced application, in the following section, performs utilizing the MRA methods and the risk and reliability aspects.

MRA Case Study

In this section, a Machinery Risk/Reliability Analysis (MRA) case study is presented by involving the ship Main Engine (M/E), three subsystems and multiple components. The case study assesses the working state reliability performance on subsystem and component levels by analyzing various probable failure case scenarios. The case study employs simulated input data that are generated utilizing normal distribution (Gaussian). The safety thresholds (i.e. safety indices) are identified through the engine's manufacturer's manual and the engine's sea trials. These safety indices are selected as they fulfil the manufacturer's requirements and sea trials provide the ideal available reference point for further comparison.

The model's arrangement considers the ship Main Engine (M/E), the valve train, fuel and subsystems. In the case of the first subsystem two components are involved such as the exhaust valve and the suction valve. In the case of the fuel subsystem the fuel pumps and the fuel valves are taken into account. On the other hand, the drive train consists of the camshaft, crankpin, main engine and thrust bearings. Most of these components (where applicable) are analyzed with respect to 6 items per component as the engine's manual used is from a six-cylinder marine diesel engine. **Error! Reference source not found.** demonstrates the raw input data requirements that MRA methodology is tested.

Table 1: Raw Input Data Requirements

Subsystem	Component	Measurement	Unit
Valve train	Exhaust valve	Pressure	bar
	Suction valve	Temperature	°C
Fuel	Fuel pump	Pressure	bar
	Fuel valve	Pressure	bar
Drive train	Camshaft bearing	Temperature	°C
	Crankpin bearing	Temperature	°C
	M/E bearing	Temperature	°C
	Thrust bearing	Temperature	°C

Fig. 3 demonstrates the Main Engine (M/E) MRA network case study. This network consists of exhaust valves, suction valves, fuel pumps and valves, camshaft, crankpin, main engine bearing (one per cylinder) and a thrust bearing. There are two modelling approaches to structure this network. The first approach links the involved components directly to the subsystems (i.e. valve train, fuel system and drive train) and the subsystem to the main system. The second approach as shown in Fig. 3 takes into account an intermediate level of nodes (i.e. ExhastVlvs, SuctionVlvs, FuelPumps, FuelVlvs, CamshaftBearings, CrankpinBearings, and MEBearings) that sums up the predictions of the working state reliability performance per group of identical components.

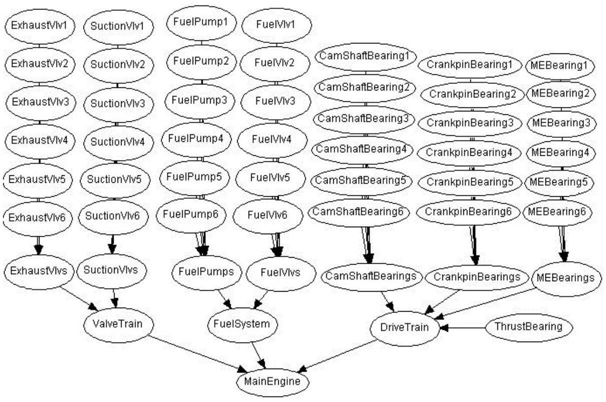

Fig. 3: Main Engine (M/E) MRA Network Case Study

Due to Equation 11, the first approach will involve multiple failure case scenarios, leading to a complex probabilistic model considering 532,488 failure scenarios. This network arrangement will cause further programming effort as well as increased calculation and processing time. On the other hand, the demonstrated network arrangement involves 484 relations of failure case scenarios. The proposed network structure advances to high calculation performance and simpler code development. On the results' perspective, the first network modeling approach (without intermediate node level) is more analytical by assessing more failure case scenarios. These scenarios assess the failure of cross-head bearings at the same time with the piston lube oil, the piston liners and the valves (as Equations 5-9 show). The combination of multiple failures creates impractical low predicted working state reliability performance. On the other hand, these analytical scenarios demonstrate the sequential failure of components (interconnections). This sequential failure assessment can be introduced in the simpler and faster proposed network arrangement by introducing the functional component interdependencies. Hence, programming and calculation effort can be gained without involving unnecessary scenarios that their results do not demonstrate the practical functionality of the system.

MRA Case Study Results

This section presents the results of the MRA Main Engine (M/E) case study. The outcomes are demonstrated on component and subsystem level. The raw input observations involve simulated datasets, 48 measurements per day and 2 days total data of historical/existing information. First of all this case study proves the ability of predicting the working state reliability performance on subsystem and component levels. This methodology introduces the requirement relation of forecasting double period of time of the provided recorded historical input. In other words, two days of existing input predicts the working state reliability performance of the following four days.

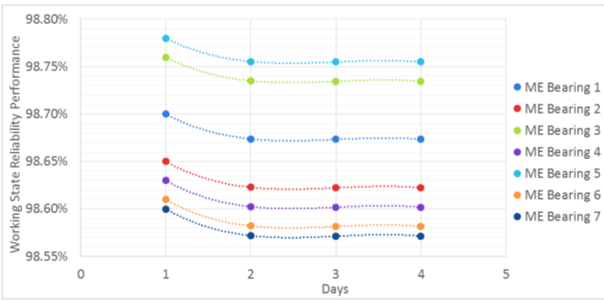

Fig. 4: Reliability Performance of M/E Bearings

The figure above demonstrates the predicted working state reliability performance of the six main engine bearings. The uniformity of the predicted results among the bearings is expected due to the utilization of simulated input datasets. Furthermore, simulating real system functioning, each component performs on different reliability levels as various parameters affect each bearing. The overall reliability performance of the bearings confirms acceptable forecasted working levels. On the other hand, negligible reliability performance loss is forecasted per bearing. This minor reliability difference is expected as the employed input datasets figure only two days of performance. Hence, the upcoming forecasts perform low reliability loss for the following four predicted days. The overall reliability demonstrates performance from 98.8% to 98.55% and almost stable temperature between 59 and 61 °C. The marine engine's manufacturer's manual identifies normal operational temperature levels from 50-70 °C and warning alarm level at 75 °C. Hence, there is no indication of upcoming failure or abnormal component functioning.

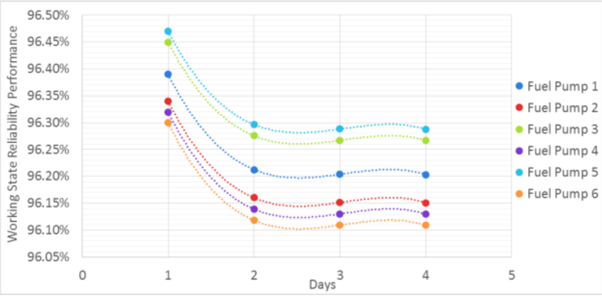

Fig. 5: Reliability Performance of Fuel Pumps

Similarly, the six fuel pumps' forecasted working state reliability performance are considered (Fig. 5). Similar prediction behavior is shown as in the main engine bearings' case. The uniform results are expected as well for the same reasoning as above. The overall working state reliability performance shows almost stable predictions at 96.1-96.5% (reliability) and 2.2-2.4 bars. The results are acceptable as the engine manufacturer sets the safety threshold at 0.5 bar (not lower). The reliability performance of the camshaft bearings, crankpin bearings and thrust bearing shows stable progress through time at higher than 95% and operational temperature at 59-60 °C. In this respect, the acceptable functional level is set within the range of 50-70 °C and the warning is specified at not higher than 75 °C. In other words, the current reliability performance of all involved components is acceptable and there is no need for maintenance actions. As the scope of this study is to identify and examine the working state reliability performance, it is essential to highlight that the stable performance so far sets the ground for further functioning of all components.

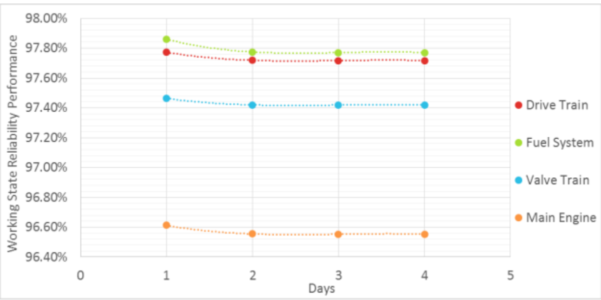

Fig. 6: Overall Reliability Performance

Similarly, Fig. 6 demonstrates the reliability performance at subsystem and system levels for the drive train, fuel and valve train subsystem as well as the main engine. The reliability levels progress stably through time higher than 96.6%. Due to the fact, all the subsystems perform stable reliability, hence the system does. In the case of the subsystem reliability assessment, there is no actual measure to classify and identify a specific threshold. However, expert judgment can provide a valid indication on which level the warning should be shown and further analysis on component level can be triggered. The overall subsystem reliability performance is expected to be increased once inspection and maintenance actions are taken on component level.

MRA DSS Case Study Results

This section aims to present the Machinery Risk/Reliability Assessment Decision Support System (MRA DSS) tool and its features. Entire development of MRA and MRA DSS is taken place utilizing Java Object Oriented Programming language. Fig. 7 presents the MRA DSS analysis of failure predictions through a user-friendly Graphical User Inter-face (GUI). The user has available information related to cost analysis, maintenance actions, reliability performance predictions and symptoms due to reliability loss. In Fig. 7 is shown the current system, subsystem and component reliability performance and the associated warning and failures.

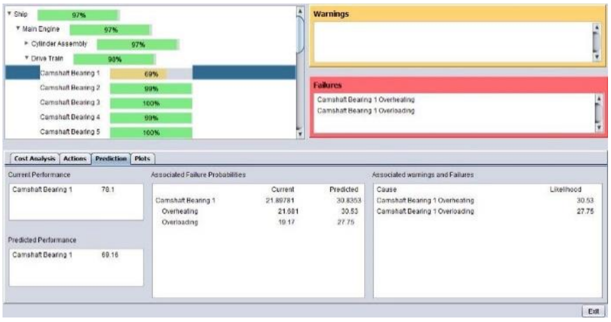

Fig. 7: MRA DSS Analysis of Failure Predictions

On the other hand, Fig. 8 demonstrates the symptoms tab in a graphical format and five days prediction in advance from the current moment. The graphs are presented in days for this occasion and with the grid marking four-hour intervals on the time axis. This is to coincide with the regular four-hourly visits the engineers onboard the ship performs.

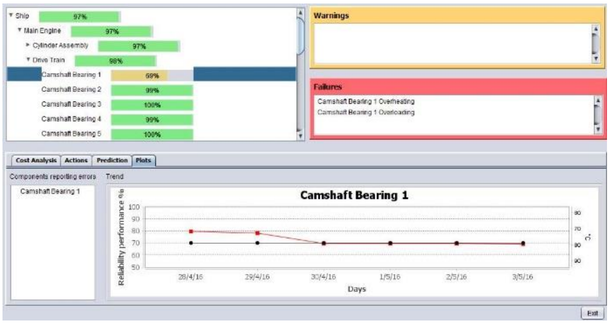

Fig. 8: MRA DSS Plotting of Results

MRA DSS plotting of results incorporates past, current and forecasted working state reliability performance (%). Furthermore, the performance within the involved timeline is demonstrated in both percentage as well as the physical unit/measure (i.e. °C, bar etc.). Lastly, actions tab includes inspection and maintenance suggestions according to the predicted working state reliability performance. Hence, as shown in Fig. 9, camshaft bearing 1 shows reliability degradation due to overheating and a probable reasoning can be overloading. This, multiple inspection actions are suggested including checks due to material fatigue, excessive wear or corrosion.

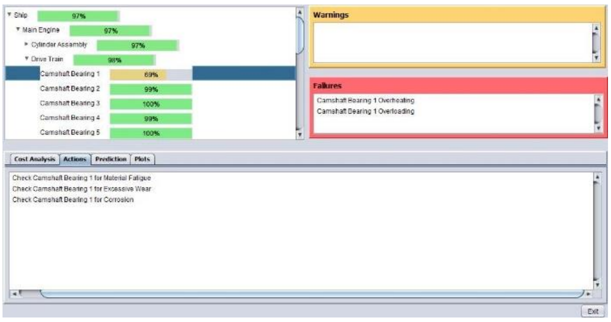

Fig. 9: MRA DSS Inspection & Maintenance Actions

Conclusions

This paper demonstrates the development of the Machinery Risk/Reliability Analysis (MRA) tool. MRA is probabilistic risk/ reliability analysis model established through the work performed in INCASS 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 is introduced by assessing the state-of-the-art of risk and reliability analysis methods.

The suggested MRA methodology is proposed as well as the MRA reliability modelling approach. The MRA methodology consists of three processing and assessment stages. The first stage involves the input data requirements, collection and processing, where-as the second stage takes into account the risk and reliability tool development. Furthermore, the third assessment stage consists of the MRA Decision Support System (DSS) and the utilization of historical, expert and predicted reliability results to assist the inspection and maintenance planning. The developed MRA methodology is focused on the risk and reliability assessment by employing various input data types such as historical, expert and real time sensor data. The methodology consists of multiple processing and assessment methods.

Firstly, the gathered datasets are analyzed by employing raw data mining process of k-means. This assessment identifies the tendency of the recorded input to downgrade and lead to safety threshold before it exceeds the warning level. The safety thresholds can be specified according to the identified requirements. In this case, engine manufacturer's manual is utilized providing accurate and tested reference points (i.e. sea trials) for setting the safety indices. 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 utilizing a six cylinder marine diesel engine, the valve train, fuel and drive train subsystem. Furthermore, multiple components are considered such as the exhaust and suction valves, fuel pump and valves, and various bearings include camshaft, crankpin, main engine and thrust bearings. The developed MRA tool predicts the working state reliability performance on system, subsystem and component levels.

On the current research development, the dynamic risk and reliability tool is 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. On the other hand, the accuracy of the reliability tool's fore-casted results is verified by employing commercial software such as Genie 2.0, Hugin 7.8 and the Markov Chain (MC) modelling using Reliability Work-bench.

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