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PREDICTIVE MAINTENANCE DECISION SUPPORT SYSTEM FOR ENHANCED ENERGY EFFICIENCY OF SHIP MACHINERY

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ABSTRACT

A decision support system (DSS) is an application that analyses data and presents results to users. DSS rapidly shift through huge amount of available data and thus allowing for faster analysis of condition monitoring data early detection of faults and improved allocation of resources. DSS can also predict and plan for future ship operators' needs in order to optimize ship machinery operations. Such a system can provide substantial benefits to the maritime industry in terms of energy efficiency as the operation of the vessel can be optimised towards this end. As part of the INCASS (Inspection Capabilities for Enhanced Ship Safety) EU FP7 project, this paper presents a novel DSS solution which interrogates data from dynamic condition monitoring and compares them with historic data to present decision support information onboard a ship. To provide for Condition Based inspection and criticality based maintenance for ship machinery, data is acquired and stored for analysis through the DSS. Moreover surveys involving off-line and real time on-line measurement approaches are combined to provide a more complete monitoring method. The result is a reliable user friendly graphical interface (GUI) developed in Java language that can be employed onboard any vessel and can provide relevant and on-time information. The proposed actions from the DSS target energy efficient operation and reduction of fuel consumption and ship emissions. Moreover, a major factor taken into account through the prediction mechanism of the DSS is to assist in better spare parts scheduling and prioritizing ship inspection, maintenance and repairs towards enhanced and efficient ship operations.

Keywords: maintenance, dynamic machinery condition monitoring, energy efficiency, decision support system, java programming

NOMENCLATURE

CBM	*Condition Based Maintenance*
CM	*Condition Monitoring*
DSS	*Decision Support System*
EC	*European Commission*
EU	*European Union*
GUI	*Graphical User Interface*
INCASS	*Inspection Capabilities for Enhanced Ship Safety*
MRA	*Machinery Risk Assessment*
OREDA	*Offshore Reliability Database*

1. INTRODUCTION

Ship procedures include mandatory maintenance of both equipment and machinery in order to comply with regulation and also sustain effective and efficient operations. Unfitting maintenance can lead to hazardous conditions onboard a ship that may result to accidents, environmental damage and loss of life. Such events can cause significant business losses and expensive fines. Moreover, monitoring and inspection requirements from regulatory bodies and Classification Societies have increased the complexity of inspection procedures. Additionally, due to market trends funds for maintenance are constantly reduced. Furthermore, nowadays the need for greener industries is a major drive for enhanced and optimised fuel consumption and minimised emissions. The INCASS (Inspection Capabilities for Enhanced Ship Safety) project through the cooperation of maritime stakeholders aims to avoid ship accidents, increase efficiency of vessel operation, promote maritime safety and protect the environment (EC, 2009).

The INCASS approach is an innovative framework that monitors ship structures, machinery and equipment. Through this, a decision support system is proposed that focuses maintenance actions toward the necessities resultant from the monitoring data in order to optimise them. INCASS is based on specific vessel case studies so as to validate and test it under real conditions. The development of the INCASS framework was based on the cooperation of experienced partners from a variety of stakeholders to the maritime industry, including universities, Classification societies, ship owners/managers, service providers and research institutes.

Data collection includes online measurements through permanently installed sensors on machinery (INCASS, 2014c). Also the capability of user input allows for offline measurements and inspection data to be incorporated to the system (INCASS, 2014c). This paper presents the methodology used within the INCASS project for the analysis of the recorded data and the incorporation of the analysis results into the proposed DSS system.

The first section of this paper introduces the literature review. The second section describes the methodology in regards to the DSS system. The resulting system is presented in the third section through a case study. Finally, the fourth section presents the conclusions of this paper and the utilisation of the DSS system in achieving efficient ship operations.

2. LITERATURE REVIEW

2.1 SHIP EFFICIENT OPERATION

2.1 (a) Energy Efficiency

Due to the increased oil prices and the fortold oil shortages the maritime industry is nowadays investigating the improvement of efficiency in operational vessels. Reduction of fuel cost is necessary for financial stability of commercial shipping companies due to reduction in freight rates (7.2% in 2013). Fuel consumption, which can be 45% to 60% of the operational cost of a vessel, is one of the two main areas of focus - other than maintenance strategies - to achieve cost reduction through efficient and effective management (Logan, 2015). The applicable methods for reduction of this cost are slow steaming, lower-cost fuel use and improving operational efficiency. For both slow steaming and operational efficiency monitoring is of paramount importance. Slow steaming is known to link to negative impact on the engine and thus close monitoring and on time intervention is important in order to sustain reliable and efficient operation of the ship. These effects are also linked to reductions in efficiency of other components such as turbo chargers. As a result a complete and comprehensive system for monitoring is of utmost importance.

Additionally the shipping industry has to face other global concerns and regulations linking to fuel emmissions due to the environmental concerns, social presure and reduced emmission footprint operations. The reduction in fuel consumtion is directly linked to a reduction of the polutant emissions. For example a reduction of speed equal to 4 knots can lead to a reduction of emissions by 40% (EC, 2011). However, it may be possible to create appropriate voyage plans and maintenance actions in order to achive the desired reduction in fuel and emmissions, the parameters to take into account are multiple and as a result optimisation is often not possible without computerised and automated means (Diakaki et al., 2015).

2.1 (b) Efficient Maintenance

Maintenance costs are a burden for US navy in sight of reduced budgets available linking to an increased trend in the reported casualties of surface combatants and amphibious warfare ships (Logan, 2015). This leads to an increased need for efficient maintenance plan. Such reductions in funds available for maintenance are not uncommon in commercial waterborne transport either. Strategic maintenance thus is a necessity for an increasingly large number of ships. Condition monitoring can be utilised in order to achive such a maintenance strategy and has been proven to increase effectivness in other industries such as airospace (Tourvalis, 2007) Additionally CBM is an effective and cost effective method for maintenance as discussed in DeMott (1978a) and (1978b). Such applications also exist in the naval industry and have proved to provide the desired results in effective and efficient maintenance (Nemarich et al., 1990). However, these methods do not include all the machinery and equipment of the ship and rather target specific areas such as parts of the main engine.

2.2 MAINTENANCE AND CONDITION MONITORING

For the maintenance of ships there are various strategies that can be followed. One of those is breakdown maintenance where replacement of a component/part takes place only after failure. However, there are other strategies that are associated with increased reliability of the ship and reduction of dry-docking (Jardine et al., 1997). Preventive maintenance considers scheduled maintenance actions based on experience or manufacturer's recommendations and is a means for increased reliability and availability of systems (Moghaddam and Usher, 2011). The use of effective tools and systems are necessary to achieve reliability, availability and maintainability of systems which affects safety as well as cost (DoD, 2005). To that end, monitoring is an important part throughout the system's operational life time in order to acquire the aforementioned experience. For that reason shipping companies invest heavily on inspection and maintenance in both personnel and expense (Lazakis et al., 2016). Advanced strategies however exist using statistical analysis and condition monitoring in order to accurately predict time of failure and schedule replacement only when necessary. These methods lead to minimisation of replacement and repair through reduction of failures and breakdowns (Pintelon and Gelders, 1992) , (Valdez-Flores and Feldman, 1989), (Cho and Parlar, 1991).

Condition based monitoring is the base of such an advanced strategy and it detects failures before they take place as defined by Mechefske (2005). This strategy achieves all the goals demanded by monitoring and provides increased reliability and availability with minimised cost. It is well established in practice as it can be used to assist in decision making in regards to timely maintenance actions based on indications that a failure is imminent (Jardine et al., 1997), Developed CBM methods heavily depend on condition monitoring and analysis of the equipment of interest. Additionally, it is demonstrated by (SFK, 2012) that CBM can reduce risk in industrial applications by increasing the warning time to failure and allowing for early intervention.

2.2 (a) Wireless Condition Monitoring

Wireless condition monitoring is a further advancement to the condition monitoring methods and has been used in existing systems within other industries such as electrical and nuclear (Baker, 2010). These are environments characterised by high electromagnetic noise with similar profiles to that of a typical ship engine room. Wireless installations are providing further cost reduction to the installation and operation of the monitoring system (Ralston, 2007) while providing reliable condition monitoring (Feng et al., 2015).

2.3 DECISION SUPPORT SYSTEMS

The use of automated systems in CBM is well established as it minimises human effort and also errors. A decision support system (DSS) can analyse large volumes of data from multiple sources and correlate them to provide information to the user. As condition monitoring data can be sourced from a large number of different equipment and machinery onboard a ship such a system can detect upcoming faults and improved allocation of resources. DSS can also assist in energy efficiency as the recorded data can be correlated with voyage data in order to optimise fuel consumption and machinery operation.

Even through there has been significant involvement of computerised systems in maintenance management there is room for development (Jones and Collis, 1996). Several DSS models have been developed for various applications based on probabilistic approaches such as the one proposed by Khac Tuan, Torres Castro et al. (2014) which is based on mean residual life time or Jardine et al. (1997) which is based on level of degradation. Effectively all the models result in a set of condition indecies for CBM decision making.

3. METHODOLOGY

The methodology is divided in two discreet parts the machinery risk assessment (MRA) and the DSS developed system. In this section an overview of the INCASS MRA methodology will be presented in order to illustrate the flow of data into the DSS system. Them the methodology followed by the DSS in order to identify areas needed attention by the crew is presented.

3.1 MRA

Data used for the MRA include historical data from statistical databases, expert data which are based on practical experience and real time monitoring from sensors and monitoring equipment. Monitoring that is used offline in an occasional bases through other monitoring equipment can also be incorporated into the system as manual user input. These sources comprise the unprocessed (raw) data and are pre-processed in order to be valid reliability MRA inputs as presented in Figure 1. At this stage the data is categorised in component, sub-system and main system level to fit to the modelled Bayesian network used for the representation of the ship's machinery and equipment and the correlation between them (INCASS, 2015a). Raw data as well as processed reliability data are stored in a local database specific to the ship that is being monitored. The preprocessed data provide input for the risk and reliability analysis of the current and predicted condition of the system which is the MRA model. The output of the model is them provided as input to the DSS to present the results of the reliability analysis in a user friendly and meaningful way and to provide decision support via suggested actions (INCASS, 2015b).

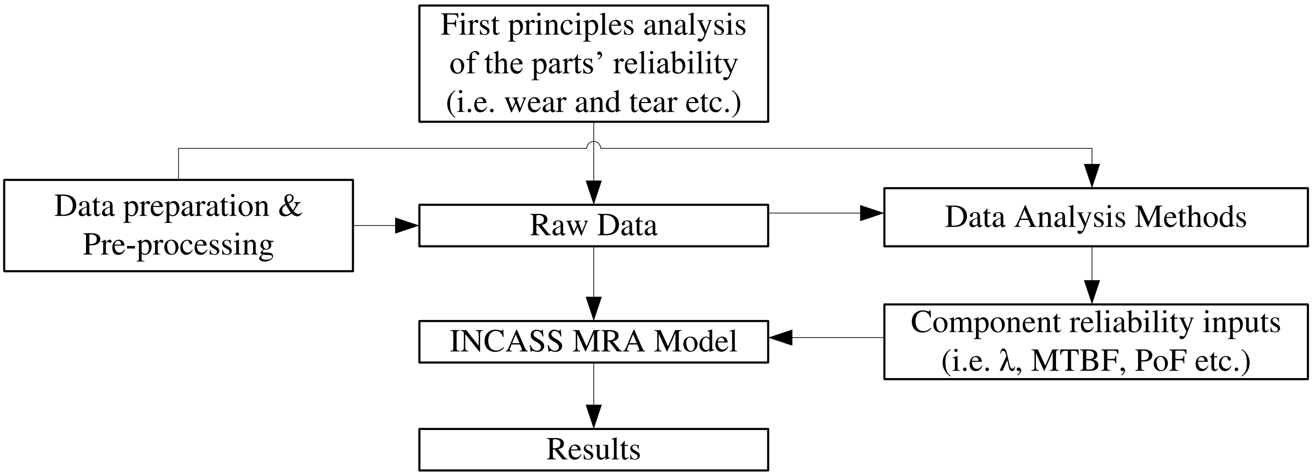

Figure 1. Machinery Risk Analysis (MRA) process diagram (Dikis et al., 2015)

The MRA model uses various methods for the condition and failure diagnosis. Signal pattern recognition is used in the preprocessing stage of the raw data input. Then, failure rates (λ), Mean Time Between Failures (MTBF) and Probability of Failure (PoF) are calculated based on the current and historical data available in the database. Finally, the predicted condition of the under investigation ship machinery and equipment is calculated providing both the predicted failure, the time to failure and the affected the components, sub-systems and systems.

3.2 DSS FOR MRA RESULTS

The developed DSS is separated in three main areas as can be seen in Figure 2 below. These are the current performance area (Figure 2– 1), the predicted warnings and failures (Figure 2– 2) and the analysis tabs (Figure 2– 3).The Information presented to the user through the GUI include predicted emergency situations and advised actions that can be flowed by the crew onboard the ship. This allows for better informed decision making in relation to inspection and maintenance.

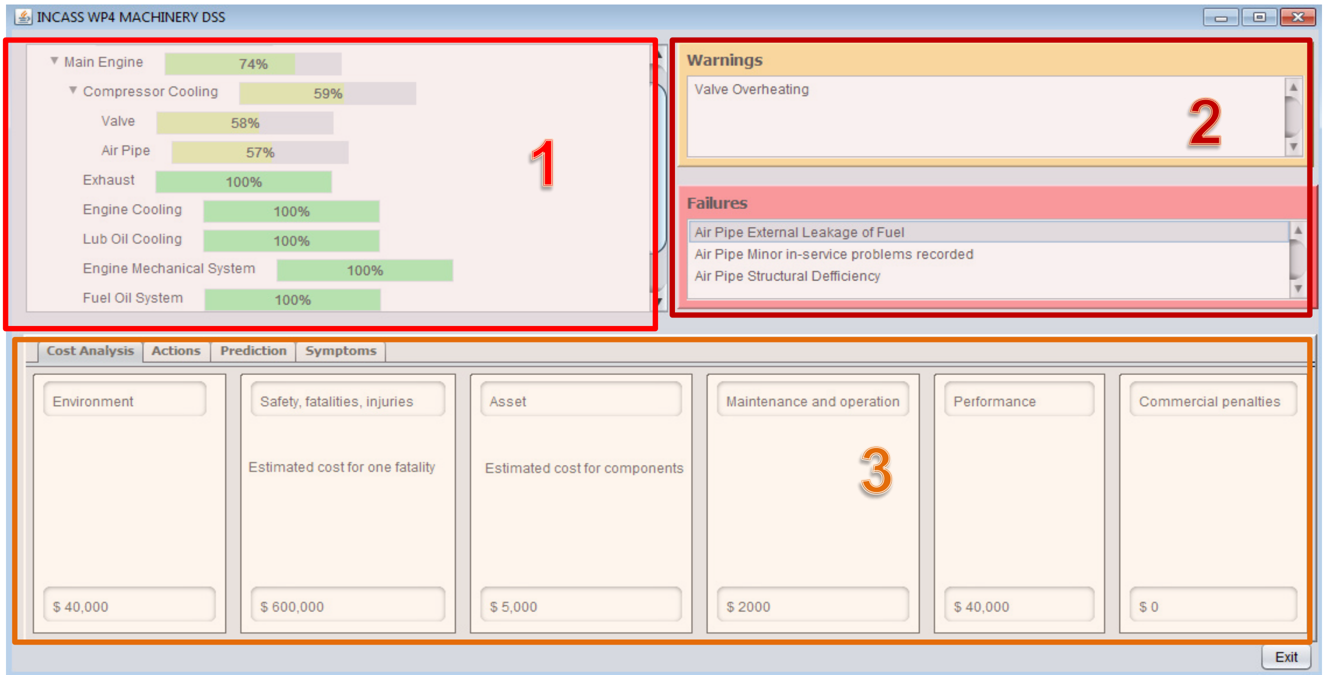

Figure 2: The three main areas of the User Interface of MRA DSS

3.2 (a) Current performance

All the monitored systems, subsystems and components on the ship and their current performance as a percentage are presented in the format of a list. The performance is the current reliability of the system in terms of a percentage as calculated by the MRA model. Traffic light colour coding is utilised to draw the user's attention to the areas where reliability is low. In Figure 2 the system presented is the Main Engine (M/E), the subsystem is the "Compressor Cooling" and its components are the "Valve" and the "Air Pipe".

3.2 (b) Predicted warnings and failures

When warnings or failures are predicted by the application they are presented to the user in the relevant lists of the GUI. In the example of Figure 2, there is one warning and several failures as the performance of the system is below the acceptable reliability threshold. If the performance of a system is deteriorating the MRA DSS will automatically recalculate the predicted performance and based on the returned values it will estimate the predicted failure of that system. This is done automatically for all the systems, sub-systems and components every time the MRA receives new raw data and calculates new reliability values. That makes the lists dynamic and when a warning/failure for any part of the ship is identified as of high likelihood then it is automatically added to the respective list in this area of the GUI. Eventually, the warning/failure lists are a true representation of all the current identified issues on the vessel at each moment.

For the DSS to calculate the likelihood of a warning/failure a system of weighted probabilities is implemented. Each component's likelihood of a failure (L) is based on the MRA resultant reliability (R) and is calculated using equation 1. The same equation is also used for calculating the sub-system's likelihood of failure and the system's likelihood of failure.

$$\mathrm{L} = 1 - \mathrm{R} \qquad (1)$$

However, each component can have more than one failure, known as failure mode, so the result is a set of calculated failure probabilities $\{L_1, L_2, \ldots, L_n\}$ each directly associated with a failure mode $\{M_1, M_2, \ldots, M_n\}$ where, L_1 is the probability of M_1 occurring in the predicted time frame returned by the MRA model. The failure modes are provided to the DSS by the MRA and are based on categorised failure modes from the OREDA database.

The overall probability of failure of the component is also returned by the MRA model and is a single value (L_c). The correlated sub-system has one probability of failure (L_{ss}) for the same predicted time frame and the same stands for the respective system (L_S).

To identify the probability of a specific failure mode being the cause of a low reliability of a sub-system the DSS calculates the weighted probability of all the failure modes of the components relevant to that sub-system using equations 2 and 3 below.

$$\mathrm{W}_{c_\mathrm{k}} = \frac{\mathrm{L}_{\mathrm{c_k}}}{\sum_{\mathrm{i=1}}^{\mathrm{m}} \mathrm{L}_{\mathrm{c_i}}} \qquad (2)$$

Where: $\mathrm{W}_{c_\mathrm{k}}$ is the weighted contribution, $\mathrm{k} = 1 \dots \mathrm{m}$ and m is the number of components contributing to the sub-system under investigation.

$$N_j = \frac{L_j \times \mathrm{W}_{c_\mathrm{x}}}{\sum_{i=1}^{n_1} L_i \times \mathrm{W}_{c_1} + \sum_{i=1}^{n_2} L_i \times \mathrm{W}_{c_2} + \dots + \sum_{i=1}^{nm} L_i \times \mathrm{W}_{c_\mathrm{m}}} \qquad (3)$$

Where: N_j is the contribution of the failure mode $j = 1 \dots l$ and l is the total number of failure modes of all the components contributing to the sub-system under investigation, m is the number of components contributing to the sub-system under investigation, $\mathrm{W}_{c_\mathrm{x}}$ is the weighted contribution of the component under which failure mode j is listed and $n_1, \dots, n_m$ are the numbers of failure modes listed under each component $c_{k=1\dots m}$.

When the calculated contribution N_j exceeds a predefined threshold which is different for each sub-system, the associated component and failure mode are presented as a warning in the relevant list of the GUI. A second higher threshold exists – dependant on the sub-system – which when exceeded, identifies the combination of this component and failure mode as a failure of the subsystem. Thus it is consequently listed under the relevant list of the GUI. These thresholds are based on manufacturer data, expert judgement data and historical data available to the DSS.

When the user selects a warning or failure from one of the lists the relevant system, sub-system or component will be highlighted on the tree representation of the ship. In this respect, the user is able to identify visually and instantly which part of the vessel is the major contributor to the reported failure.

3.2 (c) Calculated results and prediction

The bottom half of the GUI is occupied by four tabs. These are collectively presenting the analytical results of based on which the listed warning/failure was predicted. These tabs are populated when the user selects a warning/failure from the relevant GUI lists in order to investigate further the cause.

The four tabs are ‘Cost Analysis‘, ‘Actions‘, ‘Prediction’ and ‘Symptoms‘. The cost analysis tab presents the predicted costs associated with a warning or failure or a specific system, subsystem or component. The actions tab suggests maintenance activities to be taken. The prediction tab lists the performance values of the selected and the failure probabilities calculated by the DSS application. Finally, the symptoms tab presents both the historical data recorded by the sensors and the predicted data calculated by the MRA application on a graph.

3.2 (d) Cost analysis

The cost analysis is based on six major areas affecting the costs associated with ship operation. The predicted costs presented are based on fees that apply to the shipping industry or known average costs for parts or maintenance. The areas of cost are ‘Environment‘, ‘Safety Fatalities and Injuries‘, ‘Asset‘, ‘Maintenance and Operation‘, ‘Performance and Commercial Penalties‘. The values are calculated when the user chooses a listed warning/failure from the relevant are of the GUI.

The environment section, presents any costs associated with environmental damage that could potentially be applicable if the predicted warning/failure is not maintained in time. Similarly, the safety, fatalities and injuries section presents costs that are associated with a warning/failure and affect crew safety. The costs in this section are calculated based on average legal and compensation costs relevant to the shipping industry. Costs for maintenance or replacement of a component/subsystem/system are presented in the asset section, as well as the maintenance and operation sections calculated on average values for the general category of each component or by user input of specific values for the ship. Additionally, costs from reduction in performance, such as extra fuel usage and excessive emission penalties, are presented in the performance section. On the other hand, the commercial penalties section presents costs that are related to the component and result to third party incurred penalties.

3.2 (e) Actions

This tab presents suggested actions to the crew relevant to the selected warning/failure in order to avoid escalation. These actions involve maintenance tasks, inspections or even component replacements. Suggested repairs may require the ship to be out of operation in extreme cases. The actions are based on historical maintenance and inspection data as well as expert judgement available to the DSS through INCASS partners (e.g. Classification societies, ship operators etc.).

3.2 (f) Prediction

In this tab, the user is presented with the numerical calculations which were presented above. The use of this tab is in assisting the user in identifying the cause in the event that warning/failure prediction and suggested actions are not sufficient in identifying and correcting the issue under investigation or there is an intrinsic error to the DSS system.

3.2 (g) Symptoms

This tab serves as in-depth investigation of the recorded and predicted data both in reliability values and in actual measurements. The graphical representation of the data can provide the user with information such as trends and real time recordings in order to be able to study the component/sub-system/system performing in time. This may assist in both reviewing data for inspection purposes and in identifying errors.

4. RESULTS AND CASE STUDY

4.1 MONITORED EQUIPMENT

For this case study, the main engine system was chosen and in particular the compressor cooling subsystem. The components of the compressor cooling sub-system are the valve and the pipe. The failure modes from OREDA that are used in the case study are presented in Table 1.

Table 1: List of failure modes used in MRA and DSS relevant to case study

Failure Mode Abbreviation
ELF - External Leakage – Fuel
ELU - External Leakage – Utility Medium (i.e. lubricant, cooling water)
FTS - Fail To Start on demand
OHE - Overheating
SER - Minor in-service problems
STD - Structural Deficiency

4.2 PERFORMANCE CASE STUDY

The input data were sourced from the OREDA database and pre-processed in order to demonstrate a system at medium reliability level (i.e. above the critical threshold but within 15% of it). As seen in Figure 8 the application is predicting “Valve Overheating” as a warning and it is selected so the cost analysis tab is populated with the associated values (Figure 8). In this case the shipping company has no threat of costs incurred by this warning and affecting safety or commercial third party penalties. However, costs occur in all other areas including significant costs in efficiency of the ship as valve overheating would lead to decreased performance and increased energy consumption.

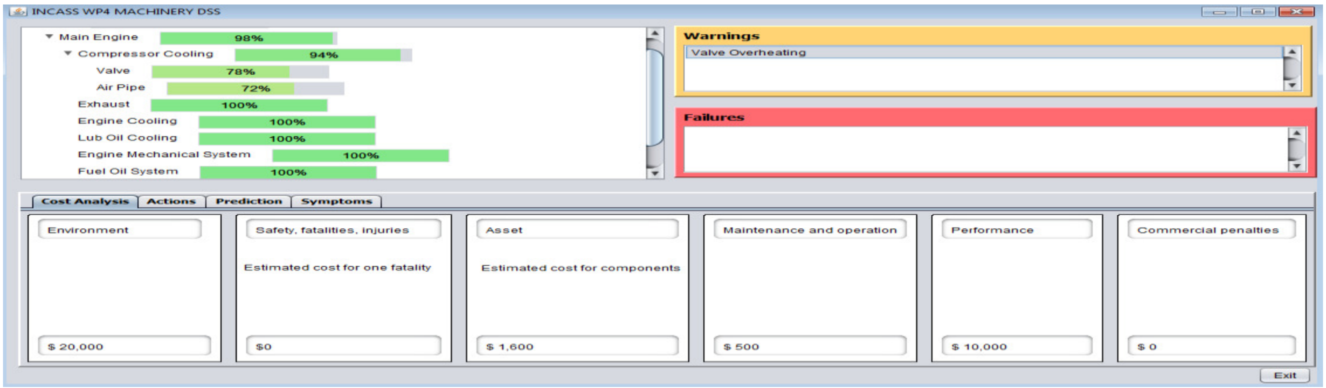

Figure 8: Medium performance: cost analysis with predicted costs

The current reliability of valve and pipe component is relatively low and the colour in the progress bar is representative of that. As a warning is predicted an associated action is also presented, to inspect the part (Figure 9).

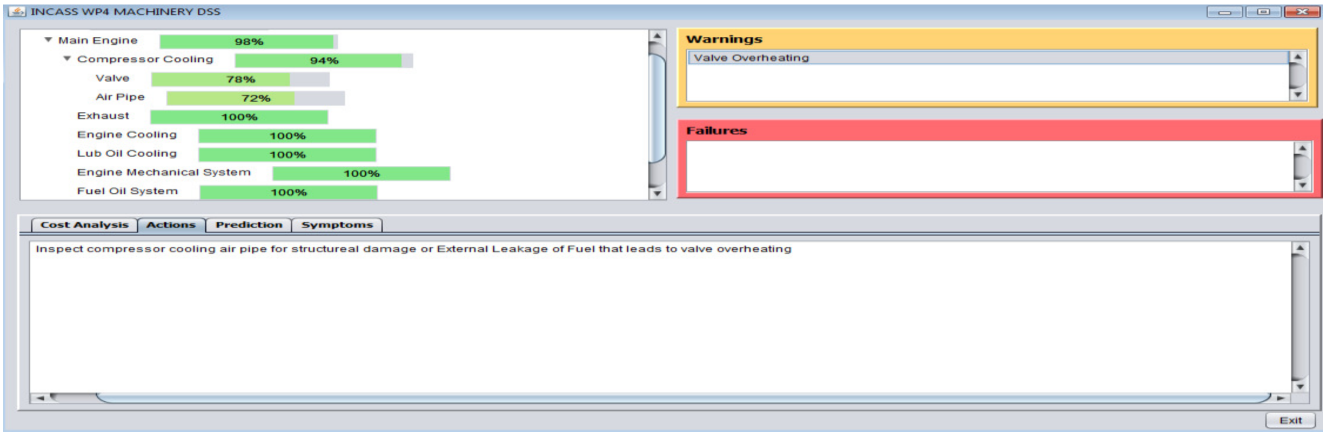

Figure 9: Medium performance: Suggested action for engineer onboard

The analysis that led to the warning is based on all the failure modes that are associated with the components of this subsystem (Figure 10). In this case the likelihood of valve overheating (OHE failure mode) is at 40%. Similarly the likelihood of the pipe failing due to SER failure mode is 23%, due to STD is19% and due to ELF 18%. As a result the only significant percentage is the valve OHE and it is above the warning threshold. The other calculated likelihood percentages are below the warning threshold, so they are not added to the list of warnings or failures. As can be seen from the presented failure probabilities the MRA has calculated lower reliability performance on component level than on sub-system based on Bayes' theorem (INCASS, 2015a) which means that the component failure probability is not linearly affecting the sub-system probability.

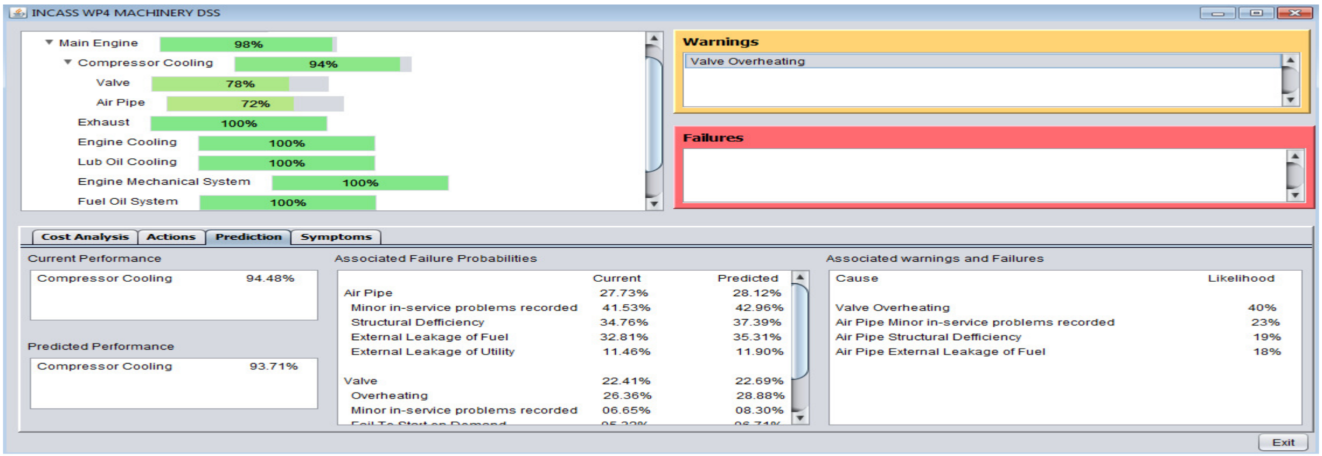

Figure 10: Medium performance: Failure prediction analysis

Finally, the graph for the subsystem is still printed with a green line as it is currently a reliable system with values over the threshold of operation of the particular subsystem (Figure 11). Thus, the condition of the system is acceptable.

Figure 11: Acceptable performance: Graphical representation of system trend

On the other hand, the components' graphs are printed with orange colour to represent the warning state that has been calculated (Figure 12, Figure 13). The threshold line for failure of the component is presented in black.

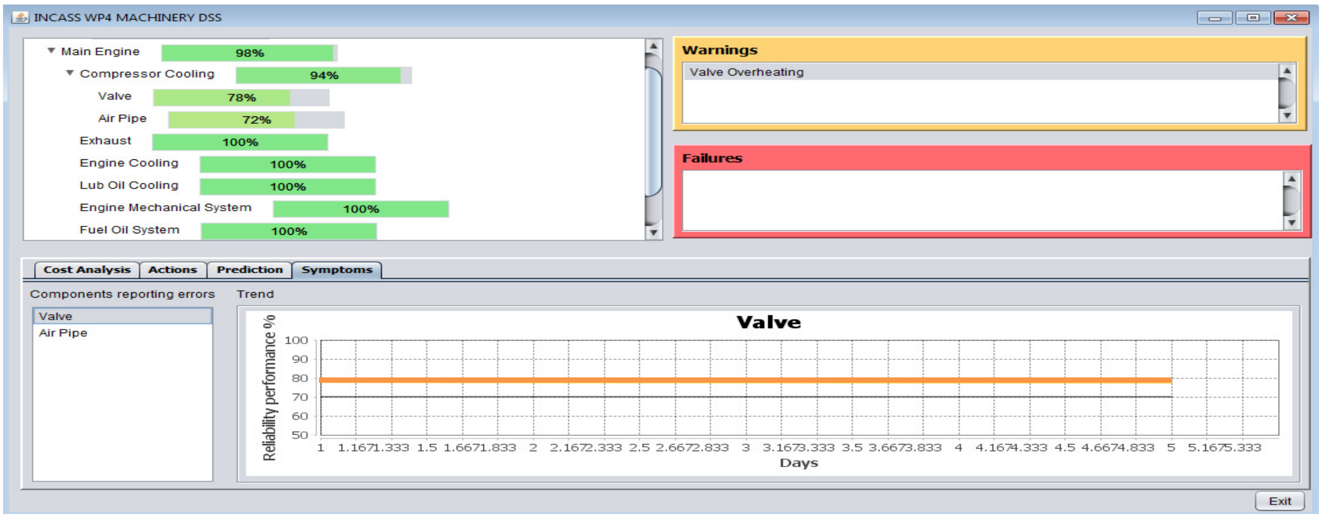

Figure 12: Warning level performance: Graphical representation of component trend (1)

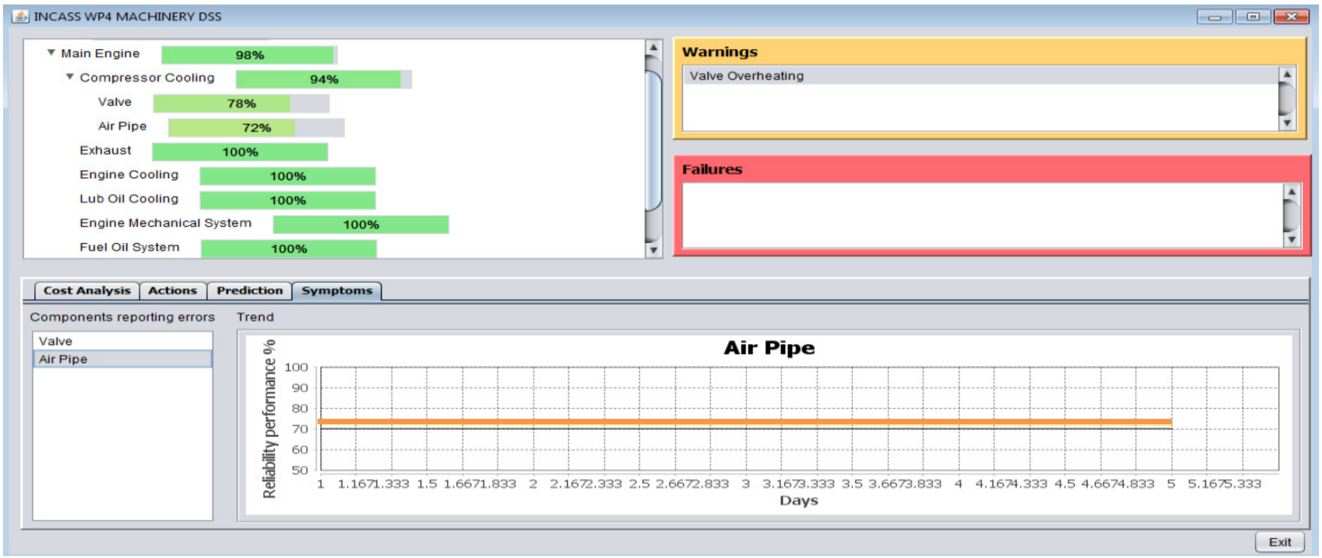

Figure 13: Warning level performance: Graphical representation of component trend (2)

5. CONCLUSIONS

This paper has presented the methodology used by the DSS of the INCASS project in evaluating and presenting to the user the current and predicted condition of a ship. Through the literature review it has been outlined that there is a financial need for better maintenance strategies and consensus towards adjusting maritime industry practices towards lower carbon footprint operations. It is generally acknowledged that condition based maintenance and decision support systems, if tailored to the needs of the ship, can provide the tool for achieving better maintenance, reduced maintenance costs and increased efficiency of operation and fuel consumption. Also, emission reduction and risk management can be enhanced. Wireless condition monitoring systems can provide the same benefits but also minimise installation costs for the condition monitoring system.

The developed system under the INCASS project incorporates CBM and DSS specifically developed for the maintenance needs of the machinery and equipment onboard a commercial vessel. The system benefits from the use of information from various sources including historical data, the OREDA database and expert judgement data from the project partners (e.g. Classification societies, ship operators etc.). By reviewing the reliability results of the developed assessment models, the DSS provides a comprehensive overview of the ship and suggests actions to the crew onboard. The DSS system also associates identified issues with costs to the shipping company and reduction in efficiency of the ship in both operation and fuel consumptionFrom the case study, the functionality of the developed DSS was presented through a ship with one sub-system in warning stage. Also, the utilisation of the DSS system in achieving efficient ship operations was demonstrated through the cost analysis that highlights the underperformance of the ship in equivalent expenses for extra fuel and extra maintenance. In this case that cost was calculated to be $10,000 only due to the cooling compressor of the main engine underperforming by 25%. By following the suggested action which is inspection of the component for damage that leads to overheating the crew could possibly fix the issue immediately and return the ship to perfect efficiency.

In conclusion, the developed DSS is a flexible tool that is designed to be combined with the monitoring system developed in the INCASS project. Based on the predicted evaluated status of the ship the crew can take informed decisions for the timely maintenance of machinery and equipment where appropriate in order to sustain optimum operational condition of the vessel and thus optimum efficiency, optimal fuel consumption and reduced pollutant emissions.

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