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A Real Time Comprehensive Analysis of the Main Engine and Ship Data for Creating Value to Ship Operators

1 - Digitalization and Connectivity - What it means to Different Applications

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ABSTRACT

During the past years, several technological incremental steps have taken place on ship and engine design. Due to extreme competition, volatile market and mature technology, today even the bigger ships generate limited profits. Digitalisation is the technological opportunity to increase engine and ship efficiency, increase asset availability and create new business models. Big impact of digitalisation is expected in the shipping ecosystem for example in the logistic integration systems, port operations, navigation system etc. However, the proper collection and analysis of the machinery and ship data implemented with the right expertise and knowledge provide a clear value to the ship operator.

Even though data collection on its own solves nothing, data need to be collected in the right way to have the preconditions of a valuable analysis. WinGD has therefore included the Data Collection Monitoring (DCM) unit in the engine scope of supply specifically for collecting and visualizing engine and ship data. Engine data are then analysed considering the requirements of the engine performance and components monitoring, troubleshooting and predictive maintenance by the Engine Diagnostic System (EDS) software that has been specifically designed to analyze the main engine data. The analysis is the result of a complex orchestration of three different analysis levels, namely: thermodynamic, know-how based and machine learning. The combination and the orchestration of such analyses give the full engine diagnostic picture and the unique valuable engine expertise to create value from machinery and ship data.

The Thermodynamic analysis has the goal to monitor the engine performance. It is based on a detailed thermo-physical process model of the engine, custom-produced for each vessel engine. The engine simulation thermodynamic model provides the “reference” engine performance for any possible engine operation setting, the ambient conditions, and the type of fuel. The model is tuned separately for each individual engine, and calibrated using the recorded data from that engine’s shop tests. It is further validated using the sea trials data. The model constantly calculates the ideal engine performance and defines a “reference optimal condition” which varies depending on the environmental and operational conditions measured in real-time on the ship. As a result, the model is the digital twin of the real engine in operation. The know-how based analysis is based on the engine design expertise and consists of specific machinery data correlated with rule sets and algorithms that are part of the engine expert implicit knowledge.

Another data analysis layer is based on advanced analytics performed on data collected with techniques and defined correlations between the signals to predict engine component malfunctions, and to generate actionable insights. The analytics used are based on expertise, statistical and predictive models, and machine learning algorithms.

A troubleshooting application provides customers with instructions on how to solve engine problems in case of an alarm or if a failure occurs. It reports the problem, the list of relevant alarms, identifies the part involved and automatically provides drawings and documents of the components affected. When end of lifetime of a specific component is predicted, the system will notify the Operator allowing timely delivery of replacement parts. This application integrates the spare part codebook of the entire engine into the EDS. It can be used to create a parts-order to request delivery to external suppliers.Engine data analytics enables predictive maintenance. Consequently, the engine maintenance plan becomes dynamic, based on the actual condition and prediction rather than machinery running hours-based scheduling. EDS Maintenance helps customers obtain an overview of the maintenance schedule and record all maintenance actions.The system is design to efficiently utilize Ship Owner’s own technical expertise, experience of people ashore and on other Vessels belonging to one fleet. On shipowner’s request, the system can be configured to allow sharing not only historical data but also of real time engine performance with sister ships and assigned experts ashore. This can significantly increase the troubleshooting efficiency comparing to conventional methods. It also adds the “virtual experience” to the Crew members self-solved cases and in effect increases the Crew awareness and confidence to the main Engine.

Together with the Engine Diagnostic System, remote support can be offered directly to the shipping company. Use of the collected data can quickly solve issues, optimise the engine, provide operational recommendations, and coordinate further technical support. As part of this service, the support centre provides regular reports on the health status of the machinery, including recommendations for optimal engine operations.

1 INTRODUCTION

The increasing investments in digitalization within the maritime industry have brought about new additional ways and approaches in the areas of energy efficiency as well as asset management and condition monitoring. Vessels and engines are more and more under advanced supervision and monitoring in order to improve reliability, economy and safety.

In 2014, a study by the Energy Institute of UCL [1], noted that among 94 ship owners/operators and management companies, the number one reason -97% of the respondents- for monitoring fuel consumption was to identify potential cost-saving or energy efficiency opportunities. That was followed -at 67%- by benchmarking and target setting purposes. That shows a trend in the industry to become more sensitive and also leverage the developing technology trends.

The digital technology gives the possibility to monitoring the ship's operational cost as well as the asset condition and to integrate the ships in the complex supply chain system.

On the monitoring side, the evolution of smart sensors and data acquisition systems, along with advanced telecommunications for transferring data from such systems to the shore office, provides a solid basis for the primary source of information needed. The term big data is more and more popular in the shipping community. The real value, however, comes neither from the collection of big data, nor from its transport to the shore office. The real value comes from extracting meaning from data which provides for effective asset performance management and condition monitoring. "Everything is logged," goes the typical complaint from a shipping company technical manager. "The problem is that the available data is not understood, interpreted or used correctly." What this Technical Manager was actually missing was the creation of value out of data as mentioned above. The quality of condition monitoring and performance evaluation depends on the existence of large amounts of reliable data collected over time, as well as the availability of analysis methods allowing for generation of the reference/benchmarking points against which these measurements are to be compared. This, in turn, is what produces useful diagnostic result used for prognostics. Mathematical simulation models in conjunction with big data technologies including machine learning techniques allow the production of all needed benchmarking set of data.

In a Financial Times article, in August 2013 [2], Brian Courtney, stated that "Industrial data is used to help us determine the health of our assets, to understand if they are running optimally or if they are in an early stage of decay. Analytics is used to predict future problems, training machines to learn algorithms that can help identify complex anomalies in large data sets that no human could interpret or understand on their own". Data Science, the study of data, brings together mathematics, statistics, data engineering, machine learning, analytics and pattern matching to help us derive meaning from data.

The present paper presents a case of applying the concepts and technologies like the ones mentioned above in the so-called 'edge' computing space, namely the vessel itself.

Winterthur Gas & Diesel Ltd. (WinGD) of Winterthur, Switzerland and Propulsion Analytics of Piraeus, Greece collaborated to develop an advanced real time Engine Diagnostic System (EDS), for all WinGD 2-stroke, diesel and dual fuel engines, as part of the WinGD Digital Expert (WiDE) on-board system [3]. The jointly developed system acquires and analyses data on the performance and condition of engines/sub-components in real time and provides fault diagnosis and live troubleshooting advice to the shipboard crew and to ship superintendents on shore. The data are analysed in using thermophysical simulation models, big data analytics & machine learning techniques as well as expert/knowledge-based algorithms. The data are further used to improve performance based on load profiles acquired over complete voyages, as well as enabling shipowners to diagnose and troubleshoot abnormalities and integrate maintenance planning and spare parts inventory.

The raw data are supplied to EDS through a Data Acquisition system [4] called DCM (Data Collection & Monitoring), which in turn reads from the engine control system and the alarm monitoring system. The data undergo timestamping, averaging (over one minute), syncing of slow and fast signals and corrections, cleansing from outliers, smoothing if/when needed etc. The system also integrates streaming data as well as any event data collected automatically or by manual input (e.g., fuel used, actions performed by the crew etc.).

EDS consists of the following parts:

- **Analysis**: The data processing and analysis take place within this pillar. The measured data are compared with reference data in order to identify discrepancies between "expected" and "actual" behaviour.

- **Consolidation and orchestration**: Once the analysis has been performed in real time for each dataset fed to the system, the results and findings are consolidated, and a combined set of activities is orchestrated in order to provide the on-board crew with tangible and clear actions and issues to consider
- **Utilities: Troubleshooting, Maintenance and Spare parts**: The outcome of the consolidation and orchestration allow the planning and automation of subsequent processes like troubleshooting, maintenance, spare parts handling and ordering.

The high-level architectural layout of EDS is presented below.

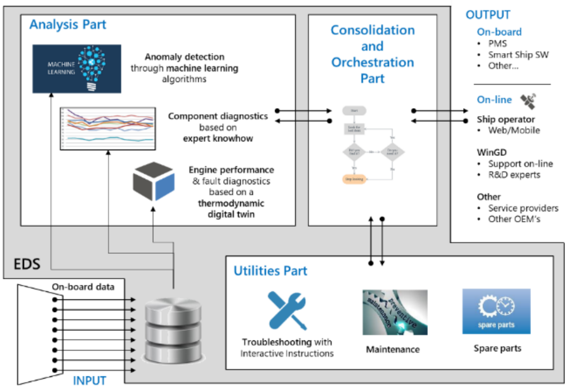

Figure 1. EDS high-level architecture

In the following sections, the above-mentioned EDS's parts are presented in greater details.

2 THE ANALYSES OF EDS: THREE LAYERS OF COMPREHENSIVE EXPERTISE FOR CREATING VALUE FROM DATA

The recommendations and outcome of the EDS's analyses are the result of a complex orchestration of three different analysis levels, namely: thermodynamic, know-how based and machine learning. The combination and the orchestration of such analyses give the full engine diagnostic picture and the unique valuable engine expertise to create value from machinery and ship data.

2.1 Thermodynamics-based analysis: the digital twin model

Each WinGD engine is simulated with a model that is a 'digital twin' of the actual engine in operation. The digital twin reflects the physical relationships of all primary engine parameters such as temperatures, pressures, rotational speeds as well as resultant values such as torque, fuel consumption, emissions and internal parameters such as heat transfer, friction, etc. The engine's sea trial and shop test data are used to calibrate and customize the engine thermodynamic model.

The thermodynamic model of each WinGD engine is custom-produced and tuned for each vessel, providing the "reference/healthy" engine performance for any possible engine operation setting, ambient conditions and fuel, allowing thus performance assessment information, fault diagnosis and optimization in service [5]. Each thermodynamic model is built up and tuned separately.

Following the model calibration, a large number of simulations for combinations of all the possible engine operating conditions and settings, are being performed a-priori. As a result, an engine hyper map is generated, which provides the "reference" values of all performance parameters at any operating condition. Finally, the engine hyper map (stored in a database), is embedded in the EDS software, which is used for the analysis providing engine performance assessment, fault diagnosis.

During WiNGD's engine operations, the EDS's digital twin is fed with real-time engine measurement data, as these are generated by the engine. Any deviation, between real measurements and model values of the corresponding parameters as given by the digital twin at the same operating conditions, reliably contributes to the engine status assessment. The digital twin can identify faulty/non-calibrated meters and through advanced engineering rulesets, provides specific diagnostic findings along with actionable recommendation for each fault identified. As an example, indicative faults could be fuel injector issues in cylinder X, exhaust valve leaking in cylinder Y, turbocharger fouling or mechanical damage, among others.

Extra value is provided with the analysis of the high-resolution pressure trace for each cylinder, which is also input to the thermodynamic model. The pressure trace is read and smoothened appropriately and then the Heat Release Rate (HRR) is calculated. By analysing the measured pressure diagram and calculated HRR, the software can arrive with higher confidence to advanced and more accurate diagnostics for in-cylinder faults.

In summary, through the thermodynamics-based analysis, EDS provides the user with:

- high-level dashboard view of engine performance
- detailed diagnostics of possible engine faults together with recommended actions
- detailed diagnostics of possible sensor and/or measurement issues
- deviations from healthy state for a number of measured parameters
- in-cylinder pressure trace analysis
- detailed per-cylinder and turbocharger view and timeline analysis on a number of engine parameters

All the thermodynamics-based analysis methodology and underlying technology is based on the Engine Hyper Cube® performance management suite of Propulsion Analytics [6], which was applied to all portfolio engines of WinGD.

2.2 Knowhow-based analysis: WinGD's knowledge to monitoring the engine components

In this part of the analysis, a number of engine sub-system components are analysed through a knowhow-based expected behaviour. The WinGD engine designer expertise is reflected into algorithms for the various subsystems, as given below:

- Fuel injection system
- Gas admission system (for dual fuel engines)
- Servo oil system
- Piston running
- Scavenge air system & Exhaust gas system
- Engine control & automation system

The knowhow-based analysis is once again based on the engine measured data already processed by the engine control and alarm systems. As noted, the analysis and subsequent prediction algorithms are based on WinGD's core competence. WinGD experts defined the signals to consider in each case as well as the main criteria (e.g., limits, thresholds, normal and abnormal conditions). Subsequently, all WinGD documentation (Failure Mode Effects Analysis (FMEA), Functional Plan of engine control system (FUP), operation manuals etc.) was utilized in order to develop specific rulesets for each component diagnostics system.

The translation of WinGD experience and documentation to fault detection rulesets consists of the following sub-processes:

- Identify various component potential failure modes (FMEA analysis).
- Connect potential failure modes with effects on component (faults).
- Identify possible causes for effects on component.
- Trace fault-influenced parameters, for which measured signals from engine control system are provided (FUP per component).
- Define reference values for traced influenced parameters.
- Define tolerance limits for the parameter deviation from reference values.
- For each fault, rulesets are defined based on the influenced parameters and their tolerance limits.

The most commonly used reference values in EDS rulesets are:

a) Set point values from the Engine Control System (e.g. fuel rail pressure)
b) Values from the digital twin model output (e.g. compression pressure)
c) Shop Tests with ISO-correction if applicable (e.g. air filter pressure drop)
d) Other similar elements (e.g. liner wall temperature).

It should also be mentioned that in a number of faults, different types of reference are used simultaneously for safer conclusions (e.g. a parameter is compared against its ISO-corrected Shop Test values and at the same time against the rest of the cylinders).

2.3 Machine Learning-based analysis: using the power of historical data for an advanced engine monitoring

Machine learning (ML) [10] is the study of algorithms and mathematical models that computer systems use to progressively improve their performance on a specific task, or in short, the scientific field of discovering relationships between data. Machine learning algorithms build a mathematical model of sample data, known as "training data", in order to make predictions or decisions without being explicitly programmed to perform the task. More and more machine learning algorithms are used in commercial, business, medical and industrial applications, such as email filtering, credit card fraud detection, tumor recognition in X-rays images, or component predictive maintenance, cases where it is practically impossible to develop an algorithm of specific instructions for performing a task.

A sample case in which a machine learning algorithm approach was applied in EDS was the case of detecting high friction in cylinder operation, otherwise known as piston scuffing. High friction in cylinder operation causes damage in piston rings and cylinder liner and if not detected early it relates to significant repair costs. High friction patterns can be correlated to liner wall temperatures, resulting in different states of operation being indicated by different patterns appearing on the liner wall temperature monitoring.

In order to identify those patterns on the temperature profiles, a “patterns recognition” approach was selected using supervised machine learning techniques, namely Classification with neural networks. The data pool utilized consisted of historical data recorded by WinGD. Historical data were processed and prepared for the supervised machine learning algorithm by removing outliers and faulty reported values. Data from various engine types and approx. 20 vessels over a period of 10 years were exploited, resulting in defining relevant software algorithms for high friction detection. The above-mentioned analytical methods were used for detecting high friction operation state and for first level labelling of the historical data.

It should be emphasized that the data labelling was extended and enhanced by fine tuning the intervals of high friction operation and by recognizing pre-high friction operation intervals. The conclusion of this data labelling technique is the identification and the possibility to recognize three different state of operations, not possible before, as follows:

- **Normal operation:** This operation state is indicated by smooth specific cylinder temperature changes following the average temperature changes of all cylinders, correlated with the changes in engine speed and load.
- **Pre-high friction operation:** In this operation state, the temperature of the specific cylinder slightly deviates from average temperature of all cylinders and significant small amplitude fluctuations appear here. These operation intervals are typically met before high friction operation intervals occur.
- **High friction operation:** This state of operation is indicated by high, frequent and irregular temperature fluctuations.

A representation of these three operation states and their sequence is shown in the following figure.

Figure 2: Example of cylinder temperature High friction event as this evolves over time.

Using the labels that were extracted and enhanced from the historical data, a training dataset was created for the training process of the algorithm. The selection was made considering all similarly unique operation states to be represented in the dataset.

It should be noted that from the work described above the following clear benefits are accomplished:

- The detection process is automated, so the need for the “human eye” observation and identification is no longer needed.
- The “green” state denoting normal operation is identified with quite high detection rates (approx. 80%) even from the limited data used so far.
- A very important and critical pre-high friction region has been identified, which was not possible before and as shown below can be detected with fairly high rate of success (approx. 60%), especially keeping in mind that this particular anomaly detection was not at all possible before.
- The high friction region (scuffing) is identified with a detection rate of 98%.

The piston running operation state recognition is performed by a Neural Network Classification Algorithm (NNCA). The NNCA is trained in the training dataset and validated in an unseen test dataset also created with the same procedure from the historical data. The NNCA takes a 25-minute observation window of temperatures as input and recognize the operation state. The performance of the NNCA is correlated with the extent of the specific operation state in the observation window. The more an operation state is extended in the observation window, the better the NNCA performance will become.

The NNCA is trained to recognize patterns referring to operation states in the historical data labelled using the analytical methods. The NNCA algorithm was embedded in the EDS software as part of the Piston running component diagnostic rule-set. A sample sequence of events as detected during operation is depicted below:

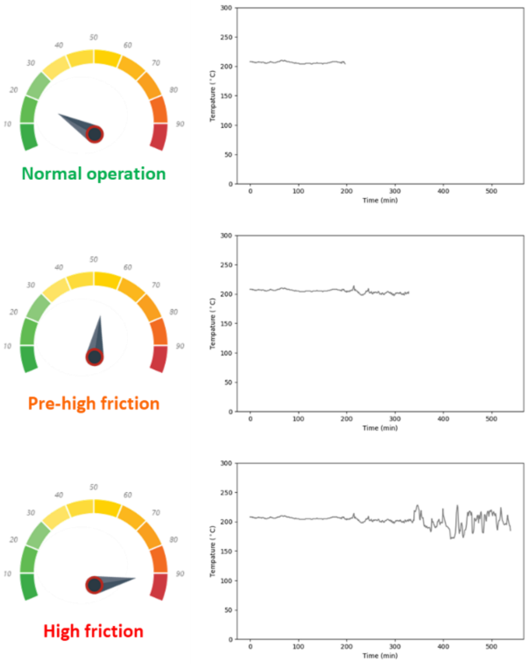

Figure 3: Example of extending the overhaul interval.

3 CONSOLIDATION AND ORCHESTRATION

Following the various layers of data analysis presented above, the Consolidation and Orchestration modules take action, in order to merge the findings of the Analysis and then moderate the subsequent actions to follow.

3.1 Consolidation

The analysis consolidation module consolidates the outcome of the findings from the three analysis methods (thermodynamic, know-how based, machine learning) generating a final ruleset, which will in turn produce the output of the analysis part to be fed into the process orchestration part described below. The analysis consolidation involves:

- Estimating fault scoring based on
  - fault severity and
  - fault importance
- Merging detected rules from the different analysis methods. For example:
  - Compression deficiency detected by the thermodynamic performance module
  - Cylinder blow-by detected by the knowhow-based rules module.
- Compiling all relevant fault information (causes, operation/maintenance action for troubleshooting, references to supporting material/engine manuals).
- Notifying the user by combined checks (rules) when the relevant parameters are predicted to exceed tolerance limits in the future.
  - EDS has embedded algorithms that take advantage of the already available data to derive trends of the parameters' evolution and predict a possible appearance of a fault in the short term.
- Applying a filter through fault monitoring to moderate momentarily arising faults.
  - Decision to show or hide a detected fault based on fault score average (30 minutes).
  - If fault has been detected by trending analysis filtering time is reduced to five minutes.

3.2 Orchestration

The orchestration process is initiated after a fault has been diagnosed and the consolidation process has been completed. If the fault is considered “critical” for the engine operation, an immediate action may be decided (by the crew), otherwise, EDS proceeds with the sequential levels/steps described below:

- The 1st level is related to the Troubleshooting process. In that level all possible fault causes, and proposed actions largely follow the directions of the engine Operating manual. It is noted that in the troubleshooting level, the proposed actions have no maintenance intervention.
- The 2nd level is related to any possible maintenance tasks associated with a detected fault. The recommended maintenance procedure is based on the engine Maintenance manual. EDS can also connect to a Planned Maintenance System (PMS) in order to update the engine maintenance plan and interchange lists of spare parts needed, as well as availability.
- The 3rd level refers to any required external help and support by potentially engaging human experts on-line and remote troubleshooting. In such a case, a specific fault case archive (containing the fault details) will be sent to a Centre of Operations ashore.

When a fault case is resolved, EDS collects all available feedback and creates relevant reports. Each fault case is archived and stored for future references. If a fault persists and none of the available procedures is working, then the fault should be considered critical and an immediate action must be decided.

The following figure depicts the above workflow as implemented in the context of EDS.

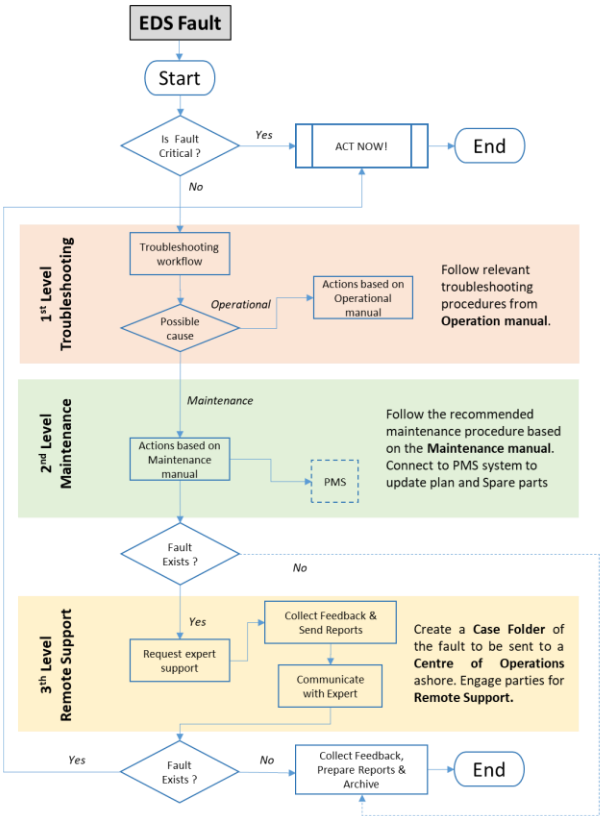

Figure 4: Orchestration workflow implemented in the EDS

4 TROUBLESHOOTING, MAINTENANCE AND SPARE PARTS MODULES: THE RESULTS OF THE ANALYSES MADE ACTIONABLE

After the findings of the analysis have been merged and consolidated, the actionable parts of EDS follow. The first module relates to the troubleshooting actions linking the possible causes identified, with suggested steps from the engine Operation manual. Further, in case a possible cause is associated with a maintenance task, EDS presents the associated set of maintenance actions and once again provides links and direct access to the engine Maintenance manual. Finally, for each maintenance task, the corresponding list of necessary spare parts is automatically generated.

4.1 The Troubleshooting module: the digital expert provides the solution

EDS Troubleshooting module is designed to achieve the following:

- Make clear which are the current issues (active) that need the user's attention.
- Gather multiple instances (events) of the same fault identified on a specific subsystem (e.g. a specific cylinder).
- Create an archive of faults that have been reported in the past.
- Organize and display the content in a self-explanatory way.

The Troubleshooting module gathers all faults with the accompanied detailed information and provides a list of possible causes as well as recommended actions assisting the user to handle the issue. The recommended actions are provided through direct reference to the specific section of the operation or the maintenance manual of the engine.

An example is shown in **Error! Reference source**

Table 1. Example of EDS troubleshooting information.Fault: Exhaust valve closes too slow

Possible causes:	Corrective actions:
Insufficient air spring pressure	**Operation**: Find the cause: leakage, pressure reducing valve, pressure in starting air bottles
	Maintenance: No action
Restricted VCU return	**Operation**: Emergency Operation with Exhaust Valve Closed
	Maintenance: Exhaust Valve Control Unit: Removal, Disassemble, Assemble, Installation
Exhaust valve stem sticking	**Operation**: Emergency Operation with Exhaust Valve Closed
	Maintenance: Exhaust Valve – Removal and Installation

not found.:

The possible cause list of each is sorted based on the following two criteria:

- Occurrence probability of the possible cause: A more probable possible cause has a higher position in the list. This allows the crew to treat it before handling other less probable possible causes and dedicate much less effort in case the fault is corrected early.
- Simplicity or ease of the respective troubleshooting action: In this way, the easiest or simplest troubleshooting actions will be addressed early enough and in case that the fault is corrected, all difficult or tedious tasks will be avoided by the crew.

The recommended corrective actions are provided through direct reference to the specific section of the engine user manual (operation or maintenance). Moreover, there is the option to add a specific task to the EDS maintenance plan in order to perform a corrective action. The EDS maintenance task is added to the PMS planned maintenance tasks.

4.2 The Maintenance module: an overview on the engine components lifetime

The maintenance module is designed to give value to the diagnostic results of the analysis and the troubleshooting findings through two functionality layers.

The first layer includes the:

- EDS-generated maintenance tasks
- Relevant engine manual documentation
- Integration with the PMS

The second layer covers predictive or condition-based maintenance (CBM) methods.

4.2.1 PMS integration into EDS

The EDS troubleshooting module, through the maintenance module, can prompt the user to create/add maintenance tasks (unplanned events) through the relevant possible causes for the diagnosed faults. The proposed maintenance tasks are then guided by the maintenance manual of the engine and are in general administered by the PMS onboard. The request for the addition or modification of the maintenance tasks is implemented through the EDS maintenance module and the PMS software interface.

In principle, this interface of the EDS maintenance module is a targeted and configurable Application Programming Interface (API), which can be used in conjunction with any PMS API available, to sync and update EDS for:

- Specific engine maintenance tasks
- Running hours for the engine components
- Component wear measurements (to be used in the machine learning algorithm for predictions)

In figure 5 the interface between EDS and PMS is presented. For EDS, the API refers to the part of it that is related to PMS. Additional parts may cover the API interface with other systems as well.

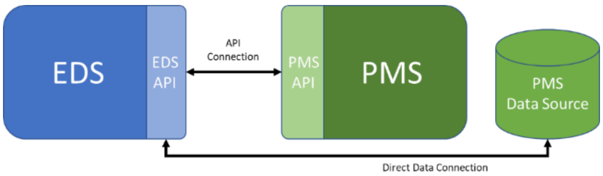

Figure 5: Schematic representation of EDS and PMS connection

4.2.2 Condition based maintenance (CBM) with both operational & maintenance data

A core goal of the CBM approach is to predict the remaining useful life (RUL) of an engine component. RUL refers to the amount of time a part of a component has remaining (before) it will need replacement. This method uses both operational (running hours, performance data) and maintenance (replacement or overhauling events, wear measurements). Maintenance data come available by the PMS.

A machine learning algorithm is trained with operational values of component influencing parameters and wear measurements to correlate the operating conditions (influencing parameters) and the component performance after the operation period.

The implementation of the machine learning algorithm is described in the following steps:

1. Train a Machine Learning algorithm based on performance data and wear measurements.
2. Use trained algorithm to estimate current total wear estimation and wear rate.
3. Calculate the time when manufacturer wear limit is reached.

The trained machine learning algorithm associates the wear influencing parameters with the wear rates of the component. As a next step, the additional wear of the component is estimated for the referring time period.

The final output of the Machine Learning System is the:

- Current total wear estimation and
- Remaining Useful Life of the component

The current total wear estimation gives an estimation of the wear without the need of inspection. The Remaining Useful Life of the component gives the amount of time that a component has, before it will need replacement. Both outputs can be used to better plan an interval measurement assessment or replacement event and predict the component's failure based on the wear rate.

4.3 The Spare parts module: easy access and identification of the engine parts

Spare parts module is tightly connected to the maintenance module and provides the ability to identify, display and share the spare parts related to specific maintenance tasks. The maintenance tasks, which are created as corrective actions to possible causes of EDS detected faults, are accompanied by the relevant spare part information.

A typical workflow would be the following:

- A fault is identified by EDS and displayed to the troubleshooting module.
- The on-board crew can go through the information related to the fault and if they decide to act upon it, they can add a task to the maintenance plan.
- The maintenance module contains the information about all the maintenance tasks that have been planned so that the crew knows what should be done and when.
- In order to perform the maintenance tasks, the crew will need the corresponding spare parts. This information is provided by the spare parts module.

The spare parts module displays all the planned maintenance tasks and the respective spare parts needed. The information provided consists of the part number, the name of the part and the number of parts needed in the assembly based on the WinGD spare parts catalogue. In the future, the ShipDex™ [11] will be the main source of information for all the spare parts details required by EDS. The number of parts in the inventory may also be displayed via the PMS-EDS connection. The module provides the ability to create spare part lists per maintenance task that can be sent to the PMS. Finally, the EDS Spare Parts Module includes an additional option of navigation throughout the spare parts catalogue, which might be quite helpful to the on-board crew.

5 CONCLUSIONS

The Engine Diagnostic System (EDS) has been designed to analyze on-board the main engine data, after these have been collected through the Data Collection Monitoring (DCM) unit, which is part of the engine scope, for all new WinGD Diesel and dual-fuel engines, contracted after January 2018. EDS comprises three core parts, namely the Analysis part, the Consolidation & Orchestration part and finally the Utilities part.

The Analysis is the result of a complex orchestration of three different analysis levels, namely thermodynamic, know-how based and machine learning-based. The combination of these three approaches provides the full engine diagnostic picture and subsequently feeds the actionable layers of EDS, namely troubleshooting, maintenance and spare part identification.

The Thermodynamic analysis is based on a detailed thermo-physical digital twin model custom-produced for each vessel engine monitors the engine performance. The model constantly calculates the ideal engine performance and defines a "reference optimal condition" which varies depending on the environmental and operational conditions measured in real-time on the ship. The know-how-based analysis is based on the engine designers' expertise and consists of specific machinery data correlated with rule sets and algorithms. Finally, a layer based on advanced analytics performed on collected signals is able to detect anomalies caused by engine component malfunctions.

After the findings of the analysis have been merged and consolidated, the orchestrator module takes care of the subsequent stages. The first such possible stage relates to the troubleshooting actions linking the possible causes identified, with suggested steps to follow from the engine Operation manual, with visual access to the digital version of the manual. Further, in case a possible cause is associated with a maintenance task, EDS presents the associated set of maintenance actions and once again provides links and direct access to the engine Maintenance manual. Finally, for each maintenance task, the corresponding list of necessary spare part names and codes are automatically generated. It is noted that all actions above are potentially aligned with the vessel Planned Maintenance System (PMS), following an integration between the two systems.

The Engine Diagnostic system has already been installed in two vessels, as part of the pilot phase testing with very encouraging results and feedback. Full deployment across all WinGD engine newbuildings is expected to take place within the second half of 2019.

In closing, as mentioned, remote support can be offered directly to the shipping company together with the Engine Diagnostic System. Use of the collected data can solve issues, optimise the engine, provide operational recommendations, and coordinate further technical support.

6 ABBREVIATIONS

API: Application programming Interface

CBM: Condition based maintenance

DCM: Data Collection monitoring

EDS: Engine Diagnostic System

FMEA: Failure Modes and Effects Analysis

FUP: Functional Plan

HRR: Heat Release Rate

ML: Machine Learning

NNCA: Neural Network Classification Algorithm

PMS: Planned Maintenance System

RUL: Remaining Useful Life

UCL: University College London

VCU: Valve Control Unit

WiDE: WinGD integrated Digital Expert

WinGD: Winterthur Gas and Diesel

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