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Propulsion Monitoring System for Digitized Ship Management: Preliminary Results from a Case Study

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Abstract

The paradigm of Industry 4.0 a fundamental driver of innovation in marine industry, where the new digital era will see the development of smart cyber-ships equipped with advanced automation systems that will progressively evolve towards fully autonomous vessels. Although the journey towards such technological frontier has started, most companies operating in the maritime sector still appear un-prepared to face the future scenario. In the maritime sector, in fact, empirical models and oversimplified approaches are still largely employed for the management of fleet operations. There is thus the necessity of developing and providing operative models for digitized ship management, which, based on structured information gathering and processing, can provide maritime companies with effective decision support systems in order to strengthen their value chain. This paper focuses on the context of the monitoring of the propulsion system, which is one of the most important systems of a ship and a main source of operation and support costs. A decision support system is presented involving automated data gathering and analysis procedures, to assess the correct functioning of the system and for early-detection of incipient failures. The methodology has been validated through a real case study, and the related results are discussed.

Keywords: industry 4.0, Continuous engine monitoring system, smart ship;

1. Introduction

The paradigm of Industry 4.0 involves a substantial technology-based innovation, which is expected to impact disruptively all industry sectors in the immediate future. Based on the application of enabling technologies like the Internet of Things (IoT), Big Data Analytics (BDA) and cloud computing, the new digital era will introduce new business models drastically changing the approach towards value creation in several business fields. In the sector of shipping, such disruptive innovation will result in a new technological paradigm known as Shipping 4.0 where, specific cyber-physical systems known as "smart ships", characterized by new design criteria and operational requirements, will replace traditional vessels, with enhanced efficiency and sustainability. Such approach will involve real time performance monitoring and data mining in order to increase the overall level of efficiency in a renewed managerial approach and to introduce new value based business models. Experimental studies demonstrate that the optimization of the ship management and propulsion efficiency may result significant power saving, which in certain cases can be as high as 15% cost reduction [1]. Additionally, with the aims of promoting, the use of more energy efficient and less polluting equipment and engines the International Maritime Organization (IMO) agenda of the United Nations responsible for maritime affairs issued in 2013

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the MARPOL convention to define the fundamental requirements for the maritime shipping sector. Such requirements, which will be tightened every five years and will substantially influence the power distribution and fuel consumption in the smart ships of the future.

In this paper, we will focus on the ship's propulsion system, generally constituted by a set of diesel generators (Genset), which is, together with hull efficiency, the main element contributing to the overall energetic performance of the ship. The manufacturers of modern marine diesel engines are starting to adopt digital sensors to assess the health of the valve actuators for fuel injection and of the after-treatment systems. Such systems allow the real-time measurement of several parameters such as cylinder head temperature, exhaust gas temperature, engine rotational speed, fuel flow, etc. It is well known that monitoring such engine parameters allows to detect impending engine problems and increase engine operational reliability. In particular, engine monitors usually have preset thresholds that, when exceeded, issue an alarm or trigger a corrective action (e.g. shutdown). Such approach is consolidated and was first implemented in the aeronautics sector since the mid-1960s when the first Exhaust Gas Temperature (EGT) gauge was introduced to General Aviation by Al Hundere of Alcor Inc. The purpose of such system was to support the pilot in making decisions about the possibility of completing the mission or returning to base considering the health status of the aircraft engines. Surprisingly enough, engine monitoring technology in the maritime sector is, at least in the commercial navy, a recent innovation, considering that the "Safe Return to Port (SRtP)" issue has been introduced in the "Safety of life at sea" (SOLAS) regulation adopted by IMO resolution MSC.216(82), which entered into force in 2010. The regulation requires passenger vessels with a length of 120 meters or more or with three or more main vertical zones to be designed for improved survivability. This means that, in the event of a flood or fire emergency, passengers and crew can stay safely on board as the ship proceeds to port under her own power. It defines a threshold where the ship's crew should be able to return to port without requiring passengers to evacuate.

Although Engine monitoring systems are commonly provided by manufacturers, many shipping companies still do not take advantage of this technology to improve their operations. In fact, even when new propulsion units are installed, the engine monitoring functions are controlled by the engine manufacturer, and the data gathered are exploited only for diagnostic and maintenance purposes. Such data however constitute an important heritage of knowledge which can significantly improve the efficiency of shipping operations, thus contributing in strengthening the related value chain. Achieving this objective, however, is not a straightforward task. Although marine engines share the common functioning principles of traditional endothermic engines, there are some substantial differences in terms of structure, materials employed, robustness, fuel, etc. in addition, as stated before, engine monitoring systems are generally designed to support the pilot, while in the maritime sector the system is intended to support also the fleet managers in their operations. For such purpose information, must be transferred to the onshore central control room of the company, and the data gathered must be appropriately processed. The "cyber" ship must hence be constantly interconnected to the control room, which is still an uncommon practice for ships navigating far from the shore, considering the current implementation of onboard networking technologies. In addition, another significant difference with the monitoring cockpits typically designed to assist the pilots is that they typically present instant engine data, while, for supporting the ship management operations the recorded time-histories are much more important. For example one of the most important indicators of the overall ship performance is the fuel cost, which is related to the fuel consumption rate as a function of the actual speed. The relation between speed and fuel consumption is frequently calculated by means of oversimplified mathematical model like the cubic assumption normally employed in the shipping industry. Real time data monitoring allows to make much more reliable calculation employing speed data gathered by the gps system, and actual fuel consumption. In such case, in order to have a realistic evaluation of the speed performance, it is necessary to compare heterogeneous data coming from different sources by means of appropriate data fusion procedures. Data Fusion (DF), also referred to as sensor fusion, has been defined by the joint directors of the DoD laboratories (JDL) in the 1980s as process dealing with the association, correlation, and combination of data and information from single and multiple sources to achieve inferences that cannot be obtained from a single sensor or source [2]. Based on the above considerations, in this paper a methodology is proposed for supporting the decision processes though automated sensor-based monitoring of the ship propulsion system and advanced post-processing procedures for knowledge extraction. Taking advantage of the increased data mining capabilities of modern ICT system, the proposed approach demonstrates how with a consistent amount of operational data accumulated over time, can be exploited for creating value by extracting the "knowledge" from information. Clearly, in order to be implemented on a real operating environment, and adequate ICT infrastructure must be built, involving appropriate data storage and processing capabilities. The recent introduction of big-data solutions as a replacement of traditional data warehouses, allows for seamless cloud-based data gathering and processing. The implementation of such systems for the maritime sector, however, presents some technical barriers (e.g. the costs of satellite ship to shore communication systems) which still hamper their implementation.

This paper describes the main features of an experimental decision support system designed and implemented in a real maritime company dealing with the transportation of passengers in the small island surrounding Sicily, in the Mediterranean Sea. The system presented has been validated in a real operational case involving a foil ship for the transport of passengers, operated in Sicily in a close-to shore interconnected environment.

2. Methodology

The employment of mathematical models to support the decision-making processes related to fleet management operations is a fundamental driver of efficiency in maritime operations management and a well established industrial practice. There is also a vast scientific literature focusing on several important topics related to the optimization of maritime fleet operation such as: operational real-time optimization [3][4], maintenance management [5][6], and vessel performance benchmarking [7]. Nevertheless, the management of shipping operations is still suffers of some important limitations, mostly due to the over-simplifying assumptions typically involved in traditional mathematical models employed in the industrial practice. Additionally, the experimental validation of such models in standardized tank tests, which is a common practice, is scarcely reliable, considering the behavior of a ship in fully loaded conditions, and under the influence of external disturbances, can be substantially different. Moreover, most shipping companies still base their performance evaluation procedures on noon reports manually edited by the crewmembers, [8][5]. Such reports, however, are a poor source of information because they are typically affected by the subjectivity of the author's judgment and prone to human errors, while the data reported is a low resolution, non-standardized dataset involving averaged values even for information that can undergo significant variations on a daily basis (e.g. weather conditions, fuel consumption, etc.). Based on such premises, the current approaches to fleet operations management in the maritime industry appear outdated and substantially inadequate to the incoming paradigm promoted by the fourth industrial revolution, which envisions smart cyber physical vessel operating in a seamless interconnected marine environment with real-time data transfer capabilities. In such context, this paper aims at proposing a novel approach to support the decision related to ship management, based on automated sensor-based monitoring of the propulsion system, which is one of the most important elements affecting the operational cost and the performance of a ship. The propulsion system of a ship can be either mechanical or electrical: Mechanical propulsion systems imply the use of one or more diesel engines to drive the ship's propelling shaft, while electrical propulsion is consist of a prime mover (a steam turbine, diesel engine, etc.), a generator and an electric motor to drive the propeller. Although electrical propulsion systems have gained popularity in the recent years, we will refer to mechanical propulsion systems based on diesel maritime engines, which are still the mostly spread in maritime commercial companies. Assessing the performance and the health status of a diesel engine is a well established topic in the scientific literature, and the physical engine parameters that are known to be most significantly linked to the operational state of a turbocharged diesel engine are reported in table 1.

In particular, exhaust gas temperature (EGT) is recognized to be one of the most important parameters for evaluating the performance for heavy-duty marine diesel engines. By providing a good indication of heat in the cylinder during combustion, in fact, EGT can be extremely helpful in diagnosing problems with fuel injection system, valve timing and many others.

Table 1. Physical engine parameters linked to the operational state of a turbocharged diesel engine.

Parameter ID	Description
EGT	Exhaust Gas Temperature
CHT	Cylinder Head Temperature
OIL Temp	Oil Temperature
OIL Press	Oil Pressure
TIT	Turbine Inlet Temperature
OAT	Outside Air Temperature
CDT	Compressor Discharge Temperature
IAT	Intercooler Air Temperature
CRB	Carburetor Air Temperature
RPM	Rotations per Minute
MAP	Manifold Air Pressure
%HP	Percent Horsepower
CLD	CHT Cooling Rate
FF	Flue Flow

Problems with injectors or valves timing can cause higher fuel consumption thus determining a growth of vessel operation costs, but, in prolonged use, they can also be the cause of a reduction in operating life of the component or of a catastrophic failure. EGT monitoring can thus provide valuable information about an incipient problem in the engine before it becomes critical, thus preventing the failure of the engine. The ability to predict and incipient failure can be extremely important in the marine sector, because a failure at sea may involve a very high cost. Establishing a Condition based predictive maintenance strategy in the maritime sector can thus be an important strategy for reducing the fleet operational cost and for enhancing the overall safety levels.

As stated before, the manufacturers of modern maritime engines have recently started to provide their products with fully integrated sensors and monitoring features, which generally include the above listed parameters. The dataset generated by such monitoring infrastructure, however, is not available to the ship manager, but only to the engine manufacturer, and it is thus employed solely for engine maintenance purposes. Such data however can be extremely important not only for diagnosing incipient problems in the propulsion system, but also to assess the overall performance of the ship, by comparing for example the fuel consumption with the engine load and the vessel speed. The approach here proposed, however, focuses on the assessment of the healthy status of the diesel engine, and to the evaluation of the operational performance of the ship by detecting possible malfunctions which could result in an increase of fuel consumption and/or decrease in the unit efficiency. The fundamental steps carried out in the development of such a decision support system are discussed in the sections below.

2.1. Establishment of optimality criteria and performance indicators

The establishment of the optimality criteria is the first and most important task when designing a decision support system. In order to perform this task, the decision problem must be first defined clarifying the objectives of the decision problem and its main features. When referring to monitoring systems for maritime industry, the most important objectives are generally the reduction of the fleet operation cost, and the enhancement of the overall security level. Such objectives are generally achieved by optimizing the ship operating speed considering the environmental conditions, and by establishing appropriate maintenance policies. An optimized maintenance policy can in fact drastically contribute to the reduction of the fleet operational cost by increasing the availability of the ship and reducing its maintenance cost.

The decision support system here presented aims at diagnosing possible failures or malfunctions affecting the performance and increasing the operational cost of the ship. As a fundamental indicator of the operational status of a diesel engine, we will focus on the evaluation of the EGT values for each cylinder. Monitoring per-cylinder EGT will allow to promptly detect a thermal overload (i.e. a condition under which the temperature of the combustion chamber is exceeded), and diagnose an incipient failure. Diagnosing possible incipient failures by monitoring EGT, however, is not a straightforward task. EGT, in fact, has a normal dynamic behavior showing a pulse from "combustion event" to "combustion event" as the engine is running, because Exhaust gases are ejected in a pulsing manner, as the exhaust valve opens and closes. Additionally, the exhaust gas temperature varies with the engine load, and high loads result in the highest temperatures. The detection of a problem hence cannot be based on a simple decision rule such as the comparison of the EGT of each cylinder with a fixed maximum or minimum threshold. In addition, a low positive trend in the EGT values over time can be the consequence of the deterioration of the engine due to normal wear and tear in components. Such deterioration can affect the performance of the engine on the long time, therefore it can be employed to trigger a preventive maintenance when the loss of performance becomes significant.

On the basis of such considerations, the optimality criterion here established is the optimization of the maintenance policy and the strategy adopted is to monitor the per-cylinder EGT in order to assess the engine 's conditions and detect possible malfunctioning or incipient failures.

2.2. Real time Data Gathering system & performance evaluation

This section discusses the features of the monitoring system employed for gathering and storing the requerid engine data. As stated before this system must allow to acquire the per-cylinder CGT values continuously while the ship is at sea, perform a local (onboard) storage and pre-processing, and transmit the data on board for further processing. As stated before such tasks are simplified in modern engines since they come equipped with an automation system constituted by pre-installed sensors and data concentration devices. Such system allows to establish a communication channel with the control unit (DCU), by means of a Controlled Area Network (CAN) bus. The system can thus communicate through a standardized interface such as CANopen and Modbus RTU, as well as Modbus TCP on standard Ethernet. Taking advantage of such features, the communication with the engine can be considered a standard Supervisory Control And Data Acquisition (SCADA) application involving a master controller requesting data, and a slave device to returning the requested information.

The monitoring system developed, hence, consists of a specifically designed software routine which polls the system's registers (provided by the manufacturer) and converts received data into readable units. Obtained data is thus stored on a local onboard embedded device, and transmitted to the on-shore control room at regular intervals. The transmission system is based on a standard GPRS communication, considering the ship is always within standard GSM coverage.

2.3. Decision rules

This paragraph concerns the definition of the decision rules that allow to determine the operational status of the propulsion system through the analysis of the EGT values and to trigger early warnings when anomalies are detected. As stated before, the effectiveness engine condition assessment and fault diagnosis through EGT monitoring is well known in the aeronautic field, where per-cylinder engine analyzers and graphic engine monitors (GEM) where introduced by Alcor and Bill Simkinson's KS Avionics back in the 60's. Such systems had no absolute temperature markings but only arrays of vertical analog meter movements showing only relative EGT information to the pilot. The absolute value of EGT was considered not particularly meaningful and presenting this information to the pilot would simply be a distraction. The GEM system is still considered nowadays an essential tool for modern engine management since improves the pilot's understanding of engine operation and removes guesswork from engine management. The essential role of the GEM is to enable the pilot to compare EGT (or CHT) levels on all cylinders to assess the working conditions of the engine(s).

For example if one EGT reading becomes substantially higher or lower than the others, this can be the indicator of a faulty behavior of the engine. In particular, a higher than normal EGT could mean less fuel (leaner and hotter) mixture is being supplied, which could be caused by a faulty fuel injector. Another reason could be a leak in the induction manifold, with extra air is being drawn into the cylinder making its' mixture leaner and hotter. Lower than normal EGT's are indicative of richer than normal fuel mixtures. This could be caused by a fuel injector which does not close completely in between cycles, or a blockage in the inlet manifold causing less air to be drawn into the cylinder. Furhtermore, a slow, rhythmic EGT oscillation (often on the order of one cycle per minute) is the unique signature of a failing exhaust valve.

Hence, although the reading of the absolute EGT measurement will not be very much meaningful for assessing the healthy status of the engine, by comparing the EGT of each cylinder with the average temperature of all the each cylinders in the bank, a meaningful indication can be obtained. Generally speaking, when the engine is operating correctly a great deal of uniformity is expected among engine parameters corresponding to temperatures of each cylinder, consequently, a cylinder malfunction can best be detected by an indication of a significant change in the normal temperature pattern between cylinders. An effective decision strategy can thus be to compare the temperature with a dynamic threshold, which changes according to the current engine load, or to compare the EGT of each cylinder with the average temperature of all the each cylinders in the bank.

Based on the above considerations, a first decision support approach can be to ensure that for each of the cylinders of the diesel engine, the EGT does either exceed an adjustable, fixed high alarm limit, nor deviates too much from the other exhaust gas temperatures. In order to formalize an appropriate decision rule, we define the main pattern vector at time t, as the vector of EGT values at time t:

$$\mathrm{v_t} = \{\mathrm{EGT_1^t}, \mathrm{EGT_2^t}, \dots, \mathrm{EGT_N^t}\} \tag{1}$$

Where N is the number of cylinders.

Minimum, maximum and mean EGT of all cylinders at each instant t can thus be determined as:

$$\mathrm{E}_{max}^{\mathrm{t}} = \max\{\mathrm{EGT_1^t}, \mathrm{EGT_2^t}, \dots, \mathrm{EGT_N^t}\} \tag{2}$$

$$\mathrm{E_{min}^t} = \min\{\mathrm{EGT_1^t}, \mathrm{EGT_2^t}, \dots, \mathrm{EGT_N^t}\} \tag{3}$$

$$\mathrm{E_{avg}^t} = \left(\sum_{\mathrm{i=1}}^{\mathrm{N}} \mathrm{EGT}_{\mathrm{i}}^{t}\right)/N \tag{4}$$

Based on such parameters, the following decision rules can be established.

Max/min EGT alarm

This decision rule triggers a warning when the EGT of each cylinder exceeds a fixed high or low alarm limit

$$\alpha < EGT_i^t \leq \beta \tag{5}$$

Where α and β are the maximum and minimum threshold. Initial values for these thresholds can be determined considering general reference values given in the literature or provided by the manufacturer. However, such thresholds are very much dependent upon the operating conditions of the engine, including the rpm, average load, etc. A more accurate formulation of the rule reported above should involve dynamic adjustable thresholds, as in the equation below

$$a(\mathrm{x}) < EGT_i^t \leq b(\mathrm{x})$$

In this case the values of alfa and beta can be a function of other parameter(s), generally represented by x. For example, a common approach is to compare individual cylinder temperatures with their instant average value and an alarm will be released, if the deviation exceeds the preset value. Allowable deviation from the average value is conveniently set during the sea trial at an average temperature corresponding to normal service conditions.

$$\alpha \cdot E_{avg} < EGT_i \leq \beta \cdot E_{avg}$$

EGT span alarm

The other relevant indicator for assessing the health status of a turbocharged diesel engine is the EGT span which can be calculated instantaneously as the difference between the highest and lowest EGT values among all of cylinders. This indicator is useful for detecting if a cylinder has gone cold, into heavy detonation or pre-ignition. Some commercial engine monitors already include a decision rule which triggers an alarm if the EGT span difference gets too high. Such a rule can thus be expressed in the form:

$$a < EGT_s^t \leq b$$

Where $\mathrm{EGT_S}$ stands for EGT span, defined at each instant as:

$$E\mathrm{GT}_s^{\mathrm{t}} = E_{max}^t - E_{\mathrm{min}}^t$$

Again, the problem arises of determining appropriate thresholds to ensure a “reactive” engine control. Although similar approaches to such problem can be found in the literature [9] Also in this case, a more accurate formulation of the rule reported above should involve dynamic adjustable thresholds, as in the equation below

$$a(\mathrm{x}) < E\mathrm{GT}_s^{\mathrm{t}} \leq b(\mathrm{x})$$

Advanced decision rules based on data mining and sensor fusion.

The decision rules reported above are more or less derived from the existing experience and the state of the art of research. Although such rules are quite simple, they are actually implemented in several commercial engine monitoring systems, and their effectiveness is generally recognized. Also, when calculating indicators from the basic values gathered by different sensors, or when comparing such indicators with dynamic thresholds depending upon other parameters, a basic approach towards multi-sensor data fusion can be recognized. However, the decision rules discussed above are all based on the instant measurement of the per-cylinder EGT values, which makes sense considering they are intended to support pilots or manufacturers in their specific tasks. However, the perception is that when a consistent amount of information is gathered through automated sensor based monitoring system, a great amount of additional information, could be extracted by analyzing the dynamic behavior of the data gathered over time. Analyzing the time series of the single measurement could in fact allow to extract long time trends and non-instantaneous anomalies which may turn useful to the ship manager to establish on-condition predictive maintenance policies. Such information can thus generate an additional value for the company, by increasing the availability of the ships, or planning the procurement of spares. Nowadays, in the era of big data, there is all the technology required to analyze dynamic data coming from multiple sources, and to turn them into valuable information. Data fusion, or data integration, is a method that integrates a series of data sources, to provide a more comprehensive and accurate outlook on a system than a single data source can. As sensors are becoming smarter, several approaches and algorithms are being developed that combine this information to create new knowledge. Such methodologies can be extremely effective for fault and damage prevention, which can be approached by finding patterns in data that do not conform to an expected behavior [10]. Unexpected patterns (also referred to as anomalies or outliers) are patterns in data that do not conform to a well-defined normal behavior [11]. In statistics, an "outlier", is one value that appears to deviate markedly from other members of the sample in which it occurs [12]. Anomaly detection techniques have been proposed in the literature, based on distribution, distance, density, clustering and classification.

3. Case Study

The system described has been tested in real operating conditions by implementing an experimental data monitoring system in a hydrofoil boat employed for passenger transport in the Mediterranean sea on routes connecting the small islands close to Sicily. In particular, the case study is referred to a transport hydrofoil ship equipped with 2 Caterpillar 3516 marine 16-cylinder marine heavy duty propulsion engines, capable of providing a power of 1920 kW at approx. 1500 rpm. The engine is equipped with an advanced monitoring control system (MCS) which provides control and monitoring capabilities, from local and remote locations, including engine start/stop capability, alarm and protection, and user interface and communication. This system has its own set of sensors for control of all relevant functions and provides Modbus communications to the ship

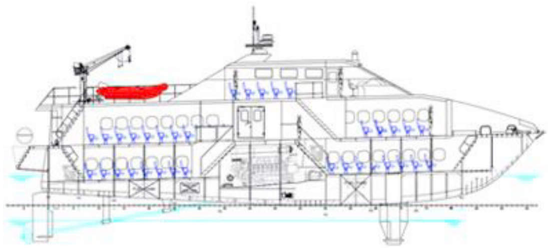

Fig. 1. Hydrofoil ship employed for the experiments.

The ship is approximately 30 meters long, has a maximum breadth of approx. 6,80 meters, and a depth of 3,89 meters. With its gross tonnage of 237 tons and dead weight (DWT) of 33 tons, the ship is technically classified as Ro/Ro passenger ship, and is capable of carrying 250 passengers. Data monitoring has been performed along the route from the port of Milazzo in Sciliy to the port of Vulcano a small island located nearby with an overall distance of approx. 23 marine miles. The ship has travelled with an average speed of approx. 30 knots. During the entire route, the regime engine load has been approx. 75%.

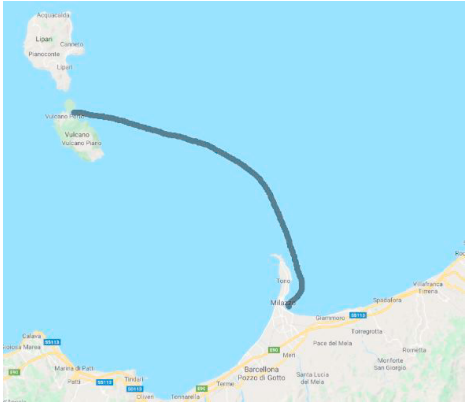

Fig. 2. Route traveled during the experiment.

The relevant engine data have been gathered by the monitoring system during the entire journey which took approx. 40 minutes, with a polling period of approx. 0,1 seconds. Considering the ship has two engines with 16 cylinders each, per cylinder EGT data consist of approx. 400,000 observations. Gathered data, given in Figures 3 and 4 separately for the two engines, show the EGT variations recorded during the test, ranging from 340°C to 680°C with an average temperature of approx. 550°C. The gathered data show the typical cyclic behaviour of the exhaust gas temperature, which is a direct consequence of the periodic 4-strokes of the engine functioning sequence. During most of intake, compression, and power strokes - because the exhaust valve is closed, no exhaust gas is flowing out, while during the one-third of the time that the exhaust valve is open the gas temperature that starts out very hot when the valve first opens but cools very rapidly as the hot compressed gas escapes and expands. Additionally the per-cylinder EGT cyclic variations are influenced by the engine load, which thus introduces additional complications.

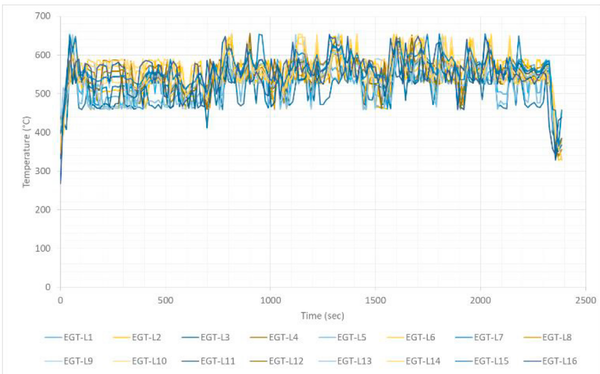

Fig. 3. Per-cylinder EGT values of the left engine

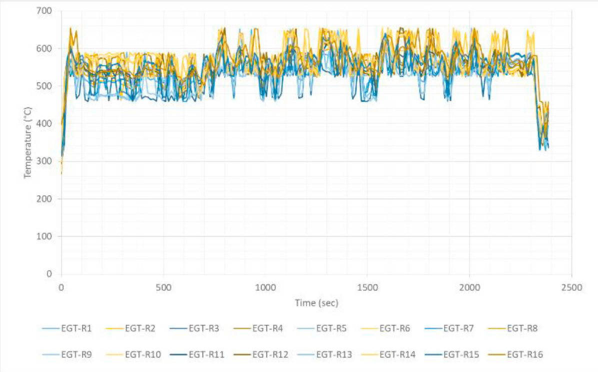

Fig. 4. Per-cylinder EGT values of the right engine

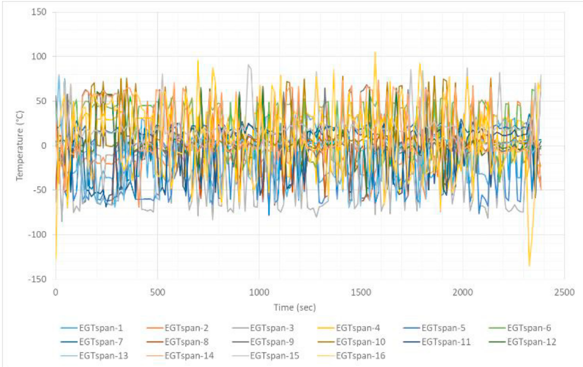

Fig. 6. Per-cylinder EGT values of the right engine

In such situation, assessing possible malfunctioning by analysing instant EGT values is a quite troublesome task, therefore in order to obtain a more reliable information the EGT span indicator has been introduced as the difference between the highest and lowest EGT among all of cylinders. Modern engine monitors include the evaluation of such indicator, and trigger an alarm if it gets too high. This is useful for detecting if a cylinder has gone cold, into heavy detonation or pre-ignition. The EGT span calculation referred to the case study here presented has been performed by evaluating the instant average deviations of the per-cylinder EGT values from the instant average EGT value of all the cylinders. The results obtained, given in figure 5 and 6, show regular oscillations generally in the range of ±80°C from the average, and the presence of some outliers. Such results is substantially aligned with the expected values that can be deduced from the engine temperature curves provided by the manufacturer, therefore representing a normal functioning condition for the engine.
Finally, it is evident that the experimental data reported lends itself to more complex calculations, involving time-series analysis and forecasting and pattern recognition/feature extraction techniques. Advanced data mining approaches are hence suggested for further information processing ad knowledge extraction.

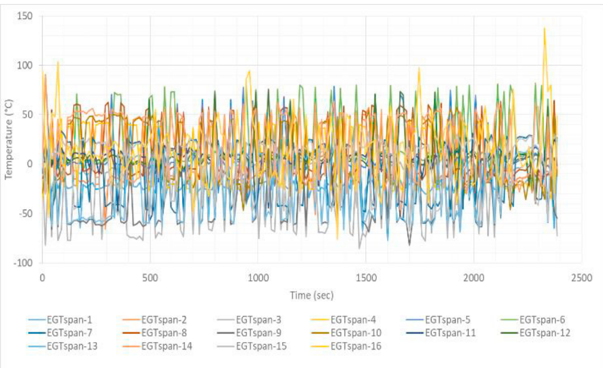

Fig. 5. Per-cylinder EGT values of the left engine

4. Conclusions

As a fundamental driver of innovation, the paradigm of Industry 4.0 promotes a new digital era in the shipping industry where smart cyber-ships equipped with advanced automation systems will be the production resources of a renewed knowledge-based approach towards value creation. Companies operating in the maritime industry, however, are traditionally linked to consolidated business models, and inert to technological innovations and still largely un-prepared to such epochal changes. There is thus the necessity of developing and providing operative models for digitized ship management, which, based on structured information gathering and processing, can provide maritime companies with effective decision support and strengthen their value chain. Based on such considerations, this paper discusses the development of a novel decision support system (DSS) for supporting fleet management operations. As discussed above, this system has been designed taking into account the specific characteristics of the marine industry, in particular:

- The end user is the fleet operations manager rather than a pilot or the engine manufacturer
- The ship monitoring system aims at building time histories of the relevant parameters, thus allowing the creation of extensive datasets (big data) to be shared with the onshore control room.
- The decision rules employed are based on data-driven procedures and data-mining techniques in order to extract valuable information for strengthening the value chain.

The methodology proposed has been validated in real operating conditions by means of a case study, involving the deployment of an experimental monitoring system in a real Ro/Ro hydrofoil ship for passenger transport. The experiment allowed to analyze the EGT values gathered during a 40 minutes journey, and to discuss the effectiveness of some basic decision rules commonly applied in many commercial engine-monitoring systems. The amount of data gathered however, allows much more complex and interesting applications, in the context of big data processing and advanced feature extraction/data mining algorithms.

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