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Review

Condition-Based Maintenance of Naval Propulsion Systems with supervised Data Analysis

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ABSTRACT

The behavior and interaction of the main components of Ship Propulsion Systems cannot be easily modeled with a priori physical knowledge, considering the large amount of variables influencing them. Data-Driven Models (DDMs), instead, exploit advanced statistical techniques to build models directly on the large amount of historical data collected by on-board automation systems, without requiring any a priori knowledge. DDMs are extremely useful when it comes to continuously monitoring the propulsion equipment and take decisions based on the actual condition of the propulsion plant. In this paper, the authors investigate the problem of performing Condition-Based Maintenance through the use of DDMs. In order to conceive this purpose, several state-of-the-art supervised learning techniques are adopted, which require labeled sensor data in order to be deployed. A naval vessel, characterized by a combined diesel-electric and gas propulsion plant, has been exploited to collect such data and show the effectiveness of the proposed approaches. Because of confidentiality constraints with the Navy the authors used a real-data validated simulator and the dataset has been published for free use through the UCI repository.

1. Introduction

Data Analysis (DA) is improving our ability to understand complex phenomena much more rapidly than a priori physical models have done in the past (Anguita et al., 2010; Boucheron et al., 2005; Coraddu et al., 2017). Real-world systems are usually very complex, and hard to model only relying on the a priori knowledge of the problem (Witten et al., 2016; Peng et al., 2010). On the contrary, Data-Driven Models (DDMs) are built exploiting advanced statistical techniques together with the historical data produced and stored by the logging and monitoring apparatus, without requiring any a priori knowledge of the underlining physical phenomena (Vapnik, 1998; Györfi et al., 2006). These characteristics make DDMs a suitable solution in all those contexts where large amount of historical data is available, such as manufacturing (Peng et al., 2010), communications (Nguyen and Armitage, 2008), finance (Shin et al., 2005), healthcare (Mannini and Sabatini, 2010), social networks (Pang et al., 2002), commerce (Das and Chen, 2001), and transportation (Petersen et al., 2012; Budai et al., 2006; Smith et al., 2013).

Many of these sectors traditionally based their profit on empirical experience of sector specialists, and on simplified models built upon a priori knowledge of the specific problems (Waeyenbergh and Pintelon, 2002; Peng et al., 2010). This approach obviously requires a significant amount of time and experience. At the same time, during the last decades, production plants and products have been equipped with many sensors for different purposes: automation, quality check, monitoring, and logging. The results of this process is the availability of a huge amount of historical and real-time data (Linoff and Berry, 2011). Recently, industries have realized that these data, despite their management costs, can be considered as an opportunity to improve their business since historical information can be adopted to create new services or improve the quality of their products (Linoff and Berry, 2011; Oneto et al., 2016b). In particular, they can leverage this huge amount of data thanks to the DMMs which can rapidly and effectively extract useful and actionable information (Witten et al., 2016).

In the shipbuilding industry, one of the main objectives of shipwrights companies is to improve the technological quality of their products. For example, they design more efficient hull shapes and propeller geometries, study innovative propulsion systems, and reduce the overall production costs (Carlton, 2011). Recently, many of these companies are evaluating different DA solutions for improving the quality of their

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Table 1
Measured values available from the continuous monitoring system.

#	Variable name	Unit
1	Lever (lp)	[ ]
2	Vessel Speed	[knots]
3	GT shaft torque (GTT)	[kN m]
4	GT Speed (GT rpm)	[rpm]
5	Controllable Pitch Propeller Thrust stbd (CPP T stbd)	[N]
6	Controllable Pitch Propeller Thrust port (CPP T port)	[N]
7	Shaft Torque port (Q port)	[kN m]
8	Shaft rpm port (rpm port)	[rpm]
9	Shaft Torque stbd (Q stdb)	[kN m]
10	Shaft rpm stbd (rpm stbd)	[rpm]
11	HP Turbine exit temperature (T48)	[°C]
12	Generator of Gas speed (GG rpm)	[rpm]
13	Fuel flow (mf)	[kg/s]
14	ABB TIC control signal (ABB Tic)	[ ]
15	GT Compressor outlet air pressure (P2)	[bar]
16	CGT Compressor outlet air temperature (T2)	[°C]
17	External Pressure (Pext)	[bar]
18	HP Turbine exit pressure (P48)	[bar]
19	TCS TIC control signal (TCS Tic)	[ ]
20	Thrust coefficient stbd (Kt stbd)	[ ]
21	Propeller rps stbd (rps prop stbd)	[rps]
22	Thrust coefficient port (Kt port)	[ ]
23	Propeller rps port (rps prop port)	[rps]
24	Propeller Torque port (Q prop port)	[kN m]
25	Propeller Torque stbd (Q prop stbd)	[kN m]

products, for monitoring the equipment, and for maintenance purposes as integrative activities to their core business (Waeyenbergh and Pintelon, 2002; Wang et al., 2015). In fact, ships are already equipped with a network of sensors that collect data for security, diagnostic and monitoring purposes, which DA can directly exploit by taking advantage of these technologies (Waeyenbergh and Pintelon, 2002; Petersen et al., 2012). DA, for example, offers the possibility to extract, from the raw sensor data, useful information about the efficiency of the ship (Smith et al., 2013), to reduce the fuel consumption (Coraddu et al., 2015), and to improve maintenance activities (Coraddu et al., 2016). These data represent strategic information for shipyards, operators, ship owners, and crews, since they can be used for advisory, control, and fault detection purposes (Oneto et al., 2016a).

Among the different problems, maintenance is probably the most critical one since it could require drydocking, and the cost of retrieving a stricken vessel offshore is non-trivial (Widodo and Yang, 2007; Mobley, 2002). Correct maintenance ensures that a ship works as it was designed, with the desired level performances, without impacting the service (Management et al., 1984). Maintenance policies can be divided into two main categories (Budai-Balke, 2009; Abu-Elanien and Salama, 2010): Corrective (CM), and Preventive (PM).

In the past, the most common approach to this problem relied on the CM where maintenance is performed only after a breakdown of a component (Kothamasu and Huang, 2007). However, replacing a malfunctioning component after it has failed during service, results in exceptional costs and inevitable lower incomes. In PM, instead, a component is replaced when it reaches the end of its life cycle, which can be computed adopting many estimations. One of the historical way to perform this operation is to determine a conservative average of the component life cycle adopting the experience gained with all the components belonging to a specific class. Similarly to CM, this particular type of PM can bring unnecessary costs too, if the replaced component could have been used more than originally forecast. Moreover, this technique does not guarantee to limit the number of faults in a fleet, since a breakdown could still happen before the replacement takes place. In this case, there is a trade-off between the number of breakdowns and the lifetime estimation of the components, which is not easy to reach since the actual ship usage can be very different from ship to ship. Nevertheless, Condition-Based Maintenance (CBM) can be considered as a specification of PM, which aims at reducing both the costs of CM and

Table 2
The 15 sub-problems corresponding to considering different decayed component at the time.

Prob. #	Decayed Component Name	Non Decayed Component Name	Decayed Component	Non Decayed Component
1	GT	GTC, HLL, PRP	$kM_t \in \mathscr{S}^{kM_t}$	$kM_c = 1$, $kH = 1$, $kK_t = 1$
2	GTC	GT, HLL, PRP	$kM_c \in \mathscr{S}^{kM_c}$	$kM_t = 1$, $kH = 1$,$kK_t = 1$
3	HLL	GT, GTC, PRP	$kH \in \mathscr{S}^{kH}$	$kM_c = 1$, $kM_t = 1$, $kK_t = 1$
4	PRP	GT, GTC, HLL	$kK_t \in \mathscr{S}^{kK_t}$	$kM_c = 1$, $kM_t = 1$, $kH = 1$
5	GT,GTC	HLL, PRP	$kM_t \in \mathscr{S}^{kM_t}$, $kM_c \in \mathscr{S}^{kM_c}$	$kH = 1$, $kK_t = 1$
6	GT,HLL	GTC, PRP	$kM_t \in \mathscr{S}^{kM_t}$, $kH \in \mathscr{S}^{kH}$	$kM_c = 1$, $kK_t = 1$
7	GT,PRP	GTC, HLL	$kM_t \in \mathscr{S}^{kM_t}$, $kK_t \in \mathscr{S}^{kK_t}$	$kM_c = 1$, $kH = 1$
8	GTC,HLL	GT, PRP	$kM_c \in \mathscr{S}^{kM_c}$, $kH \in \mathscr{S}^{kH}$	$kM_t = 1$, $kK_t = 1$
9	GTC,PRP	GT, HLL	$kM_c \in \mathscr{S}^{kM_c}$, $kK_t \in \mathscr{S}^{kK_t}$	$kM_t = 1$, $kH = 1$
10	HLL,PRP	GT, GTC	$kH \in \mathscr{S}^{kH}$, $kK_t \in \mathscr{S}^{kK_t}$	$kM_t = 1$, $kM_c = 1$
11	GT,GTC,HLL	PRP	$kM_t \in \mathscr{S}^{kM_t}$, $kM_c \in \mathscr{S}^{kM_c}$, $kH \in \mathscr{S}^{kH}$	$kK_t = 1$
12	GT,GTC,PRP	HLL	$kM_t \in \mathscr{S}^{kM_t}$, $kM_c \in \mathscr{S}^{kM_c}$, $kK_t \in \mathscr{S}^{kK_t}$	$kH = 1$
13	GT,HLL,PRP	GTC	$kM_t \in \mathscr{S}^{kM_t}$, $kH \in \mathscr{S}^{kH}$, $kK_t \in \mathscr{S}^{kK_t}$	$kM_c = 1$
14	GTC,HLL,PRP	GT	$kM_c \in \mathscr{S}^{kM_c}$, $kH \in \mathscr{S}^{kH}$, $kK_t \in \mathscr{S}^{kK_t}$	$kM_t = 1$
15	GT,GTC,HLL,PRP		$kM_t \in \mathscr{S}^{kM_t}$, $kM_c \in \mathscr{S}^{kM_c}$, $kH \in \mathscr{S}^{kH}$, $kK_t \in \mathscr{S}^{kK_t}$	

non-predictive PM by relying on the exact decay state of each component and then by efficiently planning its maintenance (Mann et al., 1995; ISO BS, 2004). Since, in most cases, the decay state of each component cannot be tracked with a sensor, CBM requires a model able to predict it based on other sensors available. Considering the estimated state of decay, it is possible to schedule each component's replacement before failures occur, maximizing its life cycle, according to the time required for each maintenance and to the geographical location of the ship (Mobley, 2002). As a result, the additional costs of CM and PM can be replaced with the lower ones of equipping the propulsion system with sensors and by collecting, storing, and analyzing these data for the purpose of creating effective predictive DDMs (Widodo and Yang, 2007; Mobley, 2002). It is worth noting that shipping companies already invested in maintenance to increase the reliability of their fleet and to reduce the costs. Several examples of Planned Maintenance System (PMS) are available and specifically designed for maintenance monitoring and integrated maintenance with class surveys (Danaos, 2017; DNV-GL, 2017; Spectec, 2017). Nevertheless, as reported in (Jackson et al., 2005), the use of effective predictive models is necessary to achieve reliability, availability and maintainability. For this reason, in this paper, the authors address the problem of building effective predictive models of the main components decay state in a Naval Propulsion System (NPS)