Reliability Engineering and System Safety 177 (2018) 12–23

Contents lists available at ScienceDirect

Reliability Engineering and System Safety

journal homepage: www.elsevier.com/locate/ress

Condition-based maintenance of naval propulsion systems: Data analysis with minimal feedback

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ARTICLE INFO

Keywords:
Data analysis
Naval propulsion systems
Condition-based maintenance
Supervised learning
Unsupervised learning
Novelty detection
Minimal feedback.

ABSTRACT

The maintenance of the several components of a Ship Propulsion Systems is an onerous activity, which need to be efficiently programmed by a shipbuilding company in order to save time and money. The replacement policies of these components can be planned in a Condition-Based fashion, by predicting their decay state and thus proceed to substitution only when really needed. In this paper, authors propose several Data Analysis supervised and unsupervised techniques for the Condition-Based Maintenance of a vessel, characterised by a combined diesel-electric and gas propulsion plant. In particular, this analysis considers a scenario where the collection of vast amounts of labelled data containing the decay state of the components is unfeasible. In fact, the collection of labelled data requires a drydocking of the ship and the intervention of expert operators, which is usually an infrequent event. As a result, authors focus on methods which could allow only a minimal feedback from naval specialists, thus simplifying the dataset collection phase. Confidentiality constraints with the Navy require authors to use a real-data validated simulator and the dataset has been published for free use through the OpenML repository.

1. Introduction

Maintenance is one of the most critical tasks to be designed and programmed by any product-selling company [1–4]. As a fact, every complex system is designed assigning it a specific life-cycle, which is influenced by different factors such as the raw materials adopted, the estimated working hours, and the environmental conditions [5,6]. Nevertheless, this time-to-live information is inevitably inaccurate as it is impossible to predict at design phase the exact working conditions in which the system will operate [7,8]. In any case, the decay of the system components will require at some point of time to be repaired or replaced, thus leading to the system halt to perform some maintenance tasks [9]. This is the reason why an efficient maintenance program can be time and costs saving since replacing a malfunctioning component after it has failed during service, results in multiple downsides for the system owner company.

The Shipbuilding industry is particularly affected by this problem, as a ship breakdown necessarily requires a drydocking, and retrieving a stricken vessel offshore is not a trivial task [10,11]. A correct maintenance program ensures that a ship works as it was designed, with the desired level performances, without impacting the service [12]. Maintenance policies can be divided into two main categories [13,14]: Corrective (CM), and Preventive (PM).

CM has been for many years the only way of performing maintenance, by replacing a component only after its breakdown, thus compromising the overall system availability and causing exceptional costs and loss in incomes [15]. In PM, instead, a component is replaced when it reaches the end of its life cycle before a possible breakdown. One of the traditional ways to perform PM is to predetermine a conservative average estimation of the component time-to-live adopting the experience gained with all the components belonging to a specific class [16]. Similarly to CM, this particular type of PM, usually called Predetermined Maintenance (PRM), can bring unnecessary costs, if the replaced component could have been used more than originally forecast. Moreover, PRM 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 another way of performing PM, which aims at reducing both the costs of CM and PRM by relying on the exact decay state of each component and

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https://doi.org/10.1016/j.ress.2018.04.015
Received 25 August 2017; Received in revised form 20 December 2017; Accepted 18 April 2018
Available online 19 April 2018
0951-8320/

then by efficiently planning its maintenance [17,18]. Note that, condition monitoring and failure prediction are two different concepts which are somehow strictly related. In fact, a failure of a component is predictable only if it is preceded by a decay in its performance or in the performance of some related component [19,20].

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. In fact, the decay state cannot be easily measured without an interruption of service or a drydock of the ship, situation which is usually avoided. To overcome this problem, the available on-board sensors can be used to collect a huge amount of real-time data which can be stored into historical datasets and adopted in order to formulate a statistical Data-Driven Model (DDM) to predict the exact components decay [21]. In fact, DDMs exploit advanced statistical techniques to build models directly based on the significant amount of data produced by the logging and monitoring apparatus, without requiring any a priori knowledge of the underlining physical phenomena [22–24]. Considering the estimated state of decay, it is possible to schedule each component's replacement before failures occur, maximising its life cycle, according to the time required for each maintenance [11]. As a result, the additional costs of CM and PRM can be replaced with the lower ones of equipping the propulsion system with sensors and by collecting, storing, and analysing these data for the purpose of creating effective predictive DDMs [10,11].

In this paper, authors address the problem of building effective DDMs to predict the main components decay state in a Naval Propulsion System (NPS) for CBM purposes. In particular, the decay of a vessel Gas Turbine (GT), Gas Turbine Compressor (GTC), Hull (HLL) and Propeller (PRP) is estimated. Many examples of Data Analysis (DA) techniques applied to different CBM problems can be found in literature [25]. Among other, Support Vector Machines [26], Hidden Markov Models [27] and Kalman filter [28] are the most frequently used. Examples of DA approaches applied to the marine industry can be found in [29], where a standard Neural Network approach is used to improve monitoring of Gas Turbines, while Kernel based methods are applied in [30,31]. In [32,33] image processing techniques are adopted for hull condition assessment. In [34] the engine and propeller state is predicted adopting an Artificial Neural Network. A complete overview can be found in [35].

In particular, this work can be seen as the continuation of Coraddu et al. [31], where a similar approach was attempted adopting a smaller amount of decayed NPS components and supervised Machine Learning (ML) regression models in order to predict their exact decay. Nevertheless, in [31] it was proven that a significant amount of historical data needed to be collected, together with the actual state of decay of each component. In the end, this approach resulted not feasible in a real-world scenario where the labelling process requires the intervention of an experienced operator and, in some cases, to stop the vessel or even to put the ship in a dry dock.

As a result, authors here propose a different approach where collecting labeled samples is an easier task that can be performed by less experienced operators since the raw information about the decay is requested and it can be retrieved without impacting the ship activities. Specifically, two approaches are here proposed and compared. First, authors build virtual sensors able to continuously estimate the need for replacement of the components based on other sensors measurements which are indirectly influenced by this decay. Then authors try to perform the same analysis, in conditions where only few labelled samples are present, by adopting a DDM which require a limited amount of information to achieve satisfying performance. To the best knowledge of the authors, the novelty of the proposed work relies on its ability of building a model whose accuracy is comparable with the state-of-the-art supervised learning techniques, adopting only an extremely limited number of labelled samples.

For this reason, firstly authors performed a traditional classification analysis where the target is to estimate the label state of the components described with an efficiency coefficient. The analysis has been carried out comparing different state-of-the-art methodologies such as Kernel Methods [36], Neural Network [37], Gaussian Processes [38], Similarity Based Method [39], and Ensemble Methods [40]. These binary classification techniques are adopted to predict if the efficiency coefficient is above or below a certain threshold defined by the accepted loss in efficiency of the NPS components. Secondly, the same problem has been tackled with another state-of-the-art approach which, in principle, does not need any labelled sample since it searches for novel behaviour in the data though a novelty detection algorithms [41,42]. Results show that with just a few labelled samples it is possible to fine tune this last methodology to achieve satisfying performances.

This work is the natural continuation of Coraddu et al. [31], where authors presented a dataset published trough the University of California Irvine (UCI) website of data coming from a simulator of a Frigate, characterised by a COmbined Diesel ELectric And Gas (CODLAG) propulsion plant. A similar simulator was adopted in this study, characterised by a higher amount of decaying components, and it will be published through the OpenML dataset repository [43].

The paper is organised as follows. Section 2 reports a general description of the vessel, the numerical model, and the degradation phenomena. Section 3 presents a description of the dataset extracted from the numerical simulator and published through OpenML. Section 4 reports the proposed DDMs. Results of the DDMs tested on the proposed data are reported in Section 5 with conclusions in Section 6.

2. Naval propulsion system

2.1. Vessel description

In this work authors focus on a Frigate, characterised by a CODLAG NPS, widespread detailed in [31]. In particular, the GT mechanically drives the two Controllable Pitch Propellers (CPP) through a cross-connected gearbox (GB). Besides, each shaft has its electric propulsion motor (EPM) mounted on the two shaft-lines. Two clutches between the GB and the two EPM and another clutch between the GT and the GB assure the possibility of using two different type of prime movers, i.e. EPM and GT. Finally, the electric power is provided by four diesel generators (DG). This particular GB arrangement, allows the vessel to operate under different propulsive configurations to achieve the requirements of the vessel's mission profile. The vessel is characterised by the following mission profiles: Anti-Submarine Warfare (ASW), General-Purpose (GEP) and Anti-Aircraft Warfare (AAW). In particular, for the ASW profile, the EPMs are prime movers while the GT is disconnected through the clutches. Under the GEP mission profile, the GT is the prime mover while the EPMs are working as shaft generators. Finally, for the AAW mission profile both the GT and the EPM are the prime movers. In this work, only the GT operating conditions have been taken into account.

2.2. Model description

In this work, authors consider an NPS numerical model developed in the Matlab® Simulink® software environment within many years of research [44]. The numerical model is composed of several modules each one representing a single propulsion component such as the hull, the main engines, the propellers, the rudders, the GB, and the control system. In the previous literature, authors presented a model that considers the GT and GTC decay performance [31]. The model is now further improved to take into account the performance decay of the HLL and PRP, and is now readily to undertake a holistic approach in addressing the performance decay by accounting the important components as follows:

1. Gas Turbine (GT);
2. Gas Turbine Compressor (GTC);
3. Hull (HLL);
4. Propeller (PRP).