Semi-Supervised Learning Approach for Optimizing Condition-based-Maintenance (CBM) Decisions

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***Abstract*—Recent heightened enthusiasm towards Industrial Artificial Intelligence (IAI) and Industrial Internet of Things (IIoT) coupled with developments in smart sensor technologies have resulted in simultaneous incorporation of several advanced Condition Monitoring (CM) technologies within manufacturing and industrial sectors. Efficient utilization of CM data leads to enhanced safety, reliability and availability of manufacturing systems. In this regard, the paper proposes an efficient and novel hybrid Maintenance Decision Support System (MDSS) for fault diagnostic and prognostic considering CM data along with event-triggered data. The proposed MDSS model is a hybrid Machine Learning (ML)-based solution coupled with statistical techniques. In order to find an optimal maintenance policy, we concentrate the attention on a time-dependent Proportional Hazards Model (PHM) augmented with a semi-supervised ML approach. The developed hybrid model is capable of inferring and fusing High-Dimensional and Multi-modal Streaming (HDMS) data sources in an adaptive and autonomous fashion to recommend optimal maintenance decisions without human intervention. To illustrate the complete structure of the proposed MDSS, experimental evaluations are designed based on a dataset provided by NASA containing run-to-failure and CM data associated with aircraft engines. The effectiveness of the proposed model is demonstrated through a comprehensive set of comparisons with different ML algorithms.**

I. Introduction

Under today's highly competitive business environment, it is critical and of paramount importance that manufacturing and industrial sectors operate at their full potential. Condition-based maintenance (CBM) as the state-of-the-art maintenance program is positioning itself as a powerful tool in prognostic and health management context. The CBM program collects information through condition monitoring (CM) and recommends maintenance actions when the observed data indicate severe system deterioration. When applying CBM, therefore, the average cost is significantly reduced by eliminating unnecessary maintenance operations [1]. Generally speaking, a CBM program consists of three main steps: (i) Data acquisition; (ii) Data processing, and; (iii) Maintenance decision-making. Nowadays, data acquisition for CBM is more affordable and feasible due to advances in the Industrial Internet of Things (IIOT) and the rapid development/employment of advanced and smart sensory devices. Availability of rich and real-time CM data collected by smart sensory devices results in an accurate and efficient maintenance decision making. CM data collected from sensory devices are versatile and can fall into three main groups: (a) Value type; (b) Waveform type, or; (iii) Multidimensional type. Due to the high variety and high-dimensionality of CM data collected by advanced sensing technologies, conventional system monitoring and control techniques are incapable of utilizing such information efficiently for proper maintenance decision making. The paper aims to address this gap.

Industrial/manufacturing production, consequently, is gradually moving to become an intelligent and autonomous system. The IIoT and Industrial Artificial Intelligence (IAI) are revolutionizing the business sector to understand the CM data better and to control and optimize the entire production process. In the near future, the IAI is expected to be business-critical. There is no doubt that developing an efficient and smart Prognostic and Health Management (PHM) system will provide a significant contribution to maintaining the integrity of complex manufacturing systems. Such an intelligent monitoring and control system in place should be able to monitor the underlying system continuously and in real-time, detect any particular trend/abnormally in the underlying system, and recommend optimal (or near-optimal) control and maintenance policies based on CM data to minimize the risk of failure.

Recently, there has been an increasing surge of interest in applying IAI and Machine Learning (ML)-based solutions for PHM. The driving key factor that increasingly empowers this hype and poses to reshape the competitive landscape of manufacturing systems is the exponential growth of High-Dimensional and Multi-modal Streaming (HDMS) CM data [2]. Although using IAI/ML techniques in predictive maintenance [3]–[5] is significantly challenging, it has the great potential to introduce exceptional benefits such as superior availability and reliability of assets, capital expenditure decrease (fleet size can be decreased with improved asset availability), and operational expense reduction (e.g., replacement costs). A recent contribution in this line of research is provided by [6] where a Deep Learning (DL)-based model is developed for Remaining Useful Life (RUL) prediction for gas turbine engines based on an open-sourced dataset provided by NASA [7]. A similar research work has been conducted by [8],

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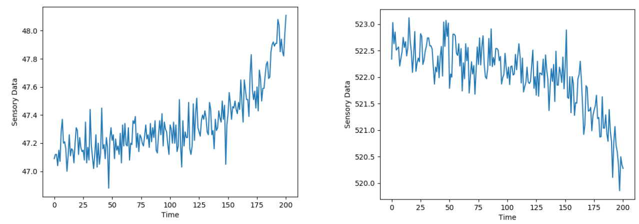
in which a DL-based RUL estimation is developed for bearings PHM tasks. The authors showed promising results with high accuracy on the RUL prediction. More related references in the RUL prediction based on DL models can be found in [9]–[13]. The increased number of successful researches on the applications of DL-based solutions in different manufacturing and industrial sectors such as automotive, transportation, healthcare, and aerospace has shown the effectiveness of such data-driven methods for CBM applications. This is the focus of the paper.

Literature Review: A model built incorporating on both event and CM data is of paramount importance and could be the basis for development of a Maintenance Decision Support System (MDSS). This is a crucial step to assist maintenance related decisions and on taking optimal and proper maintenance actions. A time-dependent Proportional Hazards Model (PHM), refereed to as the Cox's PHM, is considered as the popular model in survival analysis, which takes into consideration both event and CM data. In general, in the Cox's PHM framework, the age of the system, as well as a stochastic process describing the system's degradation, are used jointly to form the failure rate function of the system. A vast proportion of CBM literature is devoted to the statistical-based solutions to estimate the system hazard rate in Cox's PHM framework. An early and pioneer work in this line of research is development of the optimal replacement policy by [14], [15]. They considered the Cox's PHM with a right continuous stochastic covariate process under periodic monitoring. The optimal replacement policy was derived within the Semi-Markov Decision Process (SMDP) framework. They also developed a recursive algorithm for minimizing the system's long-run expected average cost (see [14], [15]). Calculation of the optimal replacement policy for a deteriorating system using PHM and the policy structure determined in [14], [15] was presented in [16], where the discrete-time approximation considered previously was relaxed. An intriguing application of CBM methodology in the PHM framework is presented by [17], where an optimal maintenance policy is developed in defense applications. Another application of CM using the PHM framework in truck wheel motors is given by [18], where the failure rate of the system was expressed using PHM. The optimal maintenance policy was developed to obtain the best time to repair the process to minimize the overall maintenance costs. More references in this line of research can be found in [19]–[22].

Contributions: While the research on IAI/ML-based solutions for CBM applications is broad, utilization and combination of HDMS monitoring data and event data smartly and intelligently are still in their infancy. Related research works in the Cox's PHM framework mainly focus on statistical methods that pose significant analytical challenges due to high-dimensionality and high-variety of CM data. This paper aims to address this gap. More specifically, we develop a novel ML-based Cox's PHM, which is the basis for implementation of smart MDSS. The proposed hybrid Cox's PHM model is based on a semi-supervised learning approach, which jointly takes into consideration both event and CM data.

TABLE I: C-MAPSS Description.

Dataset	Number of Train Data	Number of Test Data	Number of Fault Modes	Number of Conditions
FD001	100	100	1	1
FD002	260	259	1	6
FD003	100	100	2	1
FD004	249	248	2	6



(a) The 11th sensor signal. (b) The 12th sensor signal

Fig. 1: Sensor signals for the ninth engine.

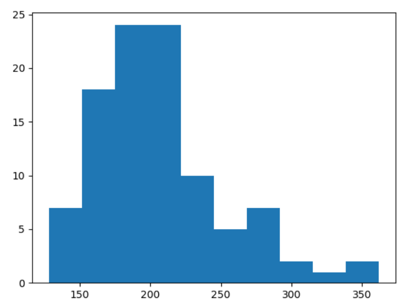


Fig. 2: Failure data histogram.

Following this introduction, the proposed hybrid model is presented in Section II, where Sub-section II-A presents the utilized data and provides data set preparation procedures. Sub-section II-B presents the PHM model followed by description of the learning model in Sub-section II-C, while Sub-section II-D provides experimental results and sensitivity analysis. Finally, Section III concludes the paper.

II. Proposed Hybrid and Semi-Supervised ML-based MDSS Framework

A. Data Set Description and Pre-Processing

Sensor Selection: The commercial modular aero-propulsion system simulation (C-MAPSS) dataset provided by NASA is used for development of the proposed ML-based model. The C-MAPSS dataset contains the run-to-failure data and is the most-widely used dataset in the context of prognosis and health monitoring. The dataset includes four subsets of data, namely, FD001, FD002, FD003, and FD004. Each subset is further divided into the train and the test subsets. The overall description of these datasets is listed in Table I. In

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this study, we concentrate the attention on the first data set, i.e., FD001, which consists of 24 features including three operational conditions and 21 sensors' measurements. For illustration purposes, the CM signals associated with the 11th and the 12th sensors for Engine 9 are shown in Fig. 1. Some sensor endearments included in the FD001 dataset have constant values over different engines. The standard deviation is calculated and the features with low standard divisions are removed. As a result, 15 sensors are selected with indices 2, 3, 4, 6, 7, 8, 9, 11, 12, 13, 14, 15, 17, 20, and 21.

Normalization: The value range of each sensor is re-scaled and normalized into a new range, i.e., between 0 and 1 to speed up the computational time and to enable an unbiased contribution from the output of each sensor. Normalization is performed as follows

$$x'_{ij} := \frac{x_{ij} - \min\limits_{j}\{x_{ij}\}}{\max\limits_{j}\{x_{ij}\} - \min\limits_{j}\{x_{ij}\}}, \tag{1}$$

where x'_{ij} and x_{ij} represent the i^{th} observation from the j^{th} sensor after and before normalization, respectively. This completes our discussion on data set preparation. Next, we briefly review the Cox's PHM.

B. The Cox's PHM Model

Hazard function is considered as an adequate measure for maintenance decision making. In order to find the hazard rate of a system, life data set (failure data) is needed. The failure time data from C-MAPSS is extracted and the histogram of the failure data is constructed as shown in Fig. 2. In most engineering applications, typically, additional concomitant information is available such as CM data, which is collected via sensory devices. In order to make a proper maintenance decision making, it is shown that this information should be taken into consideration along with the failure data. In order to model the effect of concomitant variables on the failure time, Cox's PHM has been widely used. In the Cox's PHM framework, the failure rate of the underlying system at time t is given by

$$h\big(t, Z(t)\big) = h_0(t) \times g\big(Z(t)\big), \tag{2}$$

where $h_0(t)$ represents the baseline hazard (BH) rate of the system, which only depends on the age of system. Term $g\big(Z(t)\big)$ is a positive function referred to as the hazard risk (HR) representing the effect of concomitant variables on the system's failure rate. Commonly, the BH is modeled by Weibull distribution and HR is modeled by exponential distribution. Thus, Eq. (2) can be expressed as follows

$$h\big(t, Z(t)\big) = \frac{\beta}{\eta}\big(\frac{t}{\eta}\big)^{\beta-1} \times \exp\Big(\sum_j \lambda_j \times z_j(t)\Big). \tag{3}$$

In Eq. (3), β and η are the shape and scale parameters, respectively. Term $z_j(t)$ is the value of j^{th} covariate at time t and λ_j is the j^{th} corresponding weight for j^{th} covariate. Two-parameters Weibull distribution is fitted on the failure data followed by Maximum Likelihood Estimation (MLE) to estimate the BH function's parameters. The estimated parameters are as follows

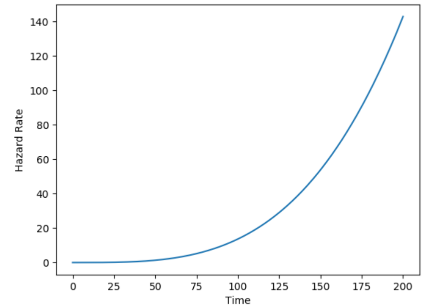

Fig. 3: Hazard rate for the 9th engine.

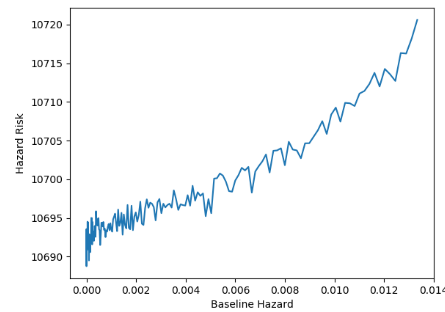

Fig. 4: Baseline hazard versus hazard risk for the 9th engine.

$$\beta = 4.409, \; \eta = 225.026. \tag{4}$$

As the result indicates, since $\beta > 1$ and the hazard function is increasing in time (Fig. 3), the system deteriorates as it ages. Therefore, the expected number of failures will decrease if the system goes under Preventive Maintenance (PM) actions. Furthermore, due to the fact that cost of failure replacement is greater than that of preventive replacement, performing PM actions will significantly improve the health condition of the system with minimum cost. Similar to the previous analysis, we computed the associated weight of covariates, i.e., λ_j for $j \in [1, 15]$. The graph of BH versus HR for the 9th engine is shown in Fig. 4. This completes our discussion on the Cox's PHM.

C. Unsupervised Learning Stage

Based on the hazard rate calculation presented in the Section II-A, we perform clustering in order to draw references from datasets consisting of input data without labeled responses. Clustering is a well-known type of unsupervised learning method when the labels associated with the input data is not available. There are several clustering algorithms in the ML literature, among which K-means clustering is a popular approach where the data is partitioned into the desired number of clusters with the nearest mean. The metric of interest, which

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TABLE II: Train accuracy average, standard division, and test accuracy.

Model	average of Train accuracy	SD of Train accuracy	Test accuracy
Random Forest	0.984	0.007	0.9908
KNN with 4 neighbors	0.9768	0.0059	0.9871
KNN with 3 neighbors	0.9783	0.0061	0.9866
KNN with 5 neighbors	0.9788	0.0063	0.9861
KNN with 1 neighbors	0.9783	0.0061	0.9859
KNN with 2 neighbors	0.973	0.005	0.9849
SVM with 10-degree polynomial kernel	0.9759	0.0037	0.9784
SVM with rbf kernel and scale coefficient	0.9749	0.0084	0.9774
SVM with 7-degree polynomial kernel	0.9763	0.0063	0.9767
SVM with 3-degree polynomial kernel	0.9722	0.0087	0.9699
SVM with 6-degree polynomial kernel	0.9761	0.0065	0.9694
SVM with 2-degree polynomial kernel	0.9708	0.0078	0.969
SVM with 5-degree polynomial kernel	0.9739	0.0078	0.9664
SVM with 4-degree polynomial kernel	0.9726	0.0082	0.9638
SVM with rbf kernel and auto coefficient	0.9577	0.0077	0.9567
SVM with sigmoid kernel and auto coefficient	0.9521	0.0085	0.9492
Gaussian Naive Bayes	0.9013	0.0212	0.8892
Multinomial Naive Bayes	0.6505	0.0003	0.6957
Complement Naive Bayes	0.6455	0.03	0.6442
SVM with sigmoid kernel and scale coefficient	0.3871	0.0856	0.338

will be minimized, is known as inertia or within-cluster sum-of-squares criterion.

In this paper, we apply the K-means clustering approach to the data set under the study such that three clusters/states are created, namely, healthy, warning and most degredated/failure states. The following procedure is perform to construct the aforementioned three states:

1) *Step 1. Individual Clustering*: Use K-means to cluster BH and HR into two clusters (i.e., healthy and unhealthy) independently:

$$C_{\text{BH}} = \begin{cases} 1 & \text{BH is healthy} \\ 0 & \text{BH is unhealthy} \end{cases}$$

$$C_{\text{HR}} = \begin{cases} 1 & \text{HR is healthy} \\ 0 & \text{HR is unhealthy} \end{cases}$$

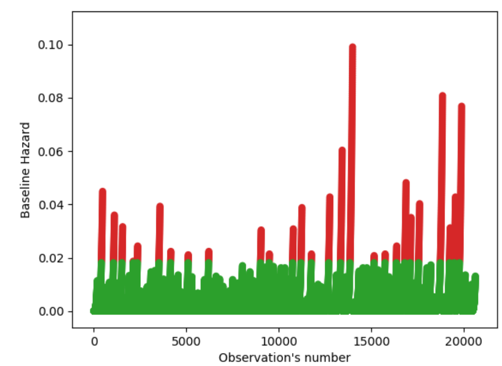
The BH and HR clusterings are shown in Figs. 5(a) and 5(b).

2) *Step 2. Aggregated Clustering*: Aggregate BH and HR clusterings for each observation such that:

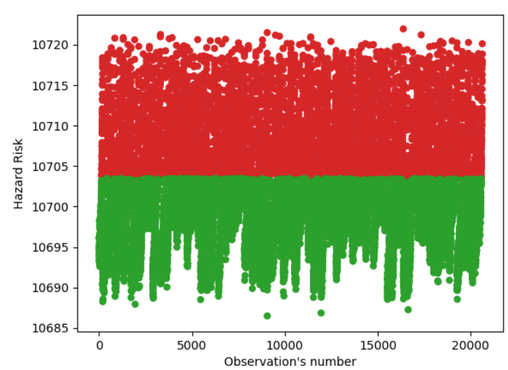
   a) For a single observation, the aggregated clustering would be the healthy state, if the observation was clustered into the healthy state based on both HR and BH clusterings obtained from the previous step.
   b) If an observation is clustered in the unhealthy state both based on HR and BH clustering, the aggregated clustering for that specific observation would be the failure state.
   c) If an observation is clustered in the healthy state based on the HR clustering, and in the unhealthy state based on the BH clustering or vice versa, the aggregated clustering for that specific observation would be the warning state. In summary, the total clustering denoted by C_{Total}, which represents the combination of all possible scenarios, can be written as follows

$$C_{\text{Total}} = \begin{cases} 2 & C_{\text{BH}} = C_{\text{HR}} = 1 \\ 1 & C_{\text{BH}} \neq C_{\text{HR}} \\ 0 & C_{\text{BH}} = C_{\text{HR}} = 0 \end{cases}$$

The result of Step 2 is shown in Fig. 6.



(a) BH clustering.



(b) HR clustering

Fig. 5: Individual Clustering.

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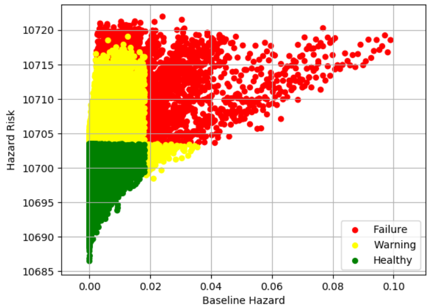

Fig. 6: Aggregated clustering

3) *Step 3. Failure Clustering*: The last d number of run-to-failure observations of each engine is clustered into the failure state, independent of the algorithms approach. The rational behind this modeling decisions is that since the failure time of engines varies between 128 to 362, the algorithm is not able to cluster the early failures of some engines against those with higher time to failure. Therefore, we have to change the d last clusters for each engine to be able to detect potential earlier failure of engines, i.e.,

$$C_{\text{Total}} := \begin{cases} 0 & \text{It is in the } d \text{ last run-to-failure data} \\ C_{\text{Total}} & \text{otherwise} \end{cases}$$

Illustration of the proposed clustering approach is presented in Fig. 6. This completes out discussion on clustering approach.

D. Train and Test Models

The main objective of the proposed framework is to design and develop a hybrid MDSS for fault diagnostic/prognostic. The proposed MDSS in place should be able to construct optimal control and maintenance policies for decision-making based on CM data. In order to achieve this objective, the hazard rate of the system should be monitored over the time. Specially, for the systems with increasing hazard rate, PM actions are recommended when a sample shows some indication of a change in the process/system state. Performing proper PM actions at a right time will increase the system's availability, reliability and efficiency. In order to design such a smart system, we should develop a multi-class classification algorithm. The output of the multi-classification algorithm will be three classes based on the estimated hazard rate of the system, which results in a decision graph to be optimally used for maintenance decision making.

After clustering and computing the labels, we can train different classification models. Using classification after clustering to predict the labels are applied in many reaserch works including but not limited to [23]–[26]. There are many popular algorithms for classification tasks such as random forest, K-nearest neighbors (K-NN), and Support Vector Machines (SVM). In each run, we divide the data into train and test sets such that 80% of the engines are considered as training set and the remaining ones are considered as the test set. In order

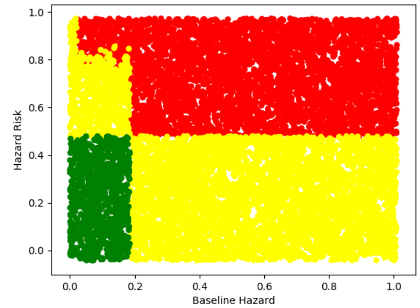

Fig. 7: Optimizing the CBM decision based on Random Forest.

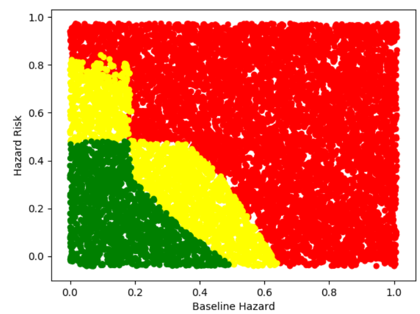

Fig. 8: Optimizing the CBM decision based on KNN with 4 neighbors.

to get the relevant train accuracy, i.e., measure of bias and variance of the models, we applied K-fold cross-validation. In addition, we apply several classification's methods to see the effectiveness of different classification algorithms. Table II shows the accuracies of train and test associated with different classification models. As the results show, the train and test accuracies for most of the models are higher than 90%, and the standard division of the test accuracy is low, which indicates that there is an acceptable trade-off between bias and variance of these models.

Based on each classification model, a decision graph is constructed. Figs. 7, 8 and 9 represent three different decision graphs with highest accuracy.

E. Results and Discussion

In addition to the above analysis, we are also interested in the shape of the decision boundaries made by each algorithm. The rational behind such an interest is that the age or failure time of different engines has a large range, therefore, in some parts of the space, we do not have enough data. Consequently, we come up with an intuitively pleasing idea to generate large amounts of data and investigate the shape of the decision boundary as well. Hence, the best model is a model that has both a relevant accuracy and a proper decision boundary. It is worthy to note that based on the industry and maintenance cost, we are able to choose different kinds of plots since some plots are more conservative than others.

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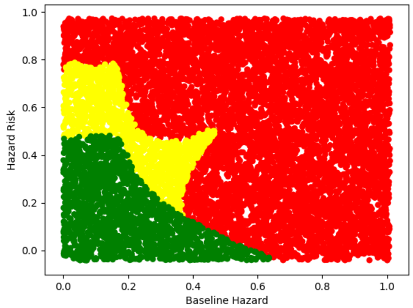

Fig. 9: Optimizing the CBM decision based on SVM with 10-degree polynomial degree.

III. Conclusion

The paper proposes an efficient and novel hybrid Maintenance Decision Support System (MDSS) for fault diagnostic and prognostic considering CM data along with event-triggered data. The proposed MDSS model is a hybrid Machine Learning (ML)-based solution coupled with statistical techniques. In order to find an optimal maintenance policy, we concentrate the attention on a time-dependent Proportional Hazards Model (PHM) augmented with a semi-supervised ML approach. To illustrate the complete structure of the proposed MDSS, experimental evaluations are designed based on a dataset provided by NASA containing run-to-failure data and CM data of aircraft engines. The effectiveness of the proposed model is demonstrated through a comprehensive set of comparisons with different ML algorithms.

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