Multiple Instance Learning with Random Forest for Event-Logs Analysis and Predictive Maintenance in Ship Electric Propulsion System

Azzeddine Bakdi, Nicolay Bjørlo Kristensen, and Morten Stakkeland

***Abstract*— A novel Weakly Supervised machine learning approach is proposed for Intelligent Predictive Maintenance (IPdM). It employs Balanced Random Forest and Multiple Instance Learning, based on Event Logs from ships Electric Propulsion Systems. The objectives are (i) predicting failure likelihood, (ii) time to failure, and (iii) explainable predictions to ensure timely crew intervention. The IPdM approach uncovers, then learns, and classifies *sequences of* events that represent early causes or symptoms to forecast imminent failures. In particular, this paper contributes effective solutions to irregular, imbalanced, and unlabeled data issues where conventional methods become obsolete. First, the events occur at irregular intervals; they include alarms, warnings, and operational information collected across multiple units and control systems. Second, the datasets exhibit extreme imbalance due to few failures and multiple failure modes; this entails biased predictions. Third, the training datasets are weakly labelled; only the failure timestamp is known without any expert input on prior causes or early symptoms. Temporal Random Indexing is proposed to transform textual log messages into a numerical lower-dimensional space where timeseries analyses are applicable. Balanced random-forest models are developed for unbiased classification and regression. The overall approach learns recursively the ungiven data labels while training the base learners. The IPdM approach is validated through millions of events of multi-thousand types collected from 2-years seagoing vessels. It successfully forecasts actual propulsion failures and performs better compared to contemporary methods.**

***Index Terms*—Alarm System, Balanced Random Forest, Event-driven Predictive Maintenance, Event Logs, Failure Prediction, Imbalance, Inexact Labeling, Inverter, LNG Carriers, Multiple Instance Learning, Temporal Random Indexing, Time to Failure, Ship Electric Propulsion System, Weakly Supervised Learning.**

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I. Introdeuction

INTELLIGENT Predictive Maintenance (IPdM) has emerged among the most attractive applications of industry 4.0. It exploits Industrial Internet of Things (IIoT) with advanced big data analytics and Machine Learning (ML) algorithms to ensure intelligent, reliable, and safe operations. In shipping 4.0, ship automation, autonomy, digitalization, safety, and maritime electrification are central objectives. IPdM as proposed in this paper, has the capability of reducing the number of unscheduled interruptions in the Electrical Propulsion Systems (EPS); Hence it reduces downtime and improves the safety of critical operations. The rising levels of system automation and integration increase complexity and room for random non-ageing-related failures, where traditional maintenance strategies are becoming obsolete [1]. Moreover, failure forecasting becomes an important component for future autonomous vessels, allowing operators to optimally schedule maintenance operations and procurement of parts. Fortunately, the rapid digitalization is a key enabler of IPdM; yet, there are still open challenges that must be addressed in order to elevate intelligent IPdM capabilities beyond its hype cycle.

The last decades have witnessed academic and industrial transformation of maintenance strategies from reactive and Preventive Maintenance (PvM) to Predictive Maintenance (PdM) strategies [2, 3]. However, the state-of-the-art PdM includes mainly fault detection [4] and diagnosis [5]. Advanced IPdM strategies involve condition-based maintenance [6] such as ageing; prognostics of deterioration; and state-of-health estimation [7]. Such PdM algorithms are classified into 4 groups. Physics-based models, e.g., digital twins that are difficult to establish for large systems. Knowledge-based expert systems, including fuzzy logic [6], are simple and explainable but less accurate. Data-driven algorithms use statistical methods, e.g., PCA [5] and ML such as SVM [8] and recurrent neural networks [9]. Their combinations form hybrid methods.

This paper considers IPdM algorithms that can (*i*) forecast the failure in advance, (*ii*) predict *time to failure*, and (*iii*) give *explainable predictions* to enable fast intervention. First, emphasis should be put on multi-unit systems IPdM [10] taking many dependencies into account. Such systems include modern ships and particularly Liquified Natural Gas (LNG) carriers, up to 300 meters long. Secondly, IPdM is crucial in modern ships which form the vital blue economy where over 90% of the worlds' merchandise is transported by sea [11]. Shipping accidents cause catastrophic fatalities, economic losses, and damage to the environment [11]. Third, the above-mentioned condition-based IPdM methods ignore volatile stochastic conditions, events, and operators' activities. They consequently miss-predict short-term failures that are related to random events instead of steady ageing or deterioration. Fourth, the paper extends the concept of maintenance beyond the traditional definition. The ultimate target is to improve safety during critical operations and avoid unscheduled interruptions in a complex system. Hence, the main goal is to perform timely prediction of failures in the EPS (*i*, *ii*, *iii*) allowing the crew to eventually perform mitigative actions, e.g., changing the

operation. The needed maintenance may be as simple as restarting the system; although more traditional maintenance may be needed in some cases. This approach can potentially reduce the risk of mid-sea propulsion loss, as in the Viking Sky incident [12]. It provides sufficient time to *fail-safe* and prevent navigational accidents as in the case of Bulk India grounding [13].

This paper hence focuses on event-driven IPdM, particularly in LNG carriers' EPSs. Numerous normal and abnormal events are recorded on board the vessels; these are usually trivial and unlikely to cause any harm. Yet, special combinations of events might propagate to other units, triggering patterns or *sequences of events* that cause a failure; e.g., {valve controller anomaly, cooling-water unit malfunction, generator blackout, propulsion failure, grounding accident} in [13].

This work also provides novel comprehensive solutions to tackle three major IPdM challenges; this consequently contributes to increased IPdM accuracy, especially to attain objectives (*i*, *ii*, *iii*). These targeted issues include the irregular event timestamps and inconsistent event messages; the extreme event-data imbalance due to few failure events and multiple failure modes; and more importantly, the lack of sufficient fully labelled data to train and test IPdM models.

The rest of this paper is organized as follows. Section II provides a literature review on maritime IPdM practices, knowledge gaps, common challenges, and the contributed solutions. Section III provides an overview on the electric propulsion system; numerical figures on data quality and quantity issues, and the designed event data processing techniques. Section IV derives and describes the implementation of balanced random forest and the overall weakly supervised IPdM approach. Section V discusses the results of real-world failures prediction, predictive maintenance explainability, and comparisons with closely related methods. Finally, this paper ends with a conclusion in section VI.

II. Literature Review

Sea-based equipment are frequently subject to both failures and defects as well as needless repairs. The current maritime maintenance culture involves three paradigms which impose opposite advantages and limitations. Traditionally, the *reactive maintenance* paradigm is referred to as the "corrective" or "curative" approach and it is widely common in the maritime industry as reviewed in [14]. *Ship's planned maintenance systems* are based on periodically scheduled replacements and repairs according to requirements established by the manufacturers and classification societies. It has been in use for a long period of time [15]. In *preventive maintenance*, the crew is responsible on keeping the equipment in good conditions through frequent inspections, conditional analyses, and preventive measures. This approach is active in the maritime industry, especially for mechanical systems [16].

Optimal maintenance strategies idealistically aim at three targets: preventing unplanned failures, subduing unnecessary maintenance-related costs and downtime, and exploiting the full lifespan of machinery. Predictive maintenance aims at predicting when the system is likely to fail and determining the required maintenance actions. Prescriptive maintenance extends this scope to identify root causes and determine recommendations to reduce operational risks. In particular, it is worth mentioning the general lack of intelligent PdM methods in the maritime literature [17]. This paper contributes here by developing PdM methods for the vital propulsion system.

[18] reviewed the PdM state-of-the-art and highlighted multiple challenges that face applied PdM methods. Similarly, the survey in [19] considered PdM as "still in its infancy" and related this to three open issues: (a) multi-source data quality; (b) identification/prediction accuracy; and (c) the combination of Artificial Intelligence (AI) methods with maintenance scheduling. With the rich and fast-evolving literature of statistics and ML, the limited accuracy (b) is primarily attributed to the data quantity and quality limitations (a). Whereas explainable AI (XAI) is essential for addressing IPdM issue (c) [20]. Motivated by these challenges, the presented paper contributes to improving IPdM accuracy; unconventional ML methods are presented herein to cope with inevitable PdM data issues and to provide interpretable failure predictions.

Notwithstanding the imperative role of alarm systems in operation safety [21], the full exploitation of their massive logged events is insufficiently explored in the PdM literature. This shortage is first related to the event data complexity. The events are textual in nature, have multiple attributes, originate from multiple equipment, occur irregularly, and exhibit parallel and sequential correlations. Secondly, the timeseries analyses literature is much richer compared to event- and time-to-event analyses [22]. Hence, very few event-driven PdM methods [23, 24, 25] are reported in the literature; and they are limited to single-unit applications. Random indexing is a text mining method [24] that is widely applied in natural language processing. Despite its success in processing textual data, the method does not incorporate the time dimension, nor the time correlation between textual inputs. Given the significance of the latter properties in event logs analyses, temporal random indexing is developed in this work. It contributes effective event data processing, after which most advanced timeseries analyses are applicable.

A second major issue is related to imbalanced data which poses a serious challenge for ML methods; it also leads to biased models and predictions. In general, data imbalance refers to skewed distribution of data points over existing classes; its common challenges are reviewed in [26]. Common remedies for this issue include weighted or cost-sensitive methods, oversampling minority classes, and undersampling majority classes. In IPdM context, the training data is extremely imbalanced including both between-class and within-class imbalances. Failure events occur infrequently and imply insufficient training data examples. Besides, the failure-cause samples are extremely minor compared to the remaining samples. Furthermore, the failure-cause samples are scattered in multiple regions due to multiple failure modes and near-failure cases. Failure causes are difficult to learn and predict. The original Random Forest (RF) is selected as a base learner for many advantages. RF is useful for high-dimensional data; it is robust to noise features; it provides explainable predictions

from interpretable features. It is also robust to small data-imbalance. However, a balancing strategy is implemented to further improve RF performance against extreme imbalance.

The most challenging IPdM issue is due to unlabeled training data [18, 19], a dominant requirement for predictive methods. Yet, the lack of sufficient labelled data –as highlighted in [25]– remains an unsolved issue in PdM literature. Conventional ML methods are classified into three categories. Clustering techniques [27] are used for unsupervised learning from unlabeled data; but their applications are limited to finding similarities between samples. On the contrary, supervised learning requires fully labelled data to construct predictive models. Semi-supervised learning [28] is based on labeled data for one representative class to train models that detect out-of-class samples as in change-point and fault detection. This includes the basic RF applications for anomaly detection and classification [29, 30]. Recently, weakly supervised learning approaches [31] have emerged as potential solutions to construct predictive models that are highly desired in practice, yet, from leveraging inexactly and/or incompletely labelled data. However, these techniques remain unexploited in the PdM literature despite the strongly connected problem. This paper proposes a weakly supervised ML approach for IPdM. The aim is to learn the ungiven data labels coordinately while tuning the parameters of the base learners. This forms a nonconvex optimization problem; It is solved as a Multiple Instance Learning (MIL) process using deterministic annealing.

III. Electric Propulsion and Event Logs

This paper proposes a new event-driven approach for intelligent IPdM in EPSs of LNG carriers. Historical event datasets are collected from hybrid diesel-electric vessels during ordinary seagoing operations. Feature engineering techniques are first developed to transfer event log files into a consistent numerical form in a lower-dimensional space.

A. Ship EPS system

Various designs of EPSs [32] depend on ship size, desired speed, loads, and performance. EPSs are superior over conventional propulsion systems in terms of increased reliability, functionality, efficient space and energy use, reduced emissions, and possibility to use energy storage devices for transient efficiency or fully electric battery propulsion.

A typical structure of a propulsion and power plant –in the vessels under this study– is illustrated in the simplified diagram of Fig. 1. The power plant is powered by the Generators (G) which convert fuel energy into electric energy in form of Alternating Current (AC), they are connected to the system through the High Voltage Main AC Switchboard (HVM-AC-S). For reliability and performance, 4 generators power the vessels and the main switchboard is symmetrically divided into 2 sections. Power transformers step up or down the voltage and current as necessary. The Direct Current (DC) bus is connected through AC to DC rectifiers. The frequency-controlled drives include the inverters as the main controllers of the variable-speed Propulsion Motors (PMs) connected to the propellers through gearbox. Battery Control Unit (BCU), braking unit, and Excitation Units (EXU) are part of the system. Overall, the Propulsion Control Unit (PCU) is the master controller that maintains a smooth and efficient vessel operation. Protection and auxiliary units, such as cooling water units, and other loads are not shown in Fig.1, but they are monitored by the collected data. This IPdM design uses event data from all monitored units, and noise features are filtered at the end.

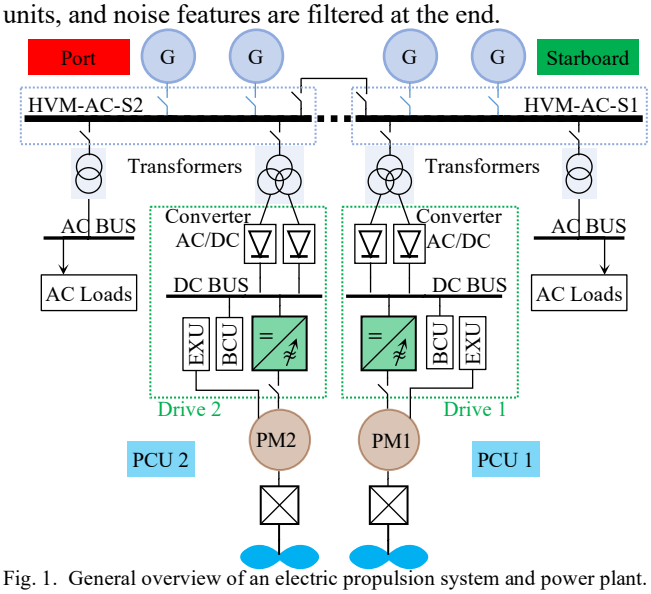

Fig. 1. General overview of an electric propulsion system and power plant.

As shown in Fig.1, the inverters are central units in the system. This work considers *trips* as the failures of concern that should be timely forecasted and prevented. This failure signifies unplanned shut-down of the inverter unit during operation. Such a failure causes propulsion loss, which may result in severe hazards, as in the incidents [12, 13].

B. Event data

Around 2 years of historical data are collected from various vessels. This paper fully describes an ith event by the octet

$$E_i = (t_i, D_i, U_i, V_i, M_i, S_i, A_i, L_i), \quad (1)$$

where

- E is the recorded event
- i is the event index or event number
- t is the timestamp when E was recorded
- D is the drive where E was detected, e.g., Port or Starboard
- U is the unit where E is detected, e.g., 'Cooling Water Unit'
- V is the severity, $V \in \{Alarm, Warning, Information\}$
- M event name, e.g., 'Over Temperature'
- S is the activation status, $S \in \{Active, Inactive\}$
- A is the Acknowledgment status, $A \in \{Acknowledged, Unacknowledged\}$
- L is the level, $L \in \{Low, High, LL, HH, \ldots\}$

The events are involuntary and occur at irregular timestamps while the surface ship operates at diverse conditions. They result from various units and locations on board the ship. The events are mainly classified into three severity categories. An *alarm* event signifies an abnormal state of a unit that requires the operator's intervention to restore the unit to the normal state. *Warning* events indicate an abnormal state, but they do not require the operator intervention and the unit can continue to function. *Informational events* report the completion of task

execution, new setpoints, and crew activities. Each event reports a categorical message that describes the happening.

Particularly, alarm events are reported as *active* when monitored states become out of safety limits, whereas alarms are reported as *inactive* when the unit condition is back within the control limits. The alarms activate as unacknowledged and they are reported again after they are acknowledged by the operators. The timespans between activation, deactivation, and acknowledging give significant insight in event-log analysis.

The events are also associated with categorical levels. In particular, alarm levels represent how far the state is outside the safety bounds, the level or risk, or intervention priority. Human–machine interface is important in alarm management to avoid alarm flooding (or overloading) [33]. However, the presented event-logs analysis uses all categories of events.

The events are transformed into a single attribute called *event type* that uniquely combines all the above discrete attributes,

$$E_i = (t_i, U^j), \forall i = 1, \dots, N_E, j \in \{1, \dots, N_U\}, \quad (2)$$

where event type is a categorical variable that takes N_U different discrete values U^j. i and j are respectively the *event index* and the *event type index*; i is ordinal while j is nominal. N_E and N_U are respectively the number of all events and the number of event types from one vessel; they are respectively proportional to sample size and dimensionality; and they are respectively in the orders of 10^5 to 10^6 and 10^3 to 10^4 in various EPSs.

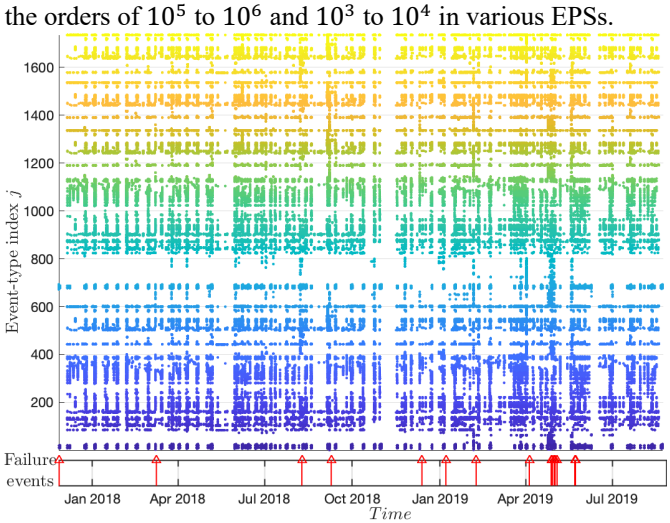

Fig. 2. Visualization of historical event data and failure events collected from one LNG-Carrier vessel.

Using the event representation in (2), historical events and failures are illustrated in Fig. 2 for one of the studied vessels. This data includes few thousands of alarm events, the rest are informational and warnings. The data sample is huge, yet it is not straightforward to train failure predictive models. Many observations in Fig. 2 reflect typical IPdM challenges:

- High-dimensional data and spatiotemporal patterns.
- Variation in both pre-failure and normal operation contexts.
- Failures make a minority class with extreme between-class imbalance.
- Multiple failure modes cause within-class imbalance.
- Only sequences of events can explain a failure perdition.
- Unlabeled data without expert knowledge to forecast a failure.
- Unknown event/ unit/ moment that caused- or witnessed symptoms before a failure.
- Event timestamps are irregular.

Finally, event logs are inconsistent in dimension and in linguistic representation across a fleet of ships equipped with the same EPS technology. Log files include long messages designed for operators and inspectors; these are inconsistent due to varying numbers and types of equipment, different alarm dictionaries and abbreviations, and even unsimilar alarm philosophies. Consequently, practically identical types of events might have different linguistic representations. Since manual data matching is impractical, feature engineering is needed to represent irregular and consistent data in a form that allows efficient training of generalizable IPdM models.

C. Feature engineering

Two feature engineering approaches are designed using an extended version of Random Indexing combined with time- and window aggregation to tackle the above issues of inconsistent, high-dimensional, and irregular data. The ith *time window* W_i represents a momentary operation context of time-length T,

$$\begin{cases} W_i = (T_i, N_i), T_i = t_0 + i \times T, i = 1, \dots, N_W, \\ N_W = \left\lceil \dfrac{(t_{N_E} - t_0)}{T} \right\rceil; \; N_i \in \mathbb{N}^{N_U \times 1} \; s.t. \\ N_{i,j} = \sum\limits_{T_i - T < t_n \le T_i} \mathbb{I}\left(E_n = (t_n, U^j)\right), \end{cases} \quad (3)$$

T_i are regular time intervals and N_i is the count of event types occurrences within a window of duration T. $\mathbb{I}$ is the indicator function that returns 1 if its argument condition is true and 0 otherwise. The time-windows approach was used in [23] to discretize raw signals into events using the concept of rising and falling edges. The full *sequence* of events S_i is modelled using rolling windows which aggregate L_S successive time-windows using aggregation functions $\mathcal{F}^k$,

$$S_i = (T_i, [\mathcal{F}^k(\boldsymbol{W})]), \boldsymbol{W} = \left[W_{i-L_S+1}, \dots, W_n, \dots, W_i\right]$$
$$\mathcal{F}^k: \mathbb{N}^{N_U \times L_S} \longmapsto \mathbb{R}^{N_U \times 1}, k = 1, 2, 3.$$
$$\begin{cases} \mathcal{F}^1(\boldsymbol{W}) = max(\boldsymbol{W}), \\ \mathcal{F}^2(\boldsymbol{W}) = min(\boldsymbol{W}), \\ \mathcal{F}^3(\boldsymbol{W}) = mean(\boldsymbol{W}). \end{cases} \quad (4)$$

These functions are chosen because momentary and total absence or overload of a particular event type can be a failure-indicator feature. In this work, t_i, T_i, and $L_s \times T$ are respectively in the order of milliseconds, minutes, and hours; whereas the objective is to predict failures few days in advance.

Unfortunately, S_i resides in a $3N_U$-dimensional space without any measure of similarity of event types. The natural language processing technique of Random Indexing (RI) [24] is used analogically to word-space model and word context representation. This work extends RI into Temporal RI (TRI) that represents event types, event contexts, and event sequences in a consistent lower-dimensional space. First, each event type U^j is assigned a unique *random index vector* I^j of dimension $d \ll N_U$ whose k^{th} elements are sparsely populated as

$$I_k^j = \begin{cases} -1, \text{probability} \dfrac{p}{2}, \\ 0, \text{probability } 1-p, \\ 1, \text{probability} \dfrac{p}{2}, \end{cases} \tag{5}$$

where p is the population rate, set around 10%.

Conventional RI measures the word context in an expression defined by a number of adjacent words. In TRI, the jth *event type context* C^j is measured in a time window of duration $2T_{RI}$,

$$\forall j \; initialize \; C^j = \mathbf{0} \in \mathbb{N}^{d\times 1}; \; \forall i = 1, \dots, N_E \; do$$
$$\begin{cases} \exists k \;\; s.t. \;\; E_i = (t_i, U^k), update \; C^k \\ C^k \leftarrow C^k + \displaystyle\sum_{\substack{t_i - T_{RI} \le t_n \le t_i + T_{RI} \\ n \ne i}} I^m \\ m \;\; s.t. \;\; E_n = (t_n, U^m), \end{cases} \tag{6}$$

$\boldsymbol{C} = [C^1, \dots, C^k, \dots, C^{N_U}] \in \mathbb{N}^{d\times N_U}$ is the *co-occurrence matrix*, and it is sparse due to skewed event types' occurrence rate. Combined with (3–4), TRI represents time-windows RIW and sequences RIS using their contexts CW and CS through an exponential weighting factor α,

$$W_i = (T_i, N_i) \Rightarrow RIW_i = (T_i, CW_i), CW_i \in \mathbb{N}^{d\times 1}$$
$$CW_i = \sum_n C^m \;\; s.t. E_n = (t_n, U^m) \;\&\; T_{i-1} < t_n \le T_i, \tag{7}$$

$$RIS_i = (T_i, CS_i), CS_i \in \mathbb{R}^{d\times 1}$$
$$CS_i = \sum_{n=n_0}^{i} \beta \, e^{\alpha(n-n_0)} \, CW_n, s.t. \tag{8}$$
$$n_0 = i - L_S + 1; \frac{1}{\beta} = \sum_{k=0}^{L_S-1} e^{\alpha \, k}.$$

The conventional RI word-space model is useful for text compression, word meaning extraction, and similarity determination. TRI inherits these advantages in IPdM data for substantial dimensionality reduction and measuring event type similarity. Event types that occur in the same operation context have similar TRI context vectors regardless of their different textual messages. TRI is an incremental method, it can be transferred to another system or updated for new event types efficiently without changing the dimensionality d.

TABLE I
DIMENSIONS OF RAW AND PROCESSED HISTORICAL EVENT DATA

V	TS	NS	N_U	N_E	NFE	N	NFS	NFST
1	638	16	1,737	339,521	36	91,562	24	6
2	690	36	3,232	443,624	40	99,142	30	14
3	697	26	3,331	1,187,118	48	100,141	17	4
4	675	24	2,308	580,914	14	96,946	12	5

The columns stand for: V Vessel number; TS Timespan in days; NS Number of raw data Sources (log files); N_U Number of unique event types; N_E Number of recorded Events; NFE Number of Failure Events in raw data; N Number of data samples after feature engineering; NFS Number of Failure Samples; NFST Number of Failure Samples in the Training data subset.

The processed data samples are represented as $X \in \mathbb{R}^{N\times M}$, where N is the number of samples and $M = 3N_U + d$ is the total number of features. In the following, samples represent event sequences, and they are categorized into:

- *Failure samples* contain a failure event, to be forecasted.
- *Infected samples* reflect causes or early symptoms before an emerging failure; The main goal is to learn and predict them.
- *Normal samples* represent problem-free operation context.

A failure sample can be an infected sample that predicts another failure in the future, but not the same failure it contains. Table I describes historical data from 4 LNG carriers equipped with EPSs; It reflects imbalance, dimensionality, and the multi-ship data heterogeneity.

IV. WEAKLY SUPERVISED IPDM MODELS

Using the engineered features, failure likelihood and time-to-failure predictions are casted into classification and regression problems. The models are based on Random Forest (RF) for its interpretability, robustness to noise features and data imbalance, and good performance under high-dimensions. Balanced RF (B-RF) and Multiple Instance Learning (MIL) extensions are introduced in MIL-B-RF to tackle two main IPdM issues: unlabeled and extremely-imbalanced data.

Given unknown infected samples, the developed weakly supervised learning approach learns the unknown actual *class labels* $c_i = 1, \dots, C$ for all samples $X_i \in \mathbb{R}^{1\times M}, i = 1, \dots, N$ while training the model that predicts future *failure likelihood*, then a second model to predict *time to failure* $y_i \in \mathbb{R}$.

A. Balanced Random Forest

RF is an ensemble of classification or regression trees which recursively model the dataset by splitting samples into M-dimensional subsets called nodes. RF uses a training dataset of pairs (X_i, c_i) or (X_i, y_i) of samples with known responses. Each decision tree is grown by minimizing a cost function, defined over *node* $\mathcal{D}$ as the squared error [34] for a regression problem

$$\mathcal{D} \subseteq \{(X_i, y_i)\}, cost(\mathcal{D}) = \sum_i (y_i - \bar{y})^2$$
$$\bar{y} = \frac{1}{|\mathcal{D}|} \sum_i y_i, \tag{9}$$

where $\bar{y}$ is the *mean response* in $\mathcal{D}$ and $|\mathcal{D}|$ is the cardinality of $\mathcal{D}$; or the Gini impurity index [34] for a classification problem,

$$\mathcal{D} \subseteq \{(X_i, c_i)\}, cost(\mathcal{D}) = \sum_{c=1}^{C} \hat{\pi}_c (1 - \hat{\pi}_c)$$
$$\hat{\pi}_c = \frac{1}{|\mathcal{D}|} \sum_i \mathbb{I}(c_i = c), \; \forall c = 1, \dots, C \tag{10}$$

where $\hat{\pi}_c$ is the *class-conditional probability*.

A leaf node $\mathcal{D}$ is worth splitting into left and right nodes $\mathcal{D}_L$ and $\mathcal{D}_R$ if the cost reduction gain $\Delta\mathcal{G}$ is significant

$$\Delta\mathcal{G} = cost(\mathcal{D}) - \left(\frac{|\mathcal{D}_L|}{|\mathcal{D}|} cost(\mathcal{D}_L) + \frac{|\mathcal{D}_R|}{|\mathcal{D}|} cost(\mathcal{D}_R) \right), \tag{11}$$

by finding the optimal splitting feature index f^* and its optimal splitting value v^* s.t. $X^{f^*} = v^*$

$$(f^*, v^*) = \arg \min_{f \in \{1,\dots,M\}} \min_{v \in R_j} \Big(cost\big(\{(X_i, r_i) | X_i^f \le v\}\big) + cost\big(\{(X_i, r_i) | X_i^f > v\}\big) \Big), \tag{12}$$

where r_i is the response (y_i or c_i) and R_j is the set of values that the feature X^j can take. The tree can be grown until a stopping

criterion, such as $\Delta\mathcal{G}$ threshold, tree depth, or $|\mathcal{D}|$ lower limit.

The jth *feature importance* $\mathcal{I}_j(\mathcal{T})$ of a trained tree $\mathcal{T}$ is easily determined as the total cost reduction gain from all $\mathcal{N}$ internal nodes where the jth feature was used for splitting.

$$\mathcal{I}_j(\mathcal{T}) = \sum_{n\in\mathcal{N}} \Delta\mathcal{G}_n \, \mathbb{I}(f_n^* = j), \tag{13}$$

and it yields a crucial explainability advantage in IPdM. The *prediction confidence* of X_i by the bth trained classification tree $\mathcal{T}^b$ is $\hat{\pi}_c$ of the leaf node where X_i ended in the model, denoted as $\hat{\pi}_c^b(X_i) = \hat{\pi}_{c,i}^b$. The *classification confidence* is defined as

$$\hat{f}_{c,i}^b = \mathcal{T}_c^b(X_i) = \hat{\pi}_{c,i}^b - \frac{1}{C}, \forall i, c, b. \tag{14}$$

The predicted response of X_i by the bth regression tree $\mathcal{T}^b$ is $\bar{y}$ of the leaf node where X_i resides, denoted as $\hat{y}_i^b = \mathcal{T}^b(X_i)$.

RF algorithm aggregates those predictions from N_T trained trees in a model $F(X)$. The responses $\hat{y}_i$ or $\hat{\pi}_{c,i}$ and $\hat{c}_i$ of X_i, and the normalized total feature impotence $\mathcal{I}_j(F)$ are determined as

$$\hat{y}_i = F(X_i) = \frac{1}{N_T}\sum_{b=1}^{N_T} \hat{y}_i^b,$$

$$\begin{cases} \hat{\pi}_{c,i} = F_c(X_i) = \dfrac{1}{N_T}\displaystyle\sum_{b=1}^{N_T} \hat{\pi}_{c,i}^b, \\ \hat{c}_i = \arg\max\limits_{c=1,\dots,C} F_c(X_i). \end{cases} \tag{15}$$

$$\mathcal{I}_j'(F) = \frac{1}{N_T}\sum_{b=1}^{N_T} \mathcal{I}_j(\mathcal{T}^b) \,.\, \mathcal{I}_j(F) = \frac{\mathcal{I}_j'(F)}{\sum_{j=1}^{M} \mathcal{I}_j'(F)}.$$

This bagging process increases robustness to overfitting and noise features, [34] showed that the RF model variance σ_F^2 is lower than the individual trees variance σ^2

$$\sigma_F^2 = \rho\,\sigma^2 + \frac{1-\rho}{N_T}\sigma^2, \tag{16}$$

and it is minimum for zero pairwise correlation of the trees ρ. $\rho = 0$ is not possible if the features are dependent. To reduce ρ, RF uses *bootstrap aggregation* by training the trees using randomly selected $m < M$ features and $n < N$ samples; [34] suggested $m^* = \sqrt{M}$. This process is further modified to avoid biased models trained through extremely imbalanced data. In B-RF, $n/2$ bootstrapped samples are first drawn randomly from the minority class then $n/2$ samples are sampled using the same process from the other class. This B-RF method is simple and robust given unknown changing imbalance rate during MIL.

B. MIL-B-RF approach

Sample class c_i and label notations are defined for IPdM as

$$(X_i, c_i): \begin{cases} c_i = 1 \Leftrightarrow X_i \text{ is Negative} \equiv \text{Normal sample} \\ c_i = 2 \Leftrightarrow \begin{cases} X_i \text{ is Positive} \equiv \text{Infected sample} \\ y_i > 0 \quad \text{is time to failure.} \end{cases} \end{cases} \tag{17}$$

Recall that c_i are in fact unknown. This unlabeled data forms a weakly supervised learning problem [31]. In *accurate supervision* frameworks, the *actual class label probability*

$$p_{i,c} = p(c_i = c|X_i), \forall c, i, \tag{18}$$

is determined using crowdsourcing, expert knowledge or labelling functions. These are unavailable for this IPdM problem that is formulated as an *inexact supervision* problem where $\tilde{p}_{i,c}$ are optimization variables to be learned. In MIL, unlabeled samples are grouped into N_B disjoint sets, called *Bags* $B^j = \{(X_i^j, c_i^j = ?)\}$ assigned some known *bag labels* c^j, yet it is desired to classify the samples and not the bags.

Given partial knowledge, each EPS failure's causes or symptoms should have occurred during $\aleph \times L_S \times T$ (few days) before the failure, i.e., at least one *witness sample* from these $\aleph$ samples (few hundreds) should predict that failure. This defines *positive bags* (denoted B^+) with positive *bag labels*. $B^j \equiv B^+$ with $c^j = 2$ is a positive bag preceding the jth failure

$$\forall\, E_f = (t_f, U \in \{Failures\}), \exists\, T_{n-1} < t_f \le T_n$$

$$\text{New} \begin{cases} \textit{Positive bag } B^j \equiv B^+, \qquad c^j = 2, \\ B^j = \{(X_k, c_k = ?) | n - \aleph < k \le n-1\} \\ y_k = t_f - T_k > 0 \\ B^j = \{(X_i^j, c_i^j = ?) | i = 1, \dots, \aleph\}. \end{cases} \tag{19}$$

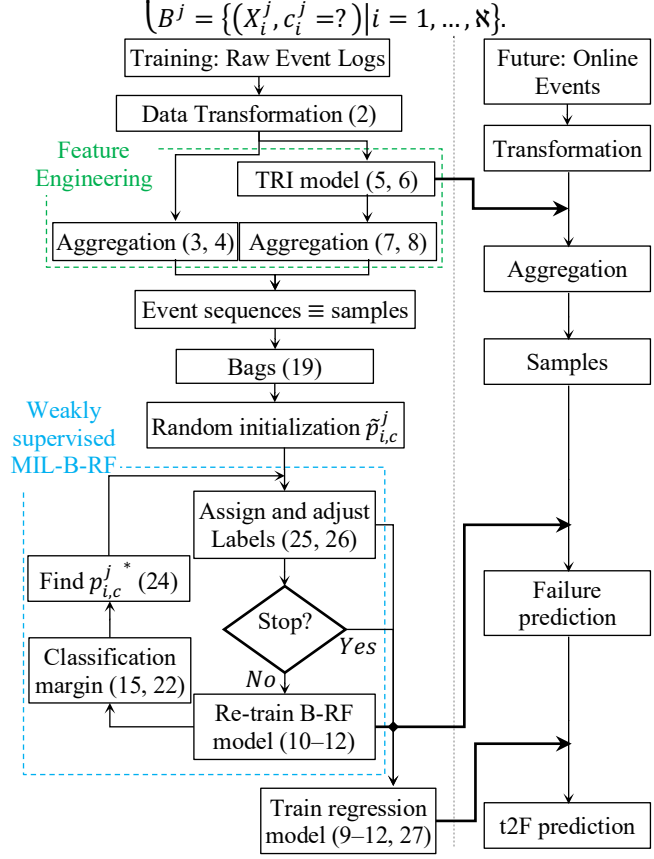

Fig. 3. General overview of the MIL-B-RF based EPS IPdM approach.

In case of short time between failures, B^+ are reduced and contain $\aleph^j \le \aleph$ samples. The remaining training samples are grouped in *negative bags* $B^-: \forall X_n \notin B^j\ s.t.\ c^j = 2, X_n \in B^q\ s.t.\ c^q = 1$. Not all samples in B^+ are positive, most are negative and similar to samples in B^-; All samples must satisfy 3 *bags conditions*

$$\begin{cases} \forall j\ s.t.\ c^j = 1 & \displaystyle\sum_i \mathbb{I}(c_i^j = 2) = 0 \\ \forall j\ s.t.\ c^j = 2 & \displaystyle\sum_i \mathbb{I}(c_i^j = 2) > 0 \\ \forall i & \displaystyle\sum_c \tilde{p}_{i,c} = 1. \end{cases} \tag{20}$$

MIL is formulated as [35]

$$(\{\tilde{c}\},\mathcal{F}^*) = \arg\min_{\{c\},\mathcal{F}(.)} \mathcal{L}\left(F_c(X)\right)\ s.t.$$
$$\begin{cases} B^+: \forall c^j = 2, \sum_i \mathbb{I}\left(\hat{c}_i^j = 2\right) \geq 1 \\ B^-: \forall c^j = 1, \sum_i \mathbb{I}\left(\hat{c}_i^j = 1\right) = 0\,. \end{cases} \tag{21}$$

Here MIL aims at training an optimal B-RF predictive model $\mathcal{F}$, $\mathcal{F}(X_i) = \hat{c}_i$, while learning the unknown actual labels $\tilde{c}$ for all training samples by minimizing a *total loss function* $\mathcal{L}$ defined over F_c such that bag conditions (20) are satisfied. The loss ℓ is selected as negative total *classification margin* $\mathcal{M}$ [36],

$$\mathcal{L}\left(F_c(X)\right) = \sum_{j=1}^{N_B}\sum_{i=1}^{\aleph^j} \ell\left(X_i^j, \tilde{c}_i^j\right),$$
$$\mathcal{M}\left(X_i^j, \tilde{c}_i^j\right) = F_{\tilde{c}_i^j}\left(X_i^j\right) - \max_{\substack{c=1,\dots,C \\ c\neq\tilde{c}_i^j}} F_c\left(X_i^j\right) = -\ell\left(X_i^j, \tilde{c}_i^j\right) \tag{22}$$

Combined with (15), notice that $\mathcal{M}$>0 for correct prediction $\hat{c}_i^j = \tilde{c}_i^j$, i.e., $\hat{c}_i^j = \mathcal{F}\left(X_i^j\right)$ matches the uncovered label $\tilde{c}_i^j$; $\mathcal{M} = 1$ if $\mathcal{F}$ has total confidence in $\hat{c}_i^j$; $\mathcal{M}$ is negative for wrong predictions, and $\mathcal{M} = -1$ for total confidence in the wrong label. Hence, this design aims at clear separation besides correct predictions. Notice that (21) is an integer programming problem since $\{\tilde{c}\}$ are integers, the problem is reformulated into finding the actual class probabilities $\tilde{p}_{i,c}^j = p\left(\tilde{c}_i^j = c \middle| X_i^j\right)\ \forall i,j,c$ defined over a space of distributions $\mathcal{P}$.

Optimizing for both $(\tilde{p},\mathcal{F}^*)$ is a nonconvex problem that can be solved using Deterministic Annealing (DA) [35] by adding a weighted entropy term to $\mathcal{L}$ and solving iteratively for

$$\tilde{p} = \arg\min_{p\in\mathcal{P}} \mathcal{L}_{DA}(F(X),p)$$
$$\mathcal{L}_{DA}(F(X),p) = \mathbb{E}_{\mathcal{P}}\left(\ell\left(F(X)\right)\right) - \tau\,\mathcal{H}(\mathcal{P}),$$
$$= \sum_{j=1}^{N_B}\sum_{i=1}^{\aleph^j}\sum_{c=1}^{C} p_{i,c}^j\,\ell\left(X_i^j, c\right) + \tau\sum_{j=1}^{N_B}\sum_{i=1}^{\aleph^j}\sum_{c=1}^{C} p_{i,c}^j \log\left(p_{i,c}^j\right), \tag{23}$$

given the constraints in (20). $\tau(r) = e^{-\gamma\, r}$ is a cooling function over iterations r with parameter $\gamma > 0$. Initial larger τ values encourage MIL *exploration*, whereas final smallest values enforce *exploitation*. At one iteration, (23) solves as [36]

$$\frac{\partial\mathcal{L}_{DA}(F(X),p^*)}{\partial p} = 0 \Rightarrow {p_{i,c}^j}^* = e^{\frac{\mathcal{M}\left(X_i^j,c\right)-\tau}{\tau}}, \tag{24}$$

optimal parameters ${p_{i,c}^j}^*$ are then adjusted to $\tilde{p}_{i,c}^j$ to satisfy (20),

$$\begin{cases} \forall c^j = 1,\ \ \tilde{p}_{i,1}^j = 1 \text{ and } \tilde{p}_{i,2}^j = 0 \\ \forall c^j = 2,\ \ \tilde{p}_{i,c}^j = \dfrac{{p_{i,c}^j}^*}{\sum_c {p_{i,c}^j}^*} \end{cases} \tag{25}$$

Labels $\tilde{c}_i^j$ are assigned to samples X_i^j using optimized adjusted probability distribution $\tilde{p}_{i,c}^j$, followed by label correction,

$$\forall c^j = 2, if \sum_i \mathbb{I}\left(\tilde{c}_i^j = 2\right) = 0,$$
$$then\ \tilde{c}_{i^*}^j = 2\ s.t.\ \ i^* = \arg\max_i \tilde{p}_{i,c}^j\,. \tag{26}$$

As shown in Fig. 3, this MIL process is repeated iteratively by training new weakly supervised B-RF models and learning the unknown actual labels. Once there are no changes in label uncovering, the final failure prediction model is returned. The time to failure (t2F) regression model is trained using only positive prediction samples and h most important features

$$R = \left\{\left(X = \left[x_{i,j}\right], y_i\right)\right\}\ s.t. \begin{cases} \hat{c}_i = 2, \\ \mathcal{I}_j(\mathcal{F}) \geq \mathcal{I}^{50}, \end{cases} \tag{27}$$

where y_i is the t2F (19) and $\mathcal{I}^h$ is the hth highest total Gini feature importance (15). $h \ll M$ to avoid noise features and a high-dimensional problem due to very few positive samples.

V. Results and Discussion

Historical EPS event datasets (Table 1) span around 2 years, the first-year dataset is used for training whereas the second is interpreted as the future data and used to test forecasting real-world failures. There is no information about the units, events, or time-slots that indicate failure causes or symptoms. IPdM models are tested with no knowledge about the failure time, the latter is only used for assessment. The time windows are constructed over $T = 10$ minutes to represent momentary operation context; the rolling sequences span one hour, $L_S = 6$. The random index vector has a population rate of $p = 0.1$ and a size $d = 100 \ll N_U$ which grants a substantial dimensionality reduction without loss of information; the event type context is measured over $T_{RI} = 10$ seconds; the exponential TRI weighting factor is selected as $\alpha = 1$. With insufficient data, feature engineering parameters are initialized reasonable values and tuned in several trials due to the lack of extra tuning dataset.

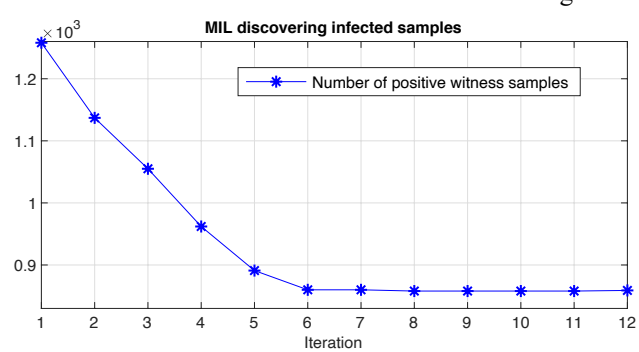

Fig. 4. MIL-B-RF convergence: Learning the unknown actual class labels.

The weakly labelled training data have a maximum positive bag size of 3 days, i.e., a witness sample forecasting an emerging failure is a candidate among 427 unlabeled pre-failure samples. The iterative MIL cooling function is controlled with $\gamma = 1/5$. This resulted in the convergence shown in Fig. 4.

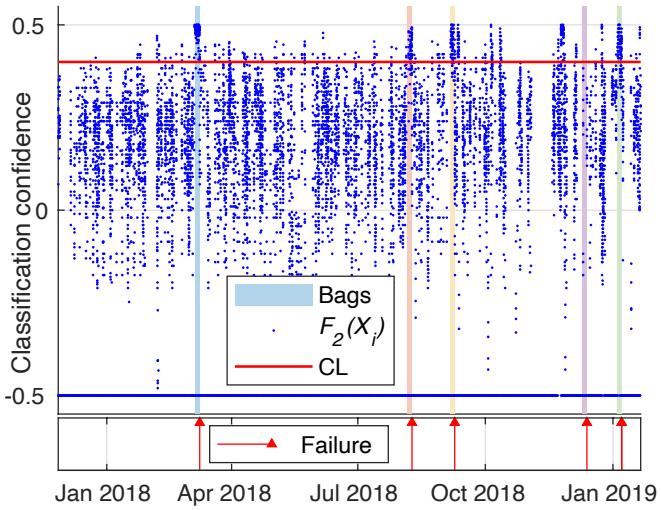

Fig. 5. MIL-B-RF uncovering actual class labels in the training dataset. Bags are 3 days before failure, $F_{c=2}(X_i)$ is the classification confidence in an infected sample, $F_2(X_i) > CL$ signifies a positive prediction.

The MIL-B-RF algorithm converges relatively slower than MIL in [35], but it is stable and identifies actual class labels with high confidence, i.e., $p_{i,c}^{j\ *}$ are very close to 0 or 1 at the last iteration.

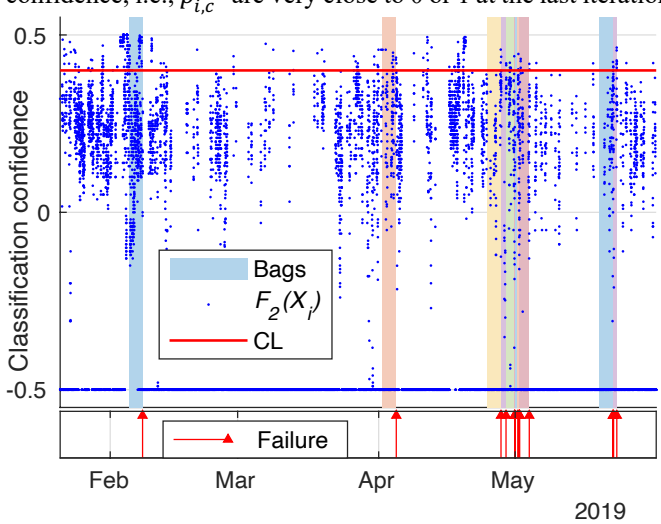

Fig. 6. MIL-B-RF real-world failure prediction in a test dataset from ship 1.

TABLE II
FAILURE PREDICTION PERFORMANCE ACROSS 4 VESSELS

	Vessel 1		Vessel 2		Vessel 3		Vessel 4	
	$\hat{c}=1$	$\hat{c}=2$	$\hat{c}=1$	$\hat{c}=2$	$\hat{c}=1$	$\hat{c}=2$	$\hat{c}=1$	$\hat{c}=2$
$X_i^j, c_i^j = 1$	28,333	281	12,603	227	19,144	553	30,912	2,081
$B^+: c^j = 2$	1	17	0	16	0	13	0	7

MIL-B-RF performance is shown in Fig. 5. Most samples are correctly flagged as negative with the highest confidence $F_2(X_i) \approx -0.5 \equiv F_1(X_i) \approx 0.5$. The default *classification Confidence Limit* $CL = 0.4$ (90% prediction confidence) is used to flag positive samples that forecast failures, $F_2(X_i) > 0.4$.

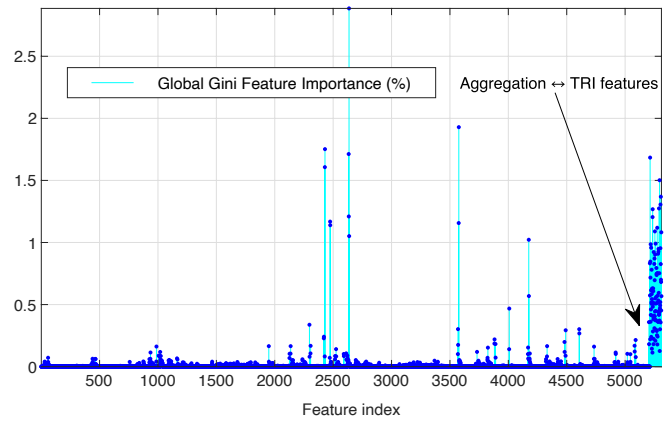

Fig. 7. MIL-B-RF total Gini feature importance; right-most 100 features are the TRI-engineered features.

The trained MIL-B-RF is tested on an independent dataset where actual failures are predicted successfully as shown in Fig. 6. False Positives Rate (FPR) is extremely low, it is attributed to near failure conditions and PvM strategies, it can be reduced by tuning CL or designing a moving filter. This, however, requires a separate hyperparameter tuning dataset. Performance results are summarized in Table II for the four vessels; the first raw lists results for negative samples, while the last row counts only failures that are forecasted by at least one witness sample in the bag (427 samples per bag); most failures are predicted successfully with nearly 100% True Positive Rate (TPR).

TABLE III
PERFORMANCE COMPARISON OF MIL-B-RF MODELS TRAINED ON SUBSETS OF FEATURES FOR VESSEL 1

	$\mathcal{F}_0$: all features		$\mathcal{F}_1$: all aggr. features		$\mathcal{F}_2$: TRI features		$\mathcal{F}_3$: *max* aggr. features	
	$\hat{c}=1$	$\hat{c}=2$	$\hat{c}=1$	$\hat{c}=2$	$\hat{c}=1$	$\hat{c}=2$	$\hat{c}=1$	$\hat{c}=2$
$X_i^j, c_i^j = 1$	28,333	281	28,364	250	28,444	170	28,319	295
$B^+: c^j = 2$	1	17	6	12	5	13	5	13

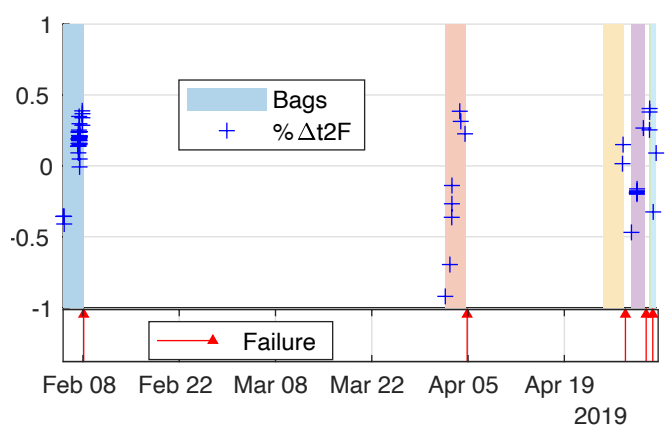

Fig. 8. Time to failure prediction error of true positives in the test dataset.

TABLE IV
MIL-B-RF PERFORMANCE COMPARISON WITH CONTEMPORARY WORKS

Approach	Application	Performance
MIL-B-RF	Multi-unit EPS in LNG carrier	$1\% \le$ FPR $\le 6.73\%$ $94.4\% \le$ TPR
[23] IPdM	Milling machine equipment	$51\% \le$ TPR $\le 69\%$
[25] IPdM	Cold forming press equipment	$0.48 \le F_1$ Score ≤ 0.61
[24] IPdM	Anonymous company	$2\% \le$ FPR $\le 48\%$ $17\% \le$ TPR $\le 93\%$

The total Gini feature importance (15) grants MIL-B-RF an

interpretability advantage. Indeed, Fig. 7 shows the few features that mostly explain the model predictions. More remarkably, the 100 TRI-engineered features contributed 60.7% cumulative feature importance compared to the remaining 5211 aggregation features; But the latter are more explainable than the TRI features which are unexplainable due to their nearly uniform importance and untraceable due to their encoded form.

The most important aggregation features are from the max operation function (4). Hence, Table III compares the testing performance of 4 MIL-B-RF models trained on subsets of the features. $\mathcal{F}_0$, $\mathcal{F}_1$, $\mathcal{F}_2$, and $\mathcal{F}_3$ use respectively all features, only aggregation features, only TRI features, and only max operation features. TRI outperforms simple aggregation again.

Although it is most important to predict the failure likelihood and explain the predictions, t2F (27) indicates the available time bonus for intervention. Fig. 8 depicts the test performance results for t2F prediction error $\Delta t2F$ normalized to the bag time length. The mean error is close to zero; the error variance is attributed to very few infected samples used for training.

Finally, Table IV compares the presented MIL-B-RF results with three closely related event-driven PdM methods [23, 24, 25]. Due to the limited IPdM reports in the maritime literature, the selected comparisons include results of various applications. However, these methods have been designed and tuned for failure prediction based on event data; Hence, their best results are comparable. First, all the compared methods have shown some sort of success in predicting some failures based on raw or synthetic event data. Compared to MIL-B-RF, the other methods did not focus on time-correlation between the events, and they did not address the issues of extreme data imbalance and weak data labels. Their performance is therefore limited. The results of [23] reflect insufficient failure prediction sensitivity and bias in the approach since the best TPR is below 70%. This observation is in line with the results of [25] showing a relatively low F_1 score (higher is better up to 1). This bias is reduced in [24] as the failure prediction rate increased up to 93%. However, the latter came at the cost of huge variance where TPR can be as low as 17% and FPR can be as high as 48%. On the contrary, the presented MIL-B-RF IPdM approach predicts failures with high TPR≥94.4%, low FPR≤6.73%, and minimum variance.

VI. Conclusion

This paper presented a novel intelligent predictive maintenance approach, driven by event sequence analysis, and applied to electric propulsion systems of large ships. It contributed to (i) predicting failure likelihood, (ii) predicting time to failure, and (iii) providing explainable predictions. Objectives (*i*) and (*ii*) were casted into weakly supervised classification and regression problems. In this regard, a threefold solution was derived to effectively remedy major limitations of event-driven techniques.

Temporal random indexing was proposed to map the irregular textual logs into a consistent numerical array form. The developed technique resulted in substantial dimensionality reduction and contributed the dominant failure predictors. In conjunction, event aggregation techniques were developed for explainable predictive maintenance to track failure sources.

Notwithstanding the extremely imbalanced data, unbiased models were developed using a balancing strategy. Despite the lack of hand-labelled data, the overall approach was successfully designed to recursively discover the unknown actual class labels of infected samples at a high confidence. It trained unbiased base learners that correctly forecast failures within extremely-minor classes. In comparison, the presented approach outperformed contemporary methods.

Finally, most of the actual failures were forecasted successfully –by at least one witness sample– within three days preceding the failure. These results are significantly important in the maritime sector to mitigate and reduce the likelihood of propulsion loss during critical maneuvers. This in turn prevents hazardous accidents, economic losses, and downtime while it promotes safety of equipment and personnel.

Future works may consider hyperparameter tuning from larger datasets, sequential (deep) learning to avoid feature-engineering information-loss, and prescriptive maintenance.

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