A Lightweight Predictive Maintenance Strategy for Marine HFO Purification Systems

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Abstract. The maritime industry heavily relies on vessel maintenance to ensure the operational integrity and safety, as it is responsible for transporting more than 80% of global trade. Despite the industry's strong need for efficient maintenance techniques, there has been a noticeable gap in research regarding the use of data-driven methods to enhance vessel reliability. This study seeks to fill this gap, by examining the feasibility of deploying deep learning models to predict the Remaining Useful Life (RUL) of Heavy Fuel Oil (HFO) purification systems, taking into account also the challenges of the limited computational resources available on maritime vessels, as well as the substantial costs associated with implementing such models. Towards this direction, the impact of various optimization techniques (early stopping and pruning) on three state-of-the-art models (Long Short-Term Memory Network, Convolutional Neural Network, Autoencoders) was evaluated using operational vessel data provided by Laskaridis Shipping Co. Ltd., demonstrating the feasibility of deploying predictive maintenance (PdM) systems in real-world edge-constrained marine settings, potentially transforming maintenance practices and reducing operational costs.

Keywords: Predictive maintenance · Pruning · Maritime industry.

1 Introduction

The maritime industry is considered the backbone of global economy facilitating transportation for more than 80% of international commodities [25]. As a result, the maintenance of maritime vessels actively transporting great amounts of these commodities, is crucial to ensure operational integrity, functionality, and safety. Nevertheless, maintenance is considered as one of the largest cost factors for maritime organizations, roughly accounting about 30% of a ship's overall operational expenses, leading to prolonged periods of downtime, thereby reducing both operational availability and financial returns. Despite the industry's pressing need for efficient maintenance practices, there has been little investigation into new data-driven methods to improve vessel reliability [18]. Furthermore, according to the Safety and Shipping Review, there have occurred 10,753 shipping accidents over the past decade, attributed to machinery damage or failure, resulting in damages concerning to the cargo, the environment and on human lives [17], [2].

The introduction of PdM is anticipated to surpass the current maintenance strategies employed by the maritime industry, enabling proactive detections of machinery issues. Despite the industry's critical need for efficient maintenance practices, novel approaches focusing on the prediction of vessel machinery health have been significantly underexplored [18]. Towards this direction, this paper aims to advance the applicability of deploying Deep Learning (DL)-based Remaining-Useful-Life (RUL) estimation models in practical maritime applications, with a particular emphasis given on a marine Heavy Fuel Oil (HFO) purification system.

In particular, we present a comprehensive analysis of related works concerning PdM applications in the maritime industry. Furthermore, we conduct extensive experimental testing of three state-of-the-art PdM models, alongside four different types of pruning methods, namely constant, polynomial and L1 and L2-norm regularization with and without early stopping, to concretely evaluate the PdM performance. It should be noted that to the best of our knowledge, this work is the first to employ DL-based PdM in a maritime purification system, while also optimizing it for a potential real-world deployment, addressing the critical need for efficient and practical PdM solutions to overcome the limitations of computational resources and the potential implementation costs [13].

The remainder of this paper is organized as follows: Section 2 provides an overview of the HFO purification systems and the latest advancements in AI-powered maintenance in the maritime industry. Section 3 outlines the experimental methodology, including information about the dataset, the models architecture, the preprocessing, the pruning techniques and the evaluation metrics emloyed. Section 4 presents the findings of the study, while Section 5 concludes the paper and summarizes the results of this work, while also highlighting potential avenues for future research.

2 Research Background

2.1 HFO Purification Systems and Challenges

For more than six decades, HFO has remained the primary fuel in the marine industry, due to its cost-effectiveness and availability [7]. HFO contains a great number of catalytic fines, which must be always kept at low levels to ensure the operational efficiency of a Main Engine (ME) as recommended by manufacturers. To achieve this, an HFO purifier is used to separate water and solid impurities (e.g., rust and iron particles) from oil, preventing ineffective combustion. However, in real-world operations, HFO purifiers may not always achieve the desired efficiency levels, while their effectiveness has shown to decrease in over time. As a result, the utilized fuel may contain significant thresholds of either catalytic fines or impurities, leading to major damages on the ME. Specifically, in this case, particles infiltrate the gaps between rubbing surfaces like in the ones found in fuel pumps and nozzles, embedding on the components, causing severe wear damage. To prevent this scenario, overhaul operations are conducted by specialized technicians when excessive anomalies are measured (i.e., vibration, overflow, worn gear, motor speed), or according to the vessel's preventive maintenance schedule [16].

2.2 Maintenance Strategies and Opportunities of Shipping 4.0

Shipping 4.0 refers to the digital transformation of the maritime industry, similar to the transition seen in the manufacturing sector known as Industry 4.0. Its goal is to empower maritime companies to effectively oversee their global fleet at both operational and strategic levels. The potential of Shipping 4.0 is demonstrated clearly through the use of Machine Learning (ML)-aided Predictive Maintenance (PdM). This technology enables the estimation of machine conditions and its RUL, resulting to accurate and cost-effective maintenance schedules, towards minimizing operational vessel downtime [23].

According to the International Convention for the Safety of Life at Sea (SOLAS) requirements and the Rules for Safety Equipment, maritime companies are obliged to conduct maintenance inspections on their vessels at least twice withing a five-year operational period [14]. Nevertheless, this policy functions as a basic maintenance framework, and the reliance of shipping companies on this requirement alone, can potentially lead to technical failures [22].

Currently, the maritime industry utilizes two maintenance strategies: run to failure (also known as reactive maintenance) and preventive maintenance. Reactive maintenance is carried out as a reaction to instances of equipment breakdown, resulting to unplanned downtime events and potentially significant negative economic and safety impacts [24]. In contrast, preventive maintenance deals with scheduled interventions, based on timeframe projections of the components, with the goal to minimize unplanned downtimes. However, this strategy can also lead to significant expenses due to unnecessary repairs and planned downtime events [4].

The introduction of PdM strategies in the maritime industry can introduce a proactive nature for maintenance. In detail, PdM offers the ability to forecast component failures based on operational vessel data enabling organizations to optimize maintenance interventions, minimizing operational expenses, while reducing both planned and unplanned downtime events [27] [15].

Furthermore, modern ML models deployed in production environments today, such as PdMs, often utilize computationally powerful cloud servers, leveraging the rapid development of powerful graphics processing units (GPUs). Meanwhile, resource-constraint devices (i.e., edge devices) are becoming increasingly popular, requiring decision-making capabilities. However, the limited computational, storage, and energy capacities of edge devices provide significant challenges to the implementation of ML in edge applications [11].

Compression techniques have been extensively studied in the scientific literature towards reducing computational demands of ML models. Pruning is a widely recognized technique utilized to reduce the number of neural network parameters while maintaining accuracy levels. In detail, pruning is categorized into two methodologies: i) Structured Pruning, a technique that involves identifying and removing the least important structural elements of the network, such as channels or filters and ii) Unstructured Pruning, a technique involving the aggressive removal of the least important neurons or weights, without significantly have an effect on prediction accuracy [10].

2.3 PdM Applications in the Maritime Industry

Conventional monitoring of marine engines primarily focuses on thermal factors such as oil and water temperature. However, these methods can only detect abnormalities after significant deterioration of the engine, thus failing to provide early warnings. Current fault diagnostic solutions have started to employ algorithms to classify faults post-occurrence or in real-time, assisting in repairs but not in providing early warnings to reduce downtime events and expenses. Therefore, the development of models able to proactively predict fault occurrence is crucial to ensure not only engine-reliability and cost-saving but also safety. Data-driven methods leveraging historical data have become prominent for early fault warning, especially with the rise of DL [20].

For instance, Han et al. used run-to-failure data of two different fault types under two distinct load profiles, to train a Long Short-Term Memory (LSTM) model, showcasing a high level of accuracy forecasting the RUL for both types of faults in a diesel ME [9]. Liu et al., developed a system for early fault warnings for diesel engine power generation based on the exhaust temperature. The authors used a CNN-BiGRU model, extracting key features from the multi-dimensional input variables using the CNN, while leveraging BiGRUs advantages in time-series predictions. The proposed model exhibited promising results related to prediction accuracy and convergence speed, compared to independent models such as RNN, LSTM, GRU, and BiGRU [20]. Angelopoulos et al., examined the application of Federated Learning (FL) in PdM for maritime applications. In detail, the authors proposed an end-to-end pipeline ensuring data privacy, forecasting naval propulsion gas turbine state. The study used a multivariate regression model based on a Fully Connected Neural Network (FCNN), comparing four FL aggregation policies, namely FedAvg [21], FedProx, FedSGD [19] and FedAvgM [12], to assess their performance under system and statistical heterogeneity. The results of this work highlighted the effectiveness of each policy, in terms of their prediction performance and the ability of FL-based algorithms to achieve comparable performance results to centralized ML models [3].

Additionally, researchers have employed autoncoders (AEs) to compress input data representations for PdM applications. Notable examples include the contributions of Yoon et al. [14], who introduced a variational AE to effectively decrease data dimensions, combined with an RNN to forecast the RUL state of turbo engines, and Tang et al. [15], who employed a sparse AE for feature extraction, along with an LSTM to predict bearing degradation, outperforming methods like PCA-LSTM, SVM, and FNN.

According to state-of-the-art works found in the literature, LSTM and CNN models are the most promising methods for accurately predicting mechanical failures in marine engines [8].

3 Methodology

3.1 Dataset

The dataset used in this work was graciously provided by Laskaridis Shipping Co. Ltd., from an operational bulk carrier equipped with a diesel ME, with a total power output of 8,833 kW (12,009 HP) and a deadweight (DWT) of 75618. The dataset includes high-frequency operational data, collected at one-minute intervals over a one and a half month period starting in January 2023, resulting in 59619 total time-series samples from 513 different features across the entire ship.

3.2 Experimental Setup

Preprocessing: Out of the 513 features measured from the vessel, the HFO Purifier RUL was selected for this work. The selected target feature indicates the remaining useful life, determined by prolonged exposure to high temperatures in the purification unit. Furthermore, for feature selection, the SelectKBest method was employed. The method identified the following key features as inputs: i) ME Lubricating Oil Inlet Pressures (bar) and ii) Turbocharger Lubricating Oil Inlet Pressures (bar), both indicating the pressure of the lubricating oil supplied at specific levels to minimize friction and wear on engine parts, and the iii) ME Air Spring Air Pressure (bar), indicating the pressure of compressed air utilized to assist the pistons in transmitting power to the engine.

These features were then normalized to a range of [0, 1] using the linear normalization to ensure that the magnitude of the value does not influence their importance. The normalization process can be expressed by the following formula:

$$x' = \frac{x - \min(x)}{\max(x) - \min(x)} \tag{1}$$

where x and x' represent the original and the normalized value, respectively, while $\min(x)$ represents the minimum and $\max(x)$ the maximum value in the dataset. Finally, the dataset was split intro training and testing sets with an 80%/20% ratio.

Network Configurations: We used and evaluated three network architectures based on the work of Bosello et al. [5], namely an LSTM, an LSTM combined with an AE, and a CNN combined with an AE. Both the CNN and LSTM models incorporate an autoencoder in order to effectively compress the extensive time series data while retaining the essential information. The RUL prediction is then performed, feeding the compressed sequence of reduced cycles to a secondary network (i.e., CNN or LSTM, with the latter leveraging the information from the previous interval to predict one ahead).

Specifically, the encoder is comprised by two 1D CNNs with 32 and 16 filters, respectively, each followed by dropout layers, feeding the extracted features to another 1D CNN with 8 filters, which is followed by a flattening and a dense layer. All CNN layers have a kernel size of 2 and a stride of 1. This sequence provides the first segment of the encoded vector containing local information, while the other branch proceeds through the decoder. The decoder is comprised by a series of dense and transposed layers, interspersed with dropout layers to mitigate overfitting. Initially, the data are fed into two CNNs with 8 and 16 filters, each followed by dropout layers. Subsequently, data are advanced to a third transposed layer with 32 filters, followed by a final transposed layer with a single filter, reconstructing the output to match the original input shape. All CNN layers have the same kernel size and stride as in the encoder part of the network.

All layers utilize the ReLu activation function. The network is trained using Adam optimization with a learning rate of 0.001, Mean Square Error (MSE) loss, 50 epochs and a batch size of 32. Additionally, the CNN and LSTM models were used as described by Bosello et al., with the same learning rate, epochs, and batch size, as for the AE.

Pruning Techniques: Pruning techniques are used in this study to effectively compress the size of networks, removing less important parameters. The pruning techniques evaluated in this work, include:

- Constant Sparsity, which enables users to determine a constant sparsity percentage throughout model training [6].
- Polynomial Decay, which enables users to apply polynomial scheduled pruning, with a gradual reduction of the percentage of pruned weights over time, according to a polynomial schedule [26].
- L1 and L2 Regularization, which both add a penalty to the model, proportional to the square of the weights to the loss function. The functions of L1 and L2 added in the model loss function are given by:

$$L1 = L_{original} + \lambda \sum_i |w_i| \tag{2}$$

$$L2 = L_{original} + \lambda \sum_i w_i^2 \tag{3}$$

where, L is the total loss, $L_{original}$ is the original loss, λ is the regularization strength and w_i are the individual weights.

Performance Indicators: To assess the prediction accuracy of the proposed PdM methods, we used Mean Absolute Error (MAE) to measure the average prediction accuracy, Mean Squared Error (MSE) to evaluate error penalties for larger deviations, $R^2_{adjusted}$ instead of R^2 as it penalized the inclusion of unnecessary features offering a more reliable measure of model fit, and CPU-based training and inference time (s) to measure computational efficiency. The mathematical expressions for these metrics are provided in the following formulas:

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i| \tag{4}$$

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2 \tag{5}$$

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{n}(y_i - \bar{y})^2} \tag{6}$$

$$R^2_{adj} = 1 - \left(\frac{(1 - R^2)(n-1)}{n-p-1}\right) \tag{7}$$

where, y_i represents the actual value, $\hat{y}_i$ represents the predicted value, $\bar{y}$ represents the mean of the actual values, n is the number of observations, and p is the number of predictors.

4 Experimental Results

Simulations and algorithmic procedures ran on a personal PC with a processor Intel(R) Core(TM) i7-13700H, 5.0 GHz, 32 GB RAM, and a 64-bit operating system. The ML models were implemented using Python 3.11.0, TensorFlow library, version 2.12.0 Neural Network Intelligence library, version 3.0, and Scikit-learn library, version 1.2.2, without GPU for model training acceleration.

4.1 Learning Parameters Tuning

We conducted a series of simulations to establish the best setup of the critical hyperparameters, such as the learning rate (η) and batch size ($|B|$), for the models in question based on literature standard values. More precisely, we conducted thorough testing on various learning rates, η = [0.001, 0.01, 0.1] and batch sizes, $|B|$=[16, 32, 64], obtaining optimal performance using η=0.001 and $|B|$=32. In addition, we incorporated Early Stopping (ES) with a patience parameter of 10 epochs.

4.2 Performance Comparison

After the optimal architecture and hyper-parameters were determined, each model was trained and evaluated with and without using ES and AE. At this stage, inference and training time were not considered, as primary focus was given on assessing model performance accuracy.

Table 1 presents the evaluation results for each model, revealing strong differences between them. Specifically, CNN models showcased to outperform their LSTM counterparts. The CNN+AE+ES model achieved the best predictive performance, with the lowest errors and highest variance explained, accounting for 98.62% of the target variance deviating by only 0.023 from the actual values according to MAE. The CNN+AE model achieved the second-best model performance, with a low MSE. Among the LSTM models evaluated, the model without AE and ES produced the best results, while the LSTM+AE+ES model showcased the highest errors and the lowest variance explained.

Additionally, the evaluation of ES demonstrated that, especially for the LSTM and CNN+AE architectures, its incorporation during the training phase increased performance. Furthermore, the inclusion of AE for data compression, was shown to decrease the LSTMs performance across all metrics. Moreover, although no direct comparison was completed regarding for a CNN model without AE, the performance of CNN+AE models indicate strong predictive capability, particularly when combined with ES.

Table 1. Comparison of model performance.

Model	**MAE**	**MSE**	$\mathbf{R}^2_{adj}$
LSTM	0.1887	0.0529	0.3401
LSTM+ES	0.1709	0.0448	0.4406
LSTM+AE	0.2107	0.0656	0.1860
LSTM+AE+ES	0.2127	0.0655	0.1778
CNN+AE	0.0401	0.0028	0.9568
CNN+AE+ES	**0.0234**	**0.0009**	**0.9862**

Since the CNN+AE+ES model yielded the best results, it was used to evaluate the effect of different pruning methods in terms of prediction accuracy, as well as training and inference time, aiming to optimize model performance for the deployment in resource-constrained devices. Table 2 showcases the evaluation results of the CNN+AE+ES model under different pruning methods.

Specifically, it is evident that the use of ES had a significant effect on training and inference time. For instance, between the CNN+AE and the CNN+AE+ES both without utilizing any pruning methods, training time significantly decreased from 203.2212s to 53.6853s, respectively, effectively reducing training time. While regarding the models inference time, it decreased from 0.8698s to 0.7863s with the use of ES.

Concerning the effect of applying pruning techniques on prediction accuracy, constant pruning demonstrated good predictive accuracy, ranking as the second-best optimized model, with an MAE of 0.0143 and an R^2_{adj} of 0.9943. In contrast, polynomial decay pruning showcased the worst performance between the different techniques, measuring the highest errors and lowest R^2_{adj} value, indicating poor predictive accuracy, while also having a significant training time. L1 regularization had the shortest training time compared to the other methods with a moderate prediction error rate, but the longest inference time, while L2 regularization achieved the highest R^2_{adj} value and the lowest errors (MAE and MSE), indicating excellent predictive accuracy. L2s training and inference time were also competitive, making it a suitable for edge-constrained environments. Note, that training time was computed to be longer (87.6353s) compared to the CNN+AE+ES without pruning (53.6853s).

Table 2. Comparison of model performance according to different pruning methods.

Pruning Method	**ES**	**MAE**	**MSE**	$\mathbf{R^2_{adj}}$	**Training (s)**	**Inference (s)**
No Pruning	✗	0.0401	0.0028	0.9568	203.2212	0.8698
No Pruning	✓	0.0234	0.0009	0.9862	53.6853	0.7863
Constant	✓	0.0143	0.0004	0.9943	97.1783	0.8524
Polynomial	✓	0.0919	0.0114	0.8272	148.6517	0.6826
L1 Regularization	✓	0.0286	0.0016	0.9760	47.2098	1.1934
L2 Regularization	✓	0.0081	0.0001	0.9977	87.6353	0.6910

5 Conclusions

The maritime industry predominantly depends on traditional maintenance schemes, such as fixed schedule preventive maintenance and reactive maintenance strategies. Nevertheless, these conventional methods frequently result in increased operational expenses and inefficient allocation of resources, negatively impacting machinery longevity. Maintaining a HFO Purifier is a critical aspect to ensure high-quality fuel supply to the ME of a vessel. Failure to achieve this can result in engine damage, impaired combustion and increased emissions of pollutant (SO_2, NOx, CO_2), consequently diminishing the operational lifespan of the vessel and increasing maintenance expenses [1].

This study introduces a PdM system tailored for a HFO purification system, focusing on optimizing it for a real-world deployment, addressing the critical need for efficient and practical PdM solutions to overcome the limitations of computational resources and the potential implementation costs. We evaluated three state-of-the-art models, namely LSTM, LSTM+AE and CNN+AE. CNNs were selected due to their superior performance on structured data, while LSTMs for their ability to manage long-term sequences, making them suitable for modeling machinery aging and long-term degradation trends [5].

The findings of our study demonstrated that CNN models had superior performance compared to LSTM models, with the CNN+AE+ES model showcasing the highest predictive accuracy. The inclusion of ES showed a substantial enhancement in model performance, particularly for LSTM and CNN+AE architectures. Moreover, despite the drop in performance across all metrics for LSTM models when AE was added for data compression, the CNN+AE+ES model produced the most favorable outcomes. Therefore, this model was selected to assess the impact of various pruning approaches.

Specifically, constant pruning exhibited a high prediction accuracy, while polynomial decay pruning exhibited poor performance. L1 regularization had the shortest training time but the longest inference time. On the other hand, L2 regularization yielded the lowest errors, making it suitable for edge-constrained environments, despite requiring a longer training time compared to the CNN+AE+ES model without pruning. The training duration of L2 can be attributed to its modification of the loss function, affecting the optimization dynamics, which often necessitates an increase in computation and longer convergence periods. Notwithstanding these difficulties, L2 enhances model robustness and generalization, therefore the trade-off for improved stability and predictive performance is justified, particularly in situations where overfitting is an issue in real life.

Concerning the potential future work of this study, there are multiple avenues to enhance PdM systems in the maritime industry. In detail, future research should concentrate on training models using larger operational datasets to improve temporal coverage, identify deeper insights on potential RUL periodicity, and improve model robustness and generalizability. Furthermore, it is important to explore the effects of pruning and quantization on processing efficiency, both individually and in combination, in order to determine the feasibility of implementing PdM systems on edge-constrained devices in maritime vessels. By investigating decentralized AI schemes, such Federated Learning, it is possible to utilize dispersed operational data while simultaneously dealing with concerns of data privacy. This is especially significant because current ML applications in the marine industry frequently utilize hierarchical training schemes, in which sensitive data is transferred in a centralized format, compromising privacy and raising cybersecurity threats.

In conclusion, the advancements presented in this work have the potential to pave the way for more effective early prediction of failures in maritime vessels, enhancing both operational efficiency and environmental sustainability.

Acknowledgments. The authors would like to thank Laskaridis Shipping Co. Ltd. for the data provisioning.

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