Arab Academy
for Science , Technology and Maritime Transport

13 Marlog 2024

The International Maritime Transport and Logistics Conference

"MARLOG 13"

Towards Smart Green Blue Infrastructure

3-5 March 2024 - Alexandria, Egypt

Miral Michel

Marine and Offshore Engineering Department

College of Engineering and Technology - AASTMT

Development of Proactive Maintenance Plan for Identification of Ship's Main Engine Failures

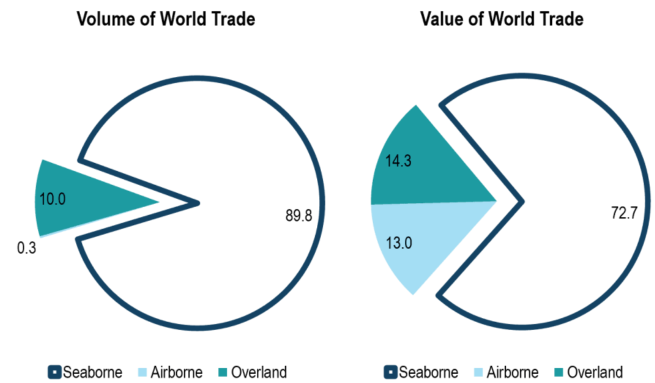
Miral Michel, Ahmed Mehana, Sherine Nagy Saleh, and Ahmed S. Shehata

Presentation Layout

- Introduction and Background
- Aim and Objectives
- Methodology
- Results and Discussion
- Conclusion and Future Work

Introduction

- The maritime industry is vital to global trade offering priceless opportunities and experiences.
- In this industry, safety, efficiency, and profitability are all directly impacted by maintenance [1].



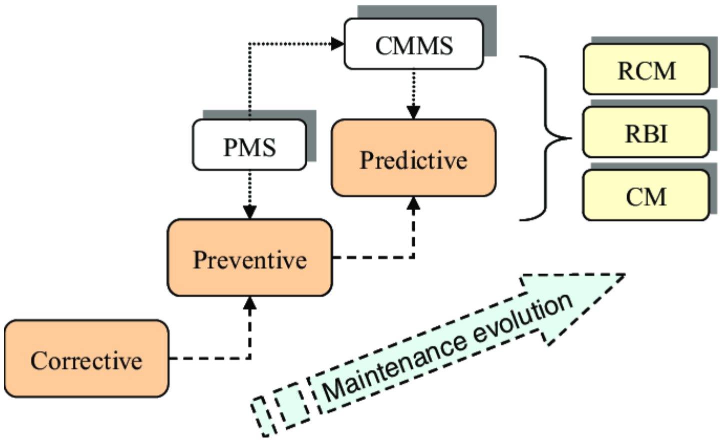
Taken from reference [2]

[1] R. Naradasu, J. Srinathu, and R. Ramakrishnan, "Towards artificial intelligence based diesel engine performance control under varying operating conditions using support vector regression," *THERMAL SCIENCE*, vol. 17, pp. 167-178, 05/01 2013, doi: 10.2298/TSCI120413218N.
[2] I. Lazakis, O. Turan, and S. Judah, *Establishing the Optimum Vessel Maintenance Approach Based on System Reliability and Criticality Analysis*. 2012.

Introduction

- Maintenance fosters an eco-sustainable maritime industry ensuring the safe operation of ships for efficient goods transportation.

- Engine maintenance is necessary to guarantee continuous functioning, limit disturbances, and maximize fuel economy [3].



Taken from [4]

[3] I. Afefy, "Reliability-Centered Maintenance Methodology and Application: A Case Study," Engineering, vol. 02, 01/01 2010, doi: 10.4236/eng.2010.211109.

[4] Lazakis, I., Turan, O., & Aksu, S. (2010). Increasing ship operational reliability through the implementation of a holistic maintenance management strategy. Ships and Offshore Structures, 5, 337-357. https://doi.org/10.1080/17445302.2010.480899

Problem Statement

- Due to factors such as weather conditions, stringent regulations, and demanding standards, maintenance procedures fall short of achieving sustainability, efficiency, and reliability goals set by the industry.

- This results in higher emissions, downtime, failure rates, safety hazards, and therefore costs.

Survey

Maintenance Approaches:

- In 2010, Afefy et al. researched the optimization of performance and safety through reliability-centered maintenance (RCM) which resulted in a decline in maintenance costs by 30% and a reduction in equipment failures by 25% [5].
- In 2021, while implementing condition-based maintenance (CBM), Ingemarsdotter et al. found difficulties due to the unavailability of accurate data collection techniques [6].

[5] I. Afefy, "Reliability-Centered Maintenance Methodology and Application: A Case Study," Engineering, vol. 02, 01/01 2010, doi: 10.4236/eng.2010.211109.
[6] E. Ingemarsdotter, M. L. Kambanou, E. Jamsin, T. Sakao, and R. Balkenende, "Challenges and solutions in condition-based maintenance implementation - A multiple case study," Journal of Cleaner Production, vol. 296, p. 126420, 2021/05/10/ 2021, doi: https://doi.org/10.1016/j.jclepro.2021.126420.

Survey

Machine Learning Based Maintenance:

- In 2020, Alshamrani investigated remote monitoring technologies, such as IoT using sensors and advanced data processing techniques which can reduce maintenance costs by up to 20% and increase equipment availability by up to 15% [7].
- In 2023, Payette and Abdul-Nour studied the use of machine learning applications using pattern recognition and historical data analysis to predict future events resulting in a 24% increase in equipment reliability and a 15% reduction in maintenance costs [8].

[7] M. Alshamrani, "IoT and artificial intelligence implementations for remote healthcare monitoring systems: A survey," Journal of King Saud University - Computer and Information Sciences, vol. 34, no. 8, Part A, pp. 4687-4701, 2022/09/01/ 2022, doi: https://doi.org/10.1016/j.jksuci.2021.06.005.
[8] M. Payette and G. Abdul-Nour, "Machine Learning Applications for Reliability Engineering: A Review," Sustainability, vol. 15, no. 7, doi: 10.3390/su15076270.

Gap Analysis

- Despite significant advances in marine maintenance techniques, the optimization of maintenance strategies for the specific needs of marine engines and their operating conditions is still lacking.

- Another problem is the integration of state-of-the-art technology into current maintenance strategies.

Aim and Objective

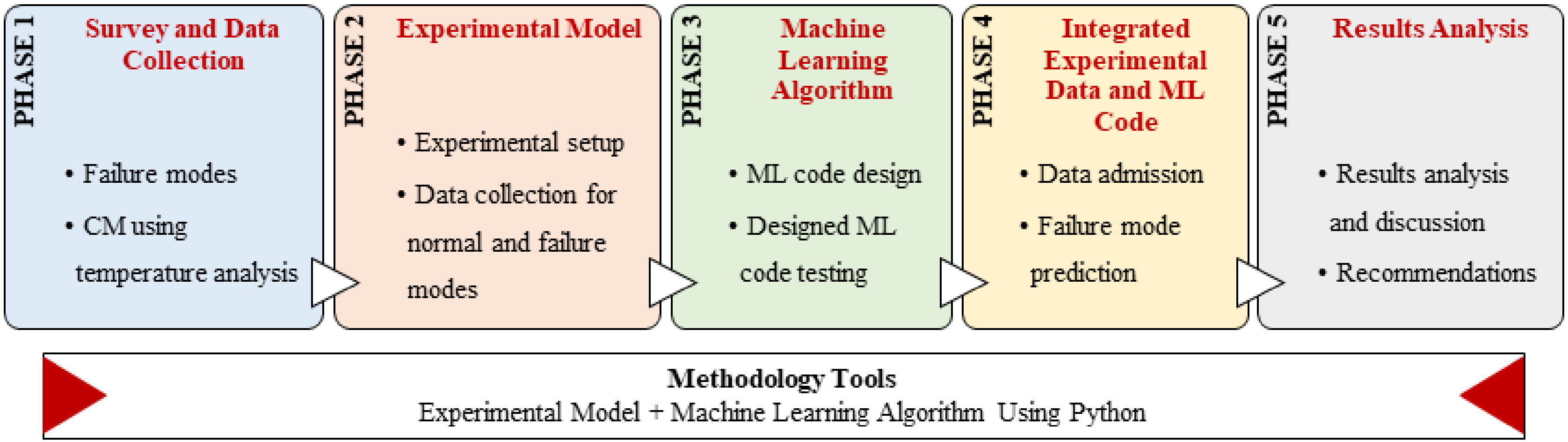
Aim:

- Implementation of proactive maintenance for marine diesel engines to classify early signs of failure thus increasing engines' longevity and dependability.

Objectives:

- Experimental investigation of marine diesel engines failures by replicating malfunctions and monitoring temperature changes.
- Development of a ML model to analyze the data, classify early signs of failure, and schedule maintenance procedures accordingly.

Methodology



Methodology

Experimental Setup:

Temperature sensors were mounted on the cylinder head and exhaust gas manifold of the diesel engine and the readings were recorded.

Specification	Value
Engine Model Number	186FA
Type	Air-cooled diesel engine
Oil	SAE 15W-40
Displacement	418 cc
Max Power	10 hp
Normal Speed	3000/3600 rpm
Injection Timing	Intake Open: BTDE 13° Intake Close: ATDE 52° Exhaust Open: BBDC 57° Exhaust Close: ABDC 8’30’’
Valve Lash	Intake: 0.1 – 0.15 (cold state) Exhaust: 0.1 – 0.15 (cold state)
Fuel	Diesel
Net Weight	48 kg
Gross Weight	55 kg

Methodology

Machine Learning Models:

- Logistic Regression
- Random Forest
- Support Vector Machine (SVM)
- K-Nearest Neighbour (KNN)
- Naive Bayes
- Decision Tree
- Multi-Layer Perceptron (MLP)
- AdaBoost models

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$

$$Precision = \frac{TP}{TP + FP}$$

$$Recall = \frac{TP}{TP + FN}$$

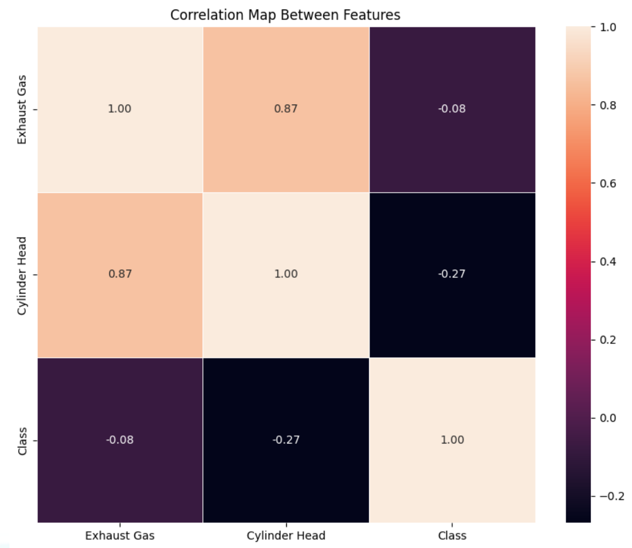
$$f1 = 2 \times \frac{Precision \times Recall}{Precision + Recall}$$

Data collected from experiments were used to train different ML models using a 5-fold cross-validation data partitioning scheme.

Methodology

Machine Learning Models:

- The correlation matrix shows the correlation between the temperatures and class.
- This makes the "Class" feature challenging to determine directly from the available features.



Experimental Results

Normal Operating Conditions Results:

- Temperature data were collected for daily operation with a clean air filter and a full oil sump.
- The data show an average exhaust gas temperature of 54.4°C and an average cylinder head temperature of 24.8°C.

Time (minutes)	Air Filter Blockage (0%)		Oil Level (100%)	
	Exhaust Gas (°C)	Cylinder Head (°C)	Exhaust Gas (°C)	Cylinder Head (°C)
10	53	24	53	24
11	53.2	24.2	53.2	24.1
12	53.3	24.4	53.5	24.2
13	53.6	24.5	53.9	24.5
14	53.7	24.7	54	24.6
15	53.9	24.8	54.3	24.4
16	54	25	54.8	24.7
17	54.9	25.4	55.1	25.1
18	55.7	25.6	55.7	25.2
19	56	25.7	56.1	25.4
20	56.5	25.8	56.4	25.7

Experimental Results

Air Blockage Failure Results:

- Temperature data were collected for failure in the air filter with various blockage percentages.
- Temperatures are greatly affected by the filter blockage percentage.

Time (minutes)	Air Filter Blockage (20%)		Air Filter Blockage (40%)		Air Filter Blockage (60%)		Air Filter Blockage (80%)	
	Exhaust Gas (°C)	Cylinder Head (°C)	Exhaust Gas (°C)	Cylinder Head (°C)	Exhaust Gas (°C)	Cylinder Head (°C)	Exhaust Gas (°C)	Cylinder Head (°C)
10	65	25.8	73	27.2	77.3	29	80.5	31.1
12	65.7	25.9	73.4	27.3	77.5	29.2	80.7	31.3
14	66.2	25.7	73.5	27.6	77.6	29.3	80.9	31.7
16	67	25.6	73.7	27.8	78	29.6	92	31.9
18	68	25.8	74.3	28.4	78.6	30	96	32.1
20	69	26	75	28.7	80.2	30.1	90	32.3

Experimental Results

Oil Level Failure Results:

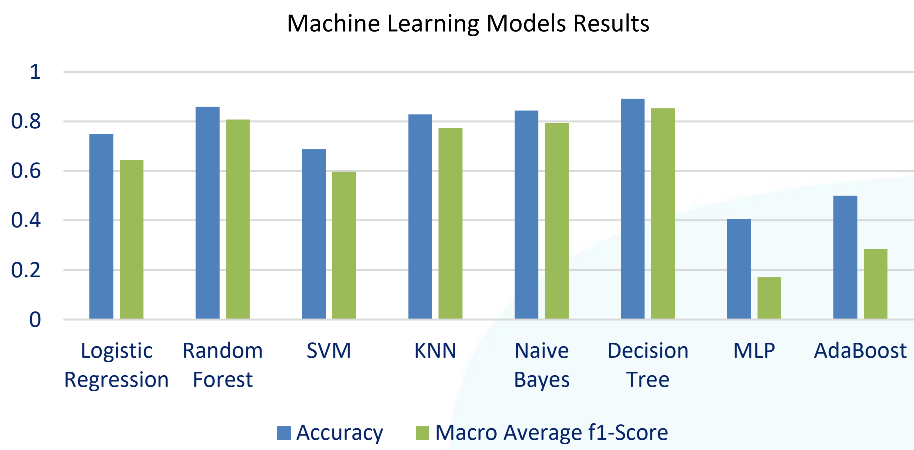
- Temperature data were collected for failure in the air filter with various blockage percentages.
- This is more challenging to detect given the small changes in temperatures between the oil level reductions.

Time (minutes)	Oil Level (75%)		Oil Level (50%)		Oil Level (25%)	
	Exhaust Gas (°C)	Cylinder Head (°C)	Exhaust Gas (°C)	Cylinder Head (°C)	Exhaust Gas (°C)	Cylinder Head (°C)
10	70	24.6	75	26	76.6	26.8
12	70.6	24.8	75.3	26.2	76.8	27
14	70.9	24.9	74.8	26.4	77.1	27.5
16	71.2	25.2	73	26.9	77.3	27.7
18	72.3	25.7	72	27.6	78.2	28.7
20	73	26.3	75.1	28	78.6	29.3

Machine Learning Results

ML Models:

The results demonstrate that the "Decision Tree" model achieved the best accuracy followed by "Random Forest" and "Naïve Bayes" models.



Conclusion

- This research aims to utilize machine learning models to maintain marine diesel engines by classifying early signs of system faults.
- The results showed a strong deviation from normal operation in the air filter blockage failure and a little deviation for the oil level failure.
- While investigating ML models, the "Decision Tree" model had the highest accuracy of 89.1% and average f1-score of 0.853.
- Future research will include the examination of various failure modes using more parameters such as machine vibration and engine load. The collected data will also be explored using deep learning models and time series analysis.

Acknowledgement

I would like to express my sincere gratitude to the enthusiastic Marine and Offshore Engineering Department professors who made a substantial contribution to our study. Your excellent help and expertise have added much value to our project. I want to sincerely thank you for all your efforts and dedication. We appreciate your unwavering dedication and cooperative attitude.

Arab Academy

for Science , Technology and Maritime Transport

13 Marlog 2024

The International Maritime Transport and Logistics Conference

"MARLOG 13"

Thank You