The Effect of Biofouling on Fuel costs – A Trial

Diane Arcas Göçmez - Shipping & Logistics MBA

Fuel oil consumption (FOC) accounts for two-thirds of a vessel's voyage expenses and more than a quarter of its operating costs, making it a key economic performance indicator. Shipping companies are prioritising the adoption of fuel efficiency strategies (Gkerekos, Lazakis, and Theotokatos, 2019), and my company is no exception. In addition, the recent regulatory push for emission reduction makes it increasingly necessary to lower the fuel amount used and the resultant emission levels (Bakka et al., 2022). Marine biofouling is well recognised for creating frictional resistance, which diminishes a ship's propulsion efficiency and increases fuel consumption. The decline in efficiency can range from 5% to 15% of propulsion power and fuel usage (Schultz et al., 2010), and hard fouling accounts for at least 110 million tons of additional carbon emissions yearly (Prevljak, 2025).
Cleaning the propeller and hull reduces fouling, but is costly and may damage the ship's anti-fouling systems; therefore, it should only be undertaken when necessary (Bakka et al., 2022; Liu et al., 2022).
This study aims to assist managers in developing condition-based predictive maintenance (James, 2025; Chen et al., 2024) models to schedule optimal cleaning timings(Liu et al., 2022) and eventually reduce fuel costs and emissions(Zeronorth.com, 2024).

Hypothesis

''We hypothesise that biofouling has a significant effect on the performance of the ship and fuel consumption''.

To determine the correlation between the ships' fouling condition and fuel performance (Bakka et al., 2022), a controlled sea trial involving two sister ships, Hilde A. (H.A.), which was recently cleaned, and Marguerite A. (M.A.), which was cleaned four years ago, has been established. This trial operates under similar, stable conditions to isolate the biofouling effect and quantify the increase in fuel consumption.

a.)Data sources and variables of interest

In conventional approaches, a diver assesses the ship's condition, providing descriptive results (Liu et al., 2022). Noon reports are still utilised but have low data frequency and are prone to human error. Modern sensors enable high-definition, accurate, real-time data collection (Zeronorth.com, 2024), which can be easily analysed using big data analysis, modelling, and AI.

Data Sources

These three devices are marine sensors designed for vast amounts of real-time data acquisition.
<u>DR(Voyage Data Recorder)</u>- Provides time-stamped navigational and engine parameters records, including speed over ground (SOG), RPM, and position.
<u>Yokogawa Mass Type Flowmeter-</u> Captures real-time fuel mass flow rates (in tonnes/hour) to calculate propulsion energy input.
<u>Trelleborg TSX5 Shaft Power meter</u>- Measures torque and RPM to calculate total shaft power (kW)
Other data sources are:

Noon Reports - To check for the last cleaning dates , weather data , and load factors .
Cloud Transmission Logs – Records the integrity and frequency of satellite-based data transmission.
AIS-based route matching is used to control for a similar voyage/environment.
Storm Geo S-Insight Monthly Reports, where vessel performance general data, such as wind, wave, current, average disposal, average speed, hull and propeller cleaning history, can be traced.

b.)Variables of interest are :

Primary variables are :

1-Fuel Mass Flow Rate(t/h): The amount of fuel consumed per hour, measured in tonnes per hour.
2-Speed Over Ground(knots): The vessel's actual speed relative to the Earth, measured in knots (nautical miles per hour).
3-Shaft Power RPM: The rotational speed of the propeller shaft in revolutions per minute shows how fast the engine is turning the shaft.
4-Total Shaft Power(kW): The mechanical power delivered by the engine to the propeller shaft, measured in kilowatts (kW), drives the ship forward.

Control variables are :
5-Weather: wind, wave, and current are analysed at similar values to eliminate confounding effects on the experiment.
6-Load Factor: Cargo weight and average disposal (mt) are analysed at similar values to eliminate confounding effects.
7-Ship specifications/technical factors: Both ships are 176m long, with a capacity of 2100 TEUs, and were built in 2005 in the same shipyard. They use the same engine and shaft generator regarding brand, number, and condition.
8. Categorical Factor: Biofouling status, cleaned vs fouled.

The sea trial measures variables 1-4 for both ships, with variables 5-7 being control variables kept constant or analysed at similar values to isolate biofouling as the leading cause of changes(Bakka et al., 2022).

c.)Data collection method

Data was collected via IoT sensors, transmitted through satellite communication servers, and processed using cloud analytics platforms. Data arrived directly at the big data solution software Storm Geo s-Insight, a fleet performance management solution that utilises AI, satellite data, IoT sensors, and advanced analytics to enhance fleet effectiveness (StormGeo, 2025). It is capable of interpreting the data in its original format and processing data files directly(Jones, 2017).

Data was collected at high frequency over 12 days, with 100–300 sensor data pulses transmitted daily, representing sampling intervals of approximately 5 to 15 minutes. Storm

Geo visualised the extracted data as a scatter plot, which has been used for further analysis and modelling.

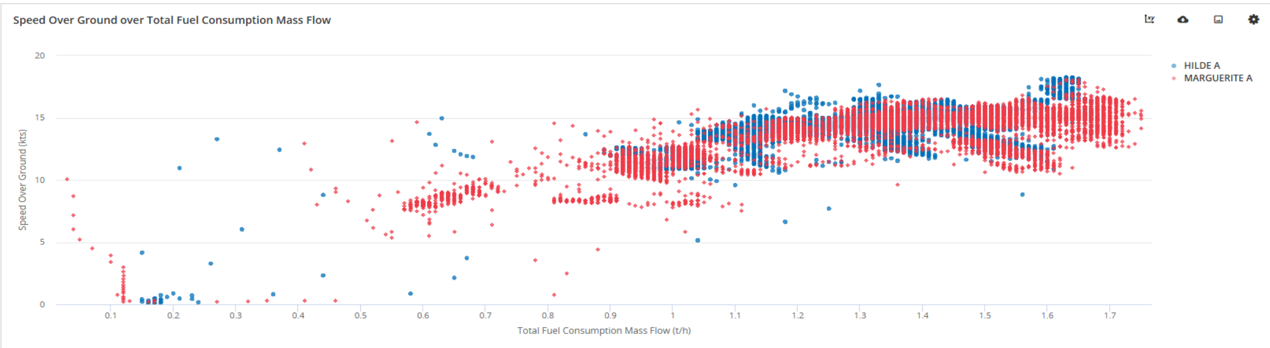
d.)Analysis discussion

The analysis is based on a supervised learning approach, where a model is trained on labelled data. For instance, in Graph 1, the input variable is Speed Over Ground(SOG), and the output (target) variable is Fuel Consumption. The objective is to learn the mapping from input to output, where each observed speed is associated with a known fuel consumption value. Once trained, the model and the historical data are used to predict fuel consumption for new speed values, enabling forecasting future consumption patterns across varying vessel speeds. Regression analysis was chosen for its *predictive modelling* capabilities(Stylianos Kampakis et al., 2022), as well as for its transparency and the simplicity of its underlying algorithm(Harris, 2022).

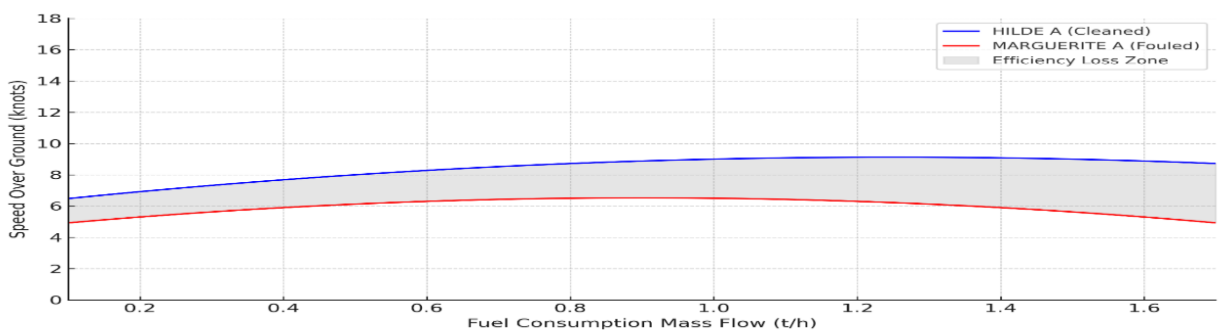
The Regression graphs were generated using AI-supported tools(Sardis, 2023), implementing Python and the Matplotlib library for data. In all the charts below, the X-axis is independent, the Y-axis is the dependent variable, and the scatter plot is raw data.

Graph 1 (Raw data scatterplot)

Speed Over Ground(SOG) vs Total Fuel Consumption Mass Flow



polynomial regression



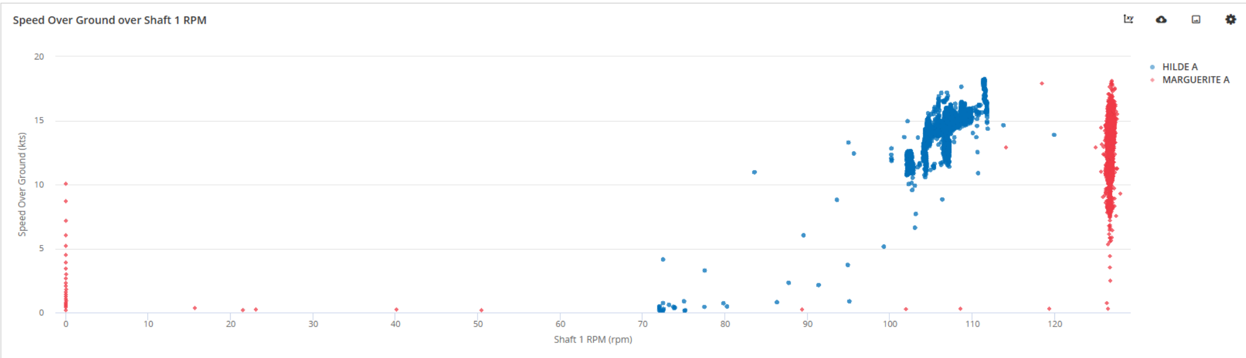
Axes : X-axis: Total fuel consumption(t/h) ; Y-axis: Speed over ground (kts)

Purpose: To measure how efficiently each vessel converts fuel into speed.
Finding: H.A. consistently achieves higher speeds than M.A. under the same fuel input. For example, M.A.'s speed is lower at a 1.2 t/h fuel flow rate.
Interpretation: Loss in propulsion efficiency caused by hull fouling and increased resistance.

The grey shaded area illustrates performance loss from fouling, specifically, the extra fuel needed to overcome increased hull resistance. Although fuel flow remains constant, vessel speed decreases in fouled conditions, requiring more fuel to match the performance of a clean hull.

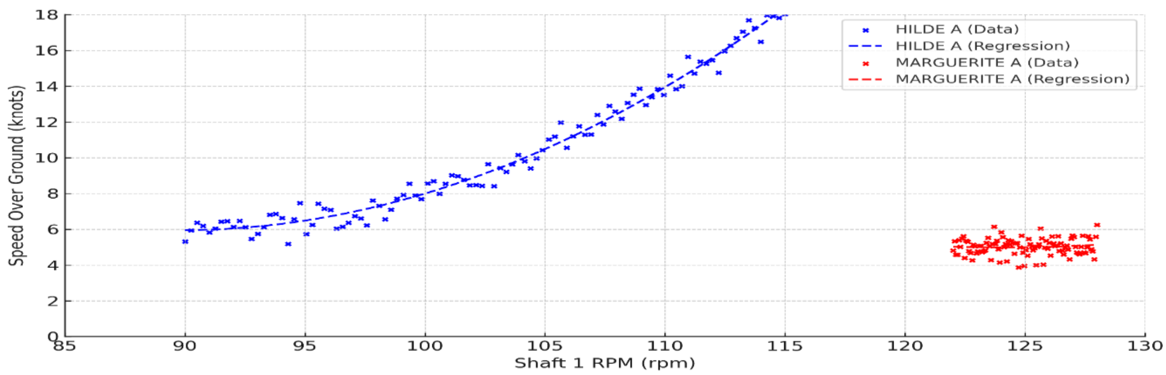
Graph 2 (Raw data scatterplot)

Speed Over Ground over Shaft 1 RPM



Note that red points near 0–10 RPM and 0–10 knots likely represent noise or low-power operation and should be excluded as outliers.

polynomial regression

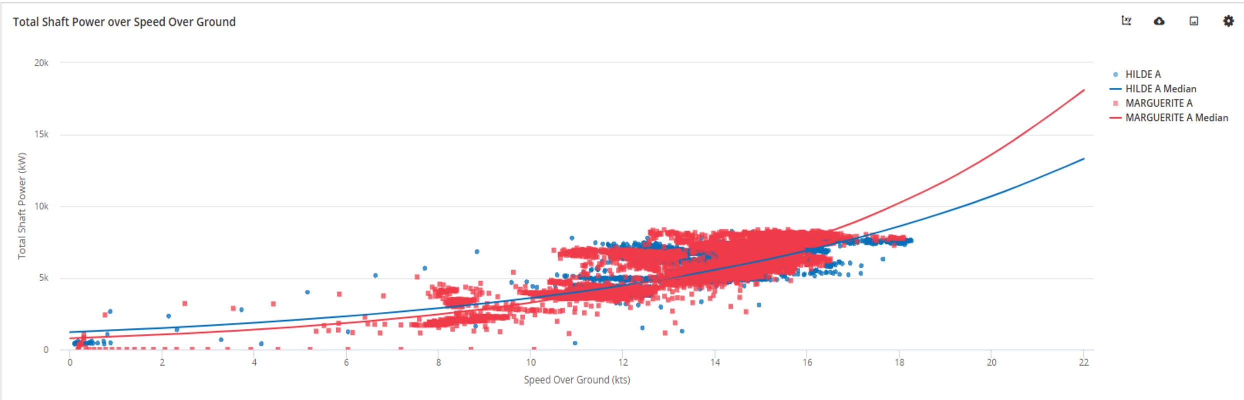


Axes: X-axis: Shaft 1 RPM(rotations per minute of the primary shaft); Y-axis: Speed over ground (knots)
Purpose: To measure propulsion efficiency by demonstrating the effect of Shaft 1 RPM on speed. Higher speed at lower RPM indicates a cleaner hull.

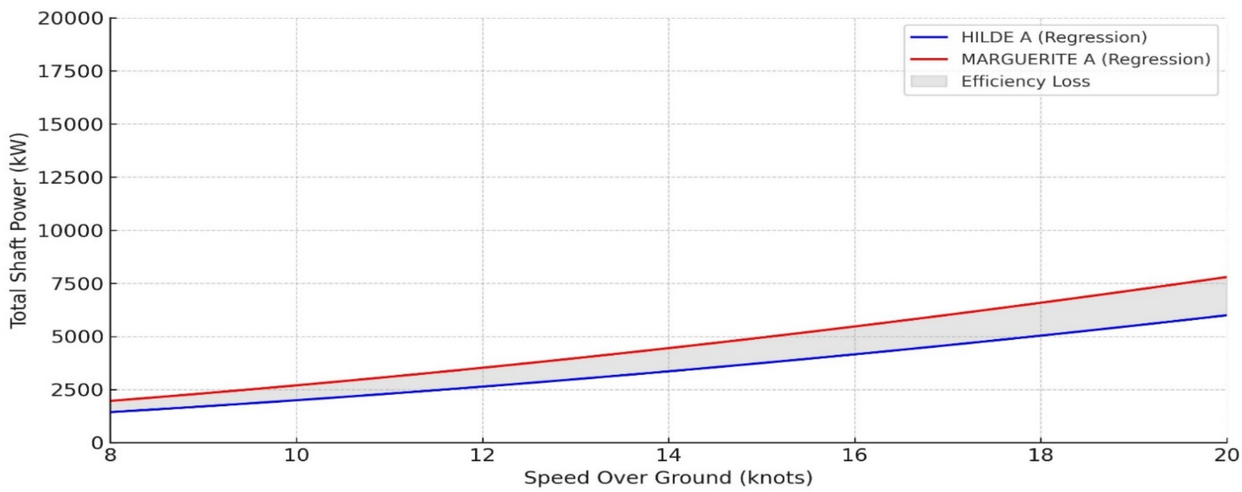
Finding: For H.A., speed increases at an accelerating rate with RPM. In contrast, M.A. speed shows a flat response- shaft RPM fails with no significant speed improvement to produce a corresponding speed gain, even at 125 RPM.
Interpretation: Clear loss of propulsion inefficiency.

Graph 3

Total Shaft Power over SOG



polynomial regression

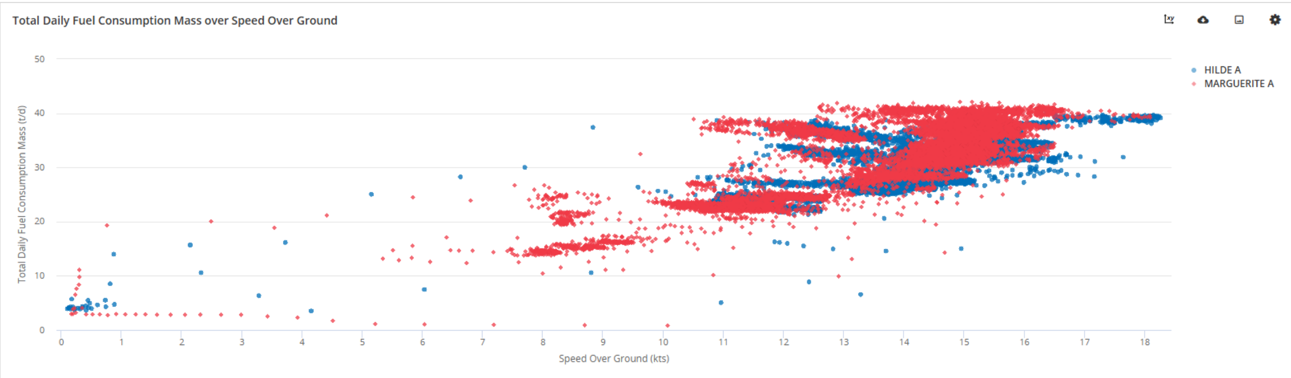


Axes : X-axis: Speed over ground (kts); Y-axis: Total Shaft Power (kW)
Purpose: To measure propulsion efficiency by demonstrating the effect of speed on Total Shaft Power.
Findings: Shaft power increases exponentially with speed. M.A. consistently requires more shaft power than H.A. at all speeds, especially above 11 knots.

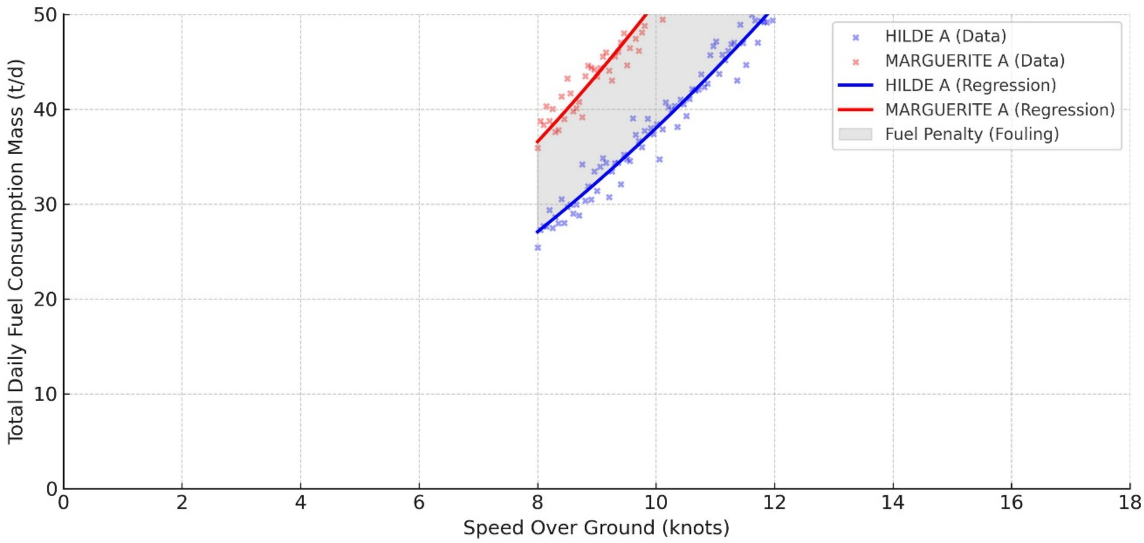
Interpretation: Indicates reduced propulsion efficiency for M.A., leading to higher fuel consumption.

Graph 4

Total Daily Fuel Consumption Mass over SOG



polynomial regression



The regression chart does not show data between 0 and 8 knots because the data was intentionally generated starting from 8 knots due to scattered outliers (Jones, 2017), likely idle/port periods, or invalid voyage data.

Axis : X-axis: Speed over ground (kts); Y-axis: Total daily fuel consumption(t/d)
Purpose: To measure propulsion efficiency by demonstrating the effect of speed on Total daily fuel consumption.
Findings: Fuel consumption rises with speed for both ships, but M.A. consistently consumes more than H.A. at comparable speeds,

Interpretation: The widening gap at higher speeds reflects the compounding fuel penalty caused by fouling, highlighting the cost of delayed cleaning.

Recommendations and expected results

The sea trial confirmed that *biofouling increases hull resistance* and raises fuel consumption by *5%–7%.*
The following actions are recommendations :

- A limitation is the short trial duration. H.A., recently cleaned, should serve as a zero-fouling performance baseline. High-frequency data collection should continue until its next drydocking (in 4–5 years) to build a long-term performance trend and train predictive models that detect degradation and trigger cleaning alerts.
- Annual comparisons between fuel use and hull fouling- ideally with visual inspections- will strengthen correlations with performance decline and improve predictive model accuracy over time(Pavin and Vlatko Knežević, 2023).
- The data can evaluate current anti-fouling paint performance and benchmark fuel efficiency against fouling progression, enabling objective assessment of new technologies for evidence-based procurement decisions.
- Drydocking usually occurs every five years due to the high cost and off-hire time. However, M.A.'s drydocking should be done earlier since the efficiency loss is significant.
- It is recommended to keep M.A.'s cruising speed at optimal levels to reduce excessive fuel use until cleaning can be performed, as higher speeds lead to exponential consumption increases.
- Since biofouling is inevitable and frequent cleaning is not cost-effective, long-term mitigation strategies- including retrofitting or upgrading propulsion systems- should be considered to offset the operational and fuel costs over time.

These actions are essential for developing an effective predictive maintenance model. By continuously collecting high-frequency data on hull condition, fuel consumption, and vessel performance, thresholds can be defined to trigger alerts when efficiency deviates beyond an acceptable range. Over time, this enables condition-based algorithms that recommend cleaning based on predicted performance loss, not fixed schedules or manual inspections.

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