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ΣΧΟΛΗ ΝΑΥΠΗΓΩΝ ΜΗΧΑΝΟΛΟΓΩΝ ΜΗΧΑΝΙΚΩΝ

Διπλωματική Εργασία:
Examination of the performance of an ALS (Air Lubrication System) using operational data

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Contents

Abstract

The goal of this study is to examine the performance of an Air Lubrication System (ALS) installed on an 174000cbm LNG carrier vessel by analyzing operational data. The research is based on data analysis of a ship in various operating modes.

For the purposes of this study, the ISO 19030 standard for “Measurement of changes in hull and propeller performance” methodology was used. The standard evaluates hull and propeller performance by measuring alterations of power. It is based on the relation between delivered power and total resistance. Total resistance is comprised of still water, wave, wind and other additional forms of resistance.

The calculation of the ship’s resistance values will enable the calculation of the ship’s power. Naturally, corrections need to be applied, in order to account for deviations from the reference sailing condition.

The quantified results of the vessel’s performance evaluation are percentage indicators highlighting the deviation of the calculated points from the expected values.

The current diploma thesis explores the potential benefit of the application of an Air Lubrication System (henceforth ALS) using operational data provided by a credible performance monitoring system. The analysis will be performed using data from approximately over a year of sailing with alternating between ALS On and Off, in comparable conditions. Having collected the data and filtered for outliers, the savings in power can be calculated, thus displaying the effect of the ALS over time.

Σύνοψη

Σκοπός της παρούσας διπλωματικής εργασίας, είναι η αξιολόγηση ενός Συστήματος Αέριας Λίπανσης της γάστρας, (Air Lubrication System – ALS) που έχει εγκατασταθεί σε ένα πλοίο, μέσω της ανάλυσης δεδομένων λειτουργίας του πλοίου αυτού. Η αξιολόγηση βασίζεται στην ανάλυση διαφορετικών καταστάσεων λειτουργίας του πλοίου όσον αφορά την φόρτωσή του και την λειτουργία του ALS.

Για τους σκοπούς της μελέτης, χρησιμοποιήθηκε η μεθοδολογία του ISO 19030 για την «Μέτρηση των αλλαγών της απόδοσης της γάστρας και της προπέλας». Η μέθοδος υπολογίζει την απόδοση της γάστρας και της προπέλας αξιολογώντας τις αλλαγές στην ισχύ. Βασίζεται στη σχέση μεταξύ ισχύος και συνολικής αντίστασης του πλοίου. Η συνολική αντίσταση, αποτελείται από την αντίσταση πλευσής σε ήρεμο νερό, την αντίσταση κυματισμού, ανέμου και άλλες μορφές αντίστασης.

Ο υπολογισμός της αντίστασης του πλοίου θα επιτρέψουν τον υπολογισμό της ισχύος του. Είναι προφανές ότι θα χρειαστούν διορθώσεις (για εκτόπισμα, βύθισμα και άνεμο) καθώς το πλοίο δεν αναμένεται να πλέει στις συνθήκες αναφοράς του.

Τα αποτελέσματα που θα υπολογιστούν, θα εκφραστούν ως ποσοστιαίοι δείκτες που θα αναδεικνύουν τις αποκλίσεις των υπολογισθέντων τιμών από των αναμενόμενων τιμών.

Από αυτήν τη διπλωματική εργασία, αναμένεται να βρεθεί το δυνητικό όφελος της εγκατάστασης ενός συστήματος Αέριας Λίπανσης, χρησιμοποιώντας δεδομένα που μας παραχωρήθηκαν από μία αξιόπιστη πηγή συλλογής δεδομένων απόδοσης. Τα δεδομένα που θα χρησιμοποιηθούν θα έχουν συλλεχθεί για περίπου έναν χρόνο πλεύσης με το ALS ενεργοποιημένο ή απενεργοποιημένο και το πλοίο σε έμφορτη ή άφορτη κατάσταση. Έχοντας συλλέξει τα δεδομένα και έχοντας πραγματοποιήσει εκκαθάριση για ακραίες τιμές, είναι δυνατός ο υπολογισμός της εξοικονόμησης ισχύος, και άρα η ανάδειξη της επίδρασης του ALS.

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Acknowledgements / Ευχαριστίες

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Thank you!

1 Introduction

The world industries, including the shipping industry, are moving towards a more environmentally friendly future. The goals set by higher regulatory authorities, such as the International Maritime Organization or IMO, are demanding reduced emissions. Considering the impracticality of a radical renewal of the global fleet, shipowners are looking for ways, to prolong the service life of their current and newbuilding fleet by retrofitting or incorporating systems and/or designs to comply with emission regulations and achieve better efficiency.

The ultimate goal for shipowners, is to deliver products in the most efficient manner, therefore maximizing profits. By implementing efficiency improving solutions, vessels are able to achieve the same results with less effort, specifically, reduced power needs to achieve the same speed.

When selecting an energy efficiency solution for vessels, performance improvements must be recorded which, when translated into financial terms, must be enough to offset the cost of installation within a reasonable timeframe. Shipping companies perform a cost benefit assessment. The costs being the installation capital and operational costs, must be offset by the benefits which include fuel consumption savings as a consequence of improved performance. This diploma thesis aims to explore the presumable performance improvement achieved by the implementation of an ALS on a vessel since new.

1.1 International Maritime Organization – IMO Goals

The international Maritime Organization is the United Nations agency responsible for safe, secure and efficient shipping and the prevention of pollution from ships [1].

One of the IMO's goals for preventing environmental pollution caused by ships, is the compliance to the 2015 Paris Agreement, which is the result of the United Nations Climate Change Conference (UNCCC) in Paris. The agreement's objective is to limit the rise in mean global temperature to 2 °C. To achieve that emissions should reach net-zero by the middle of the 21st century [2].

To achieve that, the IMO, demands from the shipping sector to reduce greenhouse gas emissions by 50% by 2050 compared to 2008 levels. This will be achieved by reducing the Carbon Intensity of ships. Carbon intensity is the measure of carbon dioxide (CO2) emissions produced per unit of transport work or cargo carried by ships.

1.2 Energy Saving Solutions

To meet the goals set by the IMO, various solutions can be applied by the sipping industry. The shipowner's approach to cutting down on emissions can vary between design, operational and technical solutions or a combination of these.

Design improvements play a significant role in emission reduction. Optimizing the hull design to minimize drag and enhance hydrodynamic efficiency, as well as enhancing the aerodynamics of the superstructure, can lead to improved fuel consumption and reduced emissions.

Operational optimization of the ship can also be an emission reduction source. By managing the fleet more efficiently and implementing voyage optimization solutions like weather routing, GHG emissions can be cut by 1-10%. Another operational parameter that can be adjusted, is the vessel's sailing speed which can be optimized to reduce emissions by 75% [3].

Technical solutions for emission reduction include the Mewis Duct, ALS, the Kort nozzle, the wake equalizing duct, which can contribute up to 15% in GHG emission reduction.

Some energy saving measures are shown in Table 1 below:

Type of Modification Employed	Description of the method	Impact	Source
Weather routing	Operational	28% fuel savings	[4]
Sailing Speed Slow Steaming	Operational	13%-19% fuel savings	[5]
Mewis Duct, Wake Equalizing Ducts	Technical	4% fuel savings	[5]
ALS	Technical	2-22% power savings	[6]
Hull Cleaning	Technical	9% fuel savings	[7]

Table 1 Options for energy saving solutions.

Incorporating these energy-saving measures can significantly contribute to emission reduction and enhance the overall environmental performance of the shipping industry.

1.3 ALS

The focus of this thesis is on the energy-saving solution known as the Air Lubrication System (ALS). The air lubrication system's basic principle of operation is to reduce the frictional resistance between the hull and the water by creating a layer of air in between which reduces the effective wetted surface area of the vessel [6].

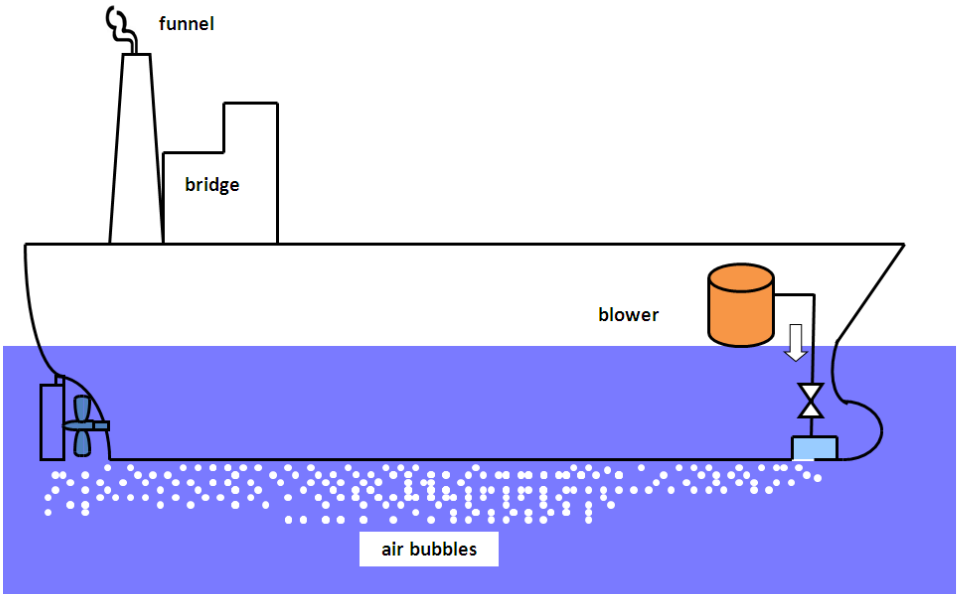

Figure 1 - Schematic Illustration of ALS [8]

The earliest adopter of air lubrication technology was the US navy. The system was used to suppress the noise caused by the engine room and the propeller, making the ship harder to detect by sonar. The concept was later picked up by scientists and scholars to reduce drag resistance on a vessel's hull.[8]

The resistance of a ship can be broken down into three main components: frictional resistance, form resistance and wave resistance. Since the form of the ship remains largely the same after fitting an air lubrication system and the waves cannot be altered, the reduction of frictional resistance which constitutes 40% [8] of the total resistance of a higher speed vessel, is an effective means of reducing overall resistance.

Skin frictional resistance depends on the wetted surface area of a ship. Air Lubrication reduces the frictional drag for vessels. Air lubrication is achieved by pumping air beneath the hull, reducing the area of hull in direct contact with the liquid flow.

ALS can be applied to various vessel types, including container ships, tankers, bulk carriers, and more. Its effectiveness may vary depending on factors such as hull design, size, and operational characteristics. Tailoring the ALS implementation to specific vessel requirements maximizes its benefits.

Real-world examples demonstrate the successful implementation of ALS. Case studies showcase its positive impact on fuel consumption, emissions reduction, and operational efficiency. These examples provide empirical evidence, offering shipowners insights into the potential performance improvements and benefits they can expect from ALS integration.

1.4 Aim and Objectives

Given that the technology of Air Lubrication has only recently been more widely adopted, there is a need to accurately validate the savings it can provide. This thesis aims to provide insight on the performance of an ALS, using over a year's worth of operational data provided from an LNG carrier operated by an esteemed shipping company.

By the completion of this thesis, one will be enabled to compare and review key performance indicators for the same ship with the ALS enabled and disabled. Additionally, a comparative analysis of the power requirements of the vessel will be presented for both scenarios - with ALS enabled and disabled.

Therefore, the objectives of the research are the following:

- Researching about the working principle of an ALS, and the effect on frictional resistance.
- Develop a methodology to collect valid data that will provide accurate results.
- Create a calculation framework to account for different sailing conditions (wind, displacement).
- Perform a regression model to best determine the P-V curves for ALS On and Off when the ship is ballast or laden.
- Perform a multiple regression model to best determine the Power needs for multiple variables (weather, draft trim, speed through water and more) for ALS On and Off when the ship is ballast or laden.
- Compare results and determine savings by the use of ALS.

1.5 Literature Review

Previously in this thesis, the imperative need for action regarding the climate change was highlighted. One potential solution to aid the shipping sector's decarbonization is the implementation of ALS in new and existing ships. In Mizokami et al paper [9], the rising prices of raw materials, including crude oil and the economic growth of developing countries are highlighted as additional incentives for the adoption of energy saving solutions.

In Mizokami et al paper "Experimental study of air lubrication method and verification of effects on actual hull by means of sea trial" the friction reduction potential by air lubrication is examined using operational data. The air lubrication method, which creates a layer of air bubbles between the hull and seawater to reduce skin friction resistance, has been recognized as an effective measure, especially for large low-speed ships. The study was a world first, it was conducted on a newly built carrier which would perform a series of speed sea trials. Before the actual trial, the air delivery conditions were tested using a full-size mock-up in a water tank. In addition, the air blow-off conditions, were tested using a ship moored in a wharf wall. The paper describes the development of the system, including model testing data and the outcomes of the actual hull trials. Figure 2 displays the coverage of the hull by an air bubble layer created by air blow off from chambers mounted on the hull bottom.

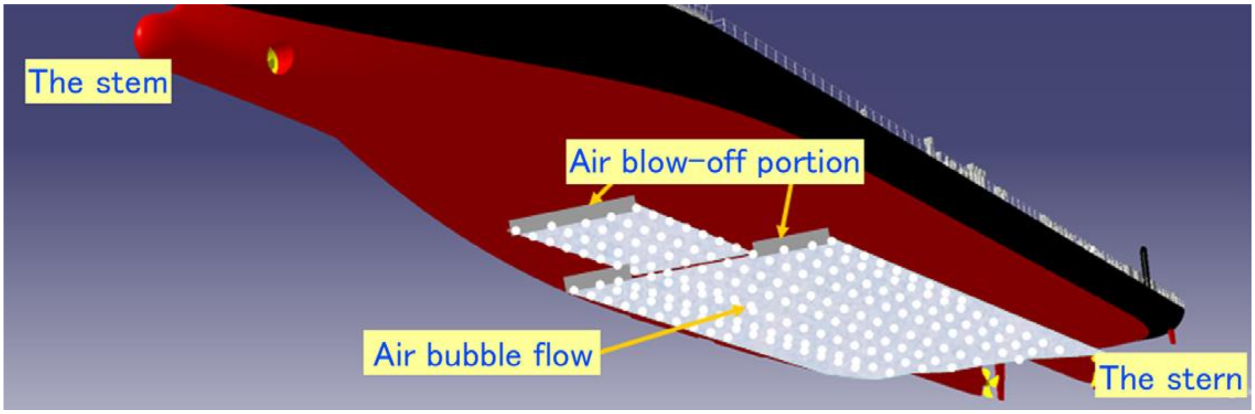

Figure 2 Image of an Air Lubrication System. Air bubbles are discharged from the bottom of the hull [9]

What is noteworthy about Mizokami's paper is that before this research, assessments of air lubrication systems were based on model testing. In this study Mizokami et al used a full scale air lubrication system on a module carrier belonging to NYK-Hinode Line, Ltd. The paper evaluates the ALS performance by including model testing data and the outcome of actual hull trials with and without the discharge of air by the air lubrication system.

The first step for the researchers was to understand the behavior of air blow off by the system. The researchers used a full mock-up air lubrication system unit and tested it in a seakeeping tank at MHI's Nagasaki Research and Development Center. Figure 3, displays the unit used for this paper, as seen, the unit used two sets of blowers to pump the air to fifteen branch pipes through a large diameter pipe. The air would be delivered to air chambers which would be mounted on the bottom of the hull, each chamber was fitted with sixteen small apertures from which air is blown off.

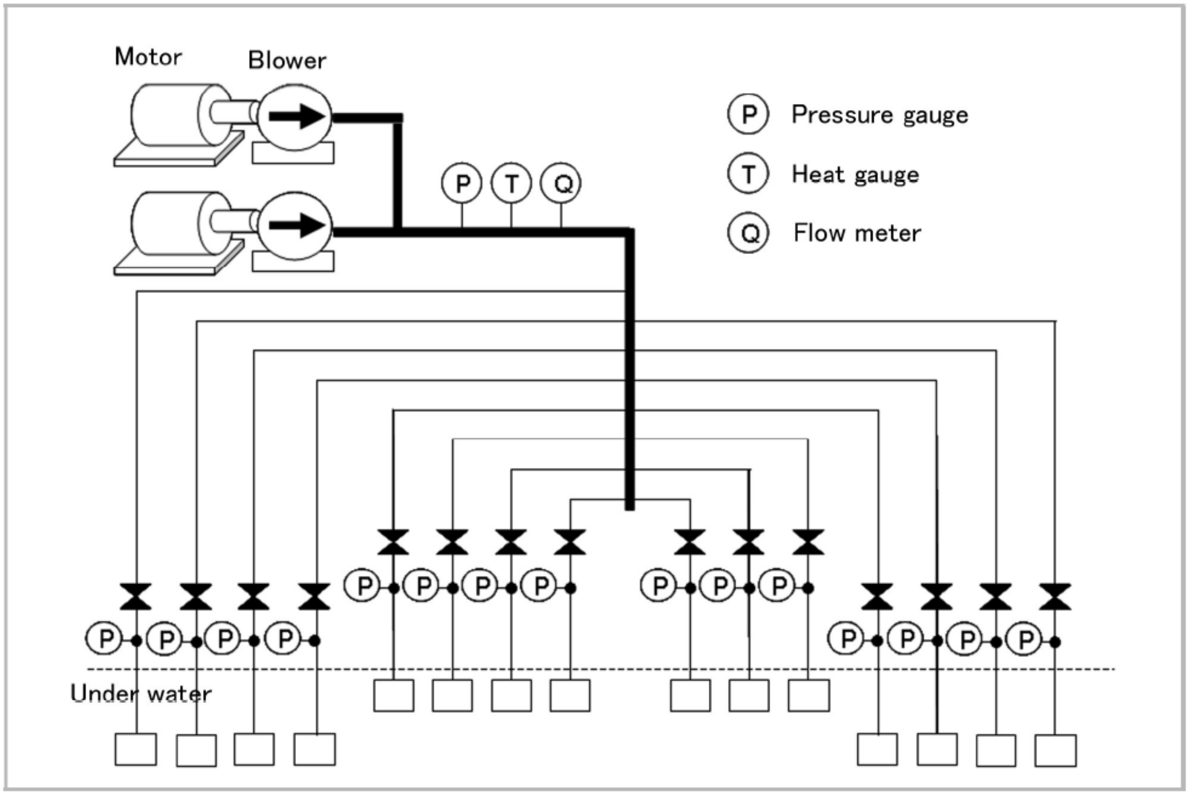

Figure 3 Simplified diagram of the ALS used for Mizokami's research [9].

The air blow off behavior was tested for different inclinations of the chambers, to mimic the behavior of ships during an actual voyage. The effectiveness of baffle boards in equalizing the flow velocity distribution was confirmed. The test also showed that air blow-off from the apertures was affected by pressure distribution in the lateral direction of the chamber. Finally, it was concluded that the air bubbles will roughly cover the bottom of the vessel.

Then the researchers employed a ship moored to a wharf wall. The wharf wall test involved sending air to the bottom of the hull and observing the blow-off conditions and flow rates in different draft and inclined conditions. The results demonstrated the need for optimal valve opening settings to achieve equalized flow rates and the effect of ship inclination on the distribution of air blow-off from the apertures.

For the final stage of the research Mizokami et al performed actual hull experiments at sea. The power-speed data produced by the testing were corrected to account for wind and tidal changes, the main engine's horsepower was calculated by load indicator readings. Valve openings were adjusted to the optimal settings based on the results produced by the wharf wall testing. The speed trial tests were carried out with three different air thickness rates: 3mm, 5mm, 7mm.

The net energy -savings were determined by subtracting the electric power consumption value needed for the operation of the ALS from the reduction value of horsepower at the time of air blow off navigation. The relationship produced by the speed trials between the power output and the vessel's speed the horsepower appeared to decrease while the speed appeared to increase. The net energy-saving effect ranged from eight to twelve percent, with higher air thicknesses resulting in greater energy savings. In Table 2, the results from several speed trials are compiled, and the energy saving effects are presented.

	Horsepower reduction	Blower electric power consumption	Net energy-saving effect
7 mm	680 kW	211 kW	469 kW (12%)
5 mm	530 kW	143 kW	387 kW (10%)
3 mm	380 kW	72 kW	308 kW (8%)

Table 2 A comparison of the energy-saving effects from several tests by air lubrication method [9]

The paper verified the reduction of skin friction resistance and decreased the load on the propeller using ALS, leading to a decrease in horsepower and an increase in speed. The findings suggest that further efficiency improvements can be achieved by adjusting the pitch angle of the propellers. Based on the successful hull experiment, the authors plan to install a full-scale air lubrication system on a second vessel and conduct further measurements and verifications.

In conclusion, the research presented above verifies the energy saving effect of an air lubrication system by reducing skin friction resistance on a ship's hull, by using experimental results from an ALS mock-up unit, an ALS fitted to a moored ship, and an ALS fitted to a ship performing sea trials. The paper suggests the application and the further research for the potential benefits of ALS on other types of vessels. In this thesis this exhortation is accepted and the potential energy savings by an ALS on an LNG carrier will be examined by comparing the Power-Speed curves of the ship with and without the discharge of air.

1.6 Study structure

Performance monitoring offers multiple benefits as it facilitates the assessment of the hull and engine condition; it evaluates the ship's design by comparing the measured operational parameters to the design/expected ones. The current study utilizes operational data collected by a vessel, in a way to facilitate performance evaluation. The system would collect sailing parameters for a fixed duration of time with the ALS activated and then the ALS was deactivated and the same parameters would be measured for the same duration. Thus, creating a comparable dataset, from which conclusions can be extracted about the effect of an ALS.

The procedure followed by this diploma thesis, includes:

- The compilation of the measured data
- the filtering of the measured data
- corrections that account for discrepancies from the reference sailing condition
- determining the power needs to be output from the main engines.
- determining the power needs from the generator engines to operate the ALS.

- determining the presumed power savings achieved
- Multiple linear regression to verify the results.

1.6.1 Data compilation

The ship performed numerous 30-minute trials with and without the discharge of air. For each trial a report in pdf format was extracted with the data collected by various measuring devices on board. In order to facilitate data analysis these reports were compiled in a single excel file using software specifically developed for this thesis.

1.6.2 Data Filtering

Data filtering is crucial because outlier datapoints need to be removed, since they can produce disorienting results. Outliers might be due to sailing in port, faulty sensors, sailing with high currents and much more.

1.6.3 Corrections for reference sailing condition

Obviously in order to be able to assess the performance gains of the ALS, we need to have comparable data. Therefore, the data need to be adjusted to reflect the same sailing condition regarding wind and displacement, draft discrepancies from reference sailing condition.

1.6.4 Extracting the Power vs Speed Curves

In order to determine the behavior of the main engines in regard to the vessel's desired speed, the Power vs Speed curves (henceforth P-V curves). Having extracted the P-V curves for the same loading condition (ballast or laden) with the ALS activated or deactivated, very concise results can be extracted for presumable power savings.

1.6.5 Determining the ALS Power needs

It is obvious that since the ALS is a subsystem of the vessel, it will need to draw power from the generator engines to operate. It is necessary to determine the ALS power needs, in order to calculate the net power savings. Obviously, the system needs to offset the power it needs to operate. The required power of the ALS depends on the vessel's speed.

1.6.6 Analyzing results

Having determined the above, we are enabled to produce tangible results about the benefits of ALS. The potential savings achieved by the implementation of the ALS, will be the power savings achieved for the same loading condition.

1.6.7 Multiple Linear regression

Having drawn conclusions about the operation of the ALS, a multiple linear regression model is constructed in order to understand how the independent variables contribute to power consumption. The results from the previous analysis will be compared to the ones from the multiple linear regression model, which will enable for a more accurate understanding of the ALS savings.

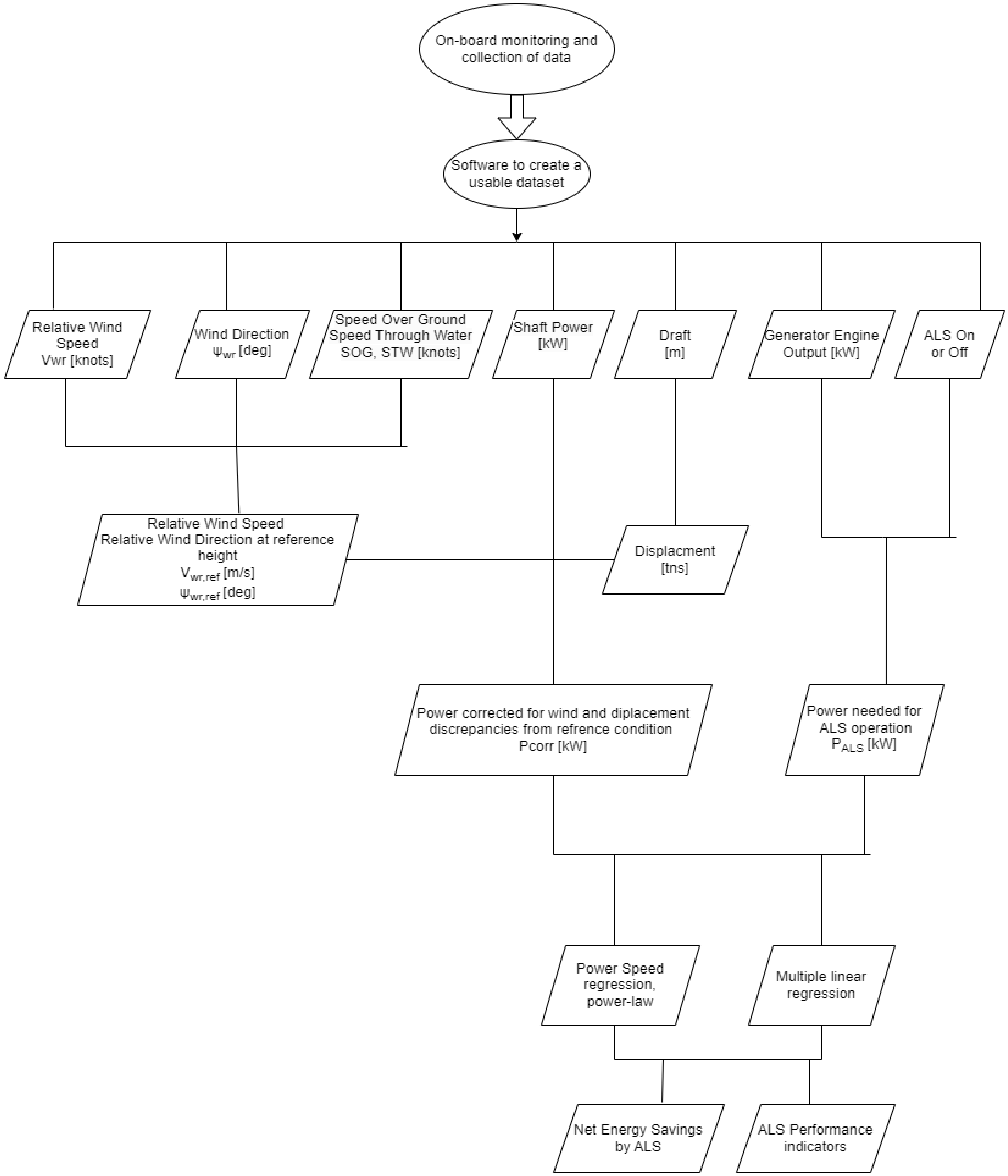

Figure 4 - Flowchart of the diploma thesis methodology

2 Under Evaluation Ship's particulars

The ship that will be examined by this thesis is an LNG carrier with a transportation capacity of 174000 cubic meters.

The main particulars of the ship are presented in Table 3. The ship's particulars at the Full Load Departure condition and Ballast Departure condition are presented in Table 4, Table 5 respectively.

Description	Symbol	Value	Unit
Length Overall	L_{OA}	294.9	m
Length Between Perpendiculars	L_{BP}	288.5	m
Beam / Breadth	B	46.4	m
Depth	D	26.5	m
Design Draft	T_d	11.522	m
Scantling Draft	T_{sc}	12.522	m
Power @ MCR	P_{MCR}	12590	kW
Power @ NCR	P_{NCR}	10700	kW
Displacement Laden	Δ_{LADEN}	118354.3	tns
Displacement Ballast	$\Delta_{BALLAST}$	99009.2	tns
Anemometer Height (from General Arrangement)	$Z_{a,ref}$	55- T_d	m
Reference height for the calculation of wind resistance coefficient	$Z_{ref, ref}$	10	m
Air Density	ρ_{air}	1.225	kg/m^3
Air Pressure	P	101325	Pa
Transverse area at design draft	A_T	523.3	m^2

Table 3 - Ship Particulars

Displacement	118354	tns
Taft	11.89	m
Tfore	10.85	m
Trim	1.04	-
Tmean	11.37	m
Cb	0.75864	-
Cb from hydrostatics	0.75449	-
Cwl	0.83982	-
Cm	0.9919	-
Aref Transverse	523.295	m^2

Table 4 - Laden Design Parameters

Displacement	99009.2	tns
Taft	10.47	m
Tfore	8.87	m
Trim	1.6	-
Tmean	9.67	m
Cb	0.74621	-
Cb from hydrostatics	0.74149	-
Cwl	0.81748	-
Cm	0.9905	-
Aref Transverse	444.425	m2

Table 5 - Ballast Design Parameters

3 Data Collection

Data were collected by using the measuring devices mentioned below. Every datapoint is a 30-minute trial, at a given day period (morning/evening). The logic behind the measurements involved collecting data for the vessel with the system deactivated for a 30-minute duration at a particular speed and rpm, come the end of this period the system would be activated, and data would be collected for another 30 minutes. This would be performed in the morning and the evening. By applying this sampling, comparable conditions can be achieved. The collection of the data took place for 1 year and 10 months (676 days) and produced 1038 datapoints.

3.1 Measuring Devices

The data used in this thesis are collected by the devices mentioned in Table 6, and are mentioned in the Trim & Stability book of the LNG carrier in question and other manuals.

DEVICE	PARAMETER
Differential Global Positioning System (DGPS)	Speed Over Ground - SOG
Speed Log	Speed Through Water - STW
Shaft torque meter	Shaft Horsepower, Revolutions Per Minute - SHP, RPM
Mass Flow meter	Fuel Oil Consumption FOC
Anemometer	Wind Speed, v_W
Pressure sensor	Mean Draft, Aft Draft, Fore Draft, Tm, Ta, Tf
Rudder Angle Indicator	Rudder Angle, RA

Table 6 Measuring Devices as seen in the Trim & Stability booklet.

3.1.1 Global Positioning System

The Global Positioning System (GPS) is a satellite-based navigation system developed by the U.S. Department of Defense [10]. The GPS retrieves information about the ship's position. By communicating constantly with a global network of satellites, it can determine a vessel's global coordinates (longitude, latitude). The vessel's speed over ground (SOG) is obtained from the arithmetical derivation of the vessel's position [11]. The accuracy of the GPS is typically within a few meters (2m-10m), making it an essential tool for evaluating the performance of the ALS.

3.1.2 Speed Log

A speed log is a device used to measure a ship's speed through water (STW). It is a type of navigation equipment that provides real time information about STW by measuring the rate of water-flow past the ship's hull. The measurement is performed by the creation of electromagnetic field and the voltage created by the flow of water [12]. The signal voltage is digitally processed in order to be translated into STW.

The STW is used in conjunction with SOG to determine the current. Modern speed logs use advanced technology, such as Doppler and acoustic sensors, to provide more accurate and reliable speed measurements.

3.1.3 Torsion Meter (Strain Gauge)

In order to assess the vessel’s performance, the engine’s power needs to be measured in contrast to the fuel consumption. The shaft horsepower is measured using strain gauge technology. The strain gauges measure the shaft torque and thrust. Signals are transmitted to a unit to be digitally analyzed along with the shaft’s RPM in order to determine the shaft horsepower. [13]

3.1.4 Mass Flow Meter

Of the most crucial performance measurement devices aboard a ship. The mass flow meter measures mass flow rate of fuel. Flow meter continuously measures the fuel consumption, so as to ensure optimal engine operation.

Mass flow meters must be installed on every fuel line that provides the engine with fuel to accurately measure fuel consumption.

3.1.5 Anemometer

An anemometer is a device used to measure wind speed and direction relative to the ship’s. On ships, anemometers are typically mounted on the ship's accommodation superstructure. Anemometers are important to navigate the vessel safely, helping the captain adjust the ship’s course in accordance with wind conditions [14].

Anemometers are important for measuring the performance of an air lubrication system because wind speed and direction can have a significant impact on the system's effectiveness. By monitoring the wind conditions, ship operators can adjust the ship’s speed and the air supply to optimize the system's performance and achieve the maximum fuel savings.

3.1.6 Pressure Sensor

Pressure sensors are used to measure the draft of a ship in water. They are placed on the hull of the ship, and the data acquisition system converts the pressure readings into draft measurements.

The pressure sensors measure the pressure at a predetermined point on the outside of the hull and compares it to the pressure at a fixed reference point (draft line) to determine the draft [15] at a specific longitude on the ship. There are pressure sensors both in the bow and the stern in order to enable trim measurement. The draft measurement can be displayed on a gauge or transmitted to a control system for use in navigation, stability calculations, or other ship operations.

3.1.7 Rudder Angle Indicator

A rudder angle indicator sensor is a device used on ships to measure the angle of the rudder [12], which is an essential component of a ship's steering system. The sensor is typically mounted on the rudder and is connected to an indicator in the ship's bridge that displays the rudder angle. This information is important for ship operators to accurately control the direction and movement of the vessel. The sensor may use a variety of technologies, including mechanical, electrical, or hydraulic, to accurately measure the rudder angle and transmit the data to the bridge.

4 DESCRIPTION OF THE METHODS USED

4.1 Retrieving measured data

Firstly, all data were inserted in an excel file from the given reports using a c# script to minimize errors. The pdf file would include in every line data collected by the onboard performance monitor system. Each line would contain the description of the data measured followed by its value and the unit of measurement.

The reports were in pdf format. to deal with the large amount of the reports effectively and in a manner that eliminates errors, each pdf's data were inserted in an excel sheet by utilizing Visual Studio's C# programming language. The C# script functioned by opening every pdf file in a specified folder path and would extract predetermined attributes such as speed, power, rpm etc. The extracted data of every file would be stored in an array. The data within the array would be separated by a certain character, called separator, thus indicating that each data would be in a different column. Every file would be a new array thus a new row in the Excel spreadsheet.

4.2 Data filtering

To achieve a reliable evaluation of the ALS performance, it is crucial to ensure the quality of the available data. This can be achieved by utilizing appropriate filtering criteria that restrict the deviation from the reference displacement and trim of each loading condition. The application of such criteria enhances the accuracy of trend analysis by excluding the presence of any outliers that may be attributed to external factors such as changes in weather, port maneuvers or faulty measurements.

All obvious outliers were removed, for example negative speed or negative power. Then the following 4 sailing conditions were examined:

1. Ballast with ALS On
2. Ballast with ALS Off
3. Laden with ALS On
4. Laden with ALS Off

For each datapoint's mean draft, the corresponding displacement was found using the hydrostatics table provided in the Trim and Stability booklet.

For each datapoint, the displacement and trim criteria were applied. (175 out of 205 datapoints remain)

$$\left|trim_{ref} - trim_{act}\right| < 0.3\frac{L_{BP}}{100}$$

Equation 4-1

$$\left|100\frac{\Delta_{d,ref} - \Delta_{act}}{\Delta_{act}}\right| < 6$$

Equation 4-2

The reference drafts for each condition, ballast and laden, were taken as the average measured draft.
The reference displacements were taken from the hydrostatics table for the aforementioned reference drafts.

4.3 Current Correction

A correction for the current speeds needs to be implemented. This is to ensure the evaluation will exclude data points of adverse current conditions. When the current is too strong, the ship resistance is increased causing greater fuel consumption. Data points are appropriate if the following condition is met:

$$|SOG - STW| < 1.5knots$$

Equation 4-3

The approach of this thesis will be based on the ISO 19030 standards as taught in the course "Performance Evaluation of Ships" by Assistant Prof. Nikolaos Themelis.

4.4 Correcting for wind resistance

The power needs to be corrected to account for the added wind resistance of each data point. This is necessary to ensure that the additional power due to wind that each datapoint requires are not considered.

The draft of each data point had to be compared to the reference draft, in order to calculate the reference height above the waterline.

- $\Delta T = T_{ref} - T$

Equation 4-4

- $A = A_{ref} - \Delta T * B$

Equation 4-5

- $Z\alpha = Z\alpha_{ref} - \Delta T$

Equation 4-6

- $Z_{ref} = \frac{A_{ref} * (Z_{ref,ref} + \Delta T) + 0,5 * B * \Delta T^2}{A}$

Equation 4-7

Where:

$\Delta T(m)$: The difference between Tref and T(measured)
$Aref\ (m2)$: transverse area
$B(m)$: Ship's beam
$Z_{a,ref}\ (m)$: anemometer height above the waterline for Tdesign
$Zref,ref(m)$: reference height above waterline for Tdesign

Speed over ground is the GPS speed.

The real wind speed at anemometer height is given by the reports.

Next, the real wind direction was calculated using the following formula:

$$\psi wt = tan^{-1}\left(\frac{V_{wr} * \sin(\psi wr + \psi o) - V_g * \sin(\psi o)}{V_{wr} * \cos(\psi wr + \psi o) - V_g * \cos(\psi o)}\right), \quad V_{wr} * \cos(\psi wr + \psi o) - V_g * \cos(\psi o) \geq 0$$

Equation 4-8

$$\psi wt = tan^{-1}\left(\frac{V_{wr} * \sin(\psi wr + \psi o) - V_g * \sin(\psi o)}{V_{wr} * \cos(\psi wr + \psi o) - V_g * \cos(\psi o)}\right) + 180, \quad V_{wr} * \cos(\psi wr + \psi o) - V_g * \cos(\psi o) \leq 0$$

Equation 4-9

Having calculated these values we are able to calculate the real wind speed at the reference height using the following formula:

$$v_{wt,ref} = v_{wt}\left(\frac{Z_{ref}}{Z_a}\right)^{1/7}$$

Equation 4-10

Where:
$Zref\ (m)$ reference height above waterline
$Za\ (m)=43.48m$: the anemometer height above the design draft waterline (taken from GA)

Then, the relative wind speed at the reference height were calculates as per below:

$$V_{wr,ref} = \sqrt{V_{wt,ref}^2 + V_g^2 + 2 * V_{wt,ref} * V_g * cos\ (\psi_{wt} - \psi_o)}$$

Equation 4-11

$$\psi_{wr,ref} = tan^{-1}\left(\frac{V_{wt,ref} * sin(\psi_{wt} - \psi_o)}{V_g + V_{wt,ref} * cos(\psi_{wt} - \psi_o)}\right), \quad V_g + V_{wt,ref} * cos\ (\psi_{wt} - \psi_o) \geq 0$$

Equation 4-12

$$\psi_{wr,ref} = tan^{-1}\left(\frac{V_{wt,ref} * sin(\psi_{wt} - \psi_o)}{V_g + V_{wt,ref} * cos(\psi_{wt} - \psi_o)}\right) + 180, \quad V_g + V_{wt,ref} * cos\ (\psi_{wt} - \psi_o) < 0$$

Equation 4-13

$V_{wr,ref}$ was calculated only for $V_{wt,ref}$<9 m/s.

Using Table 7 for the wind resistance coefficient from the Trim & Stability booklet (not different for BALLAST and LADEN)

Degrees	Crw
0	0.734
10	0.714
20	0.703
30	0.627
40	0.504
50	0.326
60	0.264
70	0.206
80	0.218
90	0.287
100	0.173
110	-0.081
120	-0.313
130	-0.558
140	-0.725
150	-0.839
160	-0.859
170	-0.761
180	-0.736

Table 7 Wind Resistance Coefficient for given wind direction

The data from Table 7 are visualized in Figure 5.

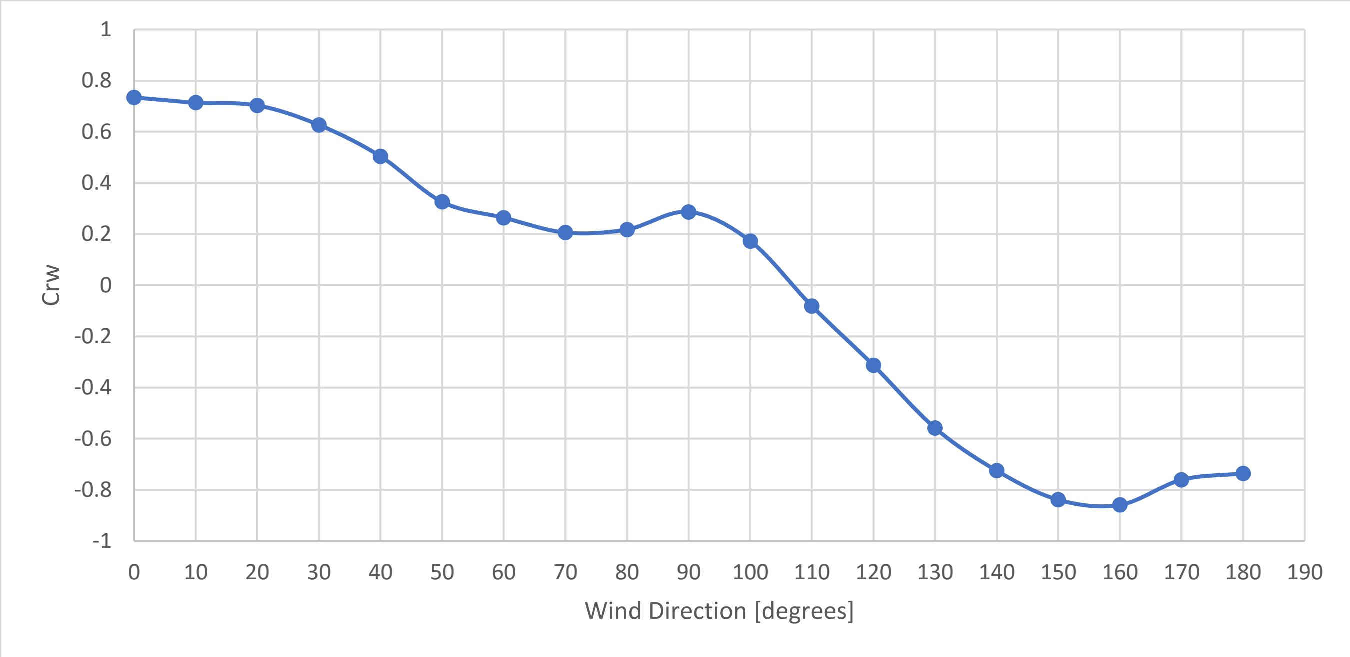

Figure 5 – The Wind Resistance Coefficient as a function of Wind Direction

Having determined the corresponding Crw for every datapoint. We are able to determine the corrected Power which will result by removing the power due to wind ΔPw from the Power Pd.

The following formulas will be used.

- $P_{D,corr} = P_D - \Delta P_w$

Equation 4-14

- $\Delta P_w = \frac{(R_{rw} - R_{0w})v_g}{n_{DO}} + P_D(1 - \frac{n_{DM}}{n_{DO}})$

Equation 4-15

- $R_{rw} = \frac{1}{2}\rho_\alpha v_{wr,ref}^2 A C_{rw}(\psi_{wr,ref})$

Equation 4-16

- $R_{0w} = \frac{1}{2}\rho_\alpha v_g^2 A C_{0w}(0)$

Equation 4-17

Where, $C_{0w}(0)$=0.734
ΔP_w (w): Wind correction,
R_{rw} (N): Resistance due to relative wind speed,
R_{0w} (N): wind resistance due to ship's movement, when wind is absent,
v_g (m/s): Speed over ground,
$v_{wr,ref}$ (m/s) : relative wind speed at reference height,
C_{rw}: Wind resistance coefficient based on relative wind direction,

C_{0w}: Wind resistance coefficient at head wind,
ρ_{α} (kg/m^3): air density,
A (m^2): Transverse projected area,
n_{DO} : Propulsion Coefficient at still water, for the purposes of this thesis will be considered equal to 0.7
n_{DM} : Propulsion Coefficient at actual condition, for the purposes of this thesis will be considered equal to 0.7

4.5 Corrections for discrepancies from reference displacement

Now, the Power at reference displacement needs to be calculated.

To determine the reference power the following Equation 4-18 must be used.

$$P_{(ref)} = P_{d,corr} \left(\frac{\Delta_{d(ref)}}{\Delta_{act}} \right)^{2/3}$$

Equation 4-18

Having corrected the datapoints for displacement differences the trendline extracted from the Pref-V, displays how the vessel is expected to consume power at a given speed at reference sailing conditions.

5 Application for different sailing conditions

To evaluate vessel's performance, the above must be applied for both loading conditions (ballast and laden) with the ALS turned on and off respectively. Thus, four modes of operation will be examined.

1. Ballast with ALS Off
2. Ballast with ALS On
3. Laden with ALS Off
4. Laden with ALS On

5.1 Ballast with ALS in operation

Using the aforementioned methodology, the P-V reference curve can be extracted. In the following Figure 6 appear two P-V curves, showing the measured Power and the Corrected Power at reference conditions (corrected for wind & draft differences). Showing the effect of those corrections.

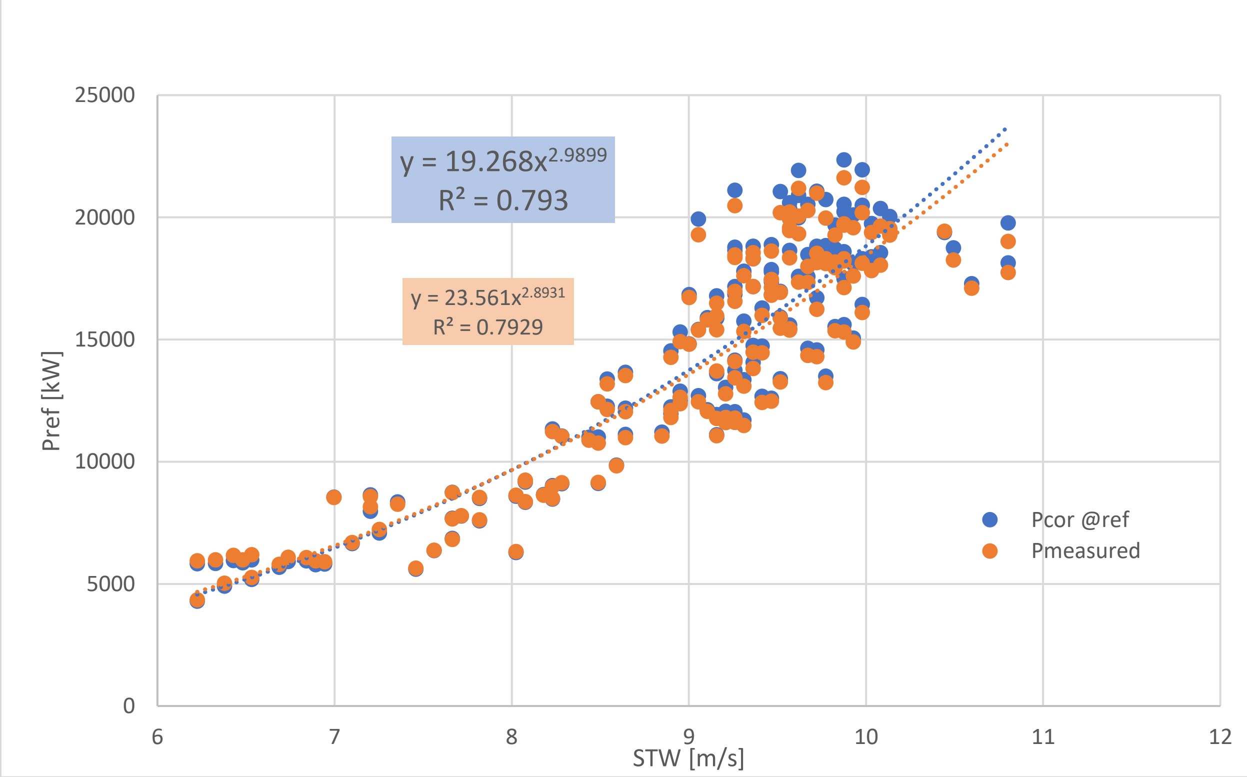

Figure 6 - P-V curves at reference Ballast sailing conditions and as measured with ALS On

The reference draft for Ballast with ALS On condition is $T_{B\text{-}On,ref}$ =8.90m. The reference P-V curve can be described by P=a*V^b. Where for Power in kW and Speed in m/s is $P = 19.268 * V^{2.9899}$

5.2 Ballast without ALS in operation

Using the aforementioned methodology, the expected P-V reference curve can be extracted, see Figure 7.

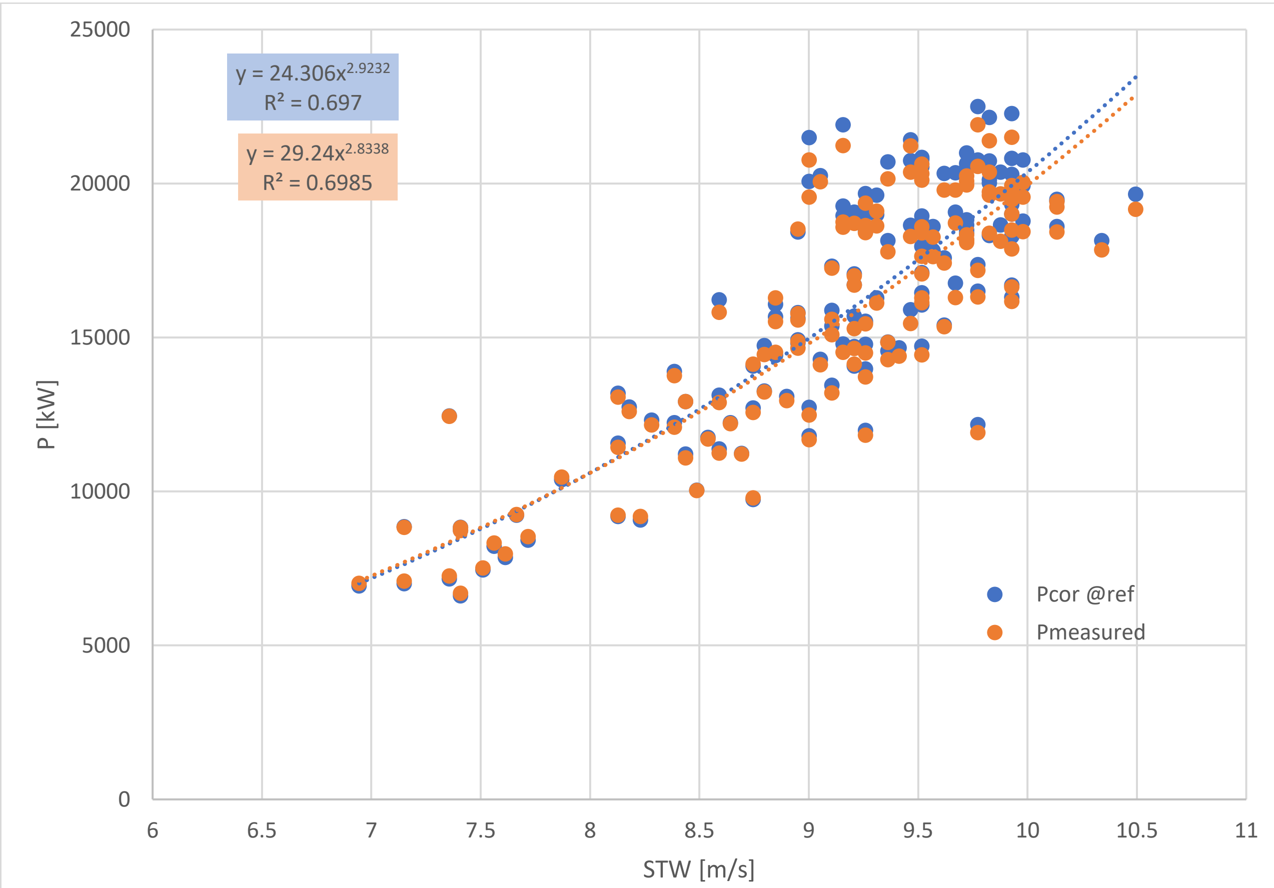

Figure 7 - P-V curves at reference sailing conditions and as measured with ALS Off for Ballast loading condition

The reference draft for Ballast with ALS Off condition is $T_{B\text{-}OFF,\ Ref}$= 8.9m. The reference P-V curve can be described by P=a*V^b. Where for Power in kWs and Speed in m/s is $P = 24.306 * V^{2.9232}$

5.3 Ballast Condition

Having calculated the above, we are able to extract useful information to assess the performance of the vessel.

Initially, for ballast voyages with the ALS turned on and off, a histogram of the vessel's speed profile can be generated, see Figure 8. The histogram provides basic information about the vessel's speed and proves that the operation of ALS takes place in comparable conditions. The information provided by the speed profile enables us to determine the ship's average speed, maximum speed and speed distribution overtime.

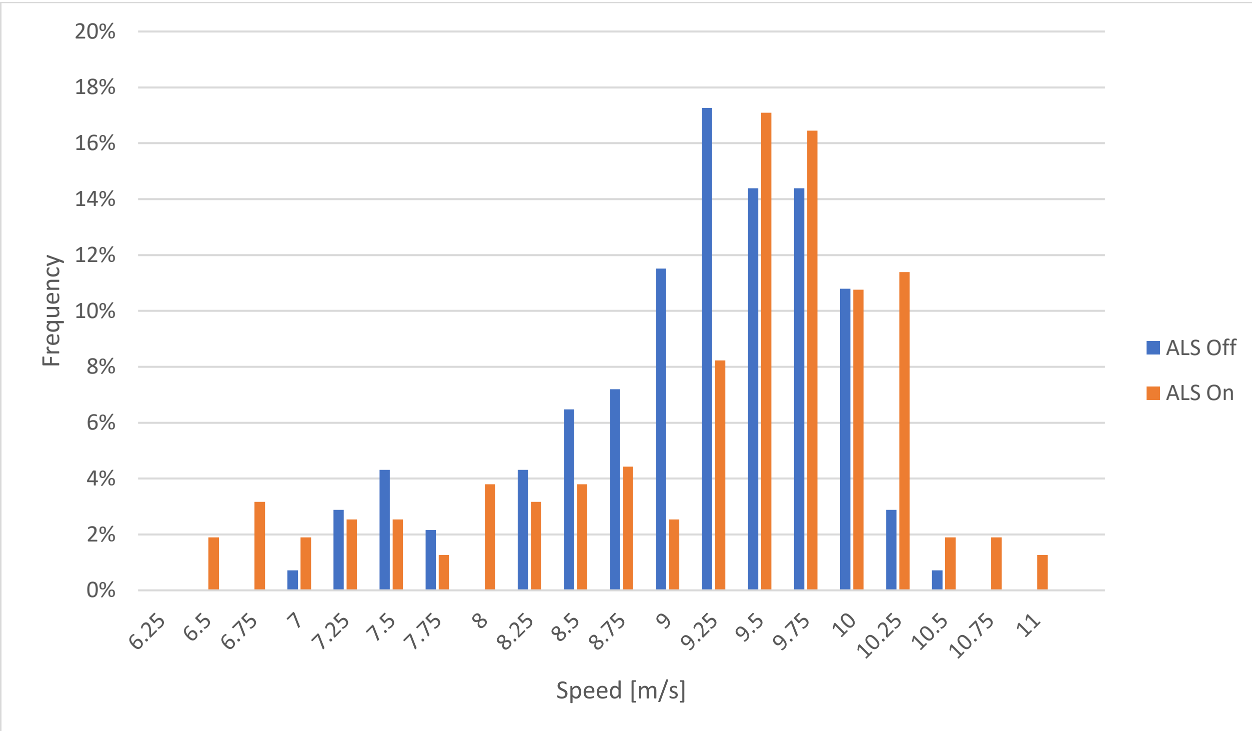

Figure 8 Speed Profile for ALS On/Off at ballast condition

Another chart that provides insight into the ship's performance is the wind profile histogram. It is generated by the frequency of the relative wind speed component projected on the ship's heading. $v_{wr,ref}*\cos(\psi_{wr,ref})$. By analyzing the frequency of the driving force of the wind, the wind profile histogram can reveal the typical wind conditions that a ship encounters during a given period, and the impact of those conditions on the ship's performance. This information is shown in Figure 9.

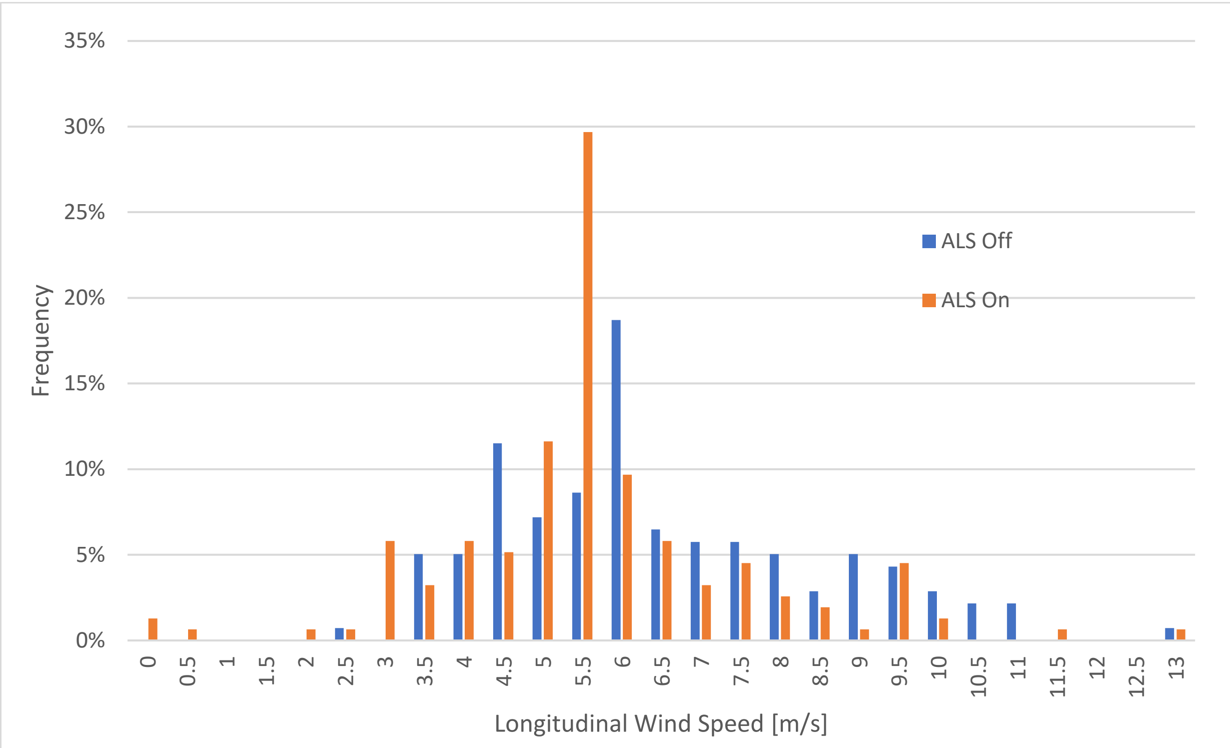

Figure 9 Wind Profile as encountered at Ballast condition for ALS On/Off

One useful method of evaluating a vessel's performance is to utilize the propeller law equation $P=c*rpm^3$. This equation allows for the determination of the relationship between engine power and RPM raised to the power of three, with the value of the "P/rpm^3" varying for each data point. By plotting these values against time, it is possible to gain insight into changes in the vessel's efficiency over time. A lower " P/rpm^3" value generally indicates higher efficiency, as the engine is producing more power per unit of RPM raised to the power of three.

As demonstrated in the following Figure 10, which displays plots of " P/rpm^3" over time for both ALS On and Off conditions. As seen below, the use of ALS generally provides a lower value of "P/rpm^3". Therefore, the use of ALS aids overall efficiency

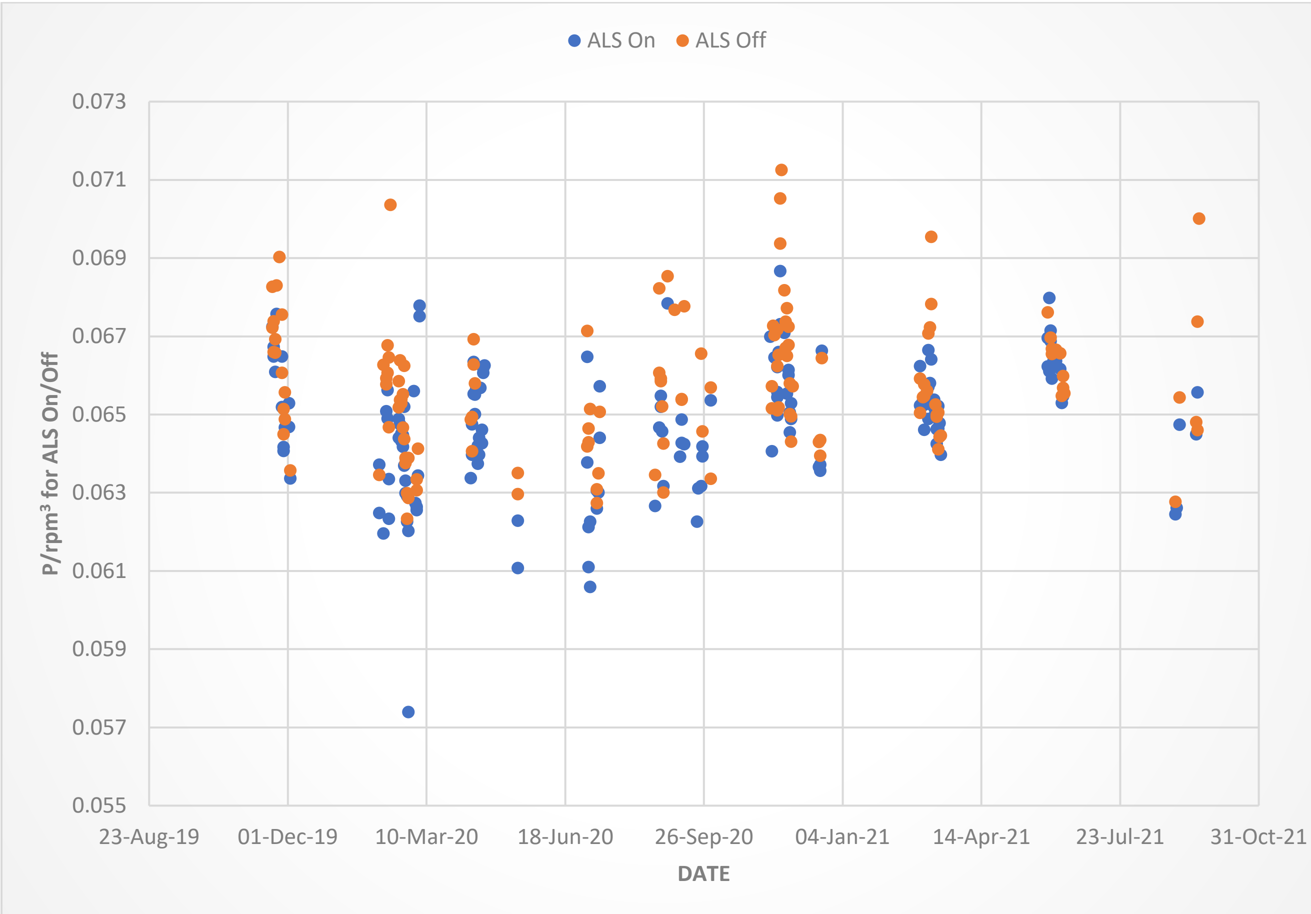

Figure 10 Propeller Coefficient comparison over time for Ballast loading condition

By conducting a comparison of the propeller law coefficient " P/rpm^3" values for a vessel under identical conditions, both with and without the air lubrication system (ALS) activated, Figure 11 is generated. Figure 11 displays the propeller law coefficient " P/rpm^3" values for ALS “On” on the y-axis and the corresponding values for ALS “Off” on the x-axis.

Any points that appear on the y=x line indicate that the propeller law coefficient " P/rpm^3" remains constant irrespective of whether the ALS system is active or inactive. Evidently, if the points appear below the y=x line, it indicates that the ALS system is contributing to enhanced efficiency of the vessel. Such an analysis can be particularly useful in understanding the performance benefits of ALS technology and optimizing its usage to maximize vessel efficiency.

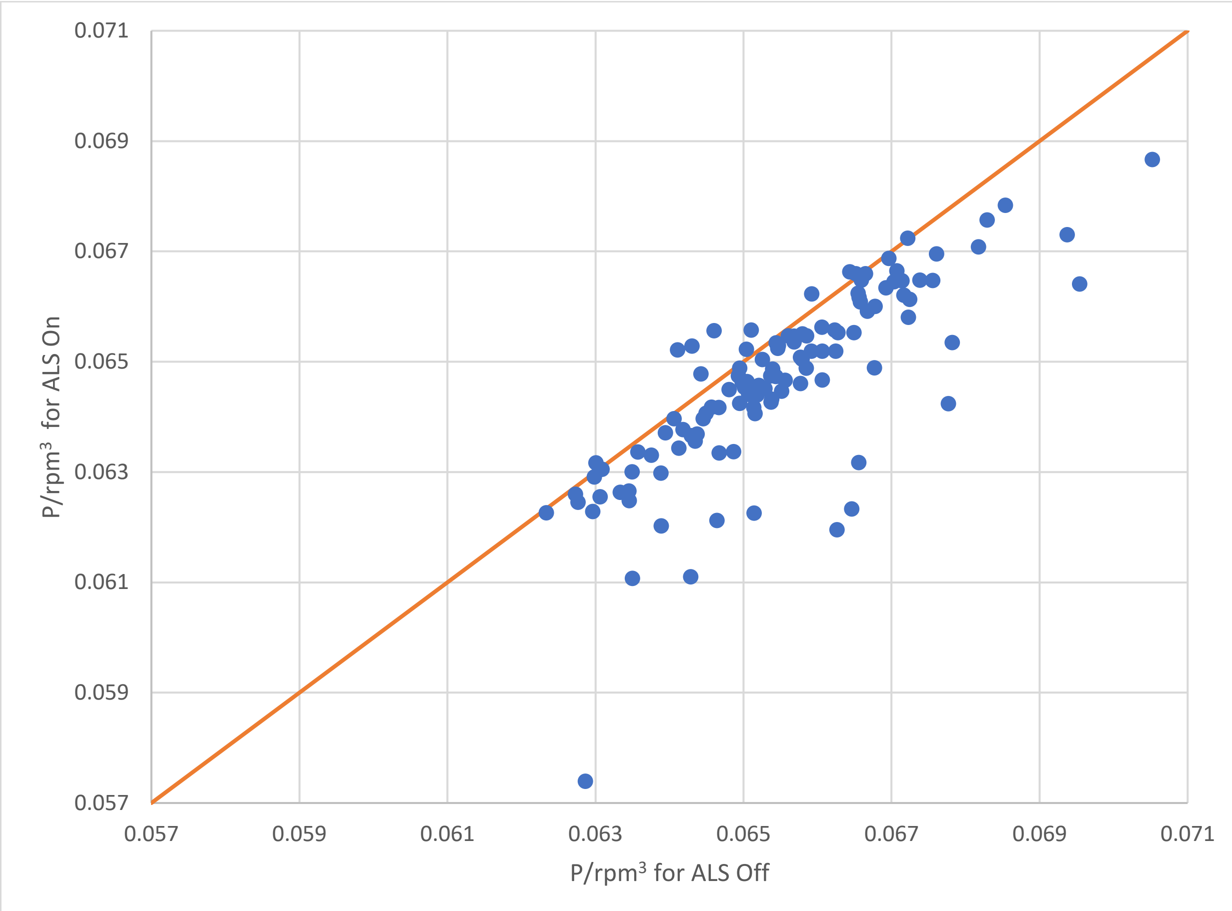

Figure 11 Propeller Coefficient comparison for ALS On/Of for Ballast loading Condition

5.4 Laden with ALS in operation

Using the aforementioned methodology, the P-V reference curve can be extracted as seen in Figure 12.

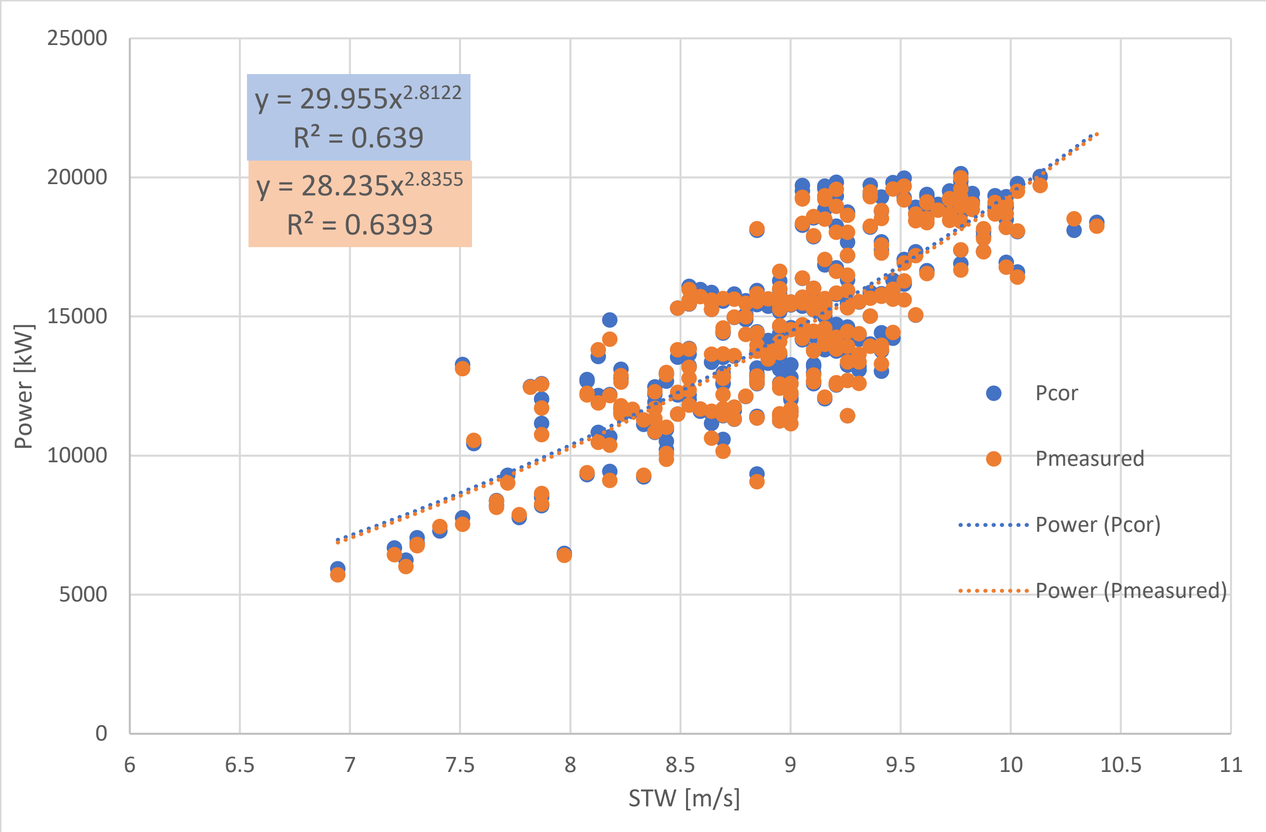

Figure 12 - P-V curves at reference Laden sailing conditions and as measured with ALS On.

The reference draft for Laden with ALS On condition is $T_{L\text{-}On}$=10.3m. The reference P-V curve can be described by P=a*V^b. Where for Power in kW and Speed in m/s is $P = 29.955 * V^{2.8122}$

5.5 Laden without ALS in operation

Using the aforementioned methodology, the P-V reference curve can be extracted, as seen in Figure 13.

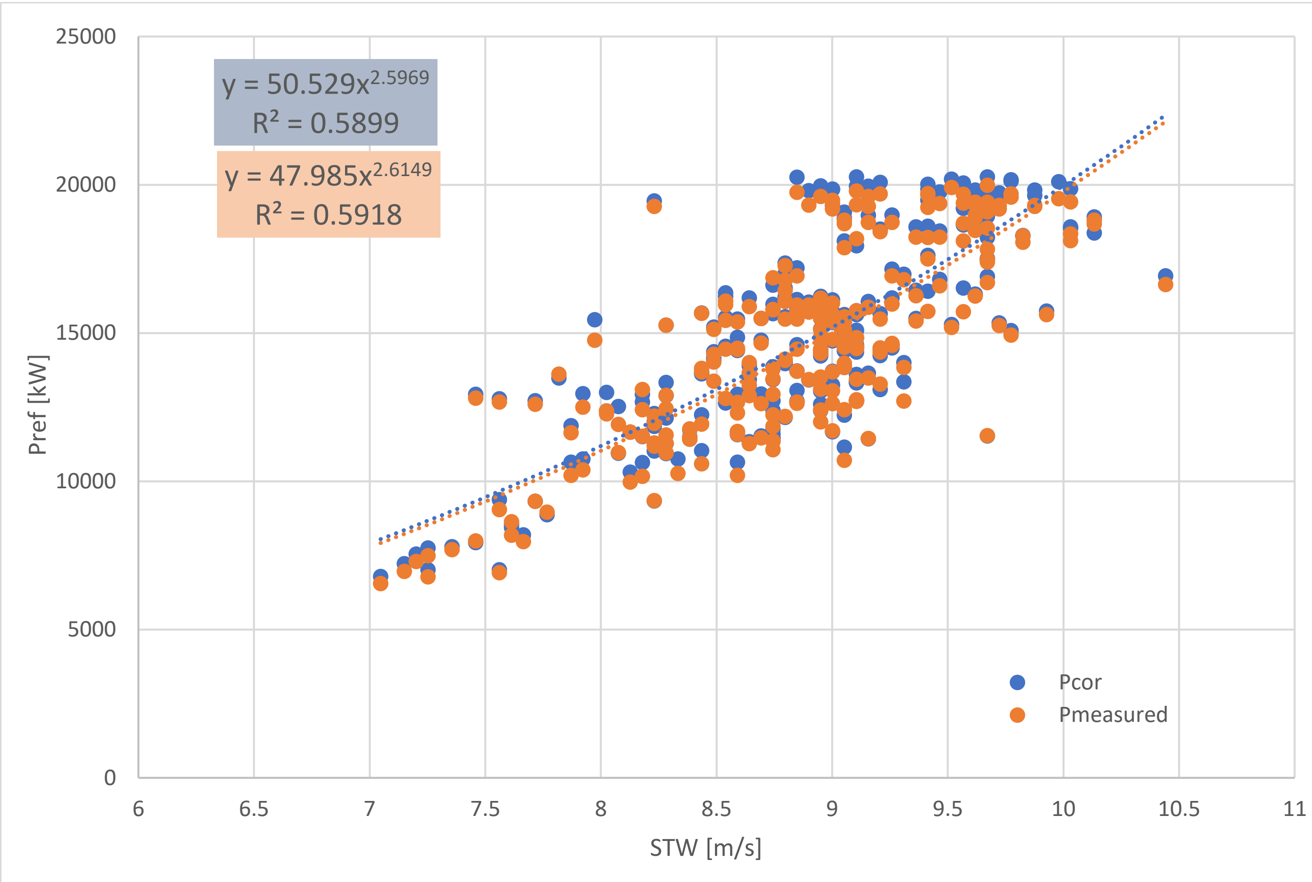

Figure 13 - P-V curves at reference Laden sailing conditions and as measured with ALS Off.

The reference draft for Laden with ALS Off condition is $T_{L\text{-}OFF,Ref}$=10.4m. The reference P-V curve can be described by P=a*V^b. Where for Power in kWs and Speed in m/s is $P = 50{,}529 * V^{2{,}5969}$.

5.6 Laden condition

For laden voyages with the ALS turned on and off, the vessel sails with the following speed profile, as seen in Figure 14:

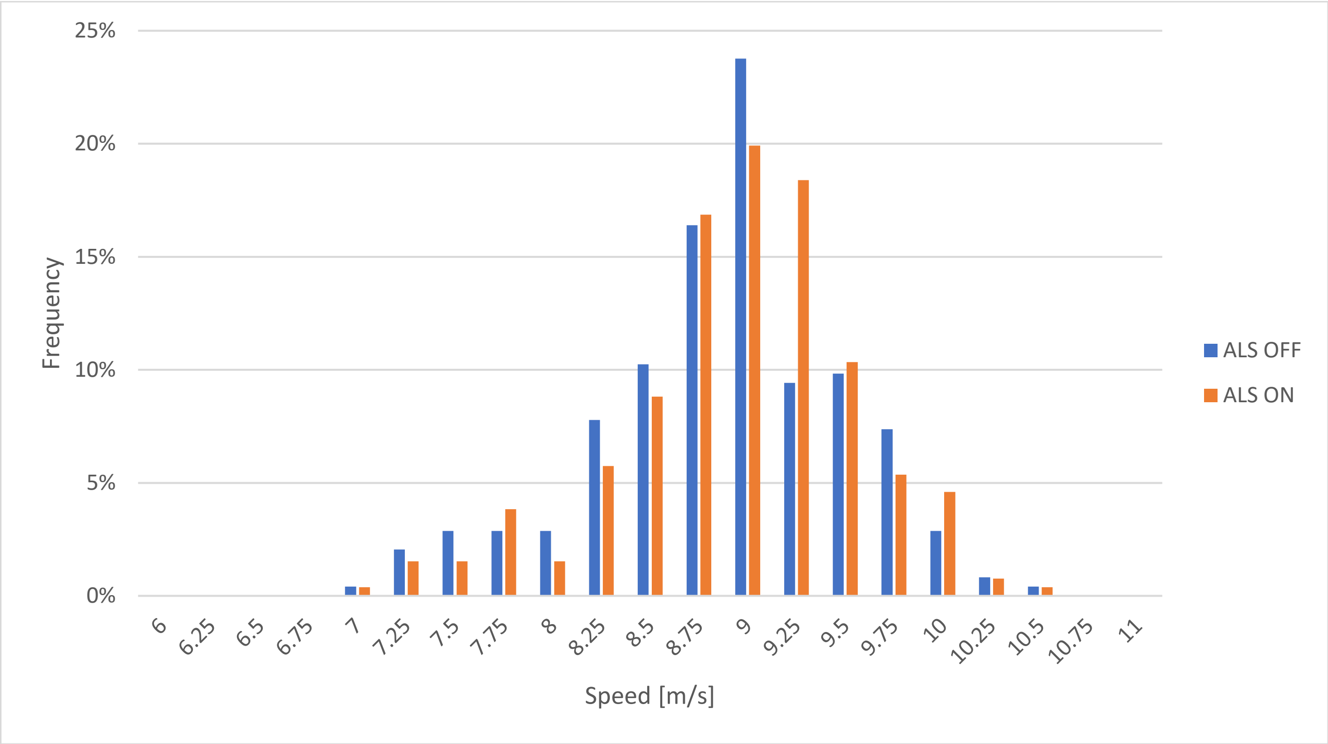

Figure 14 Speed Profile at Laden Condition with ALS On/Off

The wind profile histogram is presented below in chart 15. It is generated by the frequency of the relative wind speed component projected on the ship's heading. $V_{wr,ref}*\cos(\psi_{wr,ref})$, as seen in Figure 15.

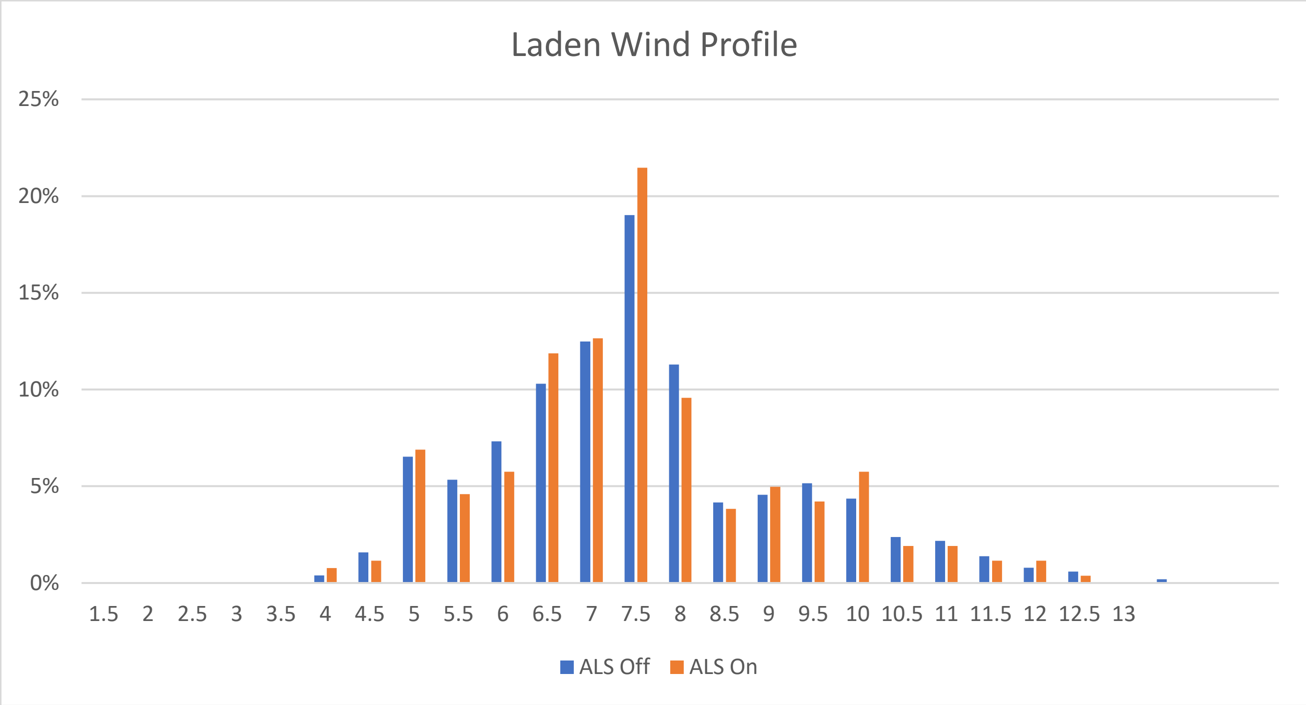

Figure 15 Wind Profile at Laden condition with ALS On/Off

As demonstrated in the following Figure 16, which displays plots of “P/rpm^3" over time for both ALS On and Off conditions, the use of ALS generally provides a lower value of “P/rpm^3”. Therefore, the use of ALS aids overall efficiency in laden as well.

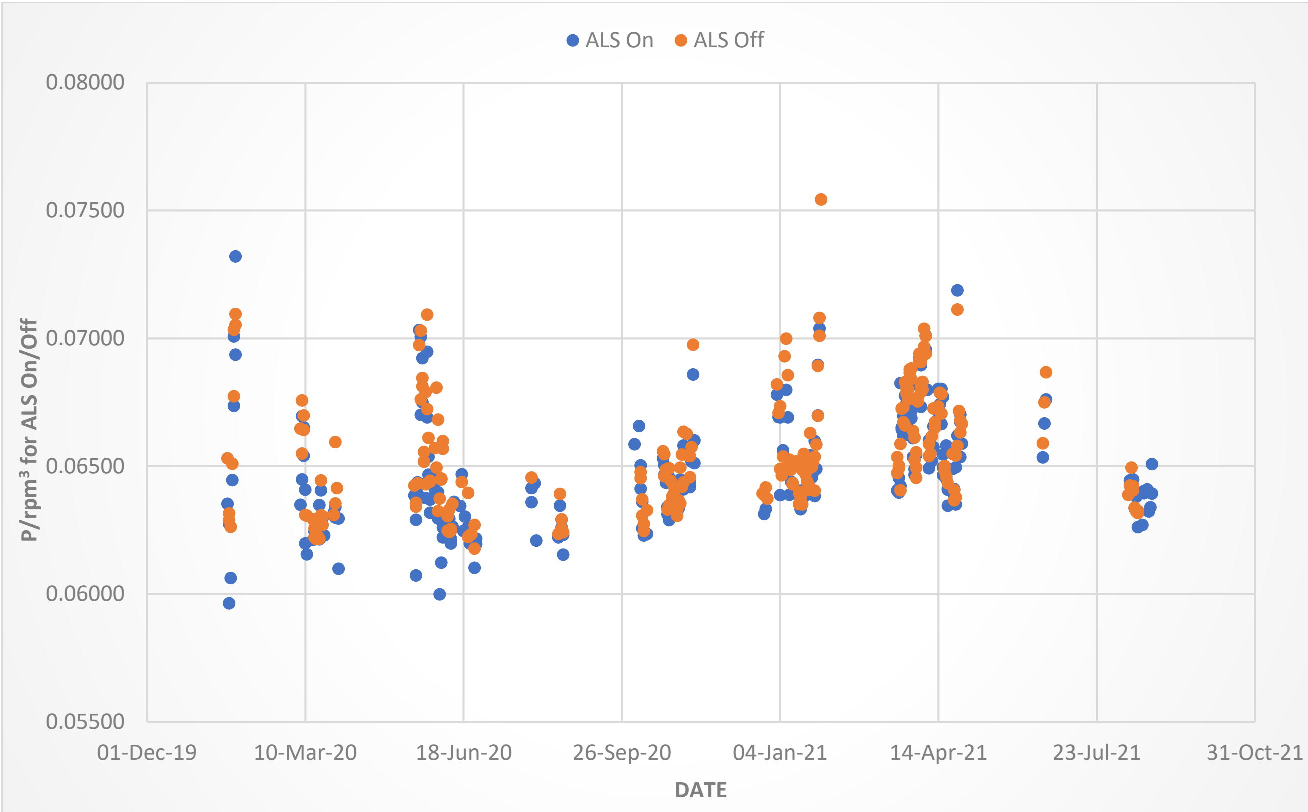

Figure 16 Propeller Coefficient comparison over time for Laden loading condition

The following Figure 17, provides the propeller coefficient for ALS On/Off. As mentioned previously, any points that appear on the y=x line indicate that the propeller law coefficient "P/rpm^3" remains constant irrespective of whether the ALS system is active or inactive. Evidently, if the points appear below the y=x line, it indicates that the ALS system is contributing to enhanced efficiency of the vessel. Such an analysis can be particularly useful in understanding the performance benefits of ALS technology and optimizing its usage to maximize vessel efficiency.

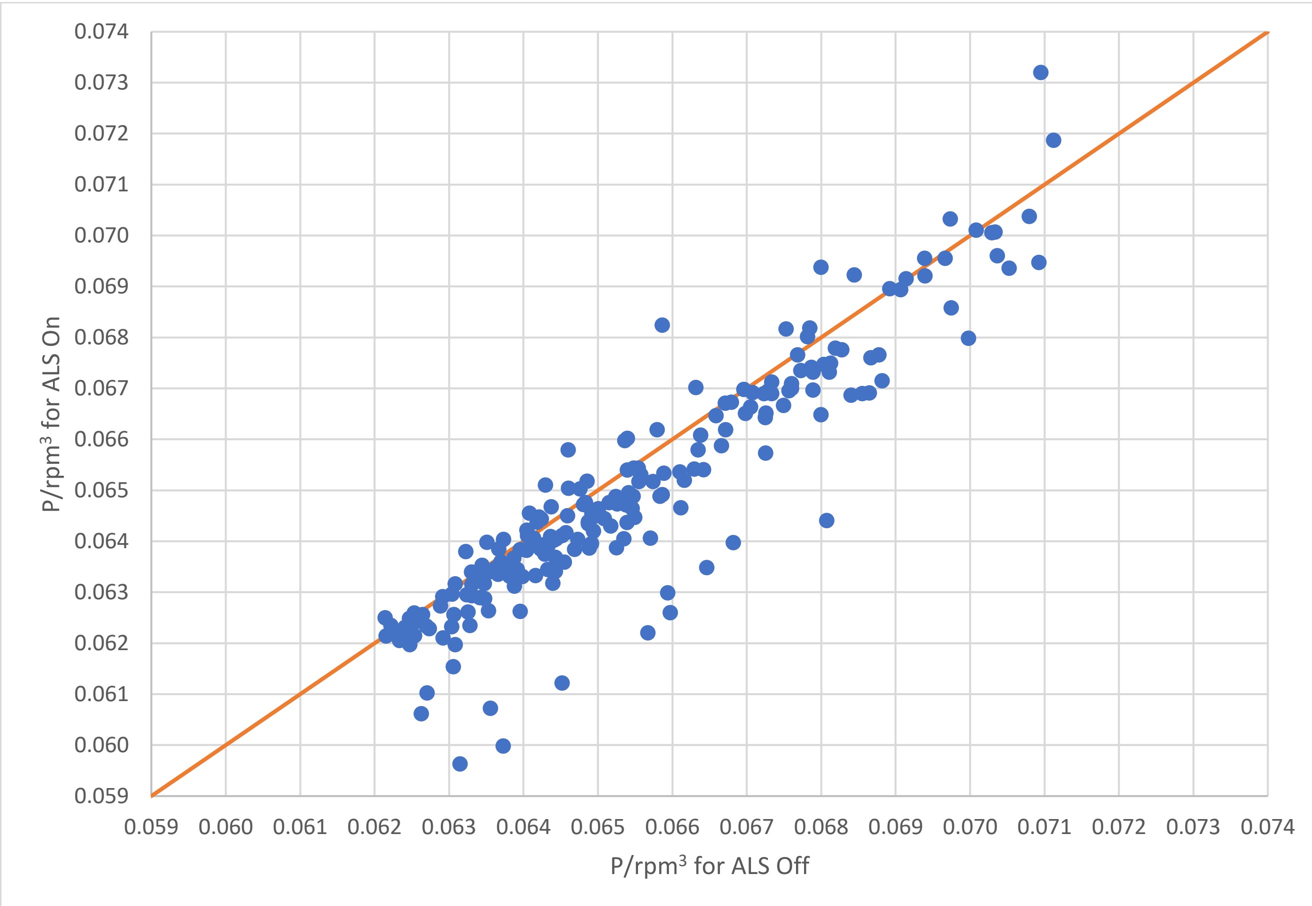

Figure 17 Propeller Coefficient comparison for ALS On/Off for Laden loading condition

In Figure 17 the majority of the points appear below the y=x line thus indicating an overall beneficial effect of the ALS.

6 Calculation of the ALS required Electric Load

In order to operate the ALS, an additional electric load is required from the Generator Engines. The additional electric load was determined by comparing the electric load required by the vessel at the same date and time, the same loading condition and same speed with the system turned on and off. The following results were produced, as seen in sample Table 8.

DATE LADEN	DAYTIME	ALS	GE1 Output [kW]	GE2 Output [kW]	GE3 Output [kW]	GE4 Output [kW]	STW [kn]	ALS Required Power [kW]
21-Jan-20	MORNING	OFF	1572	0	2141	0	16.7	
21-Jan-20	MORNING	ON	1830	0	2516	0	17	633
21-Jan-20	EVENING	OFF	1551	0	2143	0	17.2	
21-Jan-20	EVENING	ON	1817	0	2499	0	17.4	622
22-Jan-20	MORNING	OFF	1701	0	2195	0	17.2	
22-Jan-20	MORNING	ON	1932	0	2568	0	17.7	604
22-Jan-20	EVENING	OFF	1616	0	2209	0	14.3	
22-Jan-20	EVENING	ON	1819	0	2498	0	14.2	492
23-Jan-20	MORNING	OFF	1629	0	2125	0	14.7	
23-Jan-20	MORNING	ON	1879	0	2434	0	15.5	559
24-Jan-20	MORNING	OFF	1590	0	2174	0	16.9	
24-Jan-20	MORNING	ON	1842	0	2531	0	17.4	609
24-Jan-20	EVENING	OFF	1561	0	2130	0	15.4	
24-Jan-20	EVENING	ON	1790	0	2457	0	15.6	556
25-Jan-20	MORNING	OFF	1592	0	2165	0	15	
25-Jan-20	MORNING	ON	1855	0	2498	0	15.3	596
25-Jan-20	EVENING	OFF	1567	0	2142	0	15.6	
25-Jan-20	EVENING	ON	1786	0	2447	0	15.9	524
26-Jan-20	MORNING	OFF	1554	0	2119	0	14.7	
26-Jan-20	MORNING	ON	1798	0	2419	0	15.2	544

Table 8 Example of the method used for determining the ALS required additional electric load.

6.1 Additional Electric Load Required for Laden condition.

For laden condition, using the data produced from the above methodology, we were able to produce Figure 18 that displays the additional power required to operate the ALS over the total SHP without ALS $\frac{\Delta P_{ALS\,ON,OFF}}{SHP_{ALS\,off}}$ against speed:

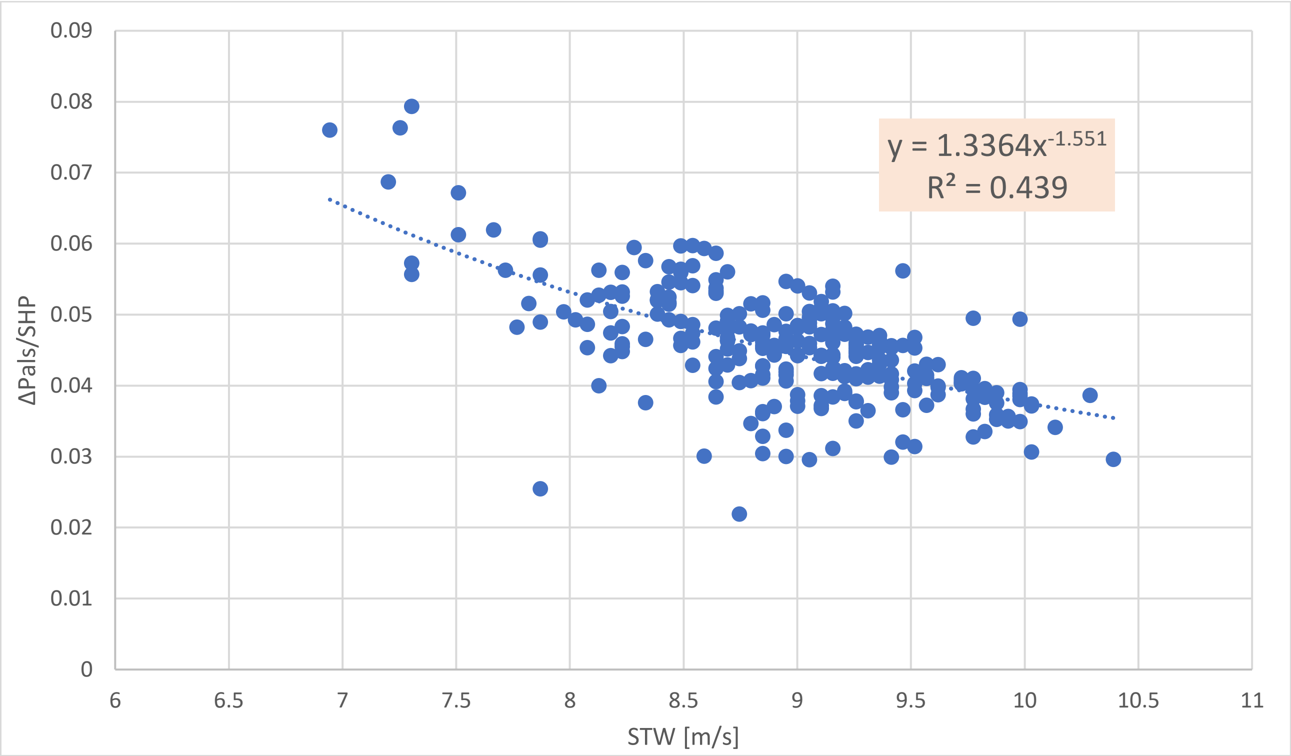

Figure 18 ALS Efficiency Ratio as a function of Speed Through Water for Laden

6.2 Additional Electric Load Required for Ballast condition.

For ballast condition, using the data produced from the above methodology, the following Figure 19 was produced:

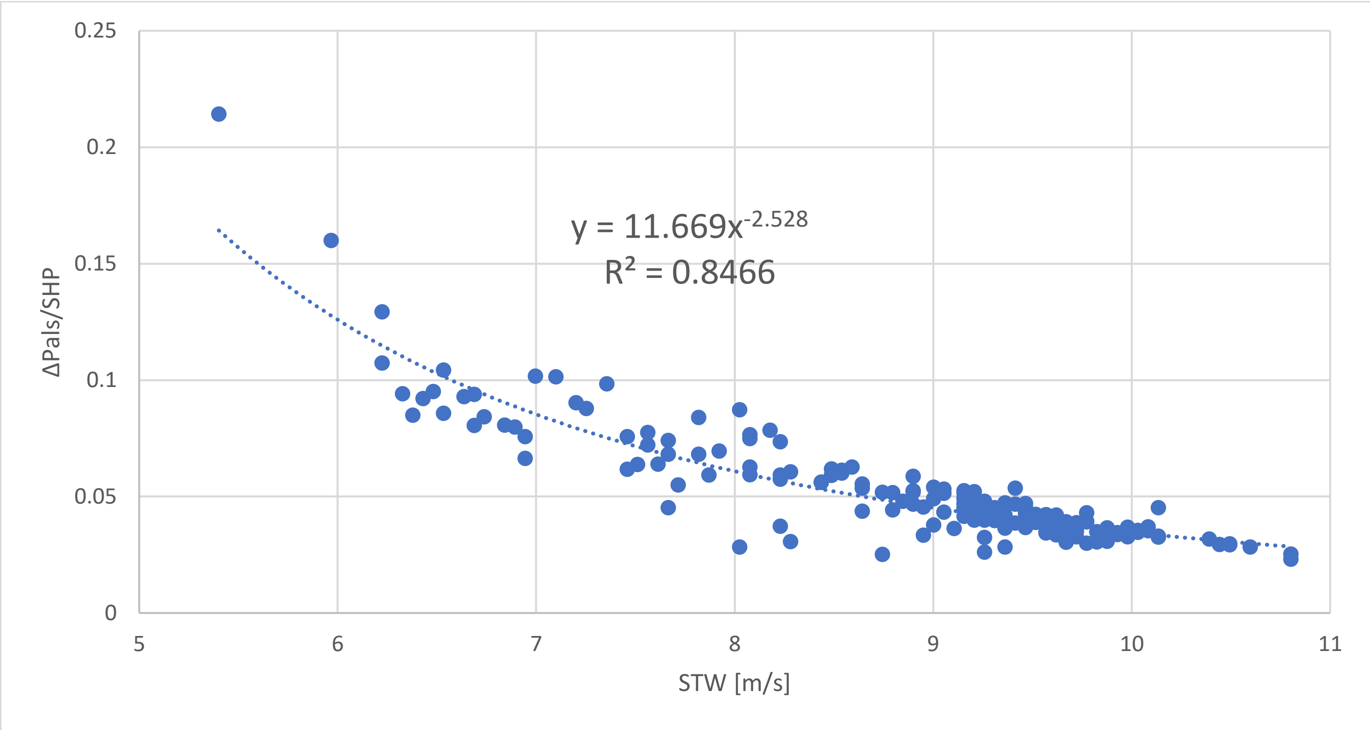

Figure 19 ALS Efficiency Ratio as a function of Speed Through Water for Ballast

The following figures show the usage profile of generator engines:

For ballast condition the usage profile of the generator engines is shown in Figure 20.

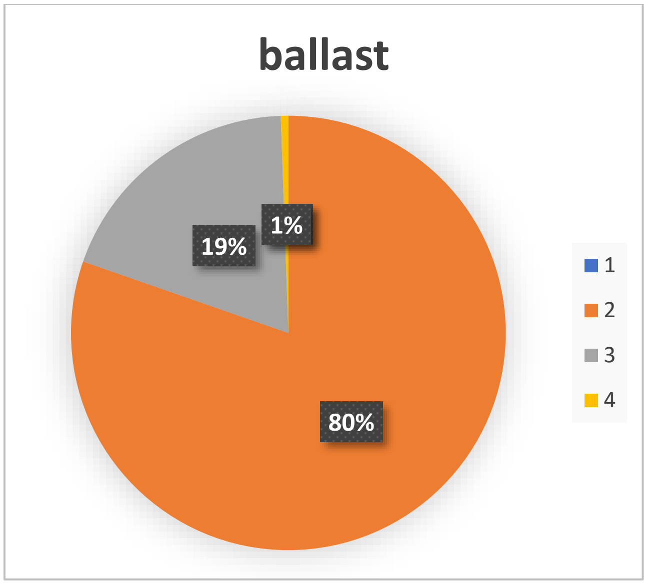

Figure 20 Usage profile of generator engines for Ballast condition

For laden condition the usage profile of the generator engines is shown in Figure 21.

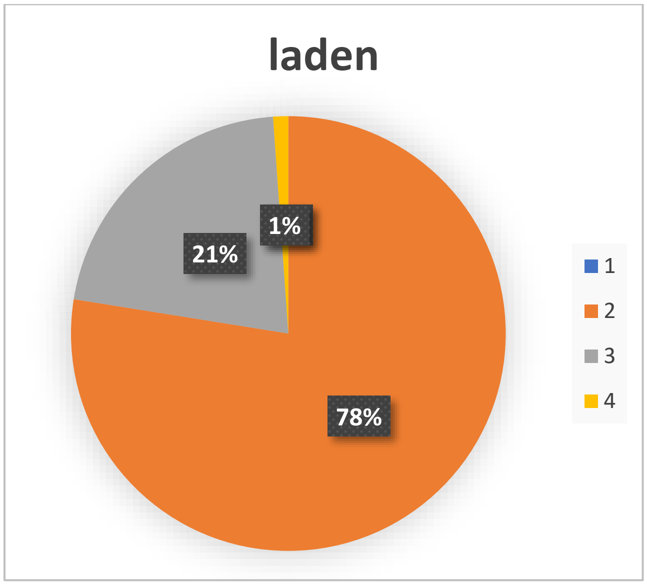

Figure 21 Usage profile of generator engines for Laden condition

Combined results are provided in Table 9 below:

No of GEs in operation	Ballast	Laden
1	0	0
2	80%	78%
3	19%	21%
4	1%	1%

Table 9 Usage profile for both loading conditions

7 Combined results

At this point, all the necessary information to determine the efficiency of the vessel is available. The table below contains the information as determined by the analysis and allows for easy comparison between sailing with ALS activated and deactivated.

To perform this comparison, the speed will increase by 0.5 knots commencing at 9.5 knots and culminating at 21 knots. Using the reference power curves generated for each condition, we are able to calculate the power needed for the MEs and the GEs at each speed.

This will allow us to determine the net savings to be expected at reference sailing conditions by the operation of ALS, and the optimal range of speeds for maximum efficiency. The power savings achieved for ALS on vs ALS off are shown in the green columns.

7.1 Calculation of Power Savings

The ME savings due to ALS Operation were calculated using the following formula:

$$ME_{savings} = \frac{P_{Off} - P_{On}}{P_{Off}} * 100\%$$

Equation 7-1

However, the operation of the ALS requires the supply of additional power from the Generator Engines. Thus the Net Power Savings are calculated as per the following:

$$Net\ Savings = ME_{savings} + P_{req.\ for\ ALS}/P_{ALS,Off}$$

Equation 7-2

7.1.1 Ballast Power Savings

Table 10 contains the calculations for savings due to ALS operation during ballast loading condition.

		Power [kW]	ALS Additional Power vs Poff [%]	Power [kW]	ALS Power [kW]	Savings [%]	Savings [%]
	Condition	B ON		B OFF	B ON	MEs	GROSS
Speed [kn]	Speed [m/s]						
9.5	4.8868	2212.85	21.14%	2511.14	530.89	11.88%	-9.26%
10	5.144	2579.62	18.57%	2917.35	541.76	11.58%	-6.99%
10.5	5.4012	2984.76	16.42%	3364.57	552.31	11.29%	-5.13%
11	5.6584	3430.17	14.59%	3854.67	562.55	11.01%	-3.58%
11.5	5.9156	3917.74	13.04%	4389.55	572.52	10.75%	-2.29%
12	6.1728	4449.38	11.71%	4971.08	582.23	10.49%	-1.22%
12.5	6.43	5026.97	10.56%	5601.13	591.70	10.25%	-0.31%
13	6.6872	5652.42	9.57%	6281.56	600.95	10.02%	0.45%
13.5	6.9444	6327.62	8.70%	7014.23	609.98	9.79%	1.09%
14	7.2016	7054.46	7.93%	7800.99	618.81	9.57%	1.64%
14.5	7.4588	7834.83	7.26%	8643.69	627.45	9.36%	2.10%
15	7.716	8670.63	6.66%	9544.18	635.91	9.15%	2.49%
15.5	7.9732	9563.75	6.13%	10504.27	644.21	8.95%	2.82%
16	8.2304	10516.08	5.66%	11525.82	652.34	8.76%	3.10%
16.5	8.4876	11529.50	5.24%	12610.65	660.32	8.57%	3.34%
17	8.7448	12605.92	4.86%	13760.58	668.16	8.39%	3.54%
17.5	9.002	13747.22	4.51%	14977.43	675.86	8.21%	3.70%
18	9.2592	14955.28	4.20%	16263.01	683.42	8.04%	3.84%
18.5	9.5164	16232.00	3.92%	17619.15	690.86	7.87%	3.95%
19	9.7736	17579.27	3.67%	19047.63	698.18	7.71%	4.04%
19.5	10.0308	18998.96	3.43%	20550.27	705.39	7.55%	4.12%
20	10.288	20492.97	3.22%	22128.88	712.48	7.39%	4.17%
20.5	10.5452	22063.19	3.02%	23785.23	719.47	7.24%	4.22%
21	10.8024	23711.49	2.85%	25521.13	726.35	7.09%	4.24%

Table 10 Combined results for Power Savings for Ballast condition for ALS On/Off

7.1.2 Laden Power Savings

Table 11 contains the calculations for savings due to ALS operation during laden loading condition.

		Power [kW]	ALS Additional Power vs Poff [%]	ALS Power [kW]	ALS Power [kW]	Savings [%]	Savings [%]
	Condition	L ON		L OFF	L ON	MEs	GROSS
Speed [kn]	Speed [m/s]						
9.5	4.8868	2595.04	11.41%	3110.77	354.82	16.58%	5.17%
10	5.144	2997.71	10.53%	3554.01	374.38	15.65%	5.12%
10.5	5.4012	3438.57	9.77%	4034.08	393.98	14.76%	5.00%
11	5.6584	3919.17	9.09%	4552.09	413.62	13.90%	4.82%
11.5	5.9156	4441.04	8.48%	5109.10	433.30	13.08%	4.59%
12	6.1728	5005.68	7.94%	5706.16	453.03	12.28%	4.34%
12.5	6.43	5614.62	7.45%	6344.30	472.79	11.50%	4.05%
13	6.6872	6269.33	7.01%	7024.54	492.59	10.75%	3.74%
13.5	6.9444	6971.31	6.61%	7747.86	512.42	10.02%	3.41%
14	7.2016	7722.02	6.25%	8515.26	532.29	9.32%	3.06%
14.5	7.4588	8522.93	5.92%	9327.70	552.18	8.63%	2.71%
15	7.716	9375.48	5.62%	10186.14	572.11	7.96%	2.34%
15.5	7.9732	10281.13	5.34%	11091.51	592.08	7.31%	1.97%
16	8.2304	11241.29	5.08%	12044.74	612.07	6.67%	1.59%
16.5	8.4876	12257.40	4.84%	13046.75	632.09	6.05%	1.21%
17	8.7448	13330.87	4.63%	14098.44	652.13	5.44%	0.82%
17.5	9.002	14463.10	4.42%	15200.70	672.21	4.85%	0.43%
18	9.2592	15655.51	4.23%	16354.43	692.31	4.27%	0.04%
18.5	9.5164	16909.48	4.06%	17560.48	712.43	3.71%	-0.35%
19	9.7736	18226.39	3.89%	18819.73	732.58	3.15%	-0.74%
19.5	10.0308	19607.64	3.74%	20133.03	752.76	2.61%	-1.13%
20	10.288	21054.57	3.59%	21501.21	772.96	2.08%	-1.52%
20.5	10.5452	22568.57	3.46%	22925.13	793.18	1.56%	-1.90%
21	10.8024	24150.99	3.33%	24405.60	813.43	1.04%	-2.29%

Table 11 Combined results for Power Savings for Laden condition for ALS On/Off

Using the above information, the P-V curves for both sailing conditions can be extracted, displaying the effect of ALS in Figure 22 and Figure 23Figure 23.

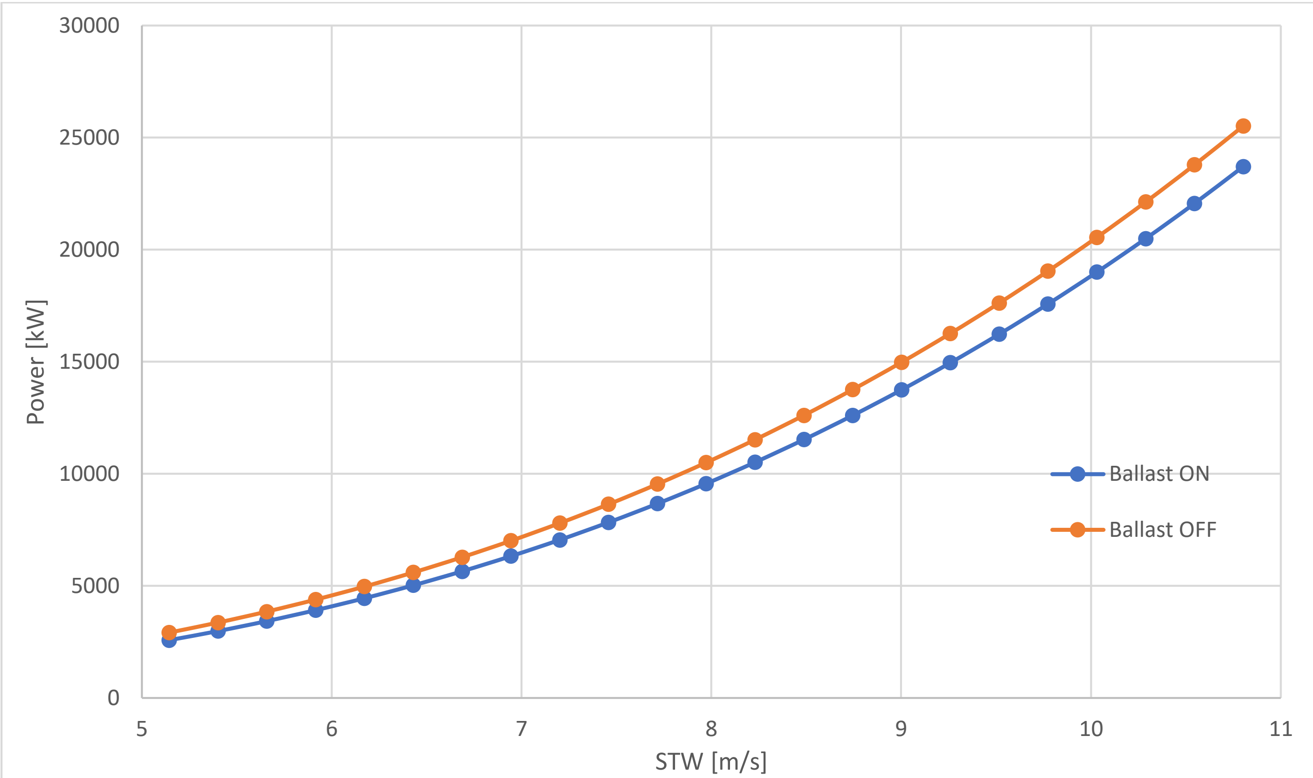

Figure 22 P-V curves at reference sailing conditions for Ballast condition with ALS On/Off

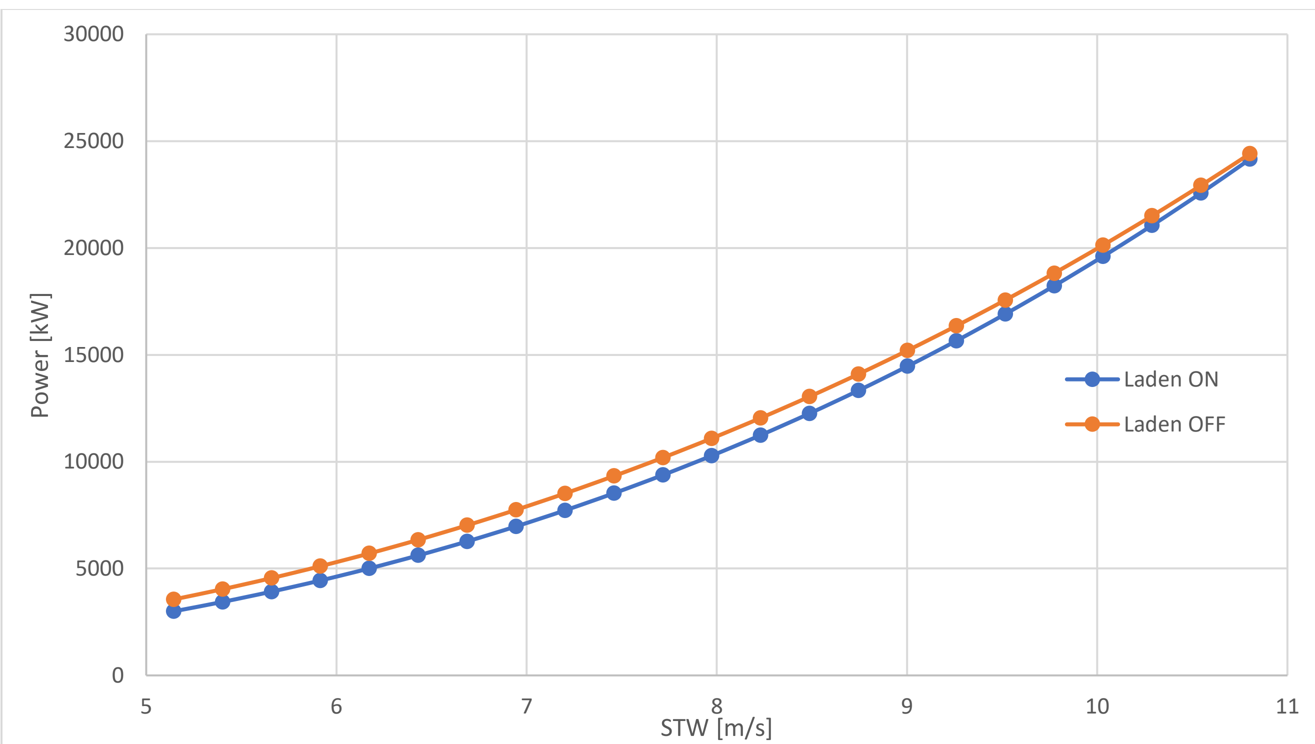

Figure 23P-V curves at reference sailing conditions for Laden condition with ALS On/Off

7.1.3 ALS Net savings for both loading conditions

Additionally, the Net savings achieved by ALS operation can be plotted against speed as seen in Figure 24. Allowing us to determine optimal operation for maximum savings.

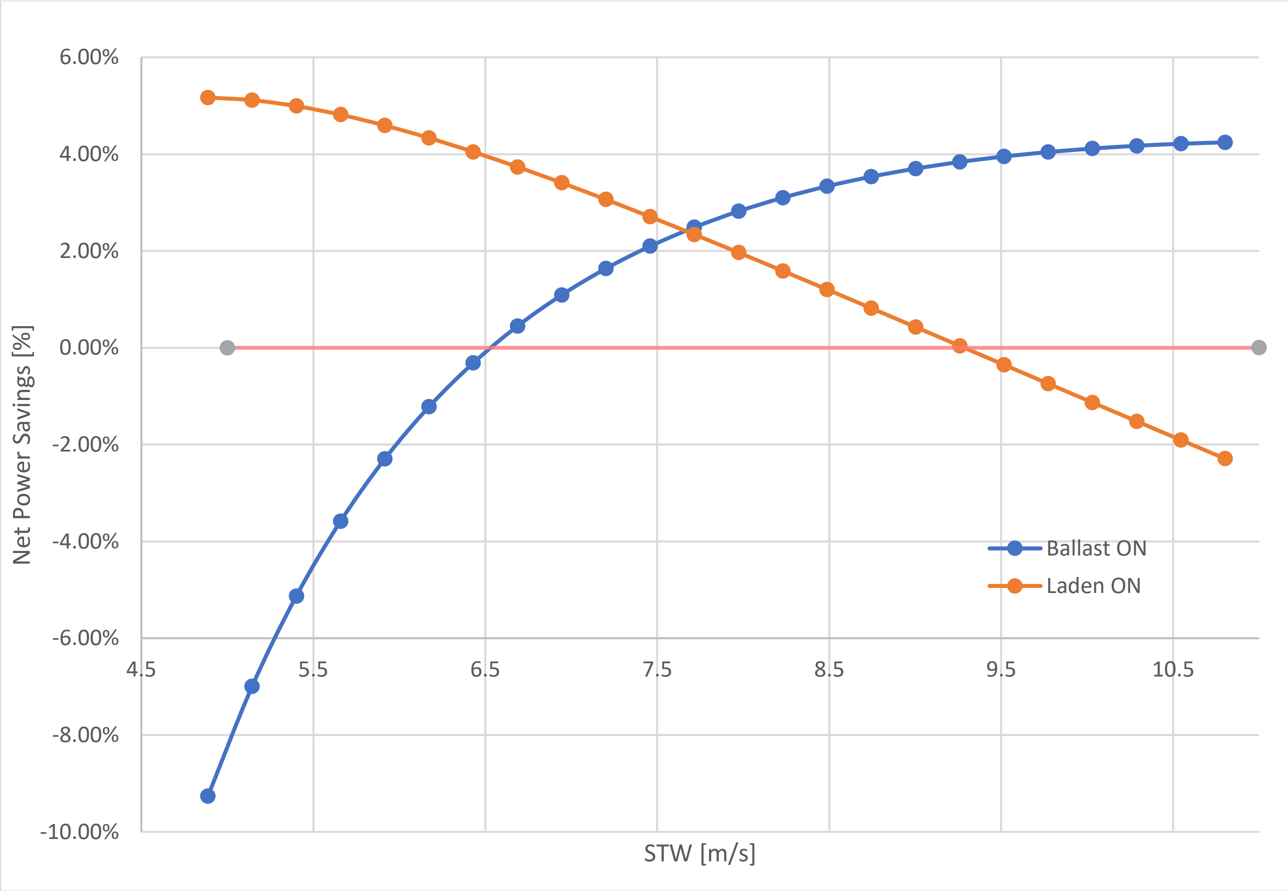

Figure 24 Net Power Savings due to ALS for both loading conditions

Figure 24 presented above reveals a positive correlation between speed and power savings for the ballast condition, indicating that greater speeds result in increased power savings. Conversely, the opposite trend is observed for the laden condition, as it is apparent that as speed increases, the level of savings decreases.

The increase in ALS power savings with increasing speed in the ballast condition can be explained by the fact that at higher speeds, the ALS becomes more effective in reducing the frictional resistance between the hull and the water. This results in a decrease in the power required and increases the power savings.

Conversely, in the laden condition, the increase in speed leads to a higher resistance due to the increased wetted surface of the vessel, resulting in a decrease in power savings as more power is required to overcome the increased resistance. The increased displacement of the vessel in the laden condition means that the air layer generated by the ALS may not be as effective in reducing frictional resistance enough to counter the increased resistance by the increased wetted surface, leading to a diminished impact on power savings.

8 Multiple Linear Regression

Regression analysis is a procedure for estimating the relationship between a dependent variable (the response) and one or more independent variables (the predictors) [17]. In this chapter of the thesis, the results produced by the previous methodology will be compared to the results produced by a multiple linear regression model.

8.1 Multiple linear regression

A population model for a multiple linear regression model that relates a response variable y to k predictor variables x can be written as:

$$y_i = \beta_0 + \beta_1 \cdot x_{i1} + \beta_2 \cdot x_{i2} + \cdots + \beta_p \cdot x_{ik} + \varepsilon_i$$

Equation 8-1

Where:
y_i: the i-th observation of the dependent variable
x_{ij}: the i-th observation of the j-th independent variable
β_0: the regression intercept term.
β_j: the slope coefficient of the j-th independent variable.
ε_i: the error term of the i-th observation (normal distribution).

For the purposes of this thesis a code in MATLAB was created [see appendix]. The operation of the code is described as per below:

First, the code reads an excel file containing one response variable ($P_{measured}$) and 7 predictors

- $Starboard\ Rudder\ Angle$ [rad]
- $Port\ Rudder\ Angle$ [rad]
- Longitudinal component of the relative wind speed at reference height i.e., $v_{wr,ref} \cdot cos(\psi_{wr,ref})$ [m/s]
- Relative wind direction at reference height $\psi_{wr,ref}$ [rad]
- Speed through water raised to the power of 3 STW^3 [$(m/s)^3$]
- ttrim
- Mean draft T_m

Then, the code determines the number of possible combinations using the above predictors: 127 different combinations (2^n-1, where n: number of predictors). [16]

Knowing the number of possible combinations, the quality of the regression model can be determined by employing the following criteria:

- R squared,
- Adjusted R squared,
- Mallows' Cp,
- AIC,

- BIC.

The above can help determine the best combination of predictors.

8.2 Predictors used.

The predictors that will constitute the regression model are the following:

8.2.1 Port and Starboard rudder angle

Rudder angle can affect the propeller's performance and the power required to reach a certain speed. Since the ship is a twin propeller LNG carrier it has two rudders one on the port side and a second on the starboard side of the vessel.

8.2.2 Speed through water (power of three)

Power consumption is dependent upon the required speed and acceleration. As the required speed increases, more power is needed to overcome water resistance. Using the speed through water raised to the power of 3 instead of the raw speed through water could potentially account for a non-linear relationship between speed and power. The selection of STW^3 is also enforced by the results in 5.1, 5.2, 5.4 and 5.5 where it can be seen that for $P=a*V^b$ b approaches 3. The selection of STW^3 improved the fit of the model and helped to better capture the effect of STW in power.

8.2.3 Mean Draft

Mean draft represents the average draft between the fore and aft peak. The draft affects hydrodynamics of the ship. A deeper draft results in increased resistance, which requires additional power to overcome it.

8.2.4 Trim

Trim, is the difference between the fore draft and the aft draft. It affects the ship's hydrodynamics. Trim affects ship resistance, thus it affects power needs.

8.2.5 The Longitudinal Component of the Relative Wind Speed

The Longitudinal Component of the Relative Wind Speed, meaning the component aligned with the ship's motion and longitudinal axis. The wind speed is crucial at determining power needs since a headwind increases ship resistance, while a tail wind reduces it.

8.2.6 Relative Wind Direction

The angle between the ship's heading and the direction from which the wind is blowing impacts the wind resistance, thus affects the power.

8.3 Determination of the optimal predictor combination

In order to predict the required power in the most efficient, accurate way, we need to determine the combination of predictors that determines the power best, using the criteria presented below.

The amount of possible combination of the seven subsets mentioned above can be calculated as following: [16]

$$number\ of\ combinations = 2^k - 1 = 2^7 - 1 = 127\ combinations$$

Equation 8-2

Where k is the number of predictors

8.3.1 R-squared (Coefficient of Determination)

R-squared, measures the variance in the dependent value (corrected Power) that is extracted by the independent variables (predictors). It ranges from 0 to 1, with 1 indicating that the model explains all the variance and 0 indicating no explanation.

$$R^2 = 1 - \frac{SS_{RES}}{SS_{tot}}$$

Equation 8-3

Where:
$SS_{tot} = \sum_i (y_i - \bar{y})^2$ The total sum of squared
$SS_{RES} = \sum_i (y_i - f_i)^2$ The sum of squares of residuals $e_i = y_i - f_i$
Where:
y_i : The dataset of the response value, in this case the corrected Power
f_i : The fitted values of the model for the corrected Power
$\bar{y}$: The mean of the observed data $\bar{y} = \frac{1}{n}\sum_i^n y_i$

8.3.2 Adjusted R-squared

Adjusted R-squared takes into account the number of predictors and the sample size to provide a more accurate measure of the model's explanatory power. It penalizes the addition of unnecessary predictors and adjusts R-squared accordingly. A higher R-squared indicates a better fit.

$$Adjusted\ R - squared = 1 - \frac{(1 - R^2)(n - 1)}{(n - k - 1)}$$

Equation 8-4

Where:
R^2 is the R-squared value
n is the sample size
k is the number of predictors in the model

8.3.3 Standard Errors

The SE column provides the standard errors associated with each coefficient estimate. It indicates the uncertainty or variability in the estimated coefficient.

$$SE = \frac{S}{\sqrt{\sum_i (x_i - \bar{x})^2}}$$

Equation 8-5

where S is the standard error of the model and is calculated as per the equation below:

$$S = \sqrt{\frac{\sum_i^N (x_i - \bar{x})^2}{n - 1}}$$

Equation 8-6

The standard error of the coefficient is always positive and it measures how precisely the model estimates the coefficient's unknown value. The smaller the standard error the more precise the estimate

8.3.4 tStat

The tStat column contains the t-statistics for each coefficient. The t-statistic is computed by dividing the estimated coefficient by its standard error and is used to test the null hypothesis that the true coefficient value is zero.

$$tStat = \frac{b}{SE}$$

Equation 8-7

8.3.5 Mallows' Cp

It measures the model quality regarding fit and simplicity. It compares the predicted values that would be obtained from the best possible model. The best regression model can be identified by comparing the Cp to p+1, where p is the number of predictors. The lower the Cp the better, while a Cp lower than p+1 indicates the model is unbiased and a good fit.

$$C_p = \frac{SS_{Res}}{MSE} - (n - 2k)$$

Equation 8-8

Where:

SS_{Res} : Sum of Squared Residuals

MSE : The Mean Squared Error $MSE = \frac{SS_{Res}}{n-k}$

n is the sample size

k is the number of predictors in the model

8.3.6 AIC (Akaike Information Criterion)

AIC is a measure of the model's goodness of fit while considering model complexity. It balances the trade-off between model accuracy and simplicity. AIC considers the likelihood of the model and adjusts it based on the number of parameters used. The best-fit model according to AIC is the one that explains the greatest amount of variation using the fewest possible independent variables. Lower AIC values indicate a better balance between fit and complexity.

$$AIC = -2 * ln(L) + 2k$$

Equation 8-9

Where:
L: is the likelihood of the model. Meaning the probability of obtaining the observed data given the parameters of the model. $L = p(x|\hat{\theta}, M)$, The propability that data x are explained by the model M, under certain model parameters θ.
k: is the number of predictors in the model.

8.3.7 BIC (Bayesian Information Criterion)

BIC, similar to AIC, evaluates model fit and complexity. BIC penalizes models with a large number of parameters more than AIC does, making it stricter in terms of model complexity. Like AIC, lower BIC values indicate a better trade-off between fit and complexity.

$$BIC = -2 * ln(L) + k * ln(n)$$

Equation 8-10

Where:
L: is the likelihood of the model
k: is the number of predictors in the model
n: is the sample size

8.3.8 pValue

This column provides the p-values associated with each coefficient. The p-value represents the probability of observing a t-statistic as extreme as the one calculated under the null hypothesis. Lower p-values indicate stronger evidence against the null hypothesis.

To determine whether each main effect and the interaction effect is statistically significant, the P-value of each term is compared to a significance level α that is usually set at 0.05. The alpha value indicates the percentage of the risk of concluding that an effect exists when it does not. If the P-value is greater than the selected significance level then the effect is not statistically significant, whereas if its equal or less then the effect of the term is statistically significant.

The P-value of the model as well as of each predictor is calculated with the help of T-value as follows:

$$pValue = 2 \cdot (1 - T(x|v)) = 2 \cdot \left(1 - \int_{-\infty}^{x} \frac{\Gamma\left(\frac{\nu+1}{2}\right)}{\Gamma\left(\frac{\nu}{2}\right)} \cdot \frac{1}{\sqrt{\nu \cdot \pi}} \cdot \frac{1}{\left(1 + \frac{t^2}{\nu}\right)^{\frac{\nu+1}{2}}} dt \right)$$

Equation 8-11

Where:

- x= T-value: the absolute t value of the model or the independent variable.
- v = n-1-p: the degrees of freedom of the error, for a model with n data points and p predictors.
- T: T-distribution's cumulative distribution function.
- Γ(x)=(x-1)! : the gamma function.

Alternatively, The P-value of the model as well as of each predictor is calculated with the help of F-value as follows:

$$pValue = 1 - F(x|v_1,\ v_2) = 1 - \int_0^x \frac{\Gamma\left(\frac{v_1 + v_2}{2}\right)}{\Gamma\left(\frac{v_1}{2}\right)\Gamma\left(\frac{v_2}{2}\right)} \cdot \left(\frac{v_1}{v_2}\right)^{\frac{v_1}{v_2}} \cdot \frac{t^{\frac{v_1}{2}-1}}{\left(1 + \frac{v_1}{v_2}t\right)^{\frac{v_1+v_2}{2}}} dt$$

Equation 8-12

where:

- x = F − value: the absolute f value of the model or the independent variable.
- v1: the degrees of freedom of the model (equal to the sum of independent variables) or of the independent variable (equals 1).
- v2 = n − 1 − p: the degrees of freedom of the error, for a model with n data points and p predictors.
- F: F-distribution's cumulative distribution function.
- Γ(x) = (x − 1)! : the gamma-function.

8.3.9 F-Value

Let y express the dependent variable and f present the fitted value which is predicted by the regression model. The F-value of the model is calculated as:

$$F - value = \frac{SS_{REG}/DF_{REG}}{SS_{RES}/DF_{RES}} = \frac{R^2}{1 - R^2} \cdot \frac{n - p - 1}{p}$$

Equation 8-13

where:

- SS_{REG} = Σ(fi − y̅)2 : the regression sum of squares.
- DF_{REG}= p : the degrees of freedom of the regression model and p is the number of the model's predictors.
- SS_{RES}= Σ(yi − fi)2 : the residual sum of squares.
- DF_{RES}= n − 1 − p : the degrees of freedom of the residuals (error) and n is the number of observations.

The F-value is also calculated for each independent variable as:

$$F - value = \frac{SS_{ADJREG}}{SS_{RES}/DF_{RES}} = \frac{SS_{ADJREG}}{S^2}$$

Equation 8-14

where:

- SS_{ADJREG} : the adjusted regression sum of squares of the independent variable.
- SS_{RES}= Σ(yi − fi)2 : the residual sum of squares.
- DF_{RES}= n − 1 − p : the degrees of freedom of the residuals (error) and n is the number of observations.

The adjusted regression sum of squares of each independent variable occurs as follows:

- The respective variable is removed from the model and a new model is formed with the rest variables as the predictors.
- For the new model, the new regression sum of squares is calculated.
- The difference between the regression sums of squares of the two models is the adjusted regression sum of squares of the removed predictor.

It can be understood that the SS_{ADJREG} quantifies the amount of variation in the response data that is explained by the respective term of the model.

8.4 Multicollinearity

Multicollinearity refers to a high degree of correlation or linear dependency among predictor variables in a regression model. It occurs when two or more predictor variables in the model are highly correlated with each other. In other words, there is a strong linear relationship between two or more predictors, which can cause issues in the regression analysis. In this situation, the coefficient estimates of the multiple regression may change erratically in response to small changes in the model or the data.

The impact of multicollinearity can be quantified by the percentage to which the variance (i.e. standard error squared) is inflated for each coefficient due to multicollinearity, this percentage is called Variance Inflation Factor (VIF).

A variance Inflation Factor is calculated for each independent variable of the model according to the following procedure:

- Assume the following regression model:

$$y \quad = \beta_0 + \beta_1 \cdot x_1 + \beta_2 \cdot x_2 + \cdots + \beta_p \cdot x_p + \varepsilon$$

Equation 8-15

- For each independent variable xj, a regression model is calculated with xj as the response and the rest of the variables as the predictors. For example, for the x1 variable the following model is produced:

$$x_1 = a_0 + a_2 \cdot x_2 + a_3 \cdot x_3 + \cdots + a_p \cdot x_p$$

Equation 8-16

- The coefficient of determination Rj 2 is calculated for the above model. The variance inflation factor of the xj variable is given by the following formula:

$$VIF_j = \frac{1}{1 - R_j^2}$$

Equation 8-17

High values of VIF indicate higher values of R_j^2 which in turn indicate multicollinearity. On the contrary, the minimum value of VIF is 1 and indicates that the predictor under examination is not correlated at all to the rest.

The VIF's threshold value for the presence of collinearity is a subject of debate. As a rule of thumb, VIF's threshold is taken at 10 but some conservative approaches reduce it to 5 or even 2.5.

8.5 Analysis of the elements returned by MATLAB's fitlm function.

8.5.1 Estimate

This column contains the estimated values of the predictors' coefficients. The intercept estimate represents the expected or average value of the response variable when all predictors are held at zero.

8.5.2 Number of Observations

This indicates the total number of data points used in the regression analysis.

8.5.3 Root Mean Squared Error (RMSE)

It is a measure of the average prediction error of the model. It indicates the average deviation from the actual values.

8.6 Development of the model

For the selected 7 predictors, a case study based on the produced model is performed, in order to evaluate the savings provided by the use of ALS.

The cases under examination will be:

1. Ballast with ALS Off
2. Ballast with ALS On
3. Laden with ALS Off
4. Laden with ALS On

8.6.1 Initial Procedure

Before beginning the case study it is best to determine the Pearson correlation coefficients of each model so as to take steps to eliminate multicollinearity issues.

For Laden with ALS On

The correlation among the variables of the model is quantified by the Pearson Correlation Coefficients which are presented in the following Table 12:

For Laden with ALS On

	STBD RA [º]	PORT RA [º]	$v_{wr,ref}$*cos($\psi_{wr,ref}$) [m/s]	$\psi_{wr,ref}$ [rad]	STW^3 [(m/s)^3]	Trim [m]	Tm [m]	$P_{measured}$ [kW]
STBD RA [º]	1.0000	0.9411	0.1368	-0.0518	-0.0723	-0.1317	-0.0423	0.1480
PORT RA [º]	0.9411	1.0000	0.1613	-0.2658	-0.0097	-0.0873	-0.1090	0.2190
$V_{wr,ref}$*cos($\psi_{wr,ref}$) [m/s]	0.1368	0.1613	1.0000	-0.2276	0.2187	-0.0587	0.0529	0.5085
$\psi_{wr,ref}$ (rad)	-0.0518	-0.2658	-0.2276	1.0000	-0.2251	-0.0523	0.2173	-0.3909
STW^3 [(m/s)^3]	-0.0723	-0.0097	0.2187	-0.2251	1.0000	0.0921	0.0771	0.8028
Trim	-0.1317	-0.0873	-0.0587	-0.0523	0.0921	1.0000	-0.0830	0.0751
Mean Draft	-0.0423	-0.1090	0.0529	0.2173	0.0771	-0.0830	1.0000	0.0923
$P_{measured}$	0.1480	0.2190	0.5085	-0.3909	0.8028	0.0751	0.0923	1.0000

Table 12 Pearson correlation coefficients for Laden with ALS On

For Laden with ALS Off

	STBD RA [º]	PORT RA [º]	$v_{wr,ref}$*cos($\psi_{wr,ref}$) [m/s]	$\psi_{wr,ref}$ [rad]	STW^3 [(m/s)^3]	Trim [m]	Tm [m]	$P_{measured}$ [kW]
STBD RA [º]	1.0000	0.9282	0.1025	-0.0302	-0.0454	-0.0138	0.0119	0.1023
PORT RA [º]	0.9282	1.0000	0.1333	-0.2437	0.0141	0.0771	-0.0660	0.1911
$V_{wr,ref}$*cos($\psi_{wr,ref}$) [m/s]	0.1025	0.1333	1.0000	-0.2879	0.2551	-0.0201	-0.0183	0.5211
$\psi_{wr,ref}$ (rad)	-0.0302	-0.2437	-0.2879	1.0000	-0.2470	-0.0975	0.2792	-0.4223
STW^3 [(m/s)^3]	-0.0454	0.0141	0.2551	-0.2470	1.0000	0.0901	0.0785	0.7843
Trim	-0.0138	0.0771	-0.0201	-0.0975	0.0901	1.0000	-0.1361	0.1606
Mean Draft	0.0119	-0.0660	-0.0183	0.2792	0.0785	-0.1361	1.0000	0.0617
$P_{measured}$	0.1023	0.1911	0.5211	-0.4223	0.7843	0.1606	0.0617	1.0000

Table 13 Pearson correlation coefficients for Laden with ALS Off

For Ballast with ALS On

	STBD RA [º]	PORT RA [º]	$v_{wr,ref}$*cos($\psi_{wr,ref}$) [m/s]	$\psi_{wr,ref}$ [rad]	STW^3 [(m/s)^3]	Trim [m]	Tm [m]	$P_{measured}$ [kW]
STBD RA [º]	1.000	0.904	-0.146	-0.019	-0.214	-0.012	-0.024	-0.074
PORT RA [º]	0.904	1.000	-0.108	-0.324	-0.280	0.000	-0.040	-0.064
$V_{wr,ref}$*cos($\psi_{wr,ref}$) [m/s]	-0.146	-0.108	1.000	-0.212	0.610	0.872	-0.566	0.577
$\psi_{wr,ref}$ (rad)	-0.019	-0.324	-0.212	1.000	0.073	-0.158	0.160	-0.143
STW^3 [(m/s)^3]	-0.214	-0.280	0.610	0.073	1.000	0.563	-0.744	0.888
Trim	-0.012	0.000	0.872	-0.158	0.563	1.000	-0.595	0.510
Mean Draft	-0.024	-0.040	-0.566	0.160	-0.744	-0.595	1.000	-0.764

$P_{measured}$	-0.074	-0.064	0.577	-0.143	0.888	0.510	-0.764	1.000

Table 14 Pearson Correlation Coefficients for Ballast with ALS On

For Ballast with ALS Off

	STBD RA [º]	PORT RA [º]	$v_{wr,ref}*cos(\psi_{wr,ref})$ [m/s]	$\psi_{wr,ref}$ [rad]	STW^3 $[(m/s)^3]$	Trim [m]	Tm [m]	$P_{measured}$ [kW]
STBD RA [º]	1.000	0.890	0.135	-0.160	-0.165	0.174	-0.085	0.003
PORT RA [º]	0.890	1.000	0.224	-0.494	-0.233	0.266	-0.145	0.010
$V_{wr,ref}*cos(\psi_{wr,ref})$ [m/s]	0.135	0.224	1.000	-0.203	0.102	0.225	-0.244	0.435
$\psi_{wr,ref}$ (rad)	-0.160	-0.494	-0.203	1.000	0.082	-0.253	0.209	-0.106
STW^3 [(m/s)^3]	-0.165	-0.233	0.102	0.082	1.000	0.198	-0.608	0.843
Trim	0.174	0.266	0.225	-0.253	0.198	1.000	-0.498	0.278
Mean Draft	-0.085	-0.145	-0.244	0.209	-0.608	-0.498	1.000	-0.667
$P_{measured}$	0.003	0.010	0.435	-0.106	0.843	0.278	-0.667	1.000

Table 15 Pearson correlation coefficients for Ballast with ALS Off

As seen in the tables above the port and Starboard rudder angles have a strong positive correlation. This suggests that they have highly similar effects on the outcome of the model. Since this is the case, it is chosen to combine the rudder angles into a single predictor, their average value.

By taking the average value, the information of port and starboard rudder angle is effectively combined into a single variable allowing for model simplification and elimination of multicollinearity issues.

8.6.2 Ballast with ALS On

The model produced by examining the data for Ballast with ALS activated are shown in Table 16 below. The table shows:

- the estimated coefficient of each predictor,
- the standard error of the coefficient,
- the T-value,
- the P-value,
- the VIF.
- The predictor domain of the model

Estimated Coefficients:

	ESTIMATE	SE	T-value	P-value	VIF	Minimum	Maximum
Intercept	48910.000	12085.000	4.047	8.22E-05			

Rudder Angle [º]	539.150	192.750	2.797	5.82E-03	1.229	0.45	4.6
$v_{wr,ref} \cdot cos(\psi_{wr,ref})$ [m/s]	248.160	66.103	3.754	2.47E-04	1.056	0.149	17.433
STW^3[(m/s)^3]	15.579	1.049	14.855	2.10E-31	2.648	241.13	1260.55
trim [m]	-703.660	661.860	-1.063	2.89E-01	1.616	0.3	1.3
T_m [m]	-5444.800	1268.900	-4.291	3.15E-05	2.608	8.5	9.3

Table 16 Ballast with ALS On MLR Model details

The multiple linear regression model produced is formulated as per below equation:

$$P_{measured}[kW] = 48910 + 539.15 \cdot RudderAngle + 248.16 \cdot v_{wr,ref} \cdot cos(\psi_{wr,ref}) + 15.579 \cdot STW\hat{}3 - 703.66 \cdot trim - 5444.8 \cdot draft$$

Equation 8-18

The goodness of fit of the predicted model are displayed in Table 17 below. Using all 5 predictors we get the following results. In this case RMSE is 1860, which is the average deviation of the model's prediction from the actual values. R-squared is 0.849 which suggests that 84.9% of the variability in the response variable is accounted by the predictors. Adjusted R-squared is 0.844. Finally, F-value is 171.26, a higher F-value indicates a more significant relationship between the predictors and the response. In this case, the F-value of 171.26 and P-value of 1.41e-60, suggest that the model is statistically significant.

R^2	0.853
AdjR^2	0.847
AIC	2832.5
BIC	2850.9
F-Value	171.26
Mallow's Cp	4
Number of observations	158
Error degrees of freedom	152
Root mean squared error	1860
p-Value	1.41e-60

Table 17 Goodness of fit for Ballast with ALS On

Figure 25 below displays the measured power against the power predicted by the above multiple linear regression model. The closer the scatter is to the y=x the better the fit. As seen below the fit is satisfactory.

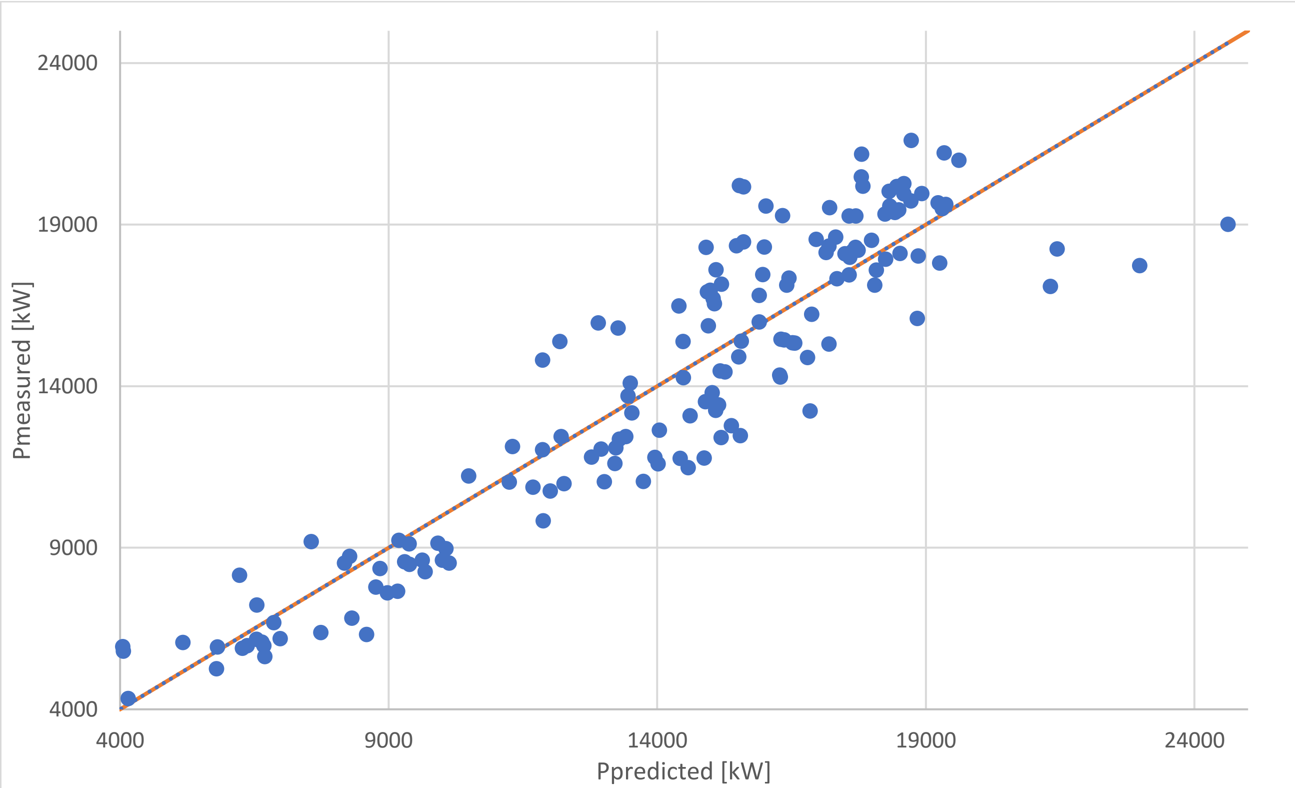

Figure 25 Comparison of the measured vs the MLR predicted power for Ballast On

8.6.3 Ballast with ALS Off

The model produced by examining the data for Ballast with ALS activated are shown in Table 18 below.

Estimated Coefficients:

	ESTIMATE	SE	T-value	P-value	VIF	Minimum	Maximum
Intercept	30219.000	11386.000	2.654	8.92E-03			
Rudder Angle [^{o}]	416.020	183.010	2.273	2.46E-02	1.205	0.5	4.5
$v_{wr,ref} \cdot cos(\psi_{wr,ref})$ [m/s]	625.690	66.537	9.404	2.05E-16	1.104	2.303	12.826
STW^3[(m/s)^3]	16.296	0.977	16.674	2.18E-34	1.789	334.89	1155.56
trim [m]	-429.720	617.920	-0.695	4.88E-01	1.409	0.4	1.4
T_m [m]	-3545.700	1186.800	-2.988	3.35E-03	2.179	8.5	9.2

Table 18 Ballast with ALS Off MLR Model details

The multiple linear regression model produced is formulated as per below equation:

$$P_{measured}[kW] = 30219 + 416.02 \cdot RudderAngle + 625.69 \cdot v_{wr,ref} \cdot cos(\psi_{wr,ref}) + 16.296 \cdot STW\hat{}3 - 429.72 \cdot trim - 3545.7 \cdot draft$$

Equation 8-19

The goodness of fit of the predicted model are displayed in Table 19 below. Using all 5 predictors we get the following results. In this case RMSE is 1510, which is the average deviation of the model's prediction from the actual values. R-squared is 0.853 which suggests that 85.3% of the variability in the response variable is accounted for by the predictors. Adjusted R-squared is 0.847. Finally, F-value is 154.21, a higher F-value indicates a more significant relationship between the predictors and the response. In this case, the F-value of 154.21 and P-value of 1.48e-53, suggest that the model is statistically significant.

R^2	0.853
AdjR^2	0.847
AIC	2435.9
BIC	2435.0
F-Value	154.21
Mallow's Cp	4
Number of observations	139
Error degrees of freedom	133
Root mean squared error	1510
p-Value	1.48e-53

Table 19 Goodness of fit for Laden with ALS Off

Figure 26 below displays the measured power against the power predicted by the above multiple linear regression model. The closer the scatter is to the y=x the better the fit. As seen below the fit is satisfactory.

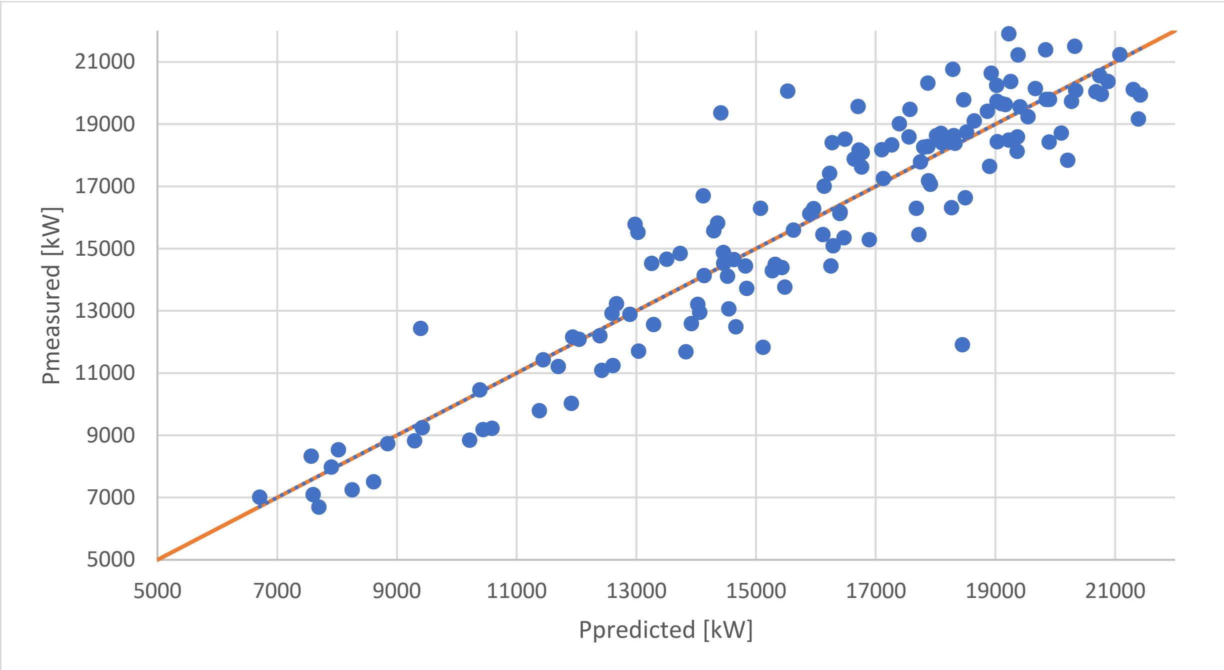

Figure 26 Comparison of the measured vs the MLR predicted power for Ballast Off

8.6.4 Laden with ALS On

The model produced by examining the data for Ballast with ALS activated are shown in Table 20 below

Estimated Coefficients:

	ESTIMATE	SE	T-value	P-value	VIF	Minimum	Maximum
Intercept	-8298.500	3554.100	-2.335	0.020			
Rudder Angle [^{o}]	535.520	83.211	6.436	0.000	1.050	0.45	6.5
$v_{wr,ref} \cdot cos(\psi_{wr,ref})$ [m/s]	610.090	56.725	10.755	0.000	1.088	2.420	10.937
STW^3[(m/s)^3]	16.219	0.657	24.694	0.000	1.070	334.89	1121.91
trim [m]	932.980	440.920	2.116	0.035	1.031	-0.2	1
T_m [m]	558.040	339.010	1.646	0.101	1.022	9.8	10.8

Table 20 Laden with ALS On MLR model details

The multiple linear regression model produced is formulated as per below equation:

$$P_{measured}[kW] = -8298.5 + 535.52 \cdot Rudder\ Angle + 610.09 \cdot v_{wr,ref} \cdot cos(\psi_{wr,ref}) + 16.219 \cdot STW^3 + 932.98 \cdot trim + 558.04 \cdot draft$$

Equation 8-20

The goodness of fit of the predicted model are displayed in Table 21 below. Using all 5 predictors we get the following results. In this case RMSE is 1450, which is the average deviation of the model's prediction from the actual values. R-squared is 0.791 which suggests that 79.1% of the variability in the response variable is accounted for by the predictors. Adjusted R-squared is 0.787. Finally, F-value is 193.51, a higher F-value indicates a more significant relationship between the predictors and the response. In this case, the F-value of 193.5 and P-value of 1.25e-84, suggest that the model is statistically significant.

R^2	0.791
AdjR^2	0.787
AIC	4545.3
BIC	4566.7
F-Value	193.5
Mallow's Cp	4.0
Number of observations	261
Error degrees of freedom	255
Root mean squared error	1450
p-Value	1.25e-84

Table 21 Goodness of fit for Laden with ALS On

Figure 27 displays the measured power against the power predicted by the above multiple linear regression model. The closer the scatter is to the y=x the better the fit. As seen below the fit is satisfactory.

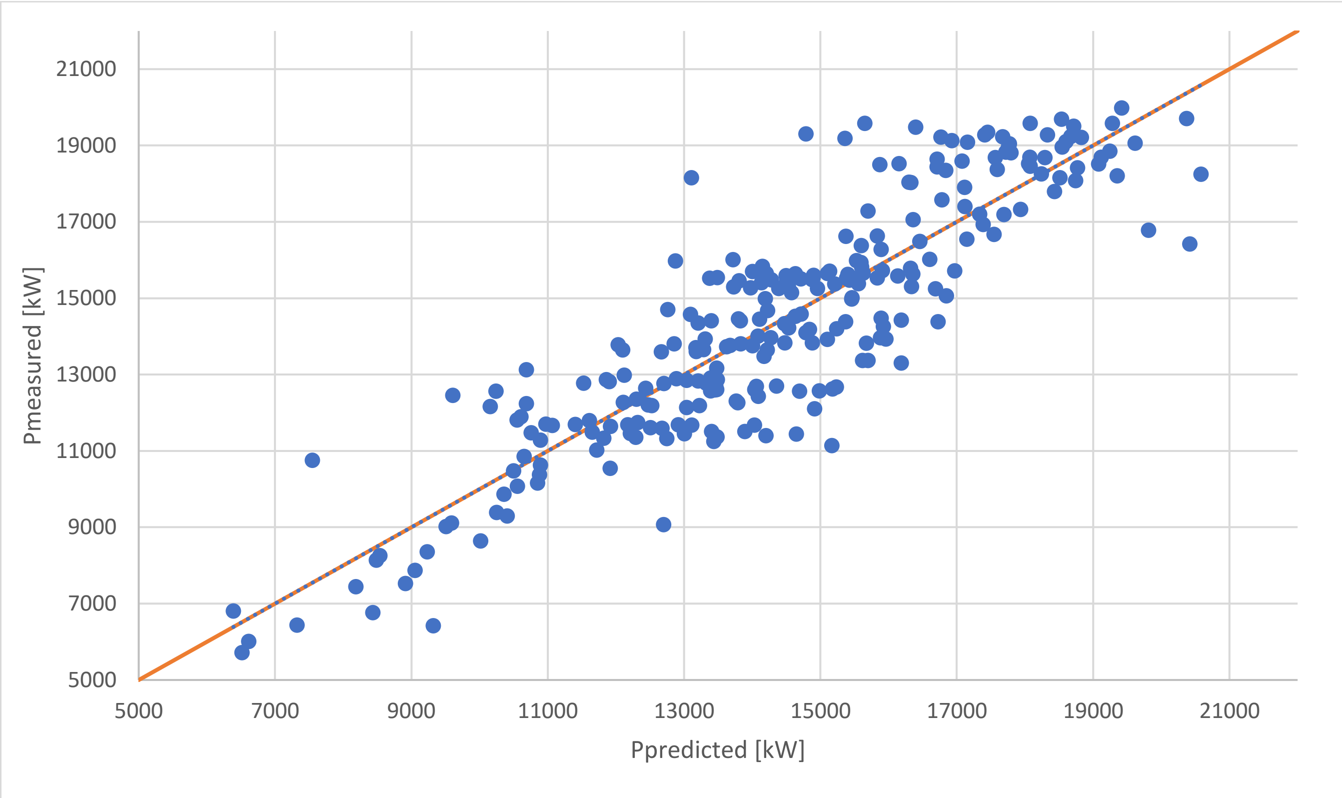

Figure 27 Comparison of the measured vs the MLR predicted power for Laden On

8.6.5 Laden with ALS Off

The model produced by examining the data for Ballast with ALS activated are shown in Table 22 below.

Estimated Coefficients:

	ESTIMATE	SE	T-value	P-value	VIF	Minimum	Maximum
Intercept	-7425.200	4750.700	-1.563	1.19E-01			
Rudder Angle [^{o}]	513.420	110.340	4.653	5.43E-06	1.022	0.45	5.05
$v_{wr,ref} \cdot cos(\psi_{wr,ref})$ [m/s]	644.070	63.375	10.163	2.19E-20	1.093	2.753	11.815
STW^3[(m/s)^3]	14.844	0.750	19.800	3.19E-52	1.089	350.00	1138.65
trim [m]	1884.400	529.190	3.561	4.46E-04	1.031	-0.2	1.1
T_m [m]	573.400	451.290	1.271	2.05E-01	1.026	9.9	10.8

Table 22 Laden with ALS Off MLR model details

The multiple linear regression model produced is formulated as per below equation:

$$P_{measured}[kW] = -7425.2 + 513.42 \cdot RudderAngle + 644.07 \cdot v_{wr,ref} \cdot cos(\psi_{wr,ref}) + 14.844 \cdot STW^3 + 1884.4 \cdot trim + 573.4 \cdot draft$$

Equation 8-21

The goodness of fit of the predicted model are displayed in Table 23 below. Using all 7 predictors we get the following results. In this case RMSE is 1630, which is the average deviation of the model's prediction from the actual values. R-squared is 0.748 which suggests that 74.8% of the variability in the response variable is accounted by the predictors. Adjusted R-squared is 0.743. Finally, F-value is 141.22, a higher F-value indicates a more significant relationship between the predictors and the response. In this case, the F-value of 141.22 and P-value of 3.93e-69, suggest that the model is statistically significant.

R^2	0.748
$AdjR^2$	0.743
AIC	4307.9
BIC	4328.9
F-Value	141.22
Mallow's Cp	4.000
Number of observations	244
Error degrees of freedom	238
Root mean squared error	1630
p-Value	3.93e-69

Table 23 Goodness of fit Laden with ALS Off

Figure 28 displays the measured power against the power predicted by the above multiple linear regression model. The closer the scatter is to the y=x the better the fit. As seen below the fit is satisfactory.

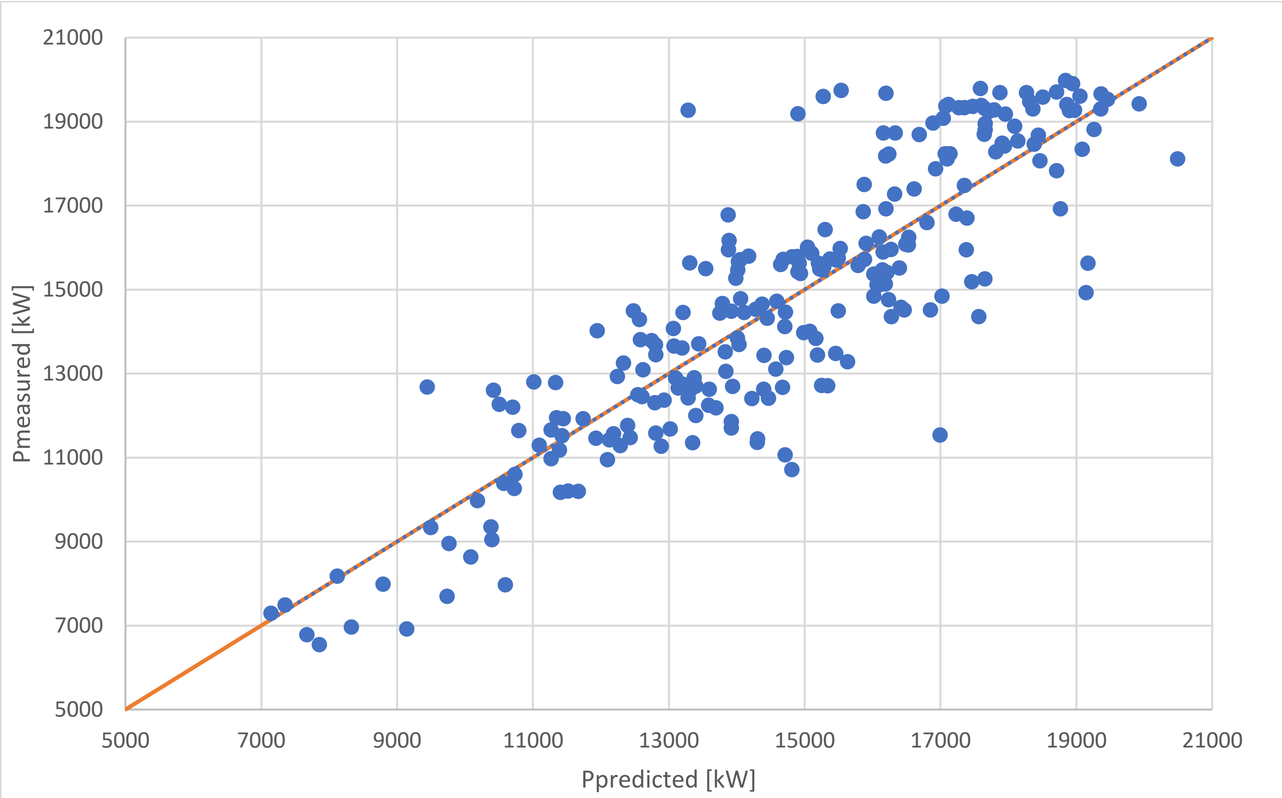

Figure 28 Comparison of the measured vs the MLR predicted power for Laden Off

8.6.6 Case study procedure

The models for each loading and ALS operation condition are clearly defined above. Therefore, case studies for various predictors can be performed.

In the following chapters, case studies about the following will be developed:

- Effect of STW
- Effect of Wind Speed
- Effect of trim

In order to proceed with these case studies, the models need to be adjusted to respond based on the above predictors. This means setting the rest of the predictors to their reference value, for each loading condition, or set them equal to 0. The reference sailing conditions are defined in Table 24 and Table 25.

$T_{m,ref}$	8.9	m
$trim_{ref}$	0.852	m
$v_{wr,ref} \cdot cos(\psi_{wr,ref}), ref$	6.15	m/s
STW_{ref}	8.745	m/s
STW_{ref}	17	kn

Table 24 Reference sailing values for Ballast

$T_{m,ref}$	10.4	m
$trim_{ref}$	0.448	m
$v_{wr,ref} \cdot cos(\psi_{wr,ref}), ref$	6.06	m/s
STW_{ref}	8.745	m/s
STW_{ref}	17	Kn

Table 25 Reference sailing values for Laden

The additional power required for the ALS will be taken as a function of STW as per Table 10 and Table 11. This will allow for the calculation of the net power savings as per Equation 7-2.

8.7 Case study for trim, draft and longitudinal wind speed at reference values

This part of the thesis will examine how the use of ALS benefits the power consumption of the vessel when the vessel sails in reference conditions. The wind speed will be set equal to the average wind speed the vessel has encountered when in ballast condition. The trim and draft will also be set to the reference values of the ballast sailing condition Rudder angle will be set to 0. The determination of multiple linear regression models for both loading conditions with ALS On and Off enables the speed power curve production for each condition.

8.7.1 Ballast

The reference values for ballast will be taken as displayed in Table 24.

The regression model for ALS On is as per below:

$$P = 1377.82 + 15.579 \cdot STW^3$$

Equation 8-22

The regression model for ALS Off is as per below:

$$P = 2143.82 + 16.296 \cdot STW^3$$

Equation 8-23

The results produced by the regression model for ALS On and ALS Off are shown in Table 26 below.

STW [kn]	STW [m/s]	Ppred On [kW]	Ppred Off [kW]	Net Savings Ballast [%]
11	5.6584	4200.23	5096.127	2.98%
12	6.1728	5042.076	5976.719	3.92%
13	6.6872	6036.6	7017.014	4.40%

14	7.2016	7196.525	8230.323	4.63%
15	7.716	8534.573	9629.953	4.71%
16	8.2304	10063.47	11229.21	4.72%
17	8.7448	11795.93	13041.41	4.69%
18	9.2592	13744.69	15079.86	4.65%
19	9.7736	15922.47	17357.86	4.60%
20	10.288	18341.98	19888.73	4.56%
21	10.8024	21015.96	22685.77	4.51%
22	11.3168	23957.12	25762.3	4.48%

Table 26 Case study for regression based on STW for Ballast condition

Figure 29 below displays the effect of ALS for this case study:

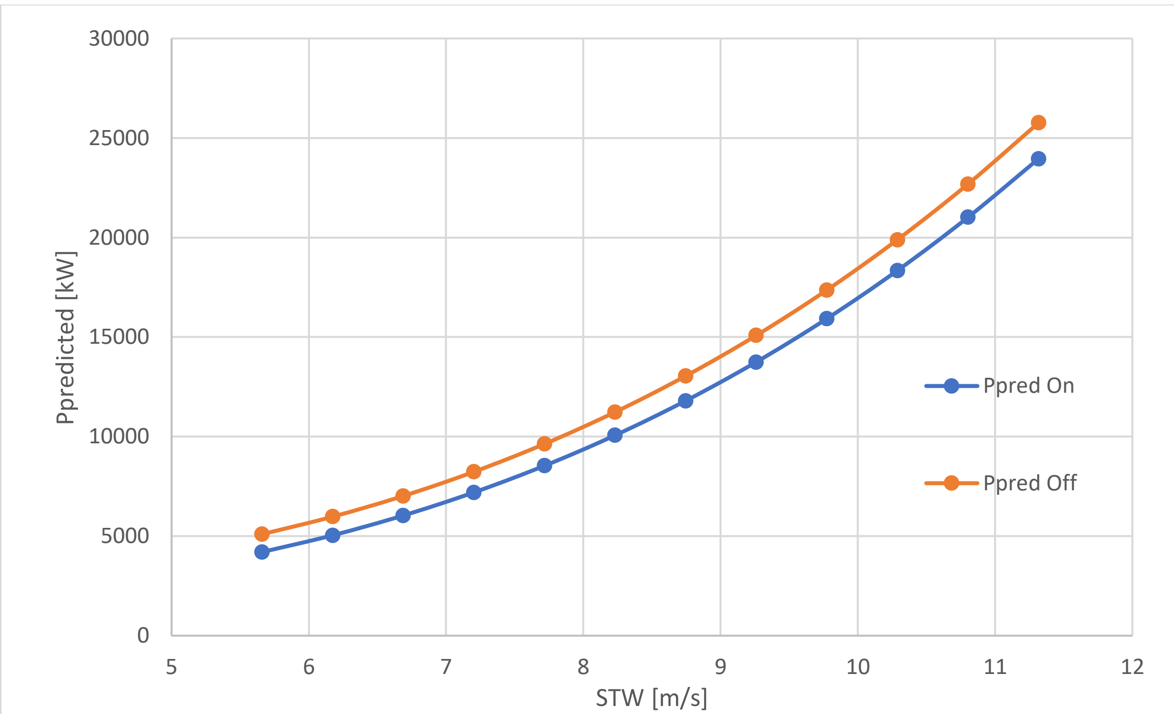

Figure 29 Predicted Power vs STW for Ballast condition

8.7.2 Laden

The reference values for ballast will be taken as displayed in Table 25.

The regression model for ALS On is as per below:

$$P = 1616.92 + 16.219 \cdot STW^3$$

Equation 8-24

The regression model for ALS Off is as per below:

$$P = 3281.48 + 14.844 \cdot STW^3$$

Equation 8-25

The results produced by the regression model for ALS On and ALS Off are shown in Table 27 below.

STW [kn]	STW [m/s]	Ppred On [kW]	Ppred Off [kW]	Net Savings Laden [%]
11	5.6584	4555.28274	5970.737	14.62%
12	6.1728	5431.7132	6772.866	11.86%
13	6.6872	6467.09326	7720.47	9.22%
14	7.2016	7674.66872	8825.671	6.79%
15	7.716	9067.68539	10100.59	4.61%
16	8.2304	10659.3891	11557.36	2.69%
17	8.7448	12463.0255	13208.08	1.01%
18	9.2592	14491.8406	15064.9	-0.43%
19	9.7736	16759.0801	17139.93	-1.67%
20	10.288	19277.9898	19445.3	-2.74%
21	10.8024	22061.8155	21993.12	-3.65%
22	11.3168	25123.803	24795.52	-4.43%

Table 27 Case study for regression based on STW for Laden condition

Figure 30 displays the effect of ALS for this case study:

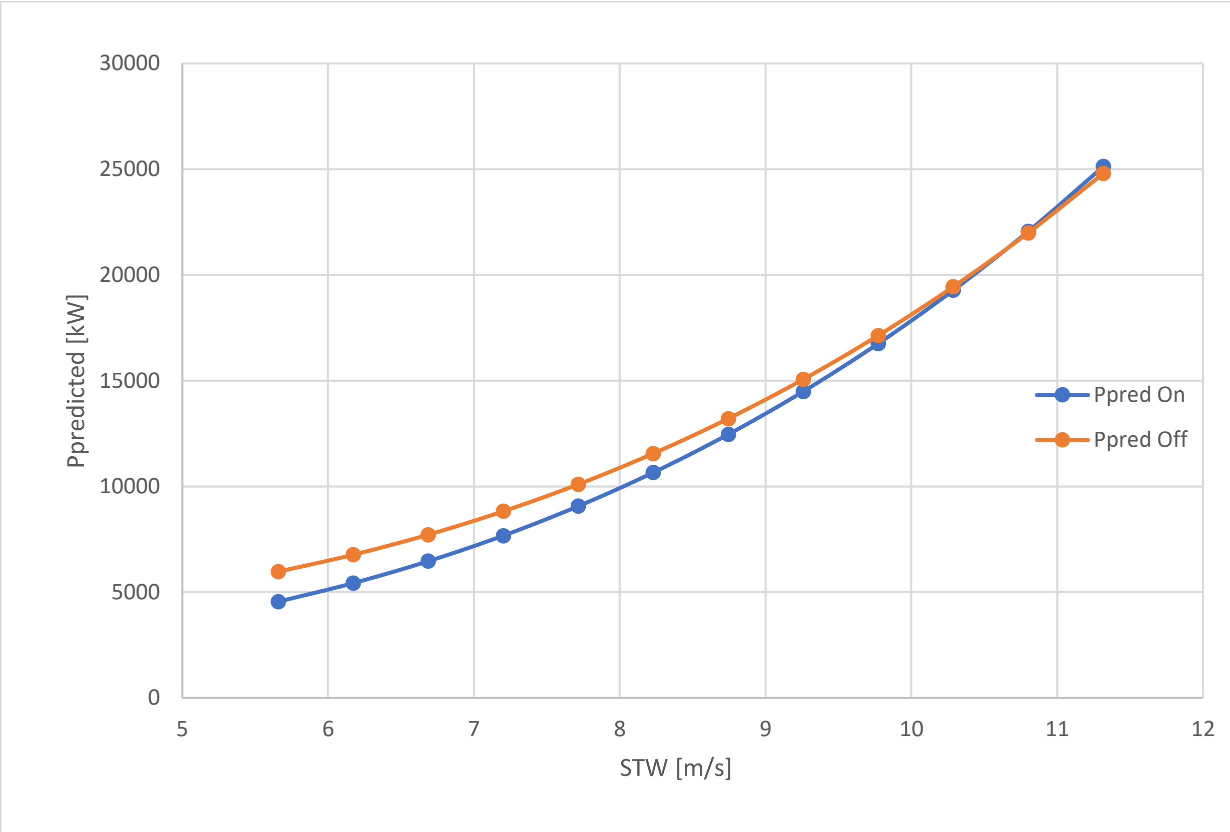

Figure 30 Predicted Power vs STW for Laden condition

8.7.3 Savings for Ballast and Laden

Based on the above case study the savings for Ballast and Laden against the STW are displayed in Figure 31 below:

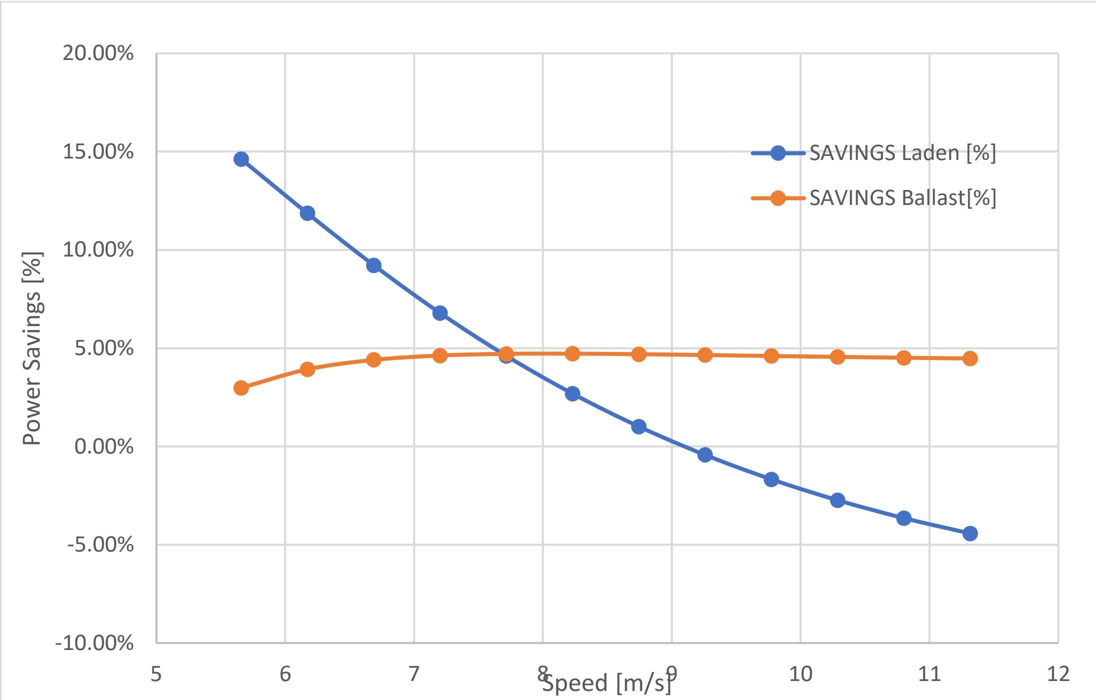

Figure 31 Savings for Ballast & Laden based on the above case study 8.7

8.8 Case study for different wind speeds

This part of the thesis will examine how the use of ALS benefits the power consumption of the vessel for different wind speeds. Since the case for wind speed of 6m/s has already been examined in 8.7. The values of wind speed under examination will be 3m/s and 9m/s. The determination of multiple linear regression models for both loading conditions with ALS On and Off enables the speed power curve production for each condition, thus the visualization of the ALS benefits.

8.8.1 Ballast

Having determined the models for the ballast condition with ALS On and with ALS Off as per 8.6.2 and 8.6.3. For Ballast condition the $v_{wr,ref} \cdot cos(\psi_{wr,ref})$ will be set equal to 3 and 9 m/s. Then the power is predicted by the 4 predictors at reference values based on Table 24 Reference sailing values for Ballast and the $v_{wr,ref} \cdot cos(\psi_{wr,ref})$ held constant at the aforementioned values.

The regression model for ALS On with $v_{wr,ref} \cdot cos(\psi_{wr,ref})$ =3m/s is as per below:

$$P = 596.24 + 15.579 \cdot STW^3$$

Equation 8-26

The regression model for ALS Off with $v_{wr,ref} \cdot cos(\psi_{wr,ref})$=3m/s is as per below:

$$P = 173.22 + 16.296 \cdot STW^3$$

Equation 8-27

In Table 28 and Table 29 the power vs STW in a range of STW from 11knots up to 23knots are shown for Ballast with ALS On and ALS Off respectively.

STW [kn]	STW [m/s]	$v_{wr,ref}$*cos($\psi_{wr,ref}$) [m/s]	Ppred On [kW]	Ppred Off [kW]	Net Savings Ballast [%]
11	5.6584	3	3418.654	3125.529	-23.97%
12	6.1728	3	4260.501	4006.12	-18.06%
13	6.6872	3	5255.025	5046.415	-13.70%
14	7.2016	3	6414.95	6259.724	-10.41%
15	7.716	3	7752.998	7659.354	-7.89%
16	8.2304	3	9281.893	9258.614	-5.91%
17	8.7448	3	11014.36	11070.81	-4.35%
18	9.2592	3	12963.12	13109.26	-3.09%
19	9.7736	3	15140.89	15387.26	-2.06%
20	10.288	3	17560.4	17918.13	-1.22%
21	10.8024	3	20234.38	20715.17	-0.53%
22	11.3168	3	23175.54	23791.7	0.06%

Table 28 Case study for regression based on STW for Longitudinal Wind Speed equal to 3m/s for Ballast condition

The regression model for ALS On with $v_{wr,ref} \cdot cos(\psi_{wr,ref})$=9m/s is as per below:

$$P = 2085.2 + 15.579 \cdot STW^3$$

Equation 8-28

The regression model for ALS Off with $v_{wr,ref} \cdot cos(\psi_{wr,ref})$=9m/s is as per below:

$$P = 32927.36 + 16.296 \cdot STW^3$$

Equation 8-29

STW [kn]	STW [m/s]	$v_{wr,ref}*\cos(\psi_{wr,ref})$ [m/s]	Ppred On [kW]	Ppred Off [kW]	Net Savings Ballast [%]
11	5.6584	9	4907.614	6879.669	14.07%
12	6.1728	9	5749.461	7760.26	14.20%
13	6.6872	9	6743.985	8800.555	13.80%
14	7.2016	9	7903.91	10013.86	13.14%
15	7.716	9	9241.958	11413.49	12.36%
16	8.2304	9	10770.85	13012.75	11.57%
17	8.7448	9	12503.32	14824.95	10.80%
18	9.2592	9	14452.08	16863.4	10.10%
19	9.7736	9	16629.85	19141.4	9.46%
20	10.288	9	19049.36	21672.27	8.88%
21	10.8024	9	21723.34	24469.31	8.38%
22	11.3168	9	24664.5	27545.84	7.93%

Table 29 Case study for regression based on STW for Longitudinal Wind Speed equal to 9m/s for Ballast condition

The data from Table 28 and Table 29 are visualized in Figure 32 and Figure 33 below:

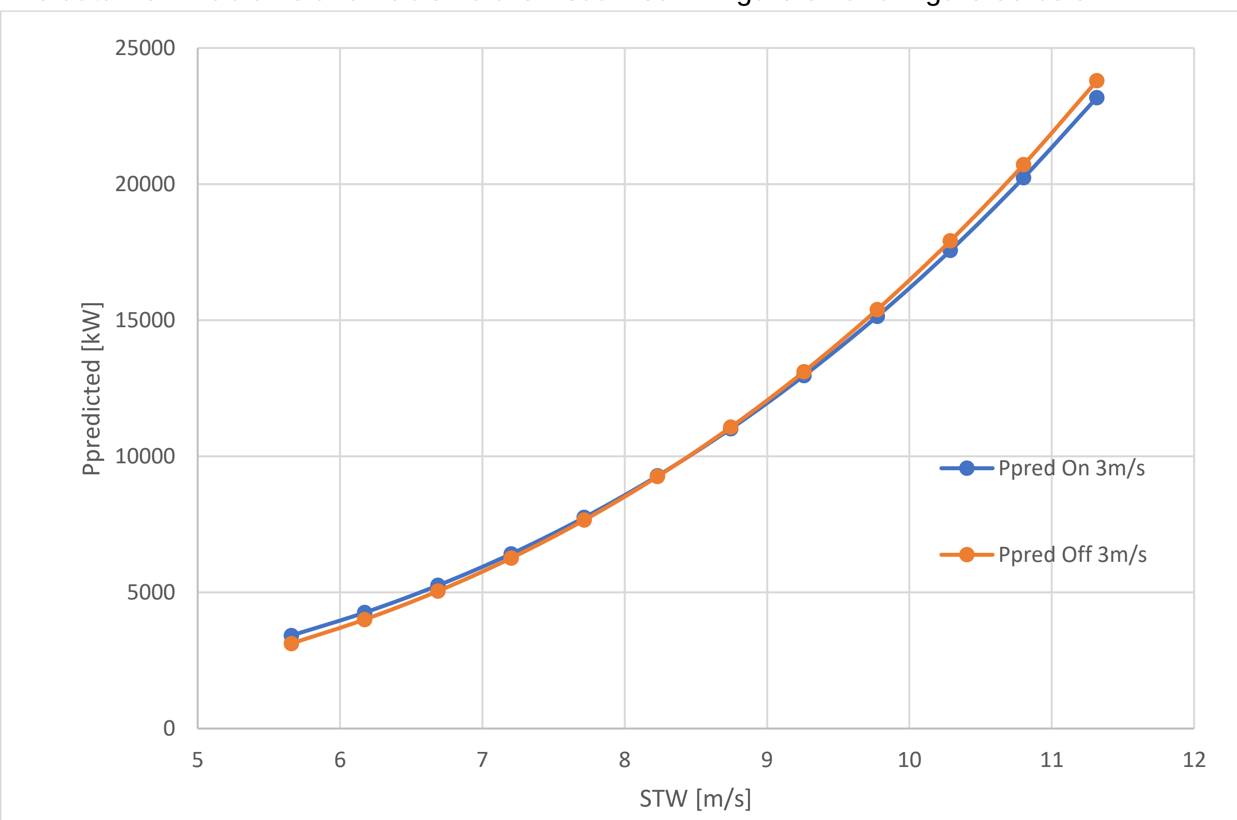

Figure 32 Predicted Power vs STW for Longitudinal Wind Speed of 3m/s for Laden condition

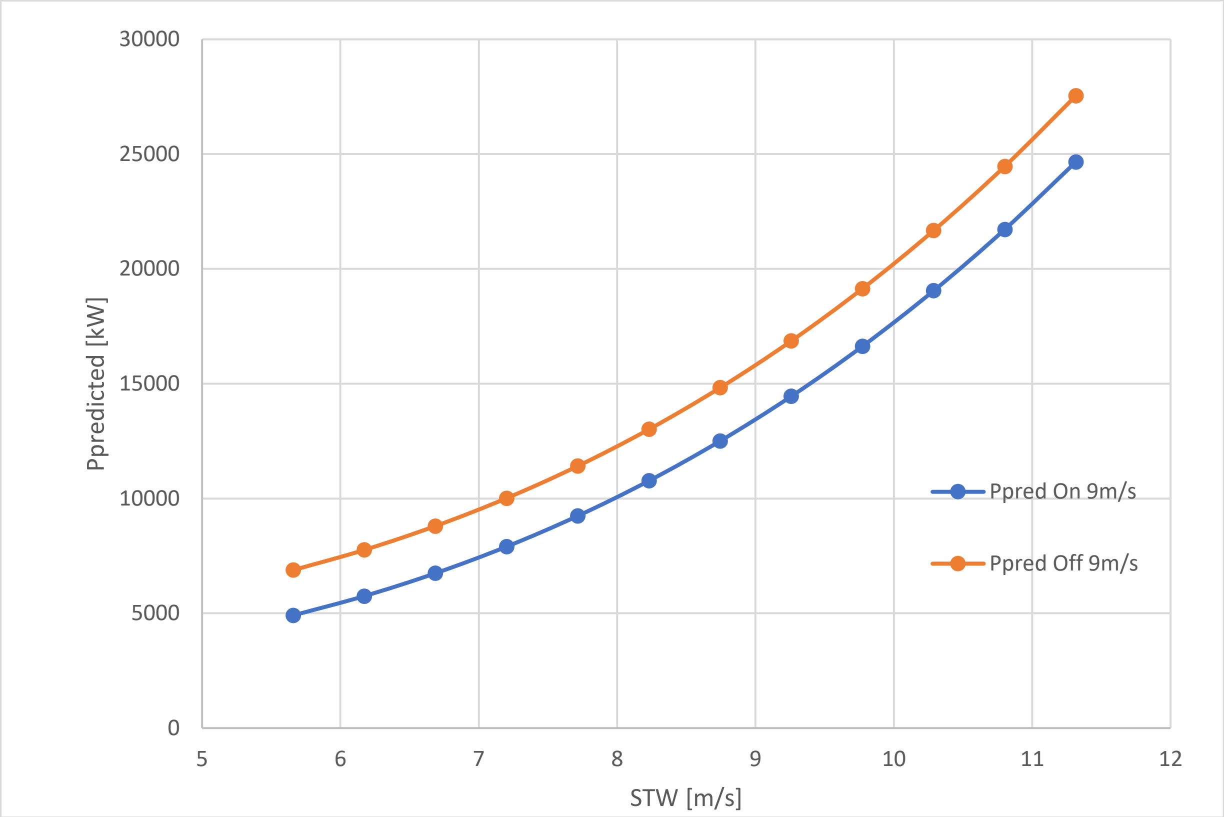

Figure 33 Predicted Power vs STW for Longitudinal Wind Speed of 9m/s for Ballast condition

8.8.2 Laden

Having determined the models for the ballast condition with ALS On and with ALS Off as per 8.6.2 and 8.6.3.

For Laden condition the $v_{wr,ref} \cdot cos(\psi_{wr,ref})$ will be set equal to 3 and 9m/s. Then the power is predicted by the 4 predictors and the $v_{wr,ref} \cdot cos(\psi_{wr,ref})$ held constant at the aforementioned range.

The regression model for ALS On with $v_{wr,ref} \cdot cos(\psi_{wr,ref})$=3m/s is as per below:

$$P = -247.11 + 16.219 \cdot STW^3$$

Equation 8-30

The regression model for ALS Off with $v_{wr,ref} \cdot cos(\psi_{wr,ref})$=3m/s is as per below:

$$P = 1313.63 + 14.844 \cdot STW^3$$

Equation 8-31

In Table 30 and Table 31 the power vs STW in a range of STW from 11knots up to 23knots are shown for Laden with ALS On and ALS Off respectively.

STW [kn]	STW [m/s]	$v_{wr,ref}$*cos($\psi_{wr,ref}$) [m/s]	Ppred On 3m/s	Ppred Off 3m/s	Net Savings Laden [%]
11	5.6584	3	2691.25	4002.884	23.68%
12	6.1728	3	3567.68	4805.013	17.81%
13	6.6872	3	4603.06	5752.617	12.97%
14	7.2016	3	5810.636	6857.817	9.02%
15	7.716	3	7203.653	8132.738	5.81%
16	8.2304	3	8795.356	9589.502	3.20%
17	8.7448	3	10598.99	11240.23	1.08%
18	9.2592	3	12627.81	13097.05	-0.65%
19	9.7736	3	14895.05	15172.08	-2.07%
20	10.288	3	17413.96	17477.44	-3.23%
21	10.8024	3	20197.78	20025.26	-4.20%
22	11.3168	3	23259.77	22827.66	-4.99%

Table 30 Case study for regression based on STW for Longitudinal Wind Speed equal to 3m/s for Laden condition

The regression model for ALS On with $V_{wr,ref}$*cos($\psi_{wr,ref}$) =9m/s is as per below:

$$P = 3413.43 + 16.219 \cdot STW^3$$

Equation 8-32

The regression model for ALS Off with $V_{wr,ref}$*cos($\psi_{wr,ref}$) =9m/s is as per below:

$$P = 5178.05 + 14.844 \cdot STW^3$$

Equation 8-33

STW [kn]	STW [m/s]	$v_{wr,ref}$*cos($\psi_{wr,ref}$) [m/s]	Ppred On 9m/s	Ppred Off 9m/s	Net Savings Laden [%]
11	5.6584	9	6351.79	7867.304	10.17%
12	6.1728	9	7228.22	8669.433	8.68%
13	6.6872	9	8263.6	9617.037	7.06%
14	7.2016	9	9471.176	10722.24	5.42%
15	7.716	9	10864.19	11997.16	3.83%
16	8.2304	9	12455.9	13453.92	2.34%
17	8.7448	9	14259.53	15104.65	0.97%
18	9.2592	9	16288.35	16961.47	-0.27%
19	9.7736	9	18555.59	19036.5	-1.37%
20	10.288	9	21074.5	21341.86	-2.34%
21	10.8024	9	23858.32	23889.68	-3.20%
22	11.3168	9	26920.31	26692.08	-3.96%

Table 31 Case study for regression based on STW for Longitudinal Wind Speed equal to 9m/s for Laden condition

The data from Table 30 and Table 31, are visualized in Figure 34 and Figure 35 below:

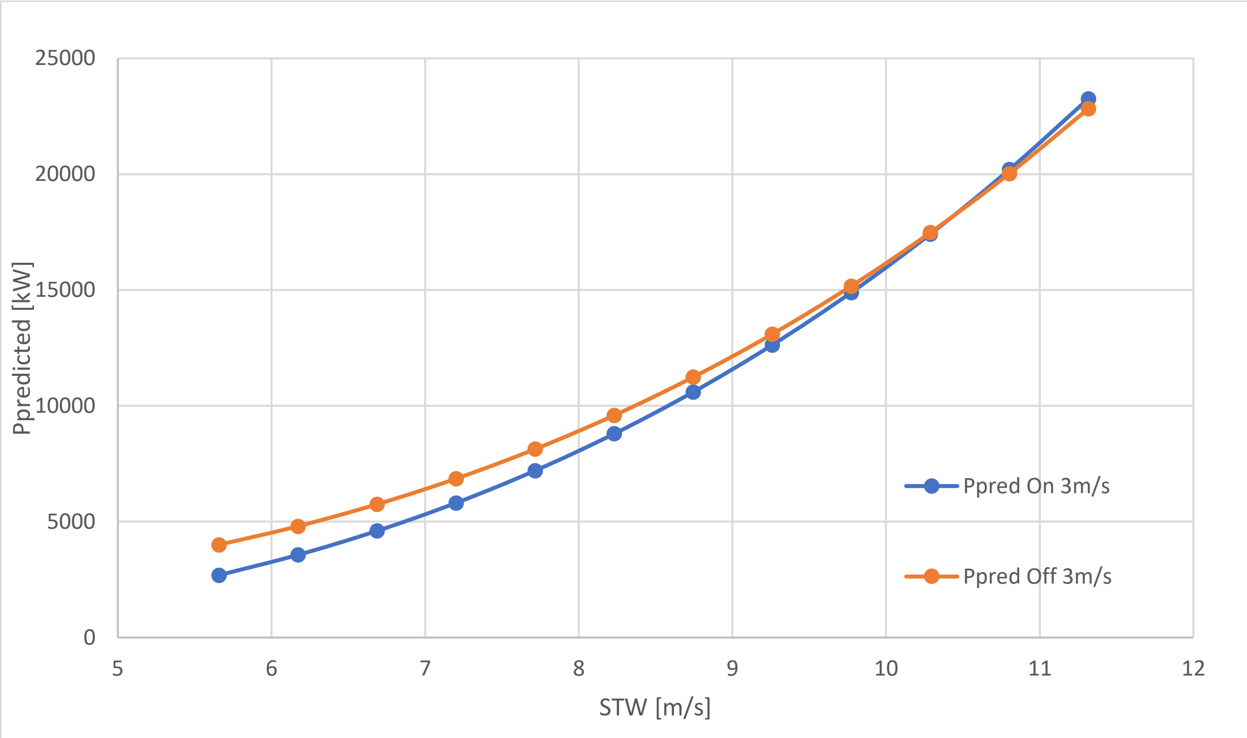

Figure 34 Predicted Power vs STW for Longitudinal Wind Speed of 3m/s for Laden condition

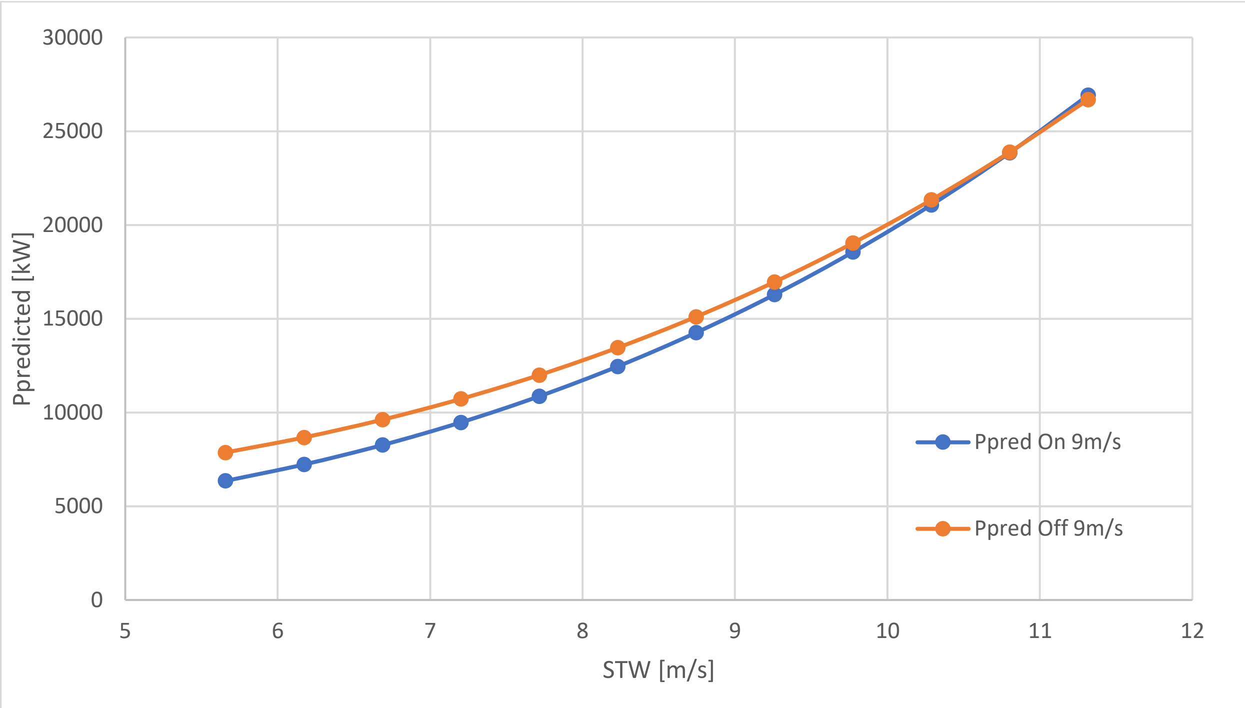

Figure 35 Predicted Power vs STW for Longitudinal Wind Speed of 9m/s for Laden condition

8.9 Case study for the effect wind speed for STW=const.

For this case study we will assume that the following predictors:

- Mean Draft
- Trim
- Speed through water

are set to the reference sailing values. Rudder angle will be set to 0.

Hence, the power will depend upon the Longitudinal wind speed.

8.9.1 Ballast

The reference values for ballast will be taken as displayed in Table 24.

The regression model for ALS On is as per below:

$$P = 10269.88 + 248.16 \cdot v_{wr,ref} \cdot cos(\psi_{wr,ref})$$

Equation 8-34

The regression model for ALS Off is as per below:

$$P = 8714.27 + 625.69 \cdot v_{wr,ref} \cdot cos(\psi_{wr,ref})$$

Equation 8-35

$v_{wr,ref}*\cos(\psi_{wr,ref})$ [m/s]	Ppred On [kW]	Ppred Off [kW]	Net Savings Ballast [%]
2	10766.2	10445.12	-7.93%
3	11014.36	11070.81	-4.35%
4	11262.52	11696.5	-1.15%
5	11510.68	12322.19	1.73%
6	11758.84	12947.88	4.33%
7	12007	13573.57	6.69%
8	12255.16	14199.26	8.84%
9	12503.32	14824.95	10.80%
10	12751.48	15450.64	12.61%
11	12999.64	16076.33	14.28%

Table 32 Case study for regression based on Longitudinal Wind Speed for Ballast condition

The results from the case study are visualized in Figure 36 below.

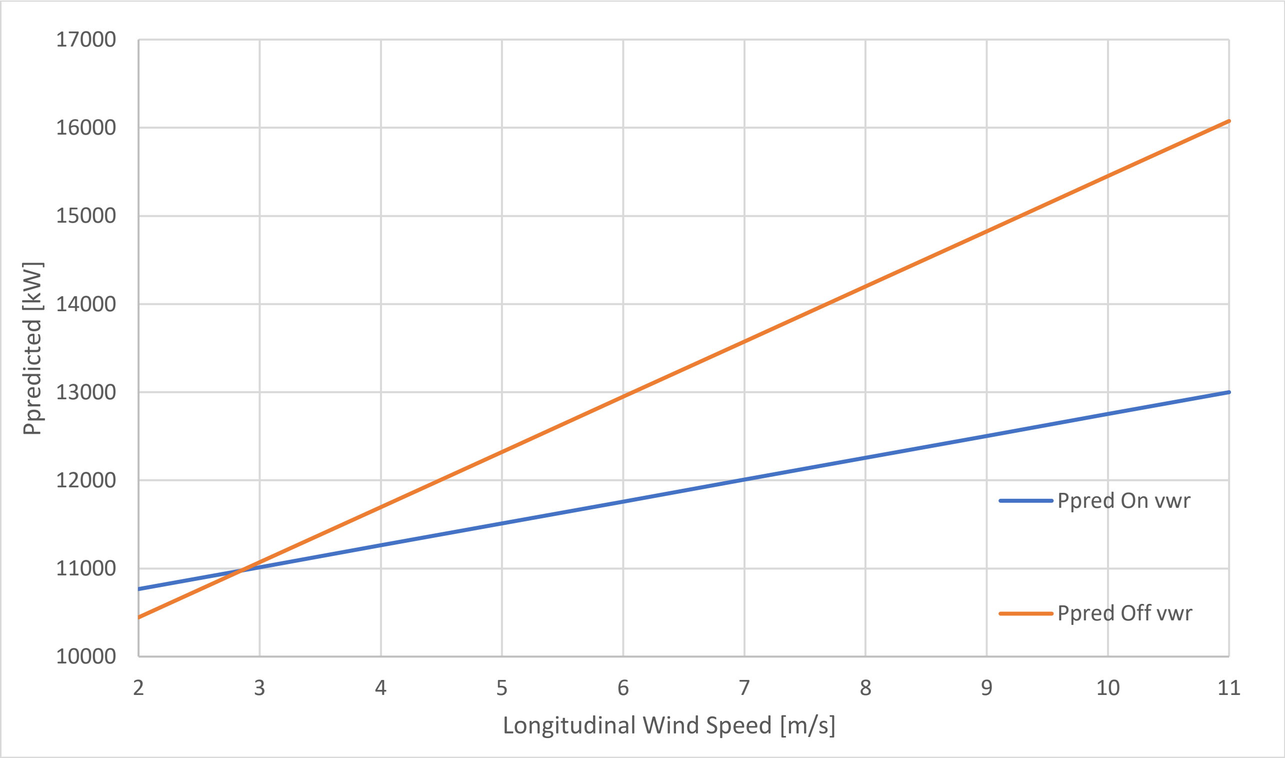

Figure 36 Predicted Power vs Longitudinal Wind Speed for Ballast condition

8.9.2 Laden

The reference values for ballast will be taken as displayed in Table 25.

The regression model for ALS On is as per below:

$$P = 10269.88 + 248.16 \cdot v_{wr,ref} \cdot cos(\psi_{wr,ref})$$

Equation 8-36

The regression model for ALS Off is as per below:

$$P = 8714.27 + 625.69 \cdot v_{wr,ref} \cdot cos(\psi_{wr,ref})$$

Equation 8-37

$v_{wr,ref}$*cos($\psi_{wr,ref}$) [m/s]	Ppred On [kW]	Ppred Off [kW]	Net Savings Laden [%]
2	9988.903	10596.16	1.10%
3	10598.99	11240.23	1.08%
4	11209.08	11884.3	1.05%
5	11819.17	12528.37	1.03%
6	12429.26	13172.44	1.02%
7	13039.35	13816.51	1.00%
8	13649.44	14460.58	0.98%
9	14259.53	15104.65	0.97%
10	14869.62	15748.72	0.96%
11	15479.71	16392.79	0.94%

Table 33 Case study for regression based on Longitudinal Wind Speed for Laden condition.

The results from this case study are visualized in Figure 37 below.

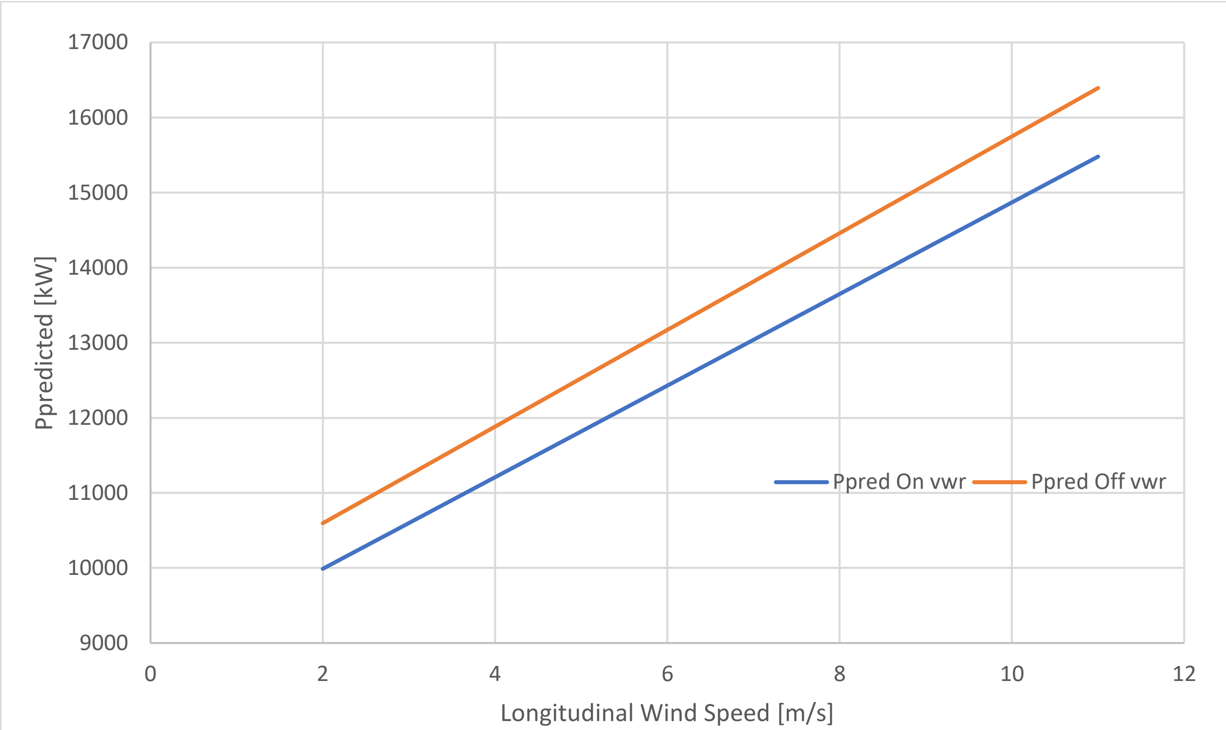

Figure 37 Predicted Power vs Longitudinal Wind Speed for Laden condition.

8.10 Case study for the effect of trim

8.10.1 Ballast

Having determined the models for the ballast condition with ALS On and with ALS Off as per 8.6.2 and 8.6.3.

For this case study for Ballast condition the trim will be set equal to 0.4m, 0.8m, and 1.3m. Then the power is predicted by the 4 predictors and the trim held constant at the aforementioned values.

The regression model for ALS On for trim=0.4m is as per below:

$$P = 2338.05 + 15.579 \cdot STW^3$$

Equation 8-38

The regression model for ALS Off for trim=0.4m is as per below:

$$P = 1695.87 + 16.296 \cdot STW^3$$

Equation 8-39

The regression model for ALS On for trim=0.8m is as per below:

$$P = 1414.41 + 15.579 \cdot STW^3$$

Equation 8-40

The regression model for ALS Off for trim=0.8m is as per below:

$$P = 2166.16 + 16.296 \cdot STW^3$$

Equation 8-41

The regression model for ALS On for trim=1.3m is as per below:

$$P = 1062.58 + 15.579 \cdot STW^3$$

Equation 8-42

The regression model for ALS Off for trim=1.3m is as per below:

$$P = 1951.30 + 16.296 \cdot STW^3$$

Equation 8-43

Table 34 below displays the predicted power for and displays the power savings for different trim values, positive saving values indicate savings from the use of ALS:

STW [kn]	STW [m/s]	Ppred On [kW] trim= 0.4m	Ppred Off [kW] trim= 0.4m	Net Savings Ballast [%]	Ppred On [kW] trim= 0.8m	Ppred Off [kW] trim= 0.8m	Net Savings Ballast [%]	Ppred On [kW] trim= 1.3m	Ppred Off [kW] trim= 1.3m	Net Savings Ballast [%]
11	5.66	4518.3	5290.4	0.00%	4236.8	5118.5	2.63%	3885.0	4903.6	6.18%
12	6.17	5360.1	6171.0	1.43%	5078.7	5999.1	3.63%	4726.8	5784.2	6.57%
13	6.69	6354.7	7211.2	2.31%	6073.2	7039.4	4.16%	5721.4	6824.5	6.60%
14	7.20	7514.6	8424.6	2.87%	7233.1	8252.7	4.42%	6881.3	8037.8	6.46%
15	7.72	8852.6	9824.2	3.23%	8571.2	9652.3	4.54%	8219.3	9437.4	6.24%
16	8.23	10381.5	11423.4	3.46%	10100.1	11251.6	4.57%	9748.2	11036.7	6.01%
17	8.74	12114.0	13235.6	3.62%	11832.5	13063.8	4.57%	11480.7	12848.9	5.79%
18	9.26	14062.7	15274.1	3.73%	13781.3	15102.2	4.54%	13429.5	14887.3	5.59%
19	9.77	16240.5	17552.1	3.81%	15959.1	17380.2	4.51%	15607.2	17165.3	5.41%
20	10.29	18660.0	20083.0	3.87%	18378.6	19911.1	4.48%	18026.7	19696.2	5.26%
21	10.80	21334.0	22880.0	3.91%	21052.5	22708.1	4.44%	20700.7	22493.3	5.12%
22	11.32	24275.2	25956.5	3.95%	23993.7	25784.6	4.42%	23641.9	25569.8	5.01%

Table 34 Case study for regression based on STW for various trim values for Ballast condition

The results for each trim value based on Table 34 are displayed in Figure 38, Figure 39 and Figure 40 below:

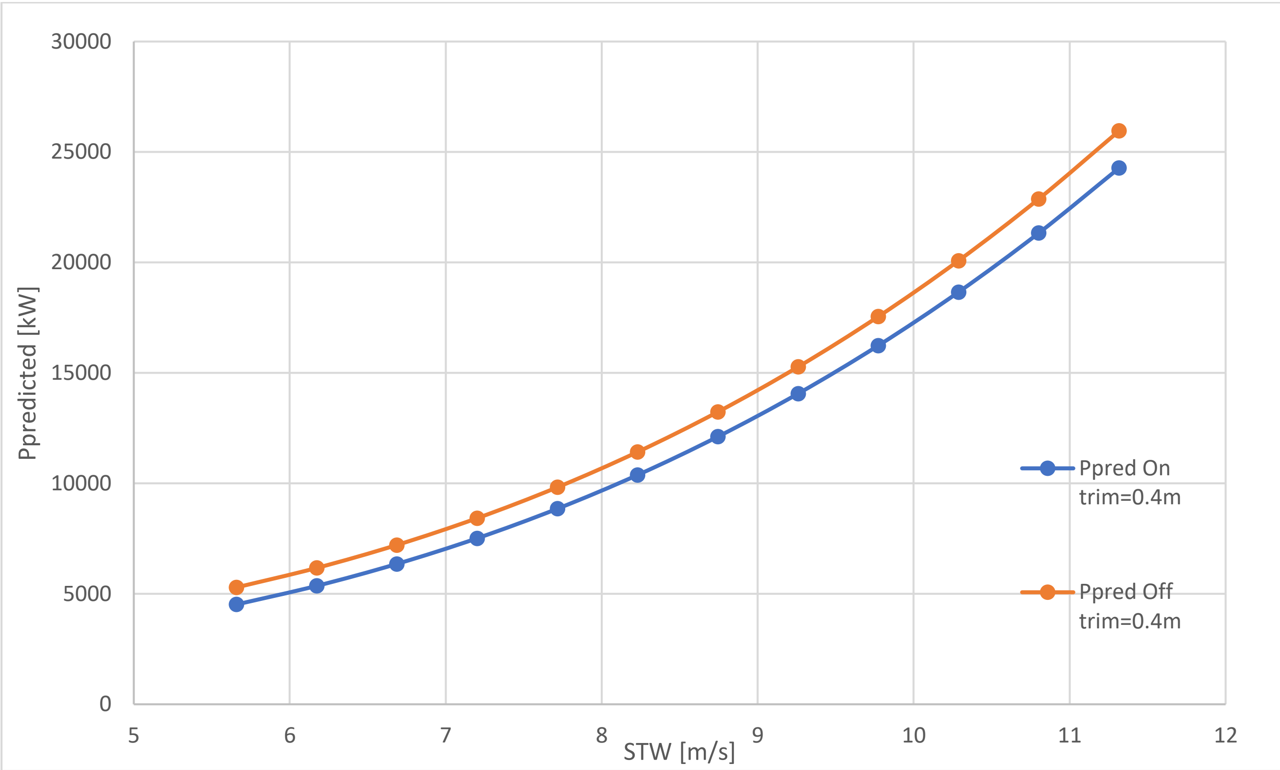

Figure 38 Predicted Power vs STW for trim =0.4m for Ballast condition.

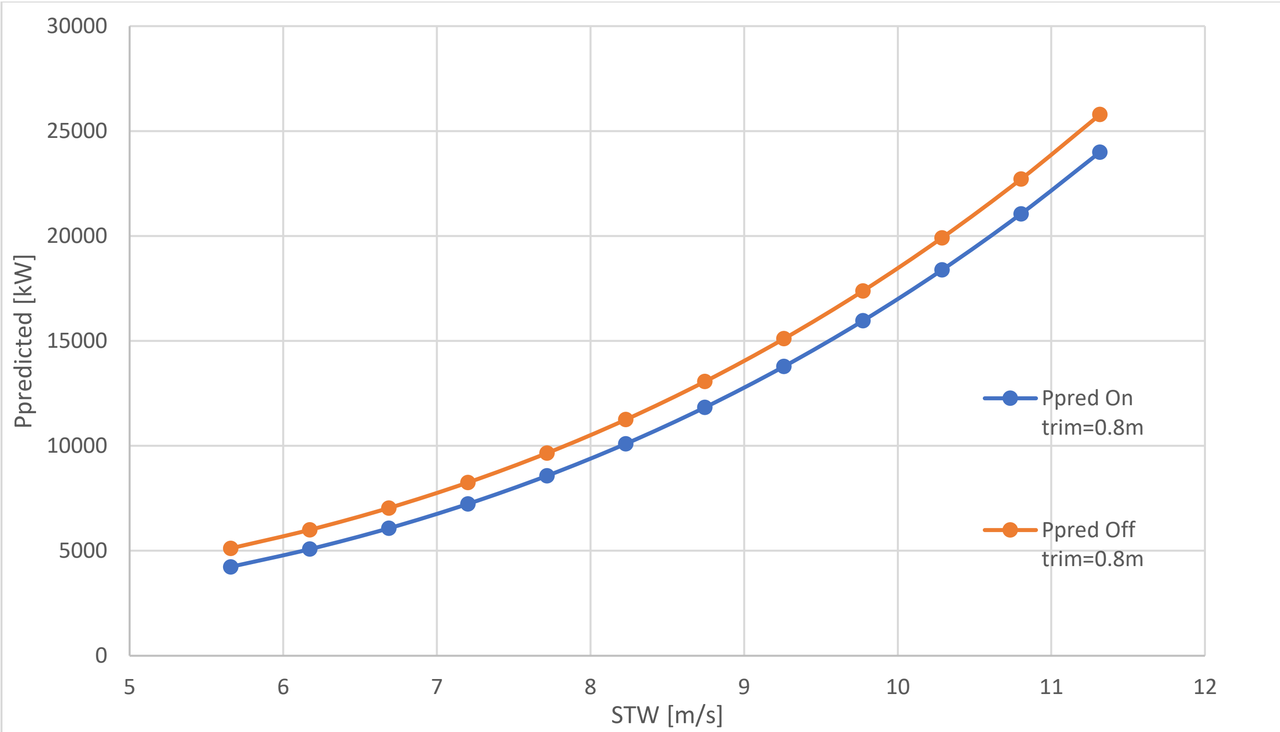

Figure 39 Predicted Power vs STW for trim =0.8m for Ballast condition.

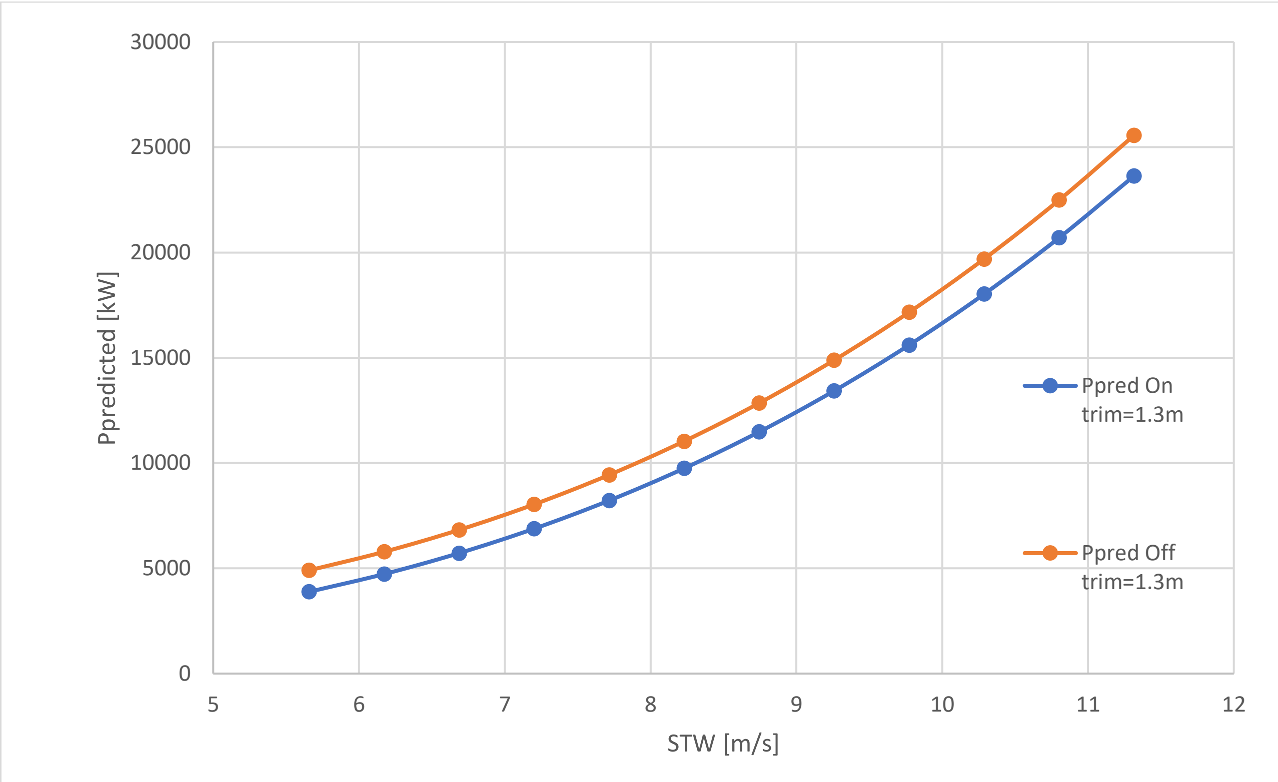

Figure 40 Predicted Power vs STW for trim =1.3m for Ballast condition.

8.10.2 Laden

Having determined the models for the ballast condition with ALS On and with ALS Off as per 8.6.4 and 8.6.5.

For this case study for Laden condition the trim will be set equal to -0.2m, 0.4m, and 1m. Then the power is predicted by the 4 predictors and the trim held constant at the aforementioned values.

The regression model for ALS On for trim=-0.2mm is as per below:

$$P = 1012.82 + 16.219 \cdot STW^3$$

Equation 8-44

The regression model for ALS Off for trim=-0.2m is as per below:

$$P = 2061.34 + 14.844 \cdot STW^3$$

Equation 8-45

The regression model for ALS On for trim=0.4m is as per below:

$$P = 1572.61 + 16.219 \cdot STW^3$$

Equation 8-46

The regression model for ALS Off for trim=0.4m is as per below:

$$P = 3191.98 + 14.844 \cdot STW^3$$

Equation 8-47

The regression model for ALS On for trim=1m is as per below:

$$P = 2132.40 + 16.219 \cdot STW^3$$

Equation 8-48

The regression model for ALS Off for trim=1m is as per below:

$$P = 4322.62 + 14.844 \cdot STW^3$$

Equation 8-49

Table 35 below displays the predicted power for different trim values:

STW [kn]	STW [m/s]	Ppred On [kW] trim= -0.2m	Ppred Off [kW] trim= -0.2m	Net Savings Laden [%]	Ppred On [kW] trim= 0.4m	Ppred Off [kW] trim= 0.4m	Net Savings Laden [%]	Ppred On [kW] trim= 1m	Ppred Off [kW] trim= 1m	Net Savings Laden [%]
11	5.66	3951.2	4750.6	7.74%	4511.0	5881.2	14.21%	5070.8	7011.9	18.59%
12	6.17	4827.6	5552.7	5.12%	5387.4	6683.4	11.45%	5947.2	7814.0	15.95%
13	6.69	5863.0	6500.3	2.79%	6422.8	7631.0	8.82%	6982.6	8761.6	13.29%
14	7.20	7070.6	7605.5	0.78%	7630.4	8736.2	6.41%	8190.1	9866.8	10.74%
15	7.72	8463.6	8880.5	-0.92%	9023.4	10011.1	4.25%	9583.2	11141.7	8.37%
16	8.23	10055.3	10337.2	-2.36%	10615.1	11467.9	2.35%	11174.9	12598.5	6.22%
17	8.74	11858.9	11987.9	-3.55%	12418.7	13118.6	0.71%	12978.5	14249.2	4.29%
18	9.26	13887.7	13844.8	-4.54%	14447.5	14975.4	-0.71%	15007.3	16106.0	2.59%
19	9.77	16155.0	15919.8	-5.37%	16714.8	17050.4	-1.93%	17274.6	18181.1	1.09%
20	10.29	18673.9	18225.2	-6.06%	19233.7	19355.8	-2.97%	19793.5	20486.4	-0.21%
21	10.80	21457.7	20773.0	-6.63%	22017.5	21903.6	-3.85%	22577.3	23034.3	-1.35%
22	11.32	24519.7	23575.4	-7.11%	25079.5	24706.0	-4.61%	25639.3	25836.7	-2.34%

Table 35 Case study for regression based on STW for various trim values for Laden condition

The results for each trim value based on Table 35 are displayed in Figure 41, Figure 42 and Figure 43 below:

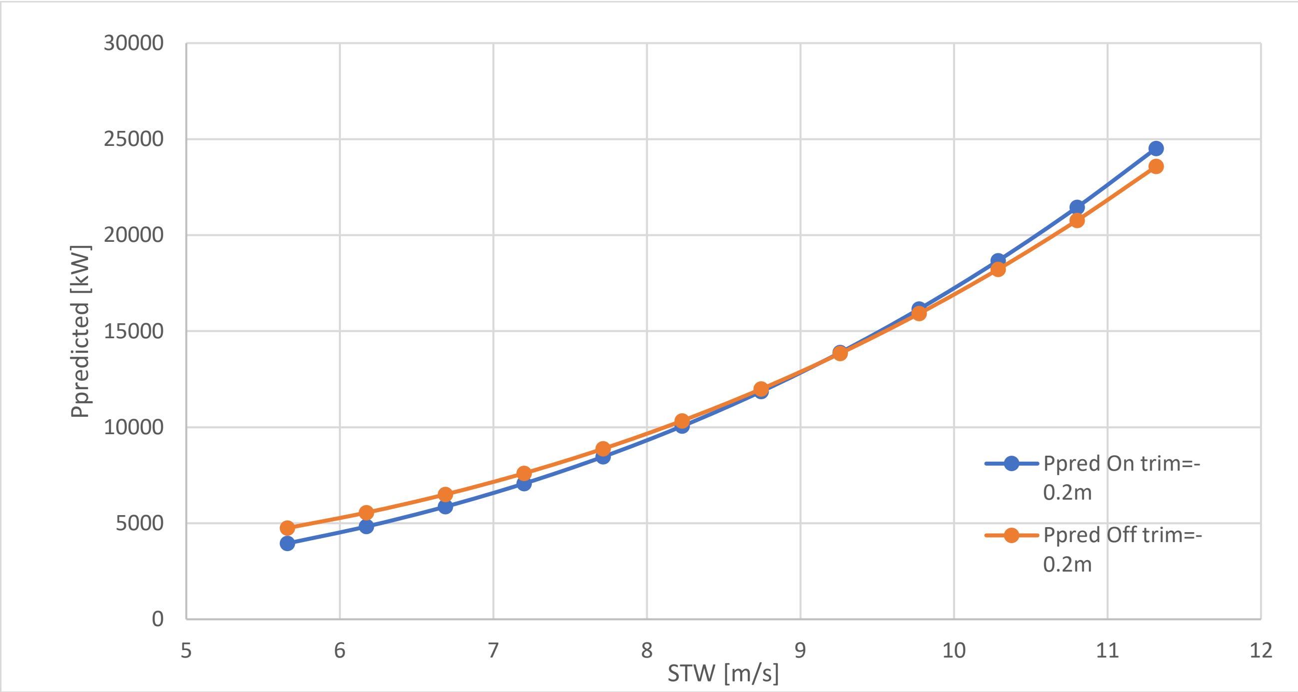

Figure 41 Predicted Power vs STW for trim =-0.2m for Laden condition.

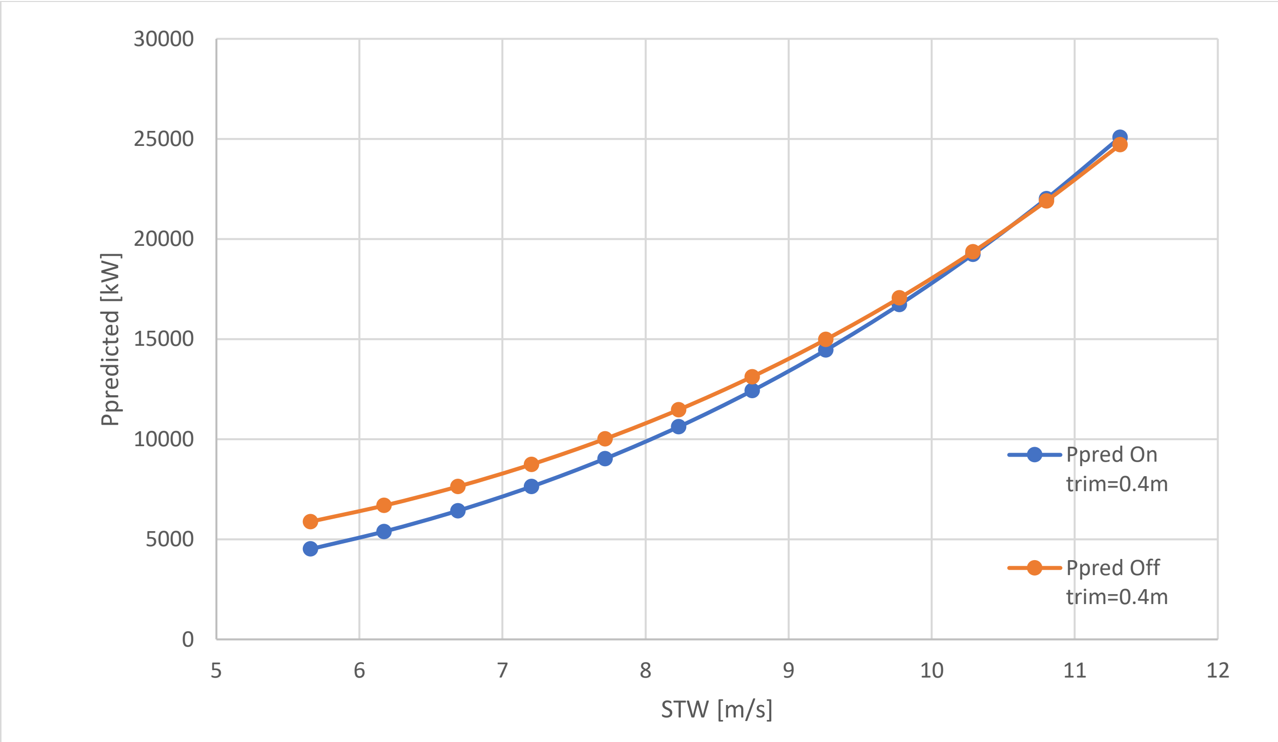

Figure 42 Predicted Power vs STW for trim =0.4m for Laden condition.

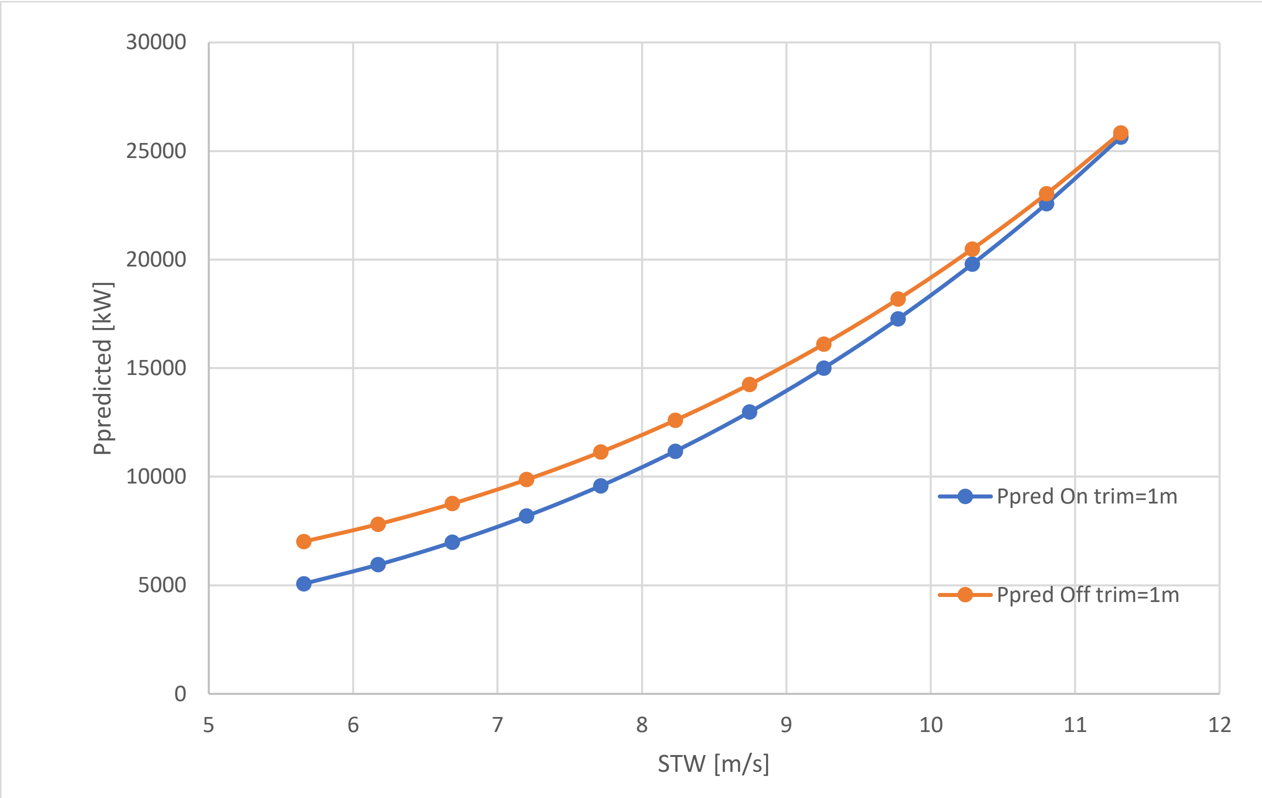

Figure 43 Predicted Power vs STW for trim =1.0m for Laden condition.

8.11 Case study for the effect of trim for STW=const.

For constant STW=17knots, the effect of trim can be examined. All other predictors, except for trim, will be set to reference values as per Table 24 and Table 25.

8.11.1 Ballast

The regression model for ALS On is as per below:

$$P = 12395.45 - 703.66 \cdot trim$$

Equation 8-50

The regression model for ALS Off is as per below:

$$P = 13407.53 - 429.72 \cdot trim$$

Equation 8-51

The results are shown in Table 36 below:

TRIM [m]	Ppred On [kW]	Ppred Off [kW]	Net Savings Ballast [%]
0	12395.452	13407.53	2.69%
0.1	12325.086	13364.56	2.92%
0.2	12254.72	13321.59	3.15%

0.3	12184.354	13278.62	3.38%
0.4	12113.988	13235.65	3.62%
0.5	12043.622	13192.67	3.85%
0.6	11973.256	13149.7	4.09%
0.7	11902.89	13106.73	4.33%
0.8	11832.524	13063.76	4.57%
0.9	11762.158	13020.79	4.81%
1	11691.792	12977.81	5.05%
1.1	11621.426	12934.84	5.30%
1.2	11551.06	12891.87	5.54%
1.3	11480.694	12848.9	5.79%

Table 36 Case study for regression based on trim for Ballast condition

The results are displayed in Figure 44 below:

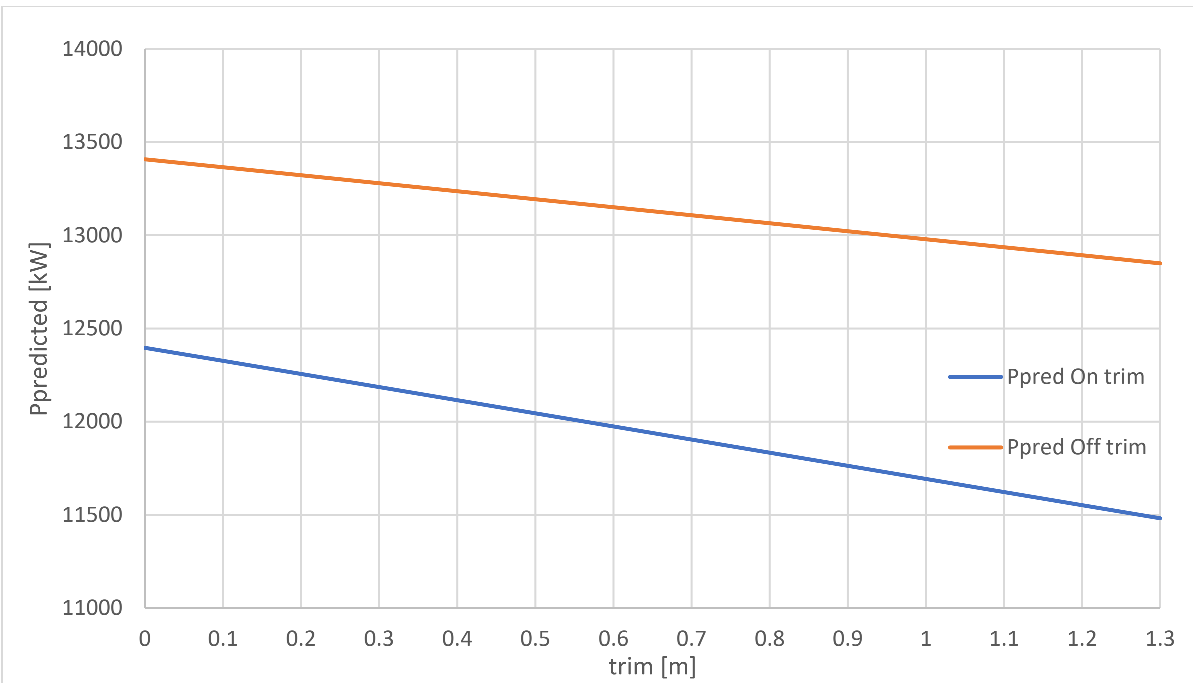

Figure 44 Predicted Power vs trim for Ballast condition.

8.11.2 Laden

The regression model for ALS On is as per below:

$$P = 12364.8 + 932.98 \cdot trim$$

Equation 8-52

The regression model for ALS Off is as per below:

$$P = 12364.8 + 1884.4 \cdot trim$$

Equation 8-53

The results are shown in Table 37 below:

Trim [m]	Ppred On [kW]	Ppred Off [kW]	Net Savings Laden [%]
-0.2	11858.9256	11987.94	-3.55%
-0.1	11952.2236	12176.38	-2.79%
0	12045.5216	12364.82	-2.04%
0.1	12138.8196	12553.26	-1.33%
0.2	12232.1176	12741.7	-0.63%
0.3	12325.4156	12930.14	0.05%
0.4	12418.7136	13118.58	0.71%
0.5	12512.0116	13307.02	1.35%
0.6	12605.3096	13495.46	1.97%
0.7	12698.6076	13683.9	2.57%
0.8	12791.9056	13872.34	3.16%
0.9	12885.2036	14060.78	3.73%
1	12978.5016	14249.22	4.29%

Table 37 Case study for regression based on trim for Laden condition

The results are displayed in Figure 45 below:

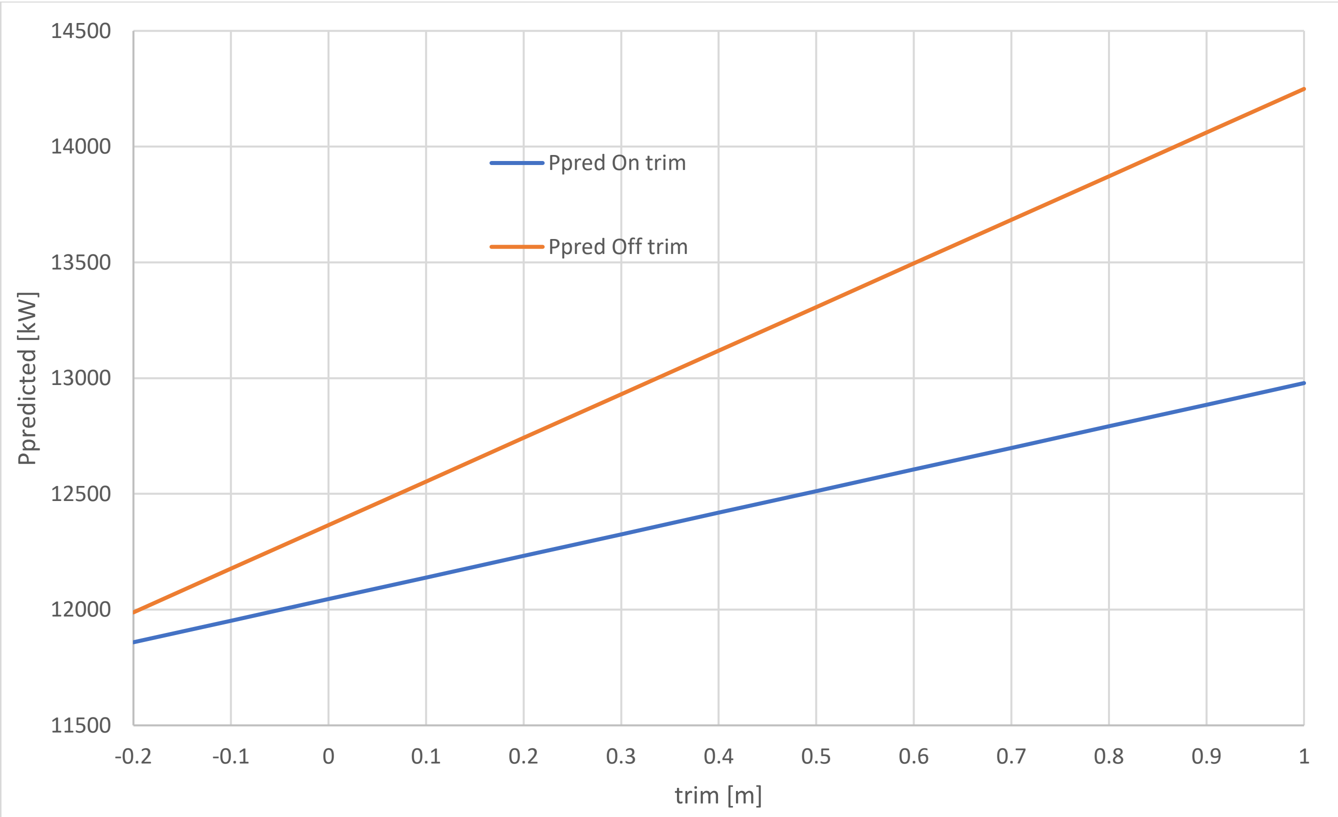

Figure 45 Predicted Power vs trim for Laden condition.

9 Conclusions

The increasing emphasis on energy efficiency and environmental sustainability has prompted the exploration of innovative technologies by the maritime industry. The Air Lubrication System (ALS) has emerged as a promising solution to reduce power consumption and enhance fuel efficiency. In this thesis, a series of case studies were conducted to evaluate the impact of ALS on power saving. The analysis considered various variables, including speed through water, headwind speed, trim, draft, and rudder angle to provide comprehensive insights into the effectiveness of ALS.

The study was based on two parts. Firstly, the operational data were analyzed to produce results about the effectiveness of ALS, and secondly the data were consolidated by a multiple linear regression model. Several case studies were conducted to examine the effects of ALS on power savings under different conditions, including speed, headwind speed, trim, and vessel draft. The analysis involved extensive data collection and analysis, leading to valuable conclusions regarding the effectiveness of ALS. The findings provide insights into the optimal implementation of ALS and its potential to improve energy efficiency in the maritime industry.

The case study results demonstrated the substantial potential of ALS in reducing power consumption. In both ballast and laden conditions, ALS consistently exhibited power savings compared to the off state. The net savings (incl. power required for ALS operation) ranged from around 2% to over 20%, depending on the specific conditions and variables involved. These findings highlight the significance of ALS as an energy-saving technology in maritime operations.

However it should be noted that the operation of ALS can also lead to increased net power consumption, by up to 5%. As seen in Laden condition in Figure 24, increased STW can lead to increased net power demand. Thus, the operation of the vessel needs to be adjusted to better obtain ALS benefits. It is noted though, that the vessel under examination sailed under favorable sailing conditions for the majority of its voyages.

The analysis revealed that ALS was particularly effective at higher speeds. As the speed through water (STW) increased, the savings achieved with ALS also increased. This trend suggests that ALS is more beneficial at higher velocities, where the impact of reduced frictional resistance becomes more pronounced. The findings emphasize the importance of considering vessel speed when assessing the potential benefits of ALS implementation.

Additionally, the interaction between headwind speed and ALS effectiveness was explored. The results showed that the influence of headwind speed on ALS efficiency was variable. In some cases, higher headwind speeds resulted in greater savings, while in others, the savings decreased as the headwind speed increased. These findings indicate that the effectiveness of ALS may be influenced by the specific conditions and the interplay between headwind and ALS-induced changes in the flow field around the vessel.

Furthermore, the analysis of trim adjustments demonstrated their significant impact on power consumption and ALS savings. Optimizing trim, particularly in the ballast condition, led to increased savings. Adjusting the trim allowed for further improvements in power reduction and fuel efficiency. These findings highlight the importance of considering trim as a factor in maximizing the benefits of ALS implementation.

In conclusion, the case study analysis provides valuable insights into the potential of Air Lubrication Systems (ALS) in reducing power consumption and improving energy efficiency in maritime operations. The results demonstrate that ALS consistently achieves power savings compared to the off state in both ballast and laden conditions. The magnitude of savings varies depending on factors such as vessel speed, headwind speed, and trim adjustments.

The findings indicate that ALS is particularly effective at higher speeds, highlighting its suitability for applications where vessels operate at elevated velocities. However, the influence of headwind speed on ALS efficiency was observed to be variable, suggesting the need for further investigation to understand the underlying mechanisms and optimize ALS performance under different wind conditions.

The results of this study provide valuable insights for maritime industry stakeholders, highlighting the potential of ALS as an energy-saving technology. The findings underscore the need for further research, development, and real-world implementation to validate and generalize the conclusions drawn from the case studies. Future studies should focus on investigating ALS under various operational conditions and vessel types to provide a comprehensive understanding of its benefits and limitations.

Overall, this study contributes to the ongoing discourse on energy-efficient technologies in maritime operations, providing valuable insights into the potential of ALS and guiding future research and industry practices for enhancing energy efficiency and sustainability in the maritime sector. It would be recommended that future research, will take into consideration the component of wave resistance, in order to better understand the behavior of ALS, under different conditions. Moreover, statistical errors should also be considered, since shipowners need to be better informed about the meaning of marginal net power savings.

10 References

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11 Appendix MATLAB code

```
% Read the CSV file using readtable
close all
clear all
clc

data = readtable('C:\Users\micha\Desktop\Διπλωματική\matlab csvs\B-On
Filt.csv'); % Replace with the actual file name and path



meanDraft=data(:, 7);
trim=data(:, 8);
stw=data(:, 9);
stw3= table(stw.STW_m_s_.^3,'VariableNames', {'stw3'});
ywr_ref_deg=(data(:, 10));
ywr_ref_rad=(data(:, 11));
VcosGWN=(data(:, 12));
portRudderAngleDeg=(data(:, 13));
STBDRudderAngleDeg=(data(:, 14));
portRudderAngleDeg = portRudderAngleDeg{:,:};
STBDRudderAngleDeg = STBDRudderAngleDeg{:,:};
% Calculate the average of the values
average = (portRudderAngleDeg + STBDRudderAngleDeg) / 2;
% Create a new table from the average array
rudderAnglesDeg = array2table(average, 'VariableNames',
{'rudderAnglesDeg'});
Pcorr_Ref=(data(:, 15));

predictors1 = [rudderAnglesDeg VcosGWN stw3 trim meanDraft];
response1 = data(:, 15);    % Subset with dimensions 158x1

X = [rudderAnglesDeg VcosGWN stw3 trim meanDraft];
y = Pcorr_Ref;

dataFormlrm = [predictors1, response1];
% Fit the multiple linear regression model
model = fitlm(dataFormlrm)

VIFs=determineVIF(model);


% Access coefficients
coefficients = model.Coefficients;

% Obtain a summary of the regression results
summarytis = anova(model,'summary');
```

```
rsquaredValues = model.Rsquared.Ordinary; % Obtain R-squared
adjustedRSquaredValues = model.Rsquared.Adjusted; % Obtain adjusted R-
squared
RSS = model.SSE;
sigma2 = model.MSE;
n = model.NumObservations;
p = model.NumPredictors;
mallowsCp = (RSS / sigma2) + 2 * p - n; % Obtain Mallows’ Cp
aicValues = model.ModelCriterion.AIC; % Obtain AIC
fValue = summarytis.F(2); % Obtain F value
bicValue = model.ModelCriterion.BIC; % Obtain BIC
vifValue = determineVIF(model); % Obtain VIFs
corrCoeffPearson = pearsonCorrCoeff(X,y); % Obtain Pearson Correlation
Coefficients
```

12 Appendix II MATLAB Determination of VIFs

```
function vif = determineVIF(model)

    X = model.Variables(:, 1:end-1); % Exclude the intercept column if
present

    % Calculate the number of predictor variables
    numPredictors = size(X, 2);

    % Preallocate an array to store VIFs
    vifs = zeros(1, numPredictors);

    % Iterate over each predictor variable
    for i = 1:numPredictors
        % Fit a regression model with one predictor variable
        X_without_i = X;
        X_without_i(:, i) = []; % Remove the i-th predictor variable
        dataFormlrmVIF=[X_without_i, X(:, i)];
        mdl_i = fitlm(dataFormlrmVIF);

        % Calculate the R-squared and tolerance values
        R2_i = mdl_i.Rsquared.Ordinary;
        TOL_i = 1 - R2_i;

        % Calculate the VIF
        vifs(i) = 1 / TOL_i;
    end

    VIF_table = table(X.Properties.VariableNames', vifs',
'VariableNames', {'Predictor', 'VIF'});
    vif=VIF_table;
end
```

13 Appendix III MATLAB Determination of Pearson Correlation Coefficients

```
function pearsonCoefficients= pearsonCorrCoeff(predictors,response)
 % model: Multiple linear regression model object obtained from fitlm


    % predictors: Table containing predictor variables
    % response: Table containing the response variable

    % Combine the predictors and response into a single table
    data = [predictors, response];

    % Calculate the Pearson correlation coefficients
    corrMatrix = corrcoef(table2array(data), 'Rows', 'complete');
    pearsonCoefficients = corrMatrix; % Extract the correlation
coefficients between predictors and response


end
```