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ABB Marine: Models of vessel hull and propeller fouling

Final Report

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1 Introduction

1.1 Overview of research problem

Research into the phenomenon known as fouling dates back to 1862 (Townsin, 2003) and is hence not a new problem. However, our understanding of the extent that fouling has and the reasons why fouling should be minimised has changed somewhat. In this report, the term fouling is used to describe the organic growth and mechanical damage of the submerged part of a vessel. Fouling can have a significant negative effect on the profitability and performance of vessels. In short, fouling is added frictional resistance to the vessel which can lead to increased fuel consumption and emissions. Research in the marine transport industry is focused on two main effects attributed to fouling; environmental and economic impacts.

In recent years, environmental impacts of fouling have received much research attention. This may be due to our increased knowledge of the impacts humans have on the planet, and the increased popularity of building a sustainable future. Fouling can lead to increased fuel consumption which in turn leads to increased greenhouse gas emissions, a known factor of global warming. Marine fouling can also cause cross-contamination of species and environments, as marine species from one geographical location can travel on the submersed hull to another. In addition, hull coatings, used in antifouling techniques, can pollute waters and habitats. These are just a few areas of environmental research into the effects of fouling.

Economic impacts due to fouling have always been of great interest to the marine transport industry. The main areas of research have been focused on reducing the increase in fuel consumption as this is a major impact on the total costs. However, in the last three decades or so, research into the scheduling of hull cleanings and effective yet non-harmful hull coatings have gained momentum. In this project, we will be focusing on the economic impacts of fouling.

1.2 Objectives

At the start of this project, ABB Marine defined three objectives; the first being to estimate the overall level of fouling of a given cruise ship, the second being to calculate the individual impacts of hull and propeller fouling, and the third being to develop a method to optimise the scheduling of hull and propeller maintenance while minimising operational costs. Over the course of this project these objectives have been refined. As stated in the interim report, objective two has been deemed unattainable in the given timeframe due to the lack of appropriate data, excessive workload and prioritisation of objectives. Objective two was identified as high-risk in the project plan, and therefore has not had a major impact on the scheduling of the tasks in the project.

1.3 Structure of report

The report is structured as follows. Section 2 provides a literature review of the causation, impact, and calculation of fouling in the marine industry. Section 3 provides a description of the ABB dataset, including the pre-processing of the data and the statistical tests performed. In Section 4, the methods used to achieve objectives one and three will be presented. Section 5 describes the results obtained from both objectives, the validation of these results, and the sensitivity analysis performed. Finally, in Section 6 conclusions are drawn and a self-assessment of the team's work to complete this project is offered.

2 Literature Review

The majority of existing research (Schultz, 2007; Atlar, 2008; Taylan, 2010; Kovanen, 2012; Meng et al., 2016) has focused on identifying and observing factors affecting the fouling rate of growth and their impact on fuel efficiency of vessels. A fouling variable depends on many factors, such as environmental conditions, the operating profile of a vessel, and maintenance operations (see Table 1). However, fouling is a challenging factor to quantify precisely due to a wide range of existing variables which must be taken into consideration. In addition, the measurable changes in the fuel consumption due to the increased frictional resistance – the fouling – are slow to appear (Kovanen, 2012). Therefore, direct measurements of the fouling are difficult to implement frequently, and measured results can be challenging to connect with the impact of hull resistance or propeller efficiency. As a consequence, existing empirical studies have focused on indirect methods to estimate and predict the degree of fouling by analysing operating data that reveals used speed and propulsion power and prevailed environmental conditions.

Table 1 Variables affecting vessel fouling (Kovanen, 2012)

Environment	Maintenance operations	Vessel
Salinity	Utilization Rate	Hull surface
Temperature	Itinerary & Speed	Antifouling
Location	Brushings	Surface Colour
Time of year	Dry docking	
Illumination		

2.1 Costs

Increased fuel consumption and maintenance costs are driving ship owners and operators to find ways to accurately predict the fouling of hull and propellers, in order to increase fuel efficiency and mitigate environmental effects (Schultz et al., 2011; Logan, 2012). The total operating costs of a ship can be divided into personnel, supplies, and maintenance cost components (see Figure 1). Fuel is the major cost driver in the marine industry and it can account for roughly three quarters of the operating costs of a vessel if bunker fuel price is over 500 USD/Metric tons (Rehmatulla and Smith, 2015; Meng et al., 2016). For comparison, the current EMEA (Europe, the Middle East and Africa) average price of bunker fuel is 422 USD as of May 2 2018 (Ship and Bunker, 2018).

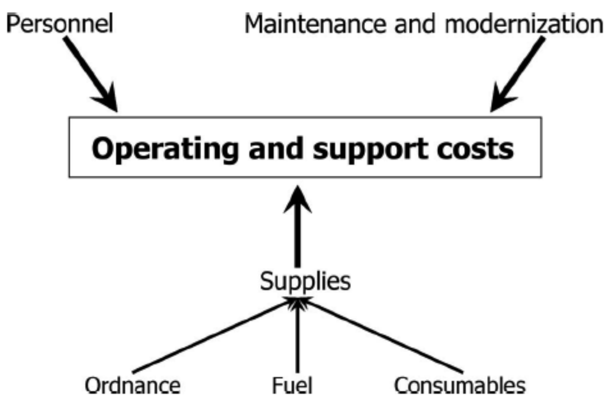


Figure 1 Operating and support cost categories (Schultz et al., 2011)

It has been shown that fuel consumption can increase up to 40% despite a low degree of fouling (Kovanen, 2012). Moreover, poorly managed hull and propeller maintenance can decrease the efficiency of the world ship fleet from 15% to 20% (Adland et al., 2018). The economic and environmental impacts are significant as marine transportation consumes approximately 300 million metric tons (MT) of fuel per year (Demirel et al., 2013) and the fuel bill is approximately 80 billion USD per year (Adland et al., 2018).

Major efforts have been taken to enhance maintenance operations and vessel material design in order to overcome the fouling phenomenon (Schultz et al., 2011). For instance, different antifouling technologies, such as special coating materials, paints and environmental-friendly hull scrubbing technologies, have been developed to reduce the growth of fouling (Demirel et al., 2013). Hull and propeller maintenance is either underwater cleaning or dry-docking. The cost of dry-docking is dependent on the size of ship and cleaning treatments such as sandblasting and new antifouling painting. The costs are estimated to account from 1.2 to 1.6 million USD per tanker (Apostolidis et al., 2012).

Predictive hull and propeller maintenance strategies are essential for decreasing fuel consumption and operating costs (Schultz et al., 2011; Logan, 2012). Schultz et al. highlight that adjustments to full hull cleaning frequency have positive effect on cumulative operating costs compared to without adjustment of interim cleanings (see Figure 2). Similar results are provided by Tribou and Swain's (2010) who suggest a high frequency waterborne hull cleaning using sensitive maintenance cleaning tools. However, it should be noted that even though the frequency of hull cleaning is increased with positive effects on operating costs, these cleaning costs are minor. Figure 2 illustrates this finding, with the largest frequency of cleanings resulting in roughly a 1% difference in cumulative operational costs over 15 years.

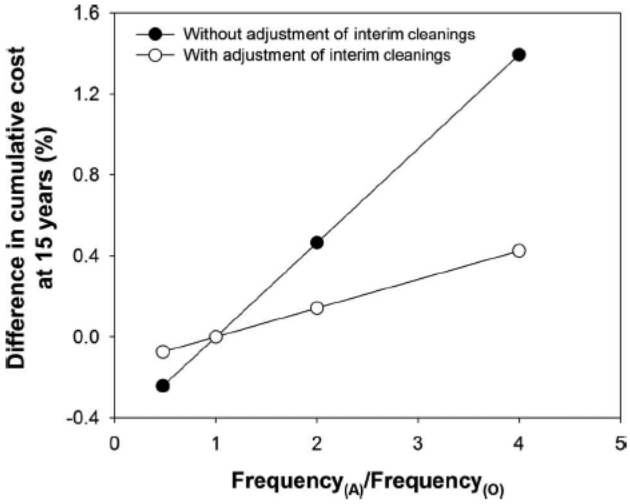


Figure 2 Cumulative operating costs of adjustment of cleanings (Schultz et al., 2011)
Variation in cleaning frequency is expressed as a multiple of the current mean frequency of full hull cleanings [Frequency(O)].

2.2 Variables used in the model

The aim of this research is to estimate the overall effect of fouling to the fuel consumption rate, and thus the existing literature related to fuel efficiency is reviewed from the viewpoint of fouling.

2.2.1 Fuel consumption rate

Many different variables, such as sailing speed, displacement, trim, and weather/sea conditions impact the fuel consumption rate of a vessel. Meng et al. (2016) found sailing speed to have the largest influence on the fuel consumption rate. Fuel consumption is measured in metric ton per day (MT/day), and is based on the total propulsion power and estimated fuel consumptions. The fundamentals of fuel consumption is discussed next.

Resistance modelling is a widely studied field as it can be used to estimate the required engine power of vessel and is defined as

$$P = cR_T V,$$

where P is power, c is a constant, R_T is total resistance, and V is speed through water. Frictional resistance, wave resistance, eddy resistance (a drag force caused by eddy currents), and air resistance are generally the variables used to comprise total resistance, R_T (Todd and Taylor, 1967).

Meng et al. (2016) use a similar formula to calculate the effective power P_E that is required to move a ship forward at the speed through water (V)

$$P_E = R_T V.$$

To calculate total resistance R_T, Meng et al. divide it into the three components; the frictional resistance R_F, the residual resistance R_R, and the air resistance R_A. These are usually proportion to V^2. The total resistance is

$$R_T = R_F + R_R + R_A.$$

The frictional resistance is affected by the irreversible deterioration of ship's hull and propeller, repairable deterioration and the biological fouling. The residual resistance is mainly caused by waves and increases quickly at higher sailing speed. Finally, the air resistance is affected by wind.

2.2.2 Technical characteristics of the vessel

It is vital to understand the technical characteristics of a vessel and their effects on performance. Many efficient trim optimisation tactics, such as position and angle of the propeller and the extent of the wetted surface of a hull, are used to improve efficiency and lower fuel expenses (Kovanen, 2012). Such variables should be taken into account when calculating the level and effect of fouling. However, the fundamentals of vessels' fuel consumption need to be fully understood before the optimisation tactics can be modelled.

3 Data

3.1 ABB Marine dataset

The ABB dataset comprised of 43 variables of operating data from a cruise ship (hereafter termed a vessel). The data were given in observations per minute for each quartile of the year 2017, resulting in 173 comma-separated values (CSV) files. Each file contained 213,120 observations in quartile one; 175,800 observations in quartile two; 77,880 observations in quartile three; and 124,440 observations in quartile four. In total, the ABB dataset consisted of 1.4 GB of data. All pre-processing and statistical analysis was performed in the statistical software RStudio (2017).

3.2 Pre-processing

In order for the data to be used as intended, the raw ABB data had to be converted into an understandable format. This was a major computational effort due to the size of the dataset, and different stages of pre-processing was involved. The first stage was to merge the data to create datasets of variables spanning all quartiles. Using these variables, basic statistics (percentiles, mean, and variance) were calculated, in addition to graphical representation in the form of time series plots and histograms. Both these techniques are widely used to increase the understanding of one's data. The second stage was to filter the variables based on wind and ground speed of the vessel. A maximum limit for the wind speed was set to the 97.5 percentile, which corresponds to the speed of 44.2 knots. The minimum and maximum limits for the ground speed were decided based on a detailed conversation with the ABB contact, which resulted in those being set to 4 and 20 knots. Time stamps which included data outside of these limits were filtered out. From the plots, it was evident that the datasets had a number of null/or missing observations (see Figure 3). Thus, the time stamps with null/or missing observations about any of the needed variables were also filtered out.

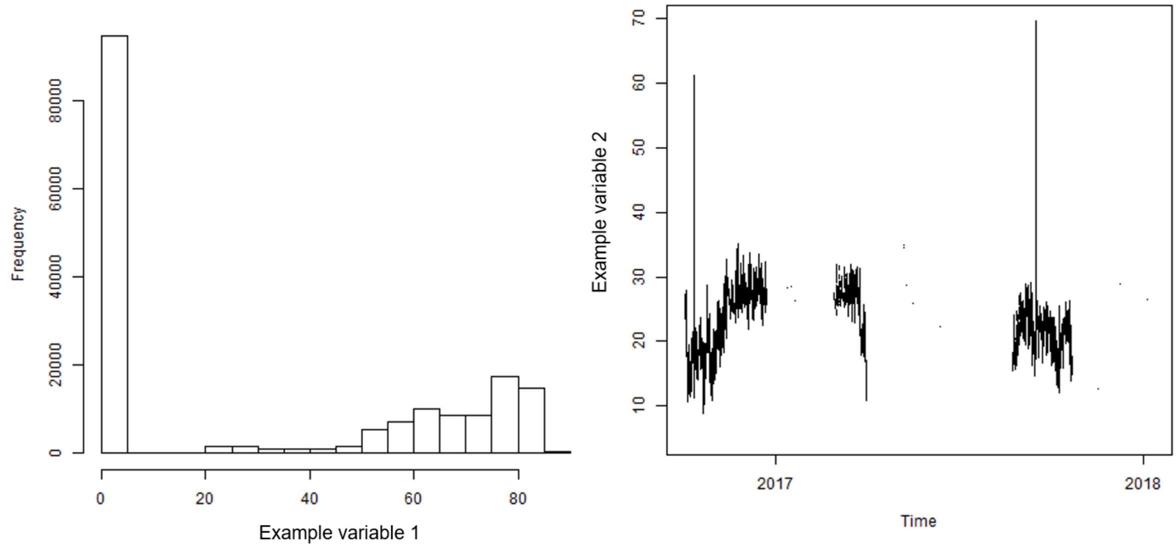


Figure 3 Pre-processed data plots

3.3 Statistical tests

In pursuance of objective one, to estimate the overall level of fouling with quantified impact on fuel consumption, correlation analysis of variables that are related to the vessel's fuel efficiency was conducted. These variables included: the total propeller power, the speed through water, the relative wind speed, the sea state, and the displacement of the vessel. Here, total propeller power is used as a proxy for fuel consumption, and sea state is defined as the effective wave height, derived as the pitch deviation. Quantile-quantile plot (QQPlot) and Shapiro-Wilk's test were performed to assess whether the variables were normally distributed, a sample size of 5,000 was chosen. The results of the normality tests are shown in Table 2 and Figure 10 (found in the Appendix).

Table 2 Shapiro-Wilk normailty test

Variable	**p-value**
Total propeller power	2.20e-16
Speed through water	2.20e-16
Relative wind speed	1.27e-14
Sea state	2.20e-16
Displacement	3.35e-16

All p-values in Table 2 are <0.05 implying that the distribution of the data are significantly different from the normal distribution, therefore we cannot assume normality. The Spearman rank correlation coefficient test was adopted due to the non-normally distributed data and the non-linear relationship between different variables, both of which are violations of the assumptions in the Pearson correlation coefficient test. The results of the correlations are provided in Table 3, and are compared to the paper of Meng et al. (2016) to validate our findings. According to the Meng et al. study, the correlations between the variables and the fuel consumption can be ranked in decreasing order as follows: speed of vessel, weather conditions (including wind and waves), and finally displacement. The results in Table 3 display the same observations in regard to rank order of correlations to the total propulsion power variable (our proxy for fuel consumption). It should be noted, however, that the correlations can vary between different vessels, also seen in Meng et al. (2016).

Table 3 Spearman rank correlation coefficients between variables

Variable	Total propeller power	Speed through water	Relative wind speed	Sea state	Displacement
Total propulsion power	1.00				
Speed through water	0.73	1.00			
Relative wind speed	0.42	0.19	1.00		
Sea state	0.34	0.21	0.38	1.00	
Displacement	0.09	0.18	0.10	0.11	1.00

4 Methodology

4.1 Consumption rate

The daily fuel consumption rate is an important variable in both objectives one and three. It enables one to quantify the impact of fouling on fuel costs and in turn can be used as a trigger for the scheduling of maintenance. The ABB dataset did not include a fuel consumption variable. Fuel consumption is in metric ton per day (MT/day), and is based on the total propulsion power (the summation of power from both propellers) and estimated fuel consumptions per kilowatt hour (~200g/kwh). RStudio was utilised in the calculation of the estimated consumption rate.

4.2 Regression model

Regression techniques were implemented to investigate the impact and co-interactions of various variables on the rate of fouling, with estimates of fuel consumption for given periods before-and-after cleaning used as a way of calculating the level of fouling. Most of the focus has been placed on the first objective because it presents the majority of the workload and enables us to be able to solve the third objective.

To find out how big of a part of the total resistance is due to the fouling, we needed to model the resistance due to conditions (hereafter conditions refer to environmental conditions such as wind speed and sea state). This turned out to be more challenging than expected, as it is quite complex, and the project team does not have great knowledge of the subject. We also lacked some essential data. In the end, with the help of ABB, we modelled the resistance as described next.

We assume that the total resistance consists of five components:

$$R_T = R_F + R_D + R_A + R_S + R_L,$$

where R_T is the total resistance,
R_F is resistance due to fouling,
R_D is base drag force of the vessel,
R_A is air resistance
R_S is the force due to the sea state, and
$R_L$is increased draft due to the loading conditions.

To observe the level of the fouling, we had to model the other four components. Drag force is modelled to be proportional to the square of the speed through water. Force due to air resistance depends on the aerodynamic design of the vessel, which is unknown, but it can be approximated to increase in proportion to the square of the relative wind speed. Sea state is a complex phenomenon, but as we have only one simple variable in our data, we assume linear increase in force from the sea state. Increased draft due to the loading conditions depends on the displacement of the vessel and the hull design, but as the information about the hull design was not available to us, we assume it to be linearly dependant on the displacement.

With this information, we needed to find a fit to model the total effect of the conditions. The exact cleaning dates were not known to us, but we knew they took place around mid-June and mid-July. We assumed the vessel to be more or less clean after the cleanings, so we used data from 20^{th} to 30^{th} of July to make a fit for the resistance without fouling.

We used RStudio's own function to fit a linear model to the data using the four variables discussed previously. We used that fit to model the resistance due to the conditions for the whole time span and calculated the level of fouling by computing the difference of the total resistance and the modelled resistance due to the conditions.

4.3 Optimisation of maintenance scheduling

Basic optimisation approaches are not suitable for this problem in that mixed integer linear programming (MILP), linear programming (LP), for instance, tend to be very restrictive. Therefore, after careful consideration, our team decided to create a decision support tool for the choice of the frequency of maintenance cleaning. The methodology of how this decision support tool is created is described in the following subsections (4.3.1 and 4.3.2). First, a simple linear case is described to demonstrate the key idea. Then, second, the non-linear case is described highlighting the challenges involved with this methodology.

4.3.1 Linear fuel consumption

First, start by making the simplifying assumption that the fuel consumption increases linearly with time, and hence so does the fouling. Figure 4 is used as example to explain a decision rule for a linear function. In Figure 4 two cleaning events occur, one at 122 days and another at 244 days. The green line, representing the cleaning scenario, drops back down to the starting fuel consumption after the cleaning event. The overall idea of the decision rule is that the area between the no cleaning scenario (the blue line) and the two cleaning scenario (the green line) must be greater than the cost of the cleanings for the cleaning schedule to be cost effective.

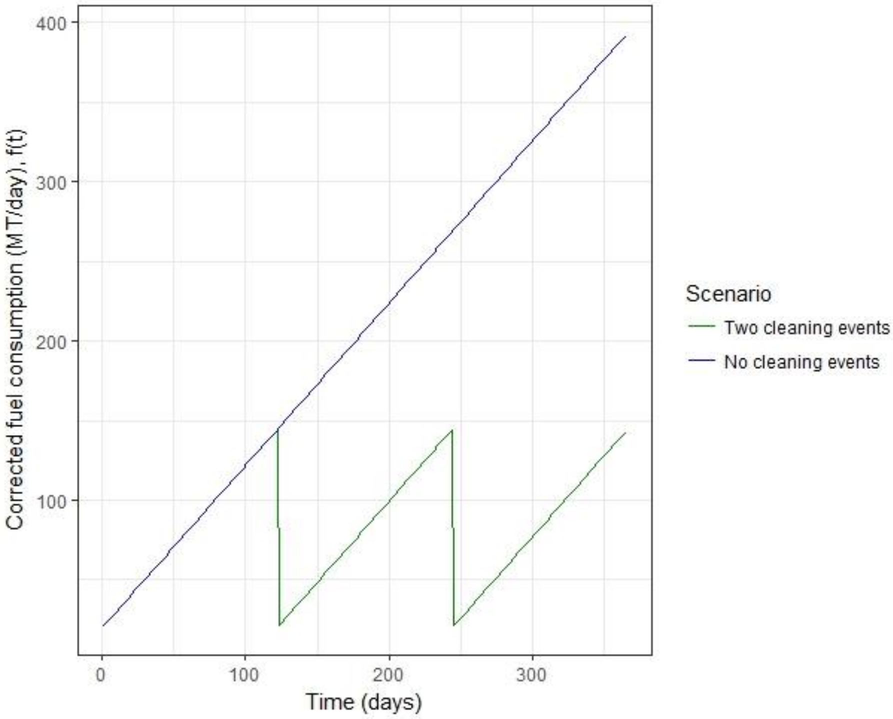


Figure 4 Linear fuel consumption example

Let's define the following variables:

f is corrected fuel consumption,

t is time period (where t/n is assumed to be an integer),

a is starting fuel consumption level, with assumption that after a cleaning it returns to this level,

m is gradient of the linear fuel consumption increase,

n is number of intermediate cleaning points,

c is cost of cleaning, and

p is fuel price per unit.

The fuel consumption function without cleaning is defined as:

$$f(t) = a + mt$$

The area under this function can be calculated to give the total cost of the fuel consumption used without a cleaning occurring, this area is called $N(t)$.

$$N(t) = \left(\frac{a + (a + mt)}{2}\right) t = at + \frac{mt^2}{2}$$

From this, the total cost of $N(t)$ can be defined.

$$C_{N(t)} = \; pN(t) = p\left(at + \frac{mt^2}{2}\right)$$

The area under the scenario where cleanings occur, $S(n,t)$, is calculated in a similar way.

$$S(n,t) = (n+1)\left(\left(\frac{a + (a + m\,{}^{t}/_{(n+1)})}{2}\right)\frac{t}{(n+1)}\right) = at + \frac{mt^2}{2(n+1)}$$

From this, the total cost of $S(n,t)$ can be defined.

$$C_{S(n,t)} = \ pS(n,t) + nc = p\left(at + \frac{mt^2}{2(n+1)}\right) + nc$$

The decision rule follows, if $C_{N(t)} - \ C_{S(n,t)} < nc$ then do not perform the maintenance cleanings, however if $C_{N(t)} - \ C_{S(n,t)} \ \geq \ nc$ then perform the cleanings.

It should be noted that opportunity costs due to not being able to operate the vessel during cleanings is not considered.

4.3.2 Non-linear fuel consumption

Second, the assumption that the increase in fuel consumption is linear is dropped, as we do not live in an ideal world and the assumption is far too restrictive. A non-linear function, $g(\cdot)$, is defined. Now, following the same logic as the simple linear version, the areas under the no cleaning scenario and cleaning scenario are:

$$N(t) = \int_0^t g(\tau)d = G(t)$$

$$S(n,t) = (n+1)\int_0^{\frac{t}{n+1}} g\left(\frac{\tau}{n+1}\right)d\tau = (n+1)G\left(\frac{t}{n+1}\right)$$

As before,

$$C_{N(t)} = \ pN(t) = nG(t)$$

$$C_{S(n,t)} = pS(n,t) + nc = p\left((n+1)G\left(\frac{t}{n+1}\right)\right) + nc$$

The decision rule still holds; if $C_{N(t)} - \ C_{S(n,t)} < nc$ then do not perform the maintenance cleanings, however if $C_{N(t)} - \ C_{S(n,t)} \ \geq \ nc$ then perform the cleanings.

At a glance, the non-linear version may not seem much more complicated than the linear version, unfortunately, this is not the case. To be able to perform the calculations a clearly defined function that represents the corrected fuel consumption over a given time period is needed, i.e. $g(\cdot)$ needs to be well defined. Problems arise in defining this function as data quality and quantity are crucial in defining an accurate fuel consumption rate, in addition to accurate fuel consumption prediction as the maintenance scheduling is produced prior to the vessel departing from its first port. This may result in a complicated function that still may not be fully representational of the actual corrected fuel consumption. Another problem is that it is assumed that after the cleaning points, the corrected fuel consumption (and hence the level of fouling) follows the same function as not cleaning, $g(\cdot)$. This is not necessarily the case. This illustrates that although the non-linear function may give more accurate results compared with the linear function, it is still not a perfect method as it includes strict assumptions.

5 Results

5.1 Overall level of fouling

The following subsection describes the results of objective one, to estimate the overall level of fouling of a given vessel.

Once the total power had been corrected for the base drag and environment conditions, it was possible to calculate the corrected fuel consumption rate of the vessel, the proxy variable in use to quantify the effect of fouling. The two dotted lines in Figure 5 illustrate the two cleaning events around mid-June and mid-July 2017 (the exact dates were not known to ABB). From the figure, one can see that the cleaning events do not appear to have a significant effect on the fuel consumption rate. The average fuel consumption rate due to fouling is mostly around 0.5 metric ton per day excluding a few outlier values.

Figure 5 depicts no noteworthy influence on the overall level of fouling as the fuel consumption rate due to fouling does not reduce immediately after the cleaning events, rather it stays at a similar level. An interesting observation is that the average fuel consumption due to fouling increases (up to 3 MT/day) around the first cleaning event. We suspect that this may be because the actual cleaning event is slightly later in the month of June, and around the time of the marked cleaning event the vessel is coming in to port, meaning there is less of an impact of the conditions that our regression model has taken into account. After the second cleaning event there is a small trend, the level of fouling increases over time since more observations are over 1 metric ton per day, however these observations are quite sparse. ABB were also not able to inform the project team which cleaning event was a full hull cleaning, and which was a propeller polish. However, from these results we are of the opinion that the first event is the hull cleaning and the second event is the propeller. This is due to the average fuel consumption due to fouling being more consistent after the first cleaning, which could allude to the fact that the full hull clean is a more thorough clean.

The overall level of fouling accounts for 1% to 4% of total daily fuel consumption as the fuel consumption is mostly between 15 and 40 metric tons per day (see Figure 8b). Therefore, the longer the time from the last cleaning event is, the higher the overall level of fouling and fuel consumption are.

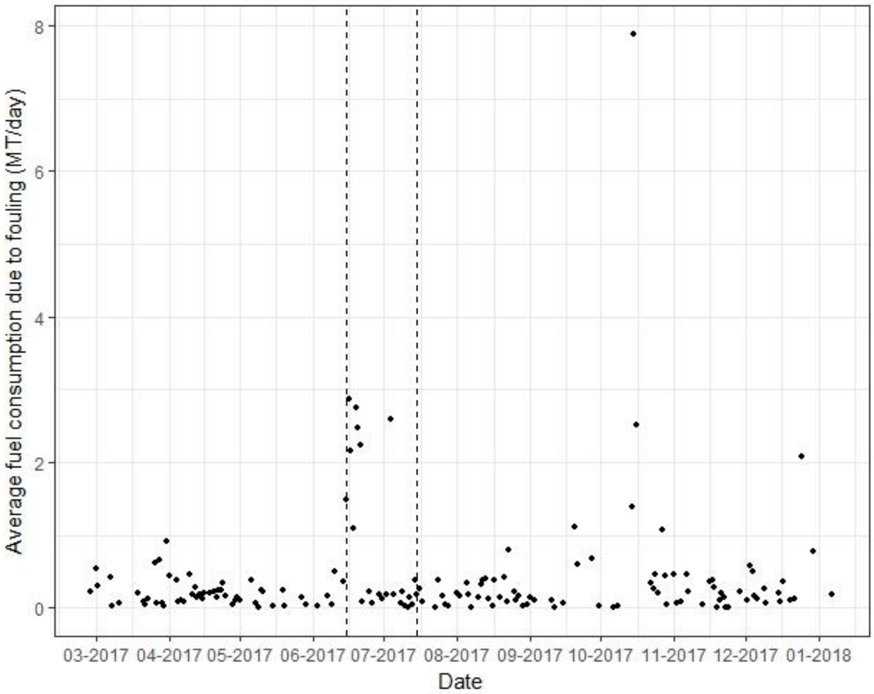


Figure 5 Average fuel consumption rate due to fouling (MT/day)

5.2 Maintenance scheduling

The following subsection describes the results of objective three, to develop a method to optimise the scheduling of hull and propeller maintenance while minimising operational costs.

Due to limited time constraints we were not able to define a function that represents the fuel consumption due to fouling to a high enough degree. Therefore, to demonstrate the ease in which our method (see subsection 4.3.2) can decide how often the vessel should be cleaned to minimise operational costs (once a non-linear function is well defined) we propose a simple example.

Assume that $g(t) = e^{t/100} + a$, where the variables are defined as before. The choice of this function is somewhat realistic as fouling does not increase the fuel consumption dramatically until a certain amount has cumulated on the vessel. This is still a relatively simple example as the fuel consumption rate, $g(t)$, is a monotonically increasing function, meaning the areas under the functions are simple to calculate. Figure 6 illustrates two cleaning scenarios with the fuel consumption function as $g(t) = e^{t/100} + a$. Notice the difference between Figure 4 and Figure 6.

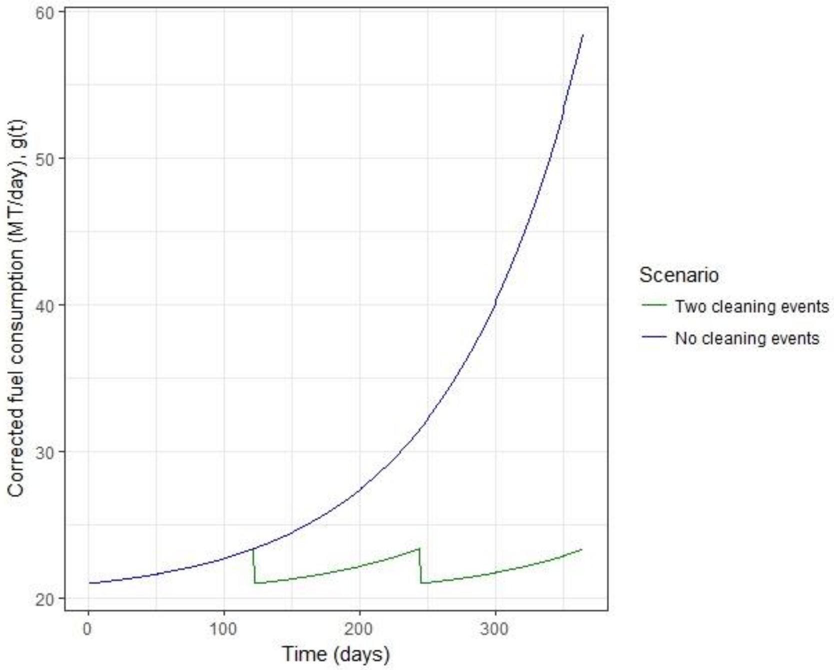


Figure 6 Non-linear fuel consumption example

Now, to calculate the area of the non-cleaning scenario we have:

$$N(t) = \int_0^t \left[e^{\frac{t}{100}} + a\right] dt = \left[100e^{t/100} + at\right]_0^t = 100e^{t/100} + at - 1$$

Assuming that the fuel consumption function after cleaning is also $g(t) = e^{t/100} + a$, the area of the cleaning scenario is (in Figure 6 $n = 2$):

$$S(n,t) = (n+1)\int_0^{t/(n+1)} \left[e^{t/100(n+1)} + a\right] dt = \left[(100n + 100)e^{\frac{t}{100(n+1)}} + at\right]_0^{t/(n+1)}$$

$$= 100e^{t/100(n+1)^2} + \frac{at}{(n+1)} - 1$$

This results in the total costs for the non-cleaning and cleaning scenarios, $C_{N(t)}$ and $C_{S(n,t)}$:

$$C_{N(t)} = pN(t) = p(100e^{\frac{t}{100}} + at - 1)$$

$$C_{S(n,t)} = pS(n,t) + nc = p\left(100e^{t/100(n+1)^2} + \frac{at}{(n+1)} - 1\right) + nc$$

We now define the following variables in order to provide numerical results:

$\mathrm{t} = \{1, \ldots, 365\}$

$\mathrm{a} = 20\ \mathrm{MT/day}$

$\mathrm{n} = \{0, 1, 2, 3\}$

$\mathrm{c} = 70{,}000\ \mathrm{USD}$

$\mathrm{p} = 422\ \mathrm{USD/MT}$

The number of time periods (t) were chosen to represent a year, however, depending on the vessel's scheduled journeys this could easily be increased or decreased. The starting fuel consumption (a) of 20 MT/day was selected as this was the most frequent fuel consumption rate in the ABB dataset (see Figure 8b). For this example four scenarios are considered, a no cleaning scenario, then three cleaning scenarios. The cost of cleaning includes a full hull cleaning estimated at 50,000 USD and a propeller polish estimated at 20,000 USD by our ABB contact. The price of fuel per unit (p) is the current EMEA average bunker fuel price as of May 2, 2018 (Ship and Bunker, 2018).

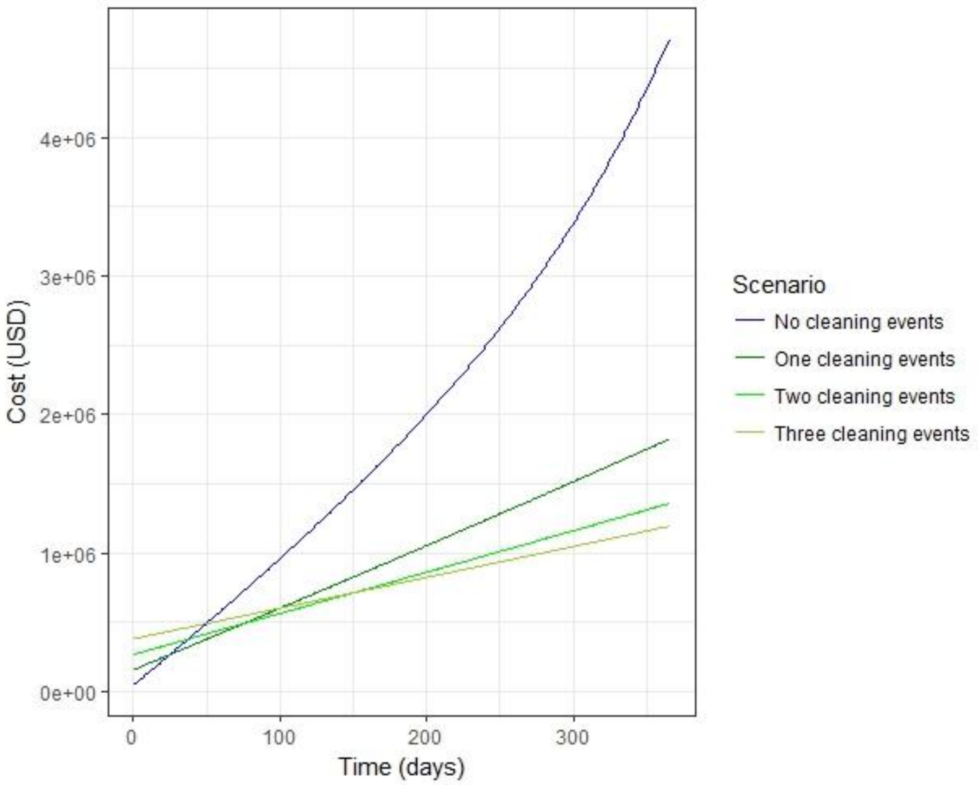


Figure 7 Total cumulative costs of cleaning scenarios

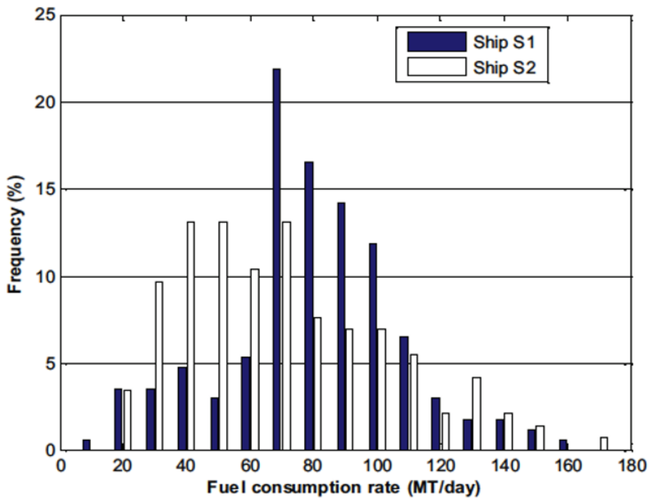
Figure 7 illustrates the total costs (fuel consumption and cleaning events) of the four scenarios. Evidently, the no cleaning event scenario is by far the most expensive. In fact, if the vessel is planning on being in use for more than 25 days, it is cost-effective to clean at least once. Comparing the three cleaning scenarios; from 25 to 75 days of use one cleaning event is shown as cost-effective, then with 75 to 150 days of use two cleaning events become more cost-effective, and finally from 150 days of use onwards three cleaning events become the most cost-effective.

These results are extremely helpful in the scheduling of maintenance as they allow the planners to state their planning horizon and the number of cleans they would like to assess. Once the least preferred scenarios have been eliminated adjustments on when the cleaning should occur can be considered, as currently the cleaning events occur at proportional points along the time period. This, however, would have to be an extension of the proposed model.

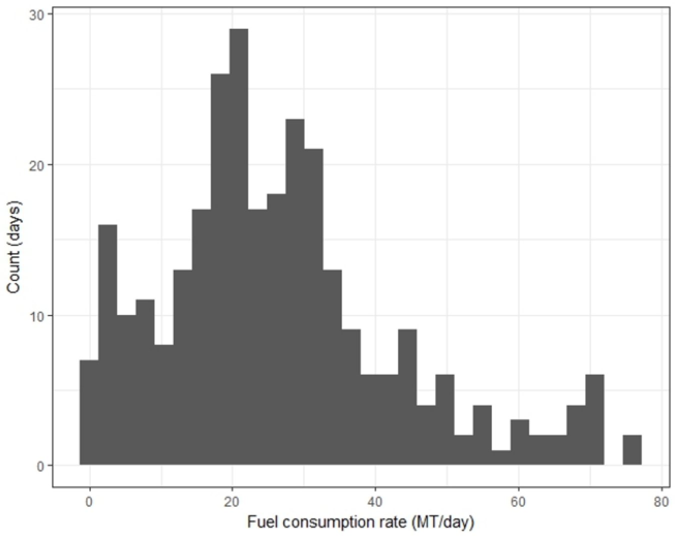
5.3 Validation, verification & sensitivity

5.3.1 Fuel consumption rate

The estimated fuel consumption rate distribution is smaller than in Meng et al.'s (2016) research but the achieved results are valid for several reasons (Figure 8). First, Meng et al. (2016) studied large container ships whose capacity was 13000-TEU and this project examined a cruise ship, meaning the vessels had different loading capacities. Second, the changing amount of cargo can explain why Meng et al. (2016) achieved higher and wider range of fuel consumption rate values. Finally, technical characteristics between the cruise and the container ship are different, which may affect fuel consumption.



(a)



(b)

Figure 8 Estimated fuel consumption rate
(a) Meng et al. (2016) distribution of two container ships (b) histogram of ABB cruise ship

5.3.2 Fuel consumption due to fouling

There are some researches which are used to validate average fuel consumption due to fouling. Lu et al. (2015) highlights how the level of fouling increases over time by examining two oil tankers (Figure 9). The total fuel consumption is increased steadily since last dry-docking, and the fuel consumption of oil tanker B stays under 4 % during the first five months, similar to our study. Unfortunately, cleaning dates were not accurate in our study but they were around mid-June and mid-July, but at the end of year 2017 it is possible identify a similar trend of increased fuel consumption due to fouling as Lu et al. (2015) did. It is also important to note that Lu et al. include engine degradation in their analysis, whereas we focus solely on fouling. In our study, it seems that the overall effect of fouling decreased marginally followed by a sudden increase immediately before the first cleaning event, which could indicate that the vessel changed sea area (Kovanen, 2012).

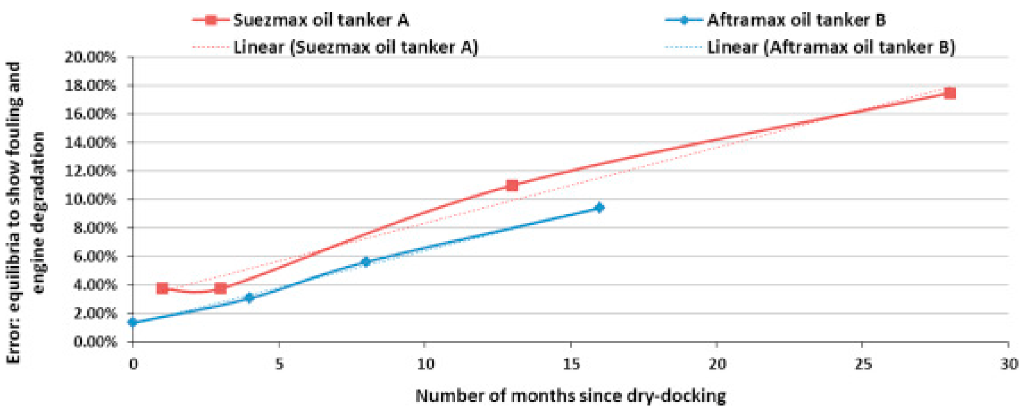


Figure 9 The effect of fouling and engine degradation to the fuel consumption, Lu et al. (2015)

Shultz (2007) examined that hull roughness and fouling can increase the required shaft power from 4 % to 59 % at the speed of 30 knots depending on the degree of fouling. Our results indicate that the overall level of fouling is low, and the coating and fouling conditions of the vessel are close to typical when antifouling coating is applied as in Shultz's (2007) study. More detailed information is gained from Shultz et al. study in 2011, where the required shaft power is increased by 1% at a speed of 15 knots and by 3% at the speed of 30 knots if antifouling coating conditions are prevalent. Thus, the impact of two cleaning events has minimal effect on the overall level of fouling. To summarise, the fuel consumption due to fouling of the vessel in this study is at an acceptable level, as in the marine industry the fuel consumption due to fouling is estimated at roughly 9 % (Smith et al., 2014) whereas our estimate is from 1% to 4% using only a years' worth of data.

5.3.3 Sensitivity of maintenance scheduling

As a way of testing the sensitivity of the decision tool and the aspects with the highest amount of uncertainty, the tool was ran multiple times with three different starting fuel consumption levels, a; four different costs of cleaning, c; and using a linear function to describe the increase in corrected fuel consumption, $f(t)$. One-way sensitivity analysis was applied, meaning that only one variable was changed at a time for the starting consumption level and cleaning costs. All variables for the linear function were as stated in subsection 5.2, with the addition of the gradient of the linear fuel consumption increase which was set at $m = 1.02$.

In the study, the starting fuel consumption level was set to 20 MT as it was the most frequently used consumption rate within the data. We acknowledge that this is most likely an overestimation, therefore we assess setting this level to 5 MT, 10 MT, and 15 MT. Figure 11 (in the Appendix) illustrates the results of adjusting the variable a. It shows a clear decrease in total costs of all scenarios, and change in the effectiveness thresholds of the four cleaning scenarios.

The cost of cleaning the vessel was set to 70,000 USD in the analysis, for the one-way sensitivity it was set to 20,000 USD representing just a propeller polish, 50,000 USD representing just a hull cleaning, 100,000 USD and 140,000 USD to represent an underestimation from ABB. The one-way sensitivity analyses displayed a minimal change in the total cost, with the main result being the change in the effectiveness thresholds for the cleaning scenarios (see Figure 12 in the Appendix).

Figure 13 (in the Appendix) illustrates the impact of the choice of function to represent the corrected fuel consumption increase over time. The linear function (Figure 13) sees a decrease in total costs compared with the non-linear function (Figure 7). However, it also displays that from roughly 50 days of use the optimal maintenance scheduling is three cleaning events, whereas it has been shown in subsection 5.2 that the optimal number of cleaning events changes will time.

6 Conclusion

This study has described a phenomenon called fouling through a literature review and a case study. There were three objectives in the project: to find out overall level of fouling, to separate hull fouling and propeller fouling, and to optimise the scheduling of hull and propeller cleanings.

A model for the first objective, to estimate the overall fouling, was developed. However, due to the limitation of the data, the model is quite limited and some assumptions had to be made that simplified the model. On the one hand, the results do not show a remarkable level of fouling, and the significance of the cleaning events is not seen clearly. On the other hand, there is no exact knowledge about the dates and types of cleaning events, which increases the uncertainty within the model.

The second objective was not pursued due to the limited data, a tight timeframe and an excessive workload. It had been estimated as a high-risk objective in the project plan, so it did not have a major impact on the progress of the project.

For the third objective, optimisation of the maintenance scheduling, a decision support tool was developed. As our model for the fouling was not totally satisfying, it was decided to make an example of the tool. In this study, we acknowledge that the non-linear function in use for the example does most likely not accurately represent the correct fuel consumption, however the results show the tool to be extremely helpful in the scheduling of vessel maintenance. Therefore, the main result of objective three is not the defined scheduling of cleaning events, but the decision support tool itself.

Overall, much more data, knowledge, and workload would be needed to end up with an accurate model for the fouling and the scheduling tool. We lacked a lot of needed information to be able to fully achieve our objectives. Despite this, we were able to make a broad literature review, develop a model for the fouling and maintenance scheduling, and validate the results.

Based on the literature review, fouling is a problem of great importance and more research is needed, as it has both a great economic and environmental impact. For the research, collection of the data should be systematic and long-term, and much more relevant information should be available than in this study. Especially the separation of the hull and propeller cleanings should be studied more, as we found a little information about this subject, but the separation could improve the optimisation of the maintenance remarkably.

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8 Appendix

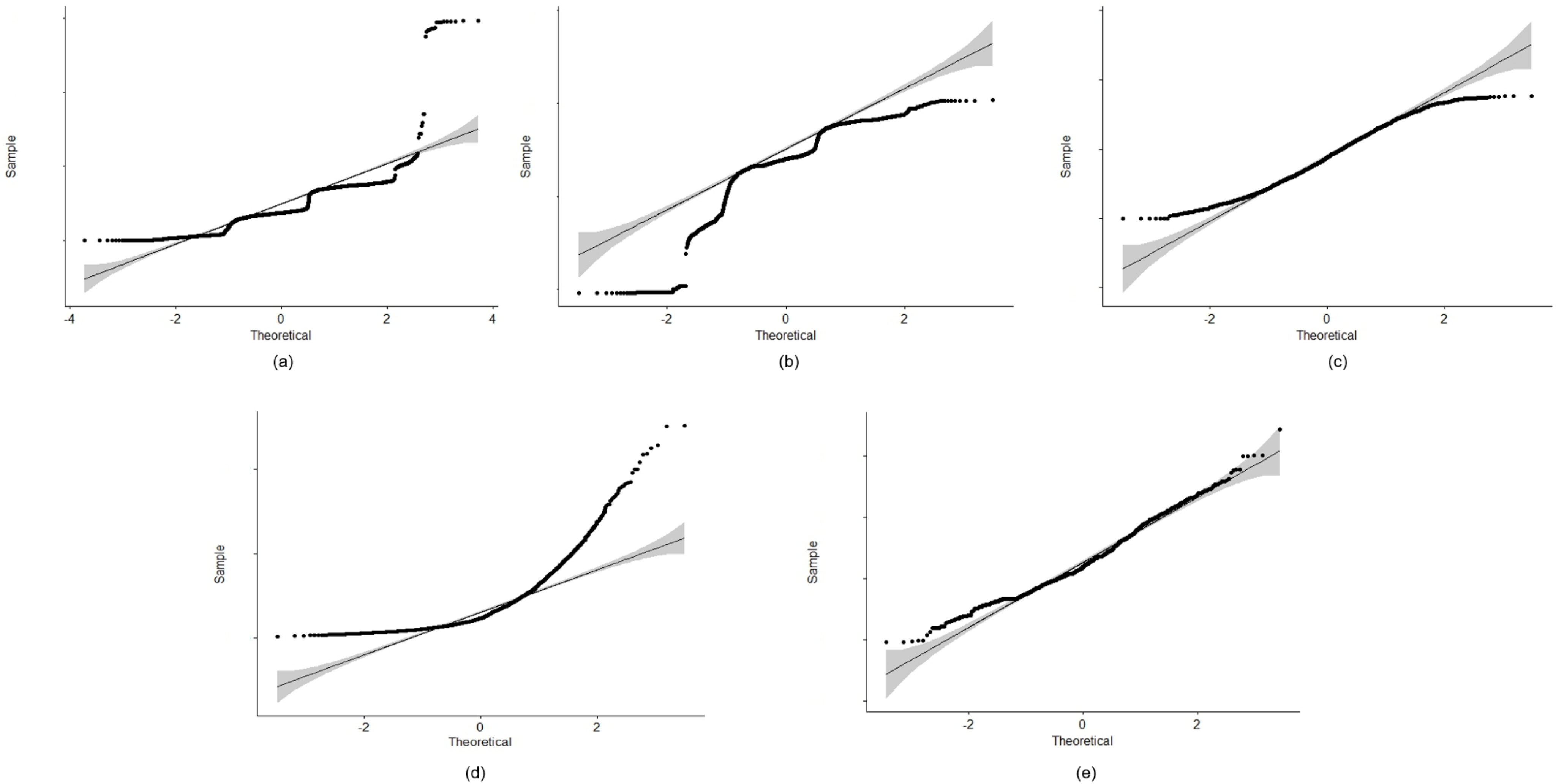

Figure 10 QQPlot (a) Total propeller power (b) Speed through **water (c) Relative wind speed (d) Sea state (e) Displacement**

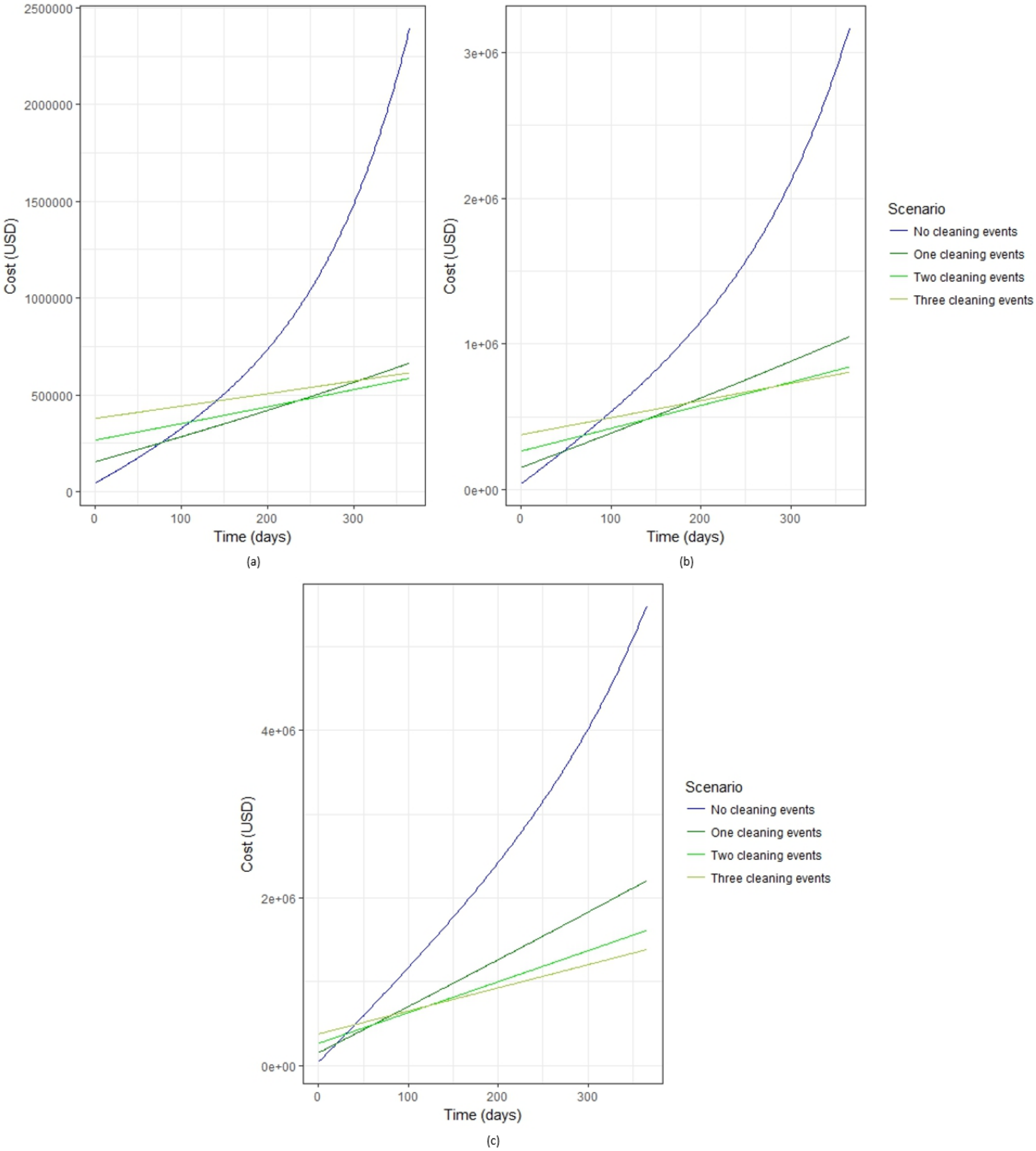

Figure 11 Sensitivity analysis of starting fuel consumption variable, a (a) a = 5 MT, (b) a = 10 MT, (c) a = 15 MT

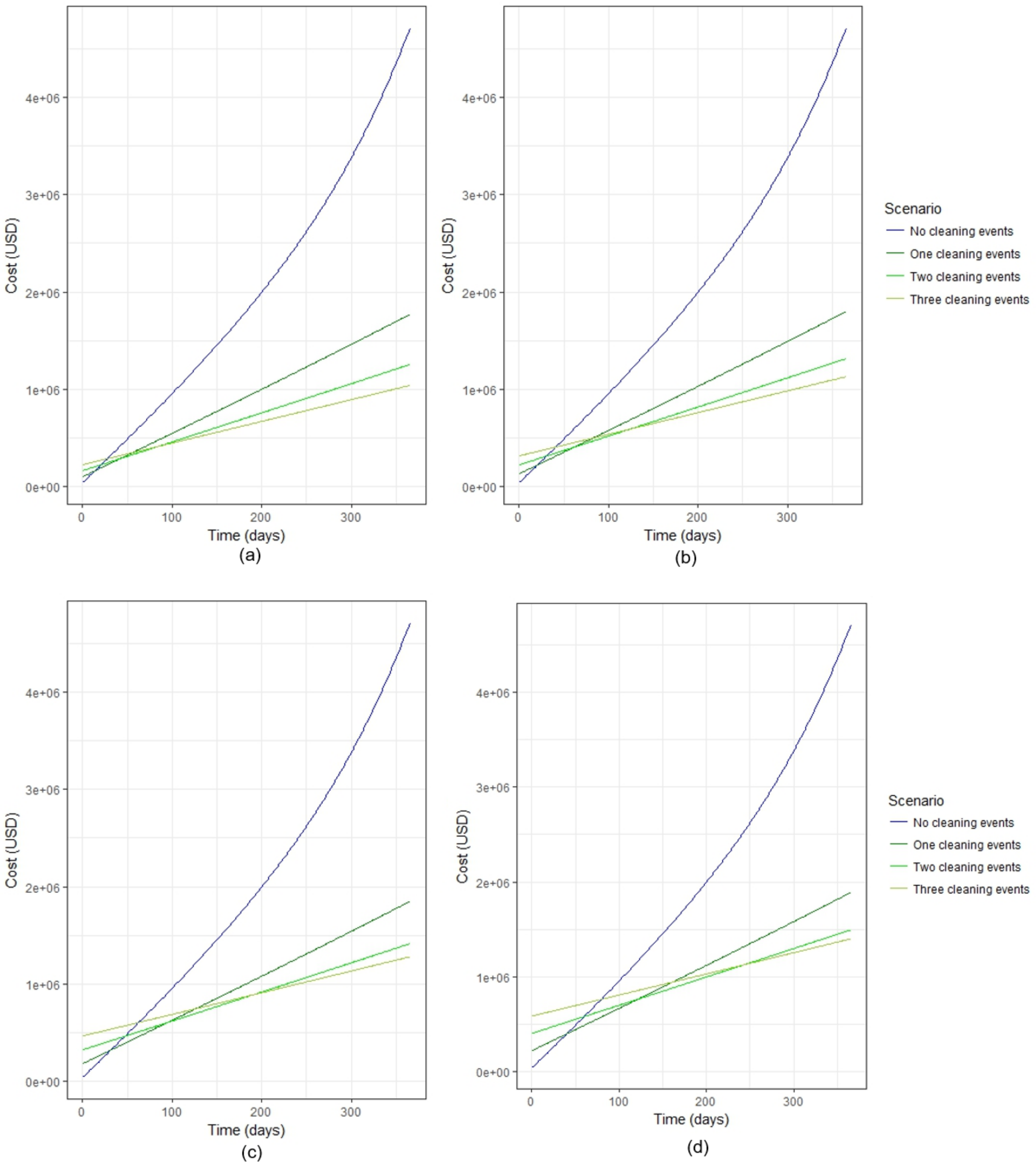

Figure 12 Sensitivity analysis of the cost of cleaning variable, c
(a) c = 20,000 USD, (b) c = 50,000 USD, (c) c = 100,000 USD (d) c = 140,000 USD

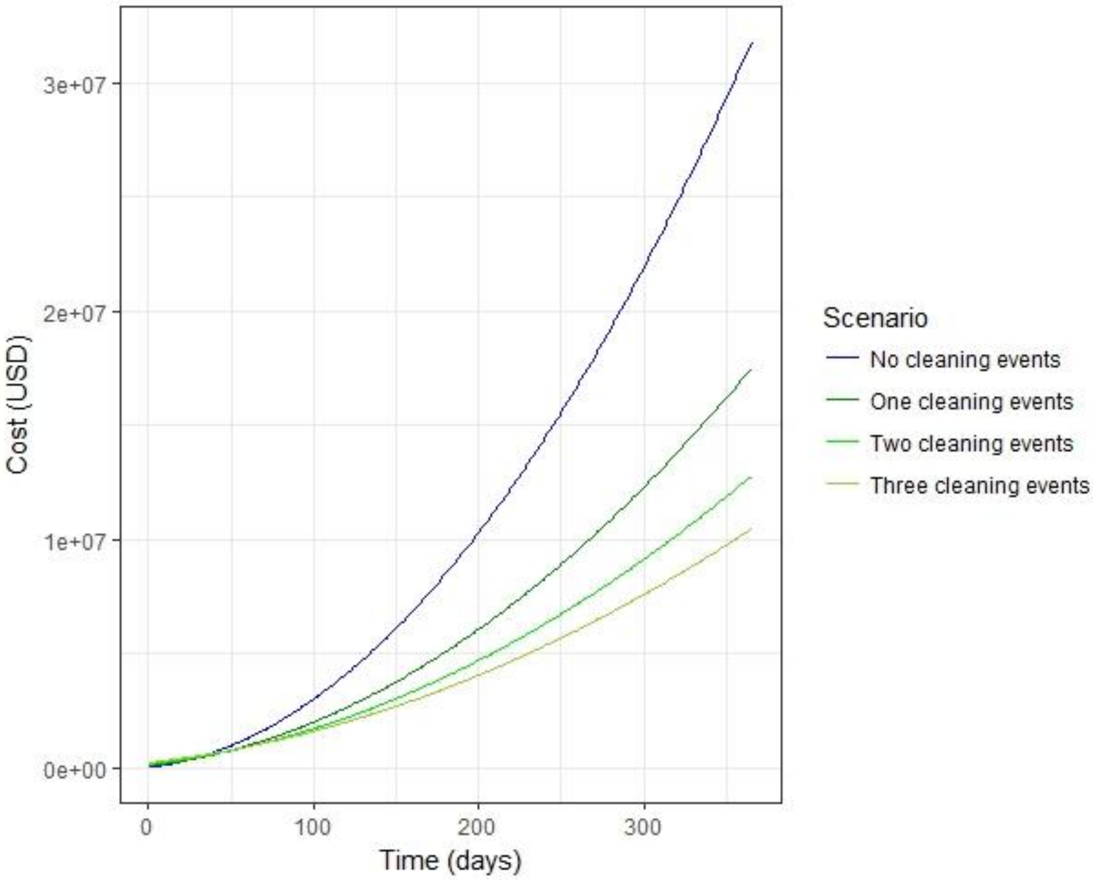

Figure 13 Total costs of linear cleaning scenarios

Task	Week start	Duration
Project planning	*1*	*2*
Literature review	*2*	*3*
Project plan report	*3*	*5*
Data pre-processing	*8*	*4*
Model construction	*10*	*6*
Interim report	*12*	*3*
Validation and verification	*16*	*3*
Final report	*15*	*6*

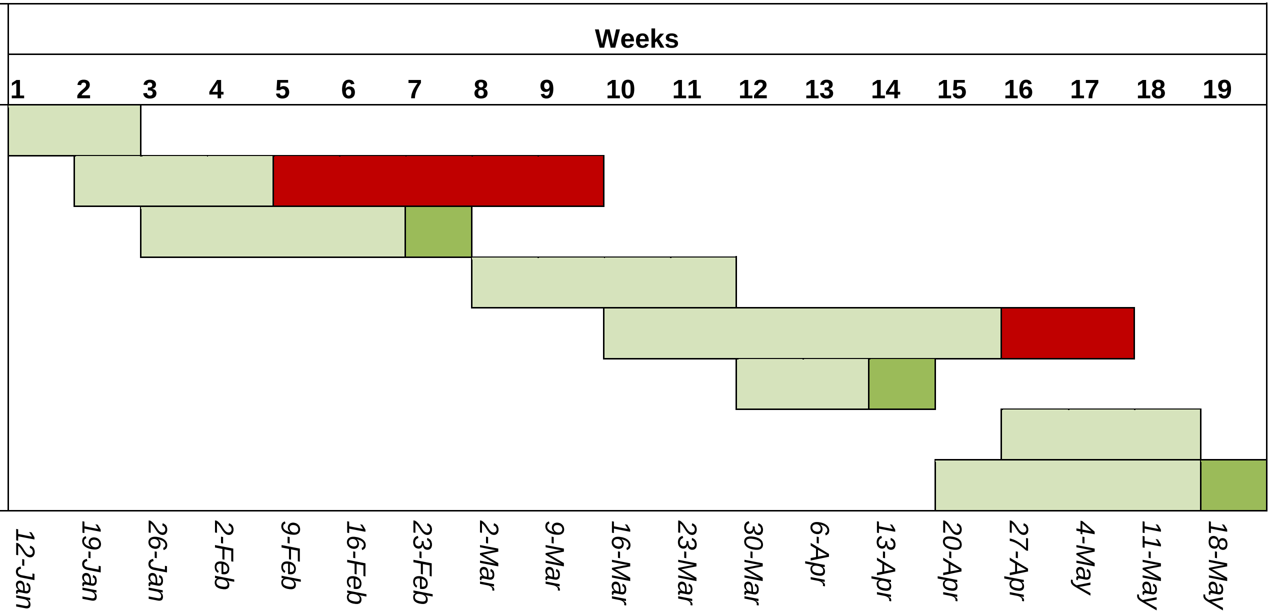

Figure 14 Final schedule ABB Team
Light green represents tasks completed on time, dark green represents completed deliverables, and extended tasks shown in red

8.1 Self-assessment of the project

Although the project was challenging and complex, time and risk management were the main areas that we succeeded to complete. All the important tasks were monitored during the project by using the Gantt chart (see Figure 14 in the Appendix). All possible risks with likelihood, risk outcome and mitigation measures were identified at the beginning of the project and the risks were controlled during the project. This was critical in achieving the main objectives and rejecting unrealistic objectives.

There were also other minor areas which were completed well. First, good social skills and the ability to work as a team, but also openness and trust were needed during the meetings and discussion. Second, regular group meetings were held weekly and questions were sent for the client to ensure that open questions were addressed. Every group member was not always able to participate in the weekly meetings, however our team had good flexibility and managed wisely to use individuals' abilities, knowledge, and experience to solve critical tasks. These absences were identified in our risk management table prior to them occurring. Finally, all vital decisions were made together as a team as there were many possible ways to proceed the tasks.

During the project, there were some areas that could have been improved upon. First, even though the scheduled tasks were well achieved, there could have been room for higher efficiency as some tasks took a considerable amount of time to complete. For instance, data pre-processing was the most laborious task in the project, which required skills of each individual. This was caused mostly by the low quality of data and the fact that the team had never encountered industrial marine data before, which leads to the second improvement area. If the data could have been pre-processed with the higher efficiency and transparency right from the beginning, there would have been more time to modify and focus on objective one and three in order to develop more accurate solutions. Finally, transparency between the client and the project team could have been closer to enhance trust to clarify and achieve the objectives of the project.