Improving operational efficiency of workboats using business process management strategies and vessel data.

Master's Thesis

N. van der Linden

TU Delft

Improving operational efficiency of workboats using business process management strategies and vessel data.

by

N. van der Linden

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Supervisors:	Dr.ir. J.F.J. Pruijn,	TU Delft
	F. Wilming	Co-founder Onboard

Cover image: Visualization of the Onboard system (sketch by Onboard (2021)).

TU Delft

Thesis for the degree of MSc in Marine Technology in the specialization of
Maritime Operations and Management

Improving operational efficiency of workboats using business process management strategies and vessel data.

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Nordin van der Linden

Performed at

Onboard

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Company supervisors
Responsible supervisor: Dr.ir. J.F.J. (Jeroen) Pruyn

Daily Supervisor(s): Florus Wilming

Thesis exam committee
Chair/Responsible Professor: Dr.ir. J.F.J. (Jeroen) Pruyn
Staff Member: Dr. W.W.A. Beelaerts van Blokland
Company Member: Florus Wilming

Author Details
Studynumber: 4466977

Preface

You are reading the report *”Improving operational efficiency of workboats using business process management strategies and vessel data.”*, a report that looks at the newly available data that *Onboard* collects of multiple workboats and describes a method to process the data and improve the operational efficiency of the workboat processes. It results from a Marine Technology Master’s Thesis conducted in 2022.

Onboard and the Delft University of Technology proposed this research. It will give workboat operators a method to stick to while optimising their workboats.

Thanks to all that supplied us with the information and knowledge necessary to write this report: Florus Wilming and Erwin Strik, thank you for all the explanations and digressions about shipping, their customers and much more, but especially for making me part of *Onboard*. Jeroen Pruyn, thanks for the insight that I forgot to think about something. A special thank you to Erik Hoogeveen, who could always help me when I got stuck with my code. And thanks go out to the Delft University of Technology for the opportunity to perform this research.

Nordin van der Linden
Rotterdam, November 2022

Summary

Organisations worldwide are decreasing their Greenhouse Gas emissions. The maritime industry is also contributing to this and trying to reduce its emissions but has done this inadequately. Reasons for this are that the required decrease in emissions varies widely between different vessels, many workboats are currently avoiding emissions regulations, and research is lagging in this area. On the other hand, many new datasets are becoming available. This research aims to show how companies can use operational data to increase the operational efficiency of workboats and decrease emissions.

The main question of this research is, how can operational data be used to improve the operational efficiency of workboat operations? This question is answered using the data *Onboard* collects and will use Business process management (BPM) tools to analyse the data. Few papers write about BPM in the maritime industry, and even less about workboats and BPM. The novelty of this study relies on the operational data-based approach, using BPM to increase the operational efficiency of workboats.

The newly collected data collected by *Onboard* is from workboats. The collected data includes location, time, distance, speed, and fuel consumption. The collected data is time series data. When the crew selects an activity, the time series data until the next activity starts as part of that activity, and all activities are grouped into voyages. To the voyages and activities, the crew can add logbook data.

BPM strategies are reviewed to find a way to use the operational data and optimise the workboats' operations. The BPM strategies are compared on the use of data, how it matches with the operational workboat data, how the focus of the BPM strategies aligns with the research, and what literature states about the methods in comparable situations. The best fitting strategy to optimise a workboat operation turned out to be Lean Six Sigma (LSS). LSS can contain many tools and has a DMAIC structure: Define, Measure, Analyse, Improve, and Control.

The available tools are chosen based on how they fit the workboat data. For the define stage, a flow chart is used. The measure phase uses a fishbone diagram, box plots, and capability analysis, including control charts and normality tests. During the analyse phase, the tools used are a fishbone diagram, scatter plots, and hypotheses tests. A Pareto chart and 5 times why are the chosen tools during the improvement phase. The control phase regulates the improvements with control charts.

The method is tested by conducting three cases. The first case of an offshore supply vessel showed how LSS could stabilise a process by removing errors from the data. The case also demonstrated how to optimise an operation by looking at the process of one vessel. The case establishes that the method can show results when the data is still quite raw, so nothing has been done to optimise the operation. The second case is about two offshore supply vessels but more focused on cargo than human transfers. The case showed two sister vessels with fewer activities than the vessels of case one. Although there were fewer activities, the number of options to choose from in the *Onboard* system was more than two times higher than in case 1, which created errors in the data. Still, the analysis resulted in insights on decreasing the difference in vessel performance and increasing the efficiency of the worse-performing vessel. The third case is the case of two similar tugs, which started improving operational efficiency a couple of months ago by setting fuel-per-hour targets. This case shows how the method works after implementing the first optimisations. The optimisations found mainly consist of several minor improvements.

The cases showed that the data is adequate when demonstrating operational efficiency issues and that potential improvements arise in three situations. Because there was not enough time to finish the control phase, the case studies cannot ensure that the method performs. The results seem promising when looking for improvements to increase operational efficiency. Not all data is analysed, and already the method shows potential.

Recommended is adding weather and cargo data and determining how this measured data can be used to improve the model. Another recommendation is testing if the improvements ultimately lead to an improved process and ensuring the sensors on board the ships work correctly. Improving data quality and analysing the time-series data can be further researched, and the used statistical tests can be further investigated.

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Abbreviations

ANOVA	Analysis of variance
API	Application Programming Interface
BPM	Business Process Management
CII	Carbon Intensity Indicator
CTQ	Critical to Quality
CTS	Critical to Safety
DCP	Data Collection Plan
DMADV	Define, Measure, Analyze, Design, and Verify
DMAIC	Define, Measure, Analyze, Improve, and Control
DOE	Design of Experiments
DP	dynamic positioning
DPMO	Defect Per Million Opportunities
EEDI	Energy Efficiency Design Index
EEXI	Energy Efficiency Existing Ship Index
FMEA	Failure Mode Effect Analysis
FMECA	Failure Mode Effect Critical Analysis
GHG	Greenhouse Gas
IMO	International Maritime Organization
IoT	Internet of Things
LCL	lower control limit
LSS	Lean Six Sigma
MSA	Measurement System Analysis
RCM	Reliability Centered Maintenance
RPN	Risk Priority Number
SEEMP	Ship Energy Efficiency Management Plan
SIPOC	Supplier, Input, Process, Output, and Customer
SPC	Statistical Process Control
SQMS	Standardized Quality Management Systems
SWOT	Strengths Weaknesses Opportunities Threats
ToC	Theory of Constraints
TQM	Total Quality Management
UCL	upper control limit
VOB	Voice of the Business
VOC	Voice of the Customer
VSM	Value Stream Mapping

1

Introduction

1.1. Background and Relevance

Global warming must be limited to avoid dangerous climate change according to United Nations (2015). The Paris agreement, set up to limit global warming, has decided that one part of this should be to decrease Greenhouse Gas (GHG) drastically. According to Miola et al. (2010), the shipping industry contributes three to five per cent of the worldwide GHG emissions, so tackling emissions from vessels would make a logical start. The International Maritime Organization (IMO) is aware of the maritime industry's contribution and has devised rules to reduce emissions. IMO (2018) states the IMO added the Energy Efficiency Design Index (EEDI) in 2011 to the MARPOL Annex VI Regulations against air pollution from vessels to decrease the impact on the environment by the shipping industry. The EEDI expounds that newly built vessels have to reduce CO_2 emissions by 40% in 2030 and by 70% in 2050 compared to 2008. New vessels must comply with new rules, and existing vessels will also be subject to new regulations.

According to Lloyd's Register (2021), on the first of November of 2022, IMO will add the Energy Efficiency Existing Ship Index (EEXI). The EEXI will oblige existing vessels to calculate their energy efficiency. A Ship Energy Efficiency Management Plan (SEEMP) was made mandatory in 2011, which obliges vessels to have a plan on how to be energy efficient. In 2019 the SEEMP Data Collection Plan (DCP) was added, which obliged vessels with a gross tonnage of 5000 and above to measure fuel oil consumption. Those vessels must calculate the Carbon Intensity Indicator (CII) starting in 2023. The CII gives all vessels a rating, and when the ratings are too low for three consecutive years, the vessel needs to increase its efficiency. These rules are now only for vessels with a gross tonnage higher than 5000 but will probably lower to a gross tonnage of 400 and higher. Other regulations, such as Carbon Credits, are also in consideration according to Schinas and Bergmann (2021). Although it is not certain which new regulations will be implemented, it can be assumed that in the near future, new regulations will be implemented to reduce greenhouse gas emissions. According to the research of Shell, and Deloitte (2020), the foundation of the decarbonisation of shipping is operational efficiency, as using less fuel simultaneously leads to less CO_2 emissions.

In addition to complying with the new regulations about CO_2 emissions, the vessels consume less fuel when increasing operational efficiency, reducing operations costs. The fuel costs can already be up to 60% of the operational costs stated by Lee et al. (2015). The impact will be even greater when shipping companies start using alternative fuels. According to Ellis and Tanneberger (2015), these alternative fuels will be more expensive than the fossil fuels used at the moment. While the SEEMP needs to contain measures to increase operational efficiency without investing extensively, Wilming (2021) claims that many organisations are missing out on an opportunity of reducing fuel consumption by up to 33% without major investments. The CII is calculated by dividing the fuel consumption by the travelled distance and vessel capacity and multiplying this by a constant value. When the goal is to lower the CII values, saving up to 33% on fuel consumption makes for significant improvement.

As reducing emissions gets more critical and the implementation of the CII, and possibly other regulations, is coming closer, it is more than logical that shipping companies are currently working hard to increase their operational efficiency. In many industries, process optimisation is the order of the day. This also counts for the shipping industry, for which more and more research into sustainability is being conducted, according to Shin et al. (2018). The research of Shin et al. (2018) indicates that few studies have focused on the efficiency of the vessel's operations. The ongoing research primarily focuses on optimising specific components such as speed, trim, draft, displacement, sea state, weather conditions, hull fouling and propeller roughness, as stated in the research of Yan et al. (2020). The literature review of Feibert et al. (2017) shows that all this research is done to optimise the shipping supply chain, as shown in Figure 1.1. *Onboard* claims companies are not focused on the operational efficiency of the entire supply chain and activities outside the port.

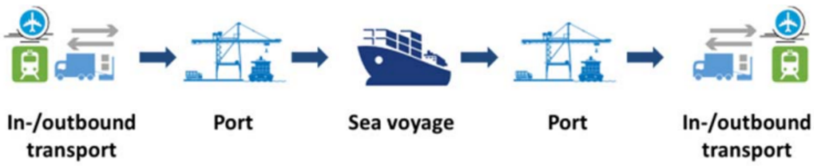


Figure 1.1: The shipping supply chain (from Feibert et al. (2017)).

Increasing operational efficiency requires a clear overview of what happens during a vessel operation. *Onboard* has created a tool that displays and collects data from vessels and subsequently maps out vessel operations. With this data, the customer can get insight into the performance of their vessels. However, *Onboard* has noticed that customers, unfortunately, do not all make full use of the data supplied, while, according to Zaman et al. (2017), data in the maritime sector gives excellent opportunities. The data currently gathered by *Onboard* can be found in Table 1.1. All data, except for the Digital LOG book data, is measured. The crew can manually add the Digital LOG book data to voyages and activities. The crew can also add notes, and the company can add customised checkboxes to add information. All the data is stored in a database and is accessible to the customers.

Table 1.1: Data collected by *Onboard*.

Data	**Components**
Location	Longitude Latitude
Time	Start time End time Total time
Distance travelled	Over ground Through water
Average speed	Over ground Through water
Fuel consumption	Per motor Total Average • per hour • per NM
Digital LOG book	Activity Voyage Destination location Planned time Fuel profile Captain or Crew Notes by crew

The first vessels which use the *Onboard* IoT gateway system are workboats. By workboats, vessels that sail out to perform an activity and return afterwards are meant, as shown in Figure 1.2. Examples of workboats include tugs, bunker vessels, walk-to-work vessels, and offshore supply vessels. These workboats do not have to comply yet with most new rules as they have a gross tonnage of less than 5000. Due to the financial advantages optimisation provides, the workboats using the *Onboard* system are improving operational efficiency. These first workboats have managed to reduce fuel consumption by up to 33%, according to Wilming (2021). These reductions were accomplished by visualising the fuel consumption during activities, which is the first step in increasing operational efficiency. During the first step, the activities these vessels are involved in are studied. From this follows the fuel consumption per activity, and with this information, the vessel owner gets a clear overview of where the fuel is going. With this insight, vessel owners can compare their expectations with reality and change company policies.

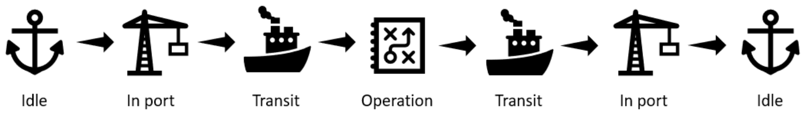


Figure 1.2: Workboat event chain.

With the increasing urgency to decrease GHG emissions and a large amount of new data available, the goal is now to see whether operational improvements can be made using this novel data. Articles like the ones from Guillemin (2021) and Czachorowski et al. (2019) indicate the importance of such data in the maritime sector. Feibert et al. (2017) showed that the sharing of data and optimisation using process management are being researched. What also becomes clear from Feibert et al. (2017) is that most of the research is based on the supply chain in the ports and the optimisation of cargo vessels, and future research could also focus on processes outside of ports.

1.2. Problem Definition

It has become clear that there is a need for optimisation, and large amounts of data are generated. The problem now is how this data can be used to optimise the vessel processes. Currently, only the most apparent waste, such as unnecessary sailing or performing activities for which the vessel was not designed, has been dealt with in some cases. A general way to find more than the most obvious waste is needed. Most vessel owners do not optimise vessel operations with the available data due to the lack of time or because it is not made a priority. So, the question is how to use the newly available data to improve operational efficiency and show the vessel owners how to effectively and efficiently optimise the vessel operations using operational data.

According to Porter and Heppelmann (2014), the first step in connecting and improving the products is to monitor the operations. The second step is to control the process, which means changing policies due to what is observed by monitoring. The third step is the optimisation of operations, which is also where this research comes in. The last and fourth step is autonomy, which repeats the statement of Shell, and Deloitte (2020) that the foundation of autonomy is optimisation. What that means in practice is monitoring the fuel consumption of every activity and subsequently analysing it to see whether this is acceptable. The optimisation step will include analyses of the activities to find waste which is usually not so easily spotted in the data, which is where this research comes in. The problem is that no standardised approach is known to increase workboats' operational efficiency.

The problem will focus on highly volatile activities rather than activities with many repetitions. The focus will be on tugs and offshore supply vessels. The event chain of the workboats is displayed in figure 1.2. These vessels have relatively many activities between departure from berth and arrival to berth, compared to cargo vessels. There is a lot to be gained according to Skjølsvik et al. (2000) if the potential of workboats is similar to the potential of cargo vessels. The objectives which can be optimised during this problem are fuel consumption, activity time, amount of activities, and utilisation.

1.3. Objective of the Thesis

This research aims to find a general way of optimising operations using the newly available operational vessel data. The goal is to have a general blueprint that explains how to indicate and remove waste from vessel operations. A method to improve operational efficiency using data needs to be made and validated. A secondary objective is to find out what additional operational data could enhance the study into operational efficiency and diminish GHG.

The goal is to use Business Process Management (BPM) strategies to increase operational efficiency. The problem is that these strategies have not been applied to workboats often. So, the objective of the thesis is to find a method and show that the method works. This strategy should optimise vessel operations by analysing operational data.

1.4. Scope of the Research

A model will be created that shows how to use operational data to find waste in the operational process. This research aims to identify waste in the operational process by constructing a model that evaluates the operational data. The model will be validated in a case study on several workboats. The evaluation is limited to the data collected by *Onboard*. The duration is too short to collect more data.

The research will investigate the optimisation of entire activities during processes rather than only perfecting one component, such as speed, trim, draft, displacement, sea state, weather conditions, hull fouling and propeller roughness. The vessels being viewed are workboats only. Due to time constraints, only hitherto collected data will be used.

1.5. Research Questions

Some questions need to be answered during this research, with the main question being: *How can operational data be used to improve the operational efficiency of workboat operations?* The other research questions which need to be answered during this thesis are stated in the following enumeration.

- What new data is available, and what kind of data is this?
- What strategies which increase operational efficiency already exist?
- Which strategies suit the problem the best?
- Which tools suit the problem the best?
- Is the available data sufficient to increase operational efficiency?
- What data could further improve operational efficiency?

1.6. Methodology

All shipping companies have seemingly different data according to Zaman et al. (2017), but it becomes similar when *Onboard* collects the data. The data can be split into three parts: transit, operations and idle. A clear overview of the available data needs to be established to use the data collected by *Onboard*. The overview of the data will be established by analysing the *Onboard* data sets and conducting a literature review. When improving operational efficiency, operational waste needs to be identified. To find and eliminate this waste by looking at data, BPM strategies will be used. These strategies will be selected by going through the literature. Those strategies will be compared using literature reviews, and the most suitable strategies or components from strategies are chosen to conduct the research. The strategies or components need to be combined in a way especially useful for the *Onboard* data set. With the strategies chosen, one method will be created. The created method needs to be validated, verified, and tested. And after all this, a conclusion can be drawn.

1.6.1. Available Data

This thesis aims to optimise the operational efficiency using the data measured by earlier performed vessel operations. This part will analyse the available operational data by studying data files, the *Onboard* API, and literature.

By looking into the *Onboard* data files and the *Onboard* API, the data behind Table 1.1 will be clarified. The frequency of the data and the useful information need to be taken into account, thus, what kind of data is worked with. When analysing the data, the limitations must be investigated, and all assumptions must be formulated. This will be done by looking into the literature.

The last part of this section will focus on how data is currently used in the transport sector. This part has two objectives. The first objective is to examine how the maritime industry uses data to optimise operations. The second objective is to find out how other sectors deal with data. To clear this up, a literature review will be conducted.

1.6.2. Analysing Strategies

During the literature study, BPM strategies that are currently used will be examined. Which strategies are used in the maritime industry, and which are used in similar industries, such as road transport and aviation? The main contents of the review will be which BPM strategies are used, the use of data within the strategies, the usability during workboat activities, and the focus of the strategies. The goal of this review will be to learn as much as possible about BPM strategies and their usability in the maritime industry.

A table showing all the best-fitting waste removal strategies will be created by looking into the literature. To decide whether the literature is fitting, the study will look into the use of the strategy in the transport sector, the use of operational data in the strategy and the effectiveness according to previous research. A small summary of the strategies will be created to ensure a clear understanding. The strategies will be compared using review papers, and the results will be displayed in a table to get a clear overview.

1.6.3. Strategy Selection

The strategy selection will use literature found in the analysing strategies section. From the literature, the strategies will be analysed by looking at their strong and weak points. The focus will be on the need and use of data, how the strategy matches the research goal, how the workboat matches the strategy and how much research was done into the strategies in a similar setting. To conclude, all aspects will receive a rating on a scale from one to five. The strategy with the highest score will be chosen to conduct the study.

1.6.4. Model Building

To build the model, more knowledge needs to be obtained about the earlier use of the strategy in relevant conditions. For this reason, a literature study will be conducted to better understand the considerations that must be considered when creating a model.

The literature on the chosen strategy will be searched using a simplified version of the systematic literature review described in Thorpe et al. (2005). A combination of keywords and variations on these keywords are used to look for all literature combining data, the transport sector, and the chosen BPM strategy or strategies. All found literature will be placed in rayyan.ai, designed to select the relevant literature.

The keywords used to go through the literature are displayed below. These are the keywords of the first search where all the bullet points need to be included, which means, in this case, maritime, the strategy, and one of the terms based on data.

- Maritime
- The chosen strategies
- Digitalisation, Internet of Things, Industry 4.0

The following steps are taken to select the proper literature from the search. These steps ensure that the literature is relevant to the development of the model. After this selection process, only the relevant studies for this thesis will remain.

1. Select literature, which is, Research articles, Book chapters, and Conferences.
2. Use rayyan.ai to remove duplicates and create an overview.
3. Use keywords to exclude literature.
4. Selecting literature by going over titles and abstracts.
5. Reading the remaining literature.

When the results are not satisfactory, a second search will be conducted. The keywords used to review the literature for the second time are displayed below. After this search, the same selection process will be conducted, as shown earlier.

- Maritime, shipping industry, road transport, aviation, Freight transport
- The chooptimisationes
- Digitalisation, Internet of Things, Industry 4.0

After this small literature review, studies will remain, indicating how to proceed with the research. There will not be a clear conclusion because the available data will differ from the data used in the conducted studies, which may cause problems. After gaining enough knowledge, the model building can start.

1.6.5. Validating and Testing

After creating the model, the first step is to control whether the model gives useful results. So, the model should be checked on whether it has implications for improving the operational process. The validation will be done on the basis of case studies.

1.6.6. Conclusion

After creating and testing the model, it must be determined whether it works properly. Conclude if the new data is useful to improve operational efficiency. If not, why and what needs to be changed to make it useful? And if the data is useful, is there data which could improve the model?

2

Theoretical Background Strategies

In this chapter, literature relevant to optimising operational efficiency will be discussed. This chapter aims to provide an overview of the current strategies used in other industries. This knowledge will be used to select the most useful strategy for improving the operational efficiency of workboats. In section 2.1, the available operational data will be analysed, which will be further analysed in section in 2.2 and compared in section 2.3. Based on this, the most suitable strategy will be chosen, which will be discussed in section 2.4. Finally, section 2.5 will look into how to use the chosen strategy, and all assumptions made will be discussed in section 2.6.

2.1. Available Data

The operational data is divided into activities. All activities are part of a voyage and a category, which include *Transit*, *Operation*, or *Idle*. From the API, all non-manual data is gathered every ten seconds. Thus, when monitoring the operation, four levels of data can be considered: Voyages, Activities, Time-series Data, and categories. The categories data is added inconsistently to the data and chosen to revise these categories in a later stadium.

The data on board vessels is collected with a Maritime Internet of Things (IoT) Gateway. According to Wortmann and Flüchter (2015), IoT combines the physical and digital components of products by measuring and monitoring the product's processes, which it subsequently uses to create large amounts of data that can be of great value. Sodhi (2020) even states that IoT is one of the drivers of Industry 4.0, the fourth industrial revolution. IoT is often linked to big data, which is also part of Industry 4.0. According to Günther et al. (2017) *, "Big data can be defined based on large volumes of extensively varied data that are generated, captured, and processed at high velocity"*. The Onboard data is not extensively varied as a quite limited amount of data is produced in a very structured way. So, the *Onboard* data will not be considered big data. However, according to Dogan and Gurcan (2018), big data analysing tools can be used to analyse the data, therefore, these tools can be considered during this research.

Working with large amounts of data comes along with some difficulties. Sanders (2016) states the four major hurdles: Number crunching, Islands of Excellence, Too many measurements, and Analysis Paralysis. Due to the nature of the *Onboard* data, only the first two are considered relevant when improving operational efficiency using operational data. It should be noted that number crunching randomly correlates data, often leading to false positives. In order to avoid number crunching, the plan must be clear and followed during the research. Islands of Excellence is meant when one of the components of a process is too optimised, resulting in it being out of sync with the rest of the operation. Keeping an eye on the bigger picture is necessary to avoid the hurdle of Islands of Excellence. This can be achieved by optimising the entire voyage instead of only one activity.

2.2. Analysing Strategies

During this literature study, BPM strategies that are currently used will be examined. Which strategies are used in the maritime industry and which in similar industries, such as road transport and aviation? The review's primary focus will be on which waste removal strategies are used, the use of data with this strategy, and the usability of the strategy in the workboat processes.

2.2.1. Improvement Strategies

The *Onboard* system displays all processes and activities. Because of this, the best fitting optimising strategies would be BPM tools that eliminate waste during the entire process. Dogan and Gurcan (2018) states that when using large data sets, strategies such as Inspection, Statistical Process Control, Total Quality Control, Zero Defects, Kaizen, and Lean Six Sigma (LSS) can be used to improve quality. When looking into these strategies, it becomes clear that even more strategies can similarly be used to optimise operations. To limit the scope of this research, it was decided to solely consider the six most relevant strategies, according to Hamrol (2018). The strategies taken into consideration are stated in the following recital.

BPM strategies;

- Theory of Constraints (ToC)
- Lean Manufacturing
- Six Sigma
- Kaizen
- Total Quality Management (TQM)
- Standardised Quality Management Systems (SQMS)

The research of Grabowska et al. (2019) explains the reasoning behind the strategies mentioned above as being the most relevant. According to the authors, ToC and Lean Manufacturing are the best strategies to eliminate waste from the process. Six Sigma and Kaizen are the best strategies to enhance the capability of the process. TQM and SQMS are considered the best strategies to motivate and support the staff.

2.2.2. Summary Strategies

This section will elaborate on the six chosen BPM strategies as recited in section 2.2.1. In particular, the focus, aim, result and implementation of the strategies will be highlighted.

Theory of Constraints (ToC)

The Theory of Constraints was first mentioned in the book *The Goal* by Goldratt and Cox (2016) in 1984. This book describes the strategy as being mainly focused on identifying bottlenecks. According to Catalano (2020), ToC adopts the common saying, *"a chain is no stronger than its weakest link"*, emphasising the ideology behind the ToC. According to Reinecke et al. (2012), it identifies the constraints in a system with a scientific approach by using system theory. The goal of ToC is to continuously increase the profits while focusing on the constraints, according to de Jesus Pacheco (2014). This way, ToC will lead to continuous improvements by taking small systematic steps, slowly resulting in better results, according to Bozdogan (2010).

The tools of ToC are The Thinking Processes, Throughput Accounting and most importantly, the 5 steps continuous improvement plan. The latter should repeat itself constantly. The 5 steps continuous improvement plan was formulated by Goldratt (1990) and is as follows:

1. Identify the System's Constraints.
2. Decide How to Exploit the System's Constraints.
3. Subordinate Everything Else to the Above Decision.
4. Elevate the System's Constraints.
5. If in the Previous Steps a Constraint Has Been Broken, Go Back to Step 1.

Implementing ToC is difficult, according to de Jesus Pacheco (2014) and Hamrol (2018). The reason behind this is that ToC is implemented by the top management. In practice, a company's culture is often a lot more complex and many management levels are faced before reaching the top management, thereby making it fairly difficult to implement ToC. ToC performs best in ”environments of medium or low stability”, according to de Jesus Pacheco (2014), and data is critical to monitor the system for bottlenecks. ToC operates in such a way that every little change creates new disturbances. Thus, the impact is deep but the data flow must be high, according to Hamrol (2018).

Lean Manufacturing

Lean Manufacturing, or just-in-time manufacturing, as it is also called, originated in Japan after the Second World War. The book *The machine that changed the world* by Womack et al. (1990) popularised the strategy. Lean Manufacturing focuses on the flow of products. The aim is to increase performance and maximise productivity. This is achieved by decreasing the waste during the processes and, when implemented properly leads to a decrease in flow time (Bozdogan (2010); de Jesus Pacheco (2015)). The five points mentioned below are the main principles of Lean Manufacturing.

- Defining customer value.
- Determining the product value stream.
- Creating a free flow for materials.
- Creating a system which pulls in the relationship between customer and supplier.
- Keep striving for perfection.

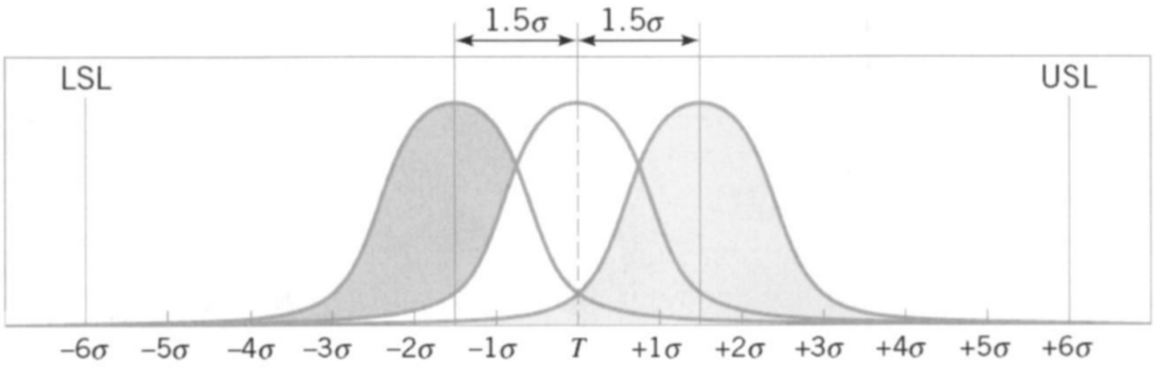
Chiarini and Kumar (2021) states the most used tools in Lean Manufacturing. The most fitting Lean Manufacturing tools that are not solely focused on production are listed below.

- Value Stream Mapping (VSM)
- 5S system
- Kanban
- Total Productive Maintenance
- Single Minute Exchange of Die
- Poka-Yoke
- Just in Time
- Kaizen

Lean Manufacturing is one of the more traditional strategies which makes the implementation relatively easy. The strategy needs to be implemented at overall management levels, which ensures that the impact ranges across the entire system. The data needed for Lean Manufacturing depends on which tools are used but is, in all cases, quite limited. Lean Manufacturing is a strategy that can be applied over the entire product-process matrix (Bozdogan (2010); de Jesus Pacheco (2015); Hamrol (2018)).

Six Sigma

The Six Sigma strategy was developed in 1986, according to Antony (2006). Six Sigma removed variability from processes, using statistical tools until the rate of defects dropped down to 3.4 per million units made. The name Six Sigma stands for the errors made within six times the variance and is 3.4 per million, as displayed in Figure 2.1. Six Sigma is not only a production strategy as Kuvvetli and Firuzan (2019) states; *”The solution can also be applied for various subjects like reducing fuel consumption or the number of breakdowns”*.



Spec. Limit	Percent inside specs	ppm Defective
±1 Sigma	30.23	697700
±2 Sigma	69.13	608700
±3 Sigma	93.32	66810
±4 Sigma	99.3790	6210
±5 Sigma	99.97670	233
±6 Sigma	99.999660	3.4

(*b*) Normal distribution with the mean shifted by $\pm 1.5\sigma$ from the target

Figure 2.1: The Motorola Six Sigma Concept (by Montgomery (2008)).

Six Sigma focuses on processes which are indicated and prioritised by process owners. Systems that negatively affect the processes' efficiency are indicated by the process owners. Once the problem is detected, Six Sigma focuses on solving the specific problem. By making sure this problem does not reoccur, the process variability decreases. So, to result in a stable process output the process needs to be stabilised by reducing variability. This subsequently maximises the business results (Bozdogan (2010); de Jesus Pacheco (2014, 2015)).

Six Sigma consists of two methods, DMAIC and DMADV. The former is in case a process needs to be optimised and the latter is used when designing a new product.

DMAIC stands for Define, Measure, Analyse, Improve, and Control. The meaning of the terms are:

- Define: Define what the problem is.
- Measure: Quantify the problem.
- Analyse: Find the source of the problem.
- Improve: Fix the problem.
- Control: Check if the improvement works.

DMADV stands for Define, Measure, Analyse, Design, and Verify. The meaning of the terms are;

- Define: Define what the problem is.
- Measure: Quantify the problem.
- Analyse: Find the source of the problem.
- Design: Find a solution for the problem.
- Verify: Check if the design works.

The tools stated below are some of the statistical tools used by Six Sigma, according to Montgomery and Woodall (2008).

- Project charter
- Process maps & flow charts
- Cause and effect analysis
- Process capability analysis
- Hypothesis tests, confidence intervals
- Regression analysis, other multivariate methods

- Gauge Repeatability and Reproducibility
- Failure mode & effects analysis
- Designed experiments
- Statistical Process Control (SPC)

Implementing Six Sigma takes a long time, requires high expertise, and the skills needed to implement it are advanced. Special project owners with top-down management involvement are needed for Six Sigma. Additionally, Six Sigma has a quite local high-depth impact on processes, meaning that data is a critical component. To get deeper into the processes, advanced statistical tools are used, and those need highly accurate and large quantities of data. The processes need variability and repetitions of the activities to be useful and for Six Sigma to give clear results (Baker (2003); Bozdogan (2010); de Jesus Pacheco (2014, 2015); Hamrol (2018); Reinecke et al. (2012)).

Kaizen

Kaizen is the Japanese word for improvement, and the strategy originated in the 1950s, according to Singh and Singh (2009). Kaizen is often called a Lean tool because of its characteristic, continuous improvement. Kaizen focuses on several minor improvements whereby the entire team is involved. The goal is to get everyone involved in finding these improvements and creating awareness among the entire staff and management Reinecke et al. (2012).

In itself, Kaizen is often seen as a tool, but it actually is a standalone strategy. Within Kaizen, a tool referred to as the Plan-Do-Check-Act tool is often used to implement new improvements.

As Kaizen is a strategy whereby everyone takes part in improving the processes, it requires only very basic skills. Its implementation requires little expertise and has a superficial local impact. Kaizen is mostly useful for lots of different activities in the process. There is little data needed, but it can play a role in checking the changes made. Kaizen is fast once implemented, and most of all, the strategy is simple to implement (Dumitrescu et al. (2011); Gandhi et al. (2019); Hamrol (2018); Reinecke et al. (2012)).

Total Quality Management

TQM originated in the USA in the 1980s and is presently used all over the world, according to Hietschold et al. (2014). The strategy strives to continuously improve the quality of products and quality services.

TQM focuses on the quality of the core business processes. It is a management system that wants to establish strong links between the design, development, production operations, and suppliers. The strategy results, when implemented properly, in a gradual system change, leading to higher quality (Bozdogan (2010); Hietschold et al. (2014)).

According to Chiarini (2011) the seven basic tools of TQM are;
1. Process flowchart
2. Check sheets
3. Pareto Analysis and Histograms
4. Fishbone diagrams
5. Run charts
6. Scatter diagrams
7. Control charts

Implementing TQM requires little expertise and basic skills. The difficulty lies with the heavy participation of all management levels. However, once implemented, TQM has a system-wide superficial impact on processes. This makes the need for data-limited (Bozdogan (2010); Hamrol (2018)).

Standardised Quality Management Systems

SQMS is a relatively new strategy. The idea of SQMS is to implement a standardised management system that must be met to receive a certificate. This certificate gives companies a norm for producing products and providing services. Zimon and Madzík (2019) state that *"Improvement of the supply chain should largely be based on the implementation of standardised management systems"*.

SQMS is similar to TQM but more focused on the standardisation of quality. The main focus is quality, and this is linked to quality standards. The result is a gradual system change. There are no common tools for SQMS, but there are common standards, such as the ISO9000 standards (Rusjan and Alič (2010); Stravinskiene and Serafinas (2020)).

Implementing SQMS normally requires medium to little expertise and medium to basic skills. SQMS has an almost system-wide medium impact on processes. This all depends on which standard is taken into account, but controlling the quality of data is very useful Hamrol (2018).

2.2.3. Combination of Strategies

An important finding from Hamrol (2018) is that nowadays, a lot of strategies are combined. For example, de Jesus Pacheco et al. (2019) shows a combination between Lean and the Theory of Constraints, and Pfeifer et al. (2004) combines Six Sigma with Total Quality Management. Chiarini and Kumar (2021) addresses the most famous combination of business management strategies, namely LSS, which combined Lean Manufacturing with Six Sigma.

Only the most used combination of strategies will be included in this literature research. In the research of Dumitrescu et al. (2011), Kaizen was compared to Six Sigma to find out which was best. The results indicate that the best strategy is to combine the two strategies, not use Six Sigma but LSS, and use LSS with Kaizen as a Lean tool. Hamrol (2018) states you can keep spending your time investigating all combinations but that combining all strategies with LSS is what gives the best results. As LSS is an integrated strategy, according to Gómez P et al. (2017), it will therefore be included in the literature study.

Lean Six Sigma (LSS)

The first time Lean and Six Sigma were combined, according to Yadav and Desai (2016), was at the beginning of the 2000s. LSS aimed to decrease the limitations of Lean Manufacturing en Six Sigma as Lean was often too superficial and Six Sigma too problem-focused. According to Yadav and Desai (2016), *"LSS has evolved from scientific management and continuous improvement theories by combining the finest elements of many former quality initiatives".*

The combination of Lean Manufacturing and Six Sigma leads to gradual continuous improvements with a long-running term. First, the waste is identified by Lean Manufacturing, and then, the source of the waste is found by Six Sigma. So, instead of only eliminating waste, it also eliminates the source of the waste Dumitrescu et al. (2011). The centralised concepts of LSS are VSM and DMAIC, according to Walter and Paladini (2019). The tools used are the same tools used in Lean Manufacturing and Six Sigma.

LSS is a more system-wide approach compared to just Six Sigma, but the strategy still needs data to be functional because LSS goes more deeply into processes compared to Lean Manufacturing. This also means there needs to be variation and similar activities. Again, all management needs to be included, and implementation can require a lot of skills, but this depends on which tools are used Pacheco et al. (2015).

2.3. Comparing Strategies

The strategies mentioned in section 2.2.1 are designed for production management, whereas this research aims to increase the efficiency of workboats. Logically, workboats perform differently from factories, and therefore strategies have to be compared to each other before using the strategy. The comparison of strategies focuses on four important factors. The first is how data is used in the strategy. The second is how the strategy matches the workboat activities. The third focuses on the focus, the aim, and the approximated effects of strategies. Lastly, the fourth focuses on the application in the transport industry, which is investigated by going through the literature.

2.3.1. Operational Data

The use of operational data is addressed in section 2.2.2. To compare the strategies on how much operational data is used, a list is formed with the strategy showing the highest data use on top of the list. At the top is Six Sigma, which can be attributed to the advanced statistical analyses of the strategy. Close after Six Sigma comes LSS. LSS also emphasises statistical tools and data but came in second due to the wider approach than Six Sigma. Thirdly comes ToC, which needs to measure performance. SQMS does measure quality during operation, but operational data is significantly less important than it is for the top three. Lean and TQM do not use that much operational data, and Kaizen uses very little data and only checks if changes work using data.

2.3.2. Matching

The BPM strategies discussed are designed for production lines, but they have to be matched with the workboat properties in order to find out about their applicability in workboats. This can be done by providing a clear overview of the process types on which the strategies are used. A product-process matrix, as created by Hayes and Wheelwright (1985), is used for this. By placing the strategies in the matrix, comparing becomes easier. A product-process matrix shows, on the y-axis, the kind of process and, on the x-axis, the kind of products being produced, as can be seen in Figure 2.2. Four process tools have been described by Hayes and Wheelwright (1985) and will be further elaborated in this subsection. The four process tools described are *Job shop, Flow shop, Line flow,* and *Continuous-flow*.

A *Job shop* is a process usually encountered when a company produces many different products in small batches. A job shop regularly has large amounts of inventory and is very flexible in producing products. An example of a *Job shop* is the block assembly when a vessel is built. Only one vessel can be assembled on the slipway at a time, and almost all of these vessels are different. To put this in vessel operations terms, it would be a vessel which can perform many different activities but can do only a few due to the relatively long duration of the activities. An example of such a vessel is a construction vessel.

A *Flow shop* is, in essence, a standardised job shop that produces a standard line of products in recurring batches. A flow shop is, therefore, faster in producing than a Job shop but is also less flexible. The block fabrication of a vessel is an example of a *Flow shop*. The blocks are produced in batches, and multiple blocks can be built simultaneously. A similar vessel type would be a vessel operating a number of specific tasks, such as a naval vessel.

In a *Line flow*, production process activities are performed in sequence to produce standardised products. The delay of one of the activities will slow down the entire process. Most assembly lines are set up to produce one product, but mixed-model assembly lines allow some variation in the process. An operations manager controls the planning and all activities to ensure the line runs smoothly. A *Line flow* can be a steel-cutting process where the standard steel plates are formed into plates which fit the vessel blocks. When a Line flow process would be translated to a vessel type it would be a vessel with one specific task, which it performs in multiple different situations. An example of such a vessel is a cargo vessel.

Continuous flow processes are fully specialised processes that only focus on one product. Continuous flow production process activities are done in sequence but contradictory to *Line flow*, processes are more automated with less variability. A *Continuous flow* process is, for example, the standardised steel plate production. A vessel comparable with a continuous flow process is a vessel with one task and performs the task in one situation, for example, a ferry.

In Figure 2.2, the areas the strategies operate are displayed. The areas are shown with a coloured oval with the strategy name in the middle. For example, Six Sigma can be used best for a flow shop or a line flow process with high-volume products and few major or standard products.

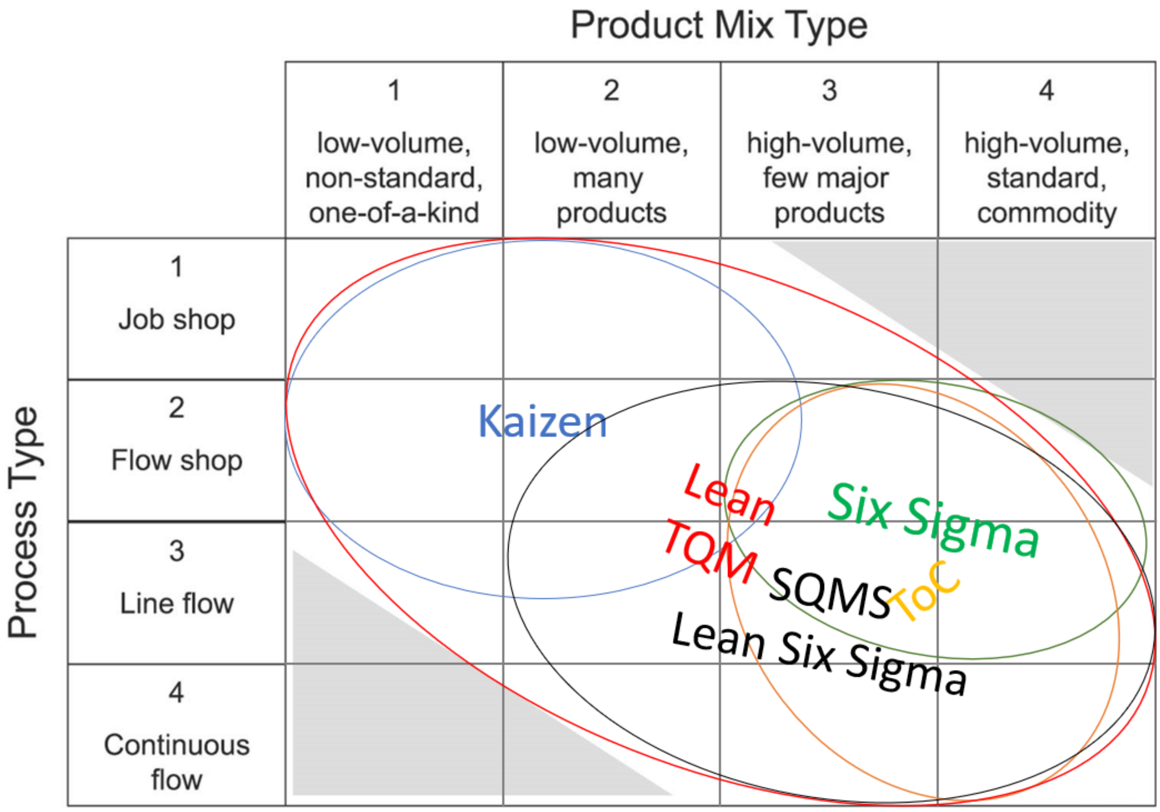


Figure 2.2: Strategies in product process matrix (Matrix from Hayes and Wheelwright (1985)).

2.3.3. Focus, Aim, and Effects

The focus, aim, and approximated effects of the BPM strategies have been previously discussed in subsection 2.2.1. In order to compare the focus, aim, and approximated effects of the strategies, a summary can be found in Table 2.1. This table clearly shows the major differences between the focus, aim, and approximated effects of the strategies.

Table 2.1: The BPM strategy focus, aim and expected effect.

	Focus	**Aim**	**Effects**
ToC	On Constraints	Finding and eliminating bottlenecks. Continuously increasing profits.	Increased gain by every bottleneck eliminated.
Lean	On the flow	Decrease flow time, increase performance, and maximising productivity.	Decrease in waste.
Six σ	The problem	Stabilise the process by reducing variability and maximise business results.	Stable process output.
Kaizen	Small improvements	Several small improvements to keep improving as a team.	Continuous small improvements.
TQM	Core business processes	Integrating development, design, and production operations. Working closely with suppliers.	Gradual system change.
SQMS	On quality	Using standards to ensure the quality of the products and services.	Gradual system change.
LSS	Effectiveness and efficiency	Analysing the system to find critical elements. Stabilising the critical elements.	Gradual continuous improvements over a long-term.

2.3.4. Strategies in Literature

To gain confidence in the feasibility of the chosen strategies for their applicability in the workboat industry, it is useful to review what previous literature has indicated on the strategies. The strategies are shown in the left column in Table 2.2. Examples in which industries the strategies are applied, as well as the insights gained into the applicability of the strategies, can be found in Table 2.2. To be eligible for this literature review, papers must clearly discuss the use of data.

Table 2.2: Strategies used in the transport sector.

	Industry	**Insight**	**References**
ToC	Road transport Collaboration	Need of Variance. Performance measurements are crucial. Chain members need to see constraints as common denominator.	Montgomery (2015) Simatupang et al. (2004)
Lean	Service industry Ports Transport Logistics	Reduces variability and waste. Needs deep understanding of services and customer needs. To keep improving information technology is required. Operations are being streamlined.	Andrés-López et al. (2015) Marlow and Casaca (2003) Garza-Reyes et al. (2018)
Six σ	Road transport Shipping Public transport	Case studies show results. Strong dependency on data. Not always necessary to use advanced analysis techniques.	Wei et al. (2021) Durai Murugan and Kannan (2021) Kuvvetli and Firuzan (2019) Feibert et al. (2017)
Kaizen	Road transport Aviation	Needs some data. Seen as a lean tool. Rapid Improvement.	Pinho and Lobo (2019) Demir and Paksoy (2021)
TQM	Shipping Road transport	Motivating and empowering their employees. Importance data is generated autonomously. Brings quality practices from management to employees.	Pantouvakis and Karakasnaki (2017) Pantouvakis and Psomas (2016) Ballantyne and Heron (2020)
SQMS	Shipping Supply chain	Varying results.	Zimon and Madzík (2019) Karakasnaki (2016)
LSS	Shipping Construction	Removes waste and variability. Big need for Data. The entire company needs to work on implementing.	Praharsi et al. (2021) Panagopoulos et al. (2017)

2.4. Strategy Selection

The literature review, as can be found in section 2.2, will be used to select the strategy used for analysing the operational data. For this, strategies will be compared based on their strengths and weaknesses, and all strategies will be graded on performance, ranging in ranks from 1-5. For example, unsuitable strategies will be graded with a 1, and extremely suitable strategies will be graded with a 5.

The strategies will be rated on four criteria, as stated below.

- The need for data
- How the workboats match with the strategy
- The focus aim and effects of the strategy
- How the literature works with the strategy

The choices made, with respect to the four criteria, will be elaborated on in the following subsections, and the final scores will be shown in subsection 2.4.5

2.4.1. Data

As this research focuses on improving the operational efficiency of workboats using operational data, strong emphasis will be put on strategies that make better use of data. Thus, the newly available operational data will also be highly considered. The seven BPM strategies will be rated on a scale of 1 to 5. The specific data rating is further elaborated on in Table 2.3.

Table 2.3: The data rating with description.

Score	Description
1	Little to no operational data
2	Small use of operational data
3	Needs for operational data
4	Big need for operational data
5	Focuses on operational data

As stated in section 2.3, Six Sigma and LSS strongly focus on operational data and are therefore both rated with a 5. After these two strategies comes ToC, which requires data and is rated with a 4. SQMS needs operational data but has no big needs and is therefore rated with a 3. Lean and TQM have small use for data, which gives them a rating of 2. Lastly, Kaizen is rated with a 1 due to the little to no use of operational data.

2.4.2. Match

Matching the workboat properties with the production processes is essential to the strategy selection. To match the workboat operations with production processes, the workboat's definition must be determined first. This research sees workboats as tugs, bunker, walk-to-work, and offshore supply vessels. All these vessels are built with a sole purpose. For example, a bunker vessel is solely designed to bunker vessels in the port and has no other purpose. A workboat loads, unloads, or moves cargo at sea. Walk-to-work vessels unload and load people offshore, and a tug moves vessels offshore. Cargo first loads onto the vessel while at berth, cargo goes to the following location, the cargo is loaded off the vessel, the cargo has to be used, the used cargo is taken away, the cargo returns to the port, and the cargo is unloaded at berth. The transit might differ in length but will be executed similarly every time, the activities will be conducted again, and the approach will be the same. And while Idle, the vessel is just inactive. For this approach, the average activity values will be pretty similar. In conclusion, this sequence can be translated into one standard process. The vessels will experience significant variance due to operating in the elements. The process type with the most similarities is the mixed-model assembly line.

Because the process happens daily with multiple vessels, the more data is collected, the bigger the volume. There are within the companies multiple machines, workboats, executing the same process, which can be compared to multiple machines in a factory which all have the same job. The options are twofold, which shows a flaw in the matrix. When we look at the examples from shipbuilding, it can be said that block building differs quite a lot from the number of activities a vessel conducts. But on the other hand, metal sheets bending and cutting happen in a higher volume. However, the outcome tends more towards plates, and thus high-volume, than section construction, but the situation remains a borderline case. This puts the workboats on the left side of the high-volume, few major products column. The choice is made because the agreements with high volume are more significant, especially if more ships are compared with each other, but it must be taken into account that there is not a lot of volume. The workboat processes area in the product-process matrix is shown in Figure 2.3. In this figure, the workboat process is placed into the product-process matrix, indicating which strategies have the most potential to improve the operational efficiency of workboats.

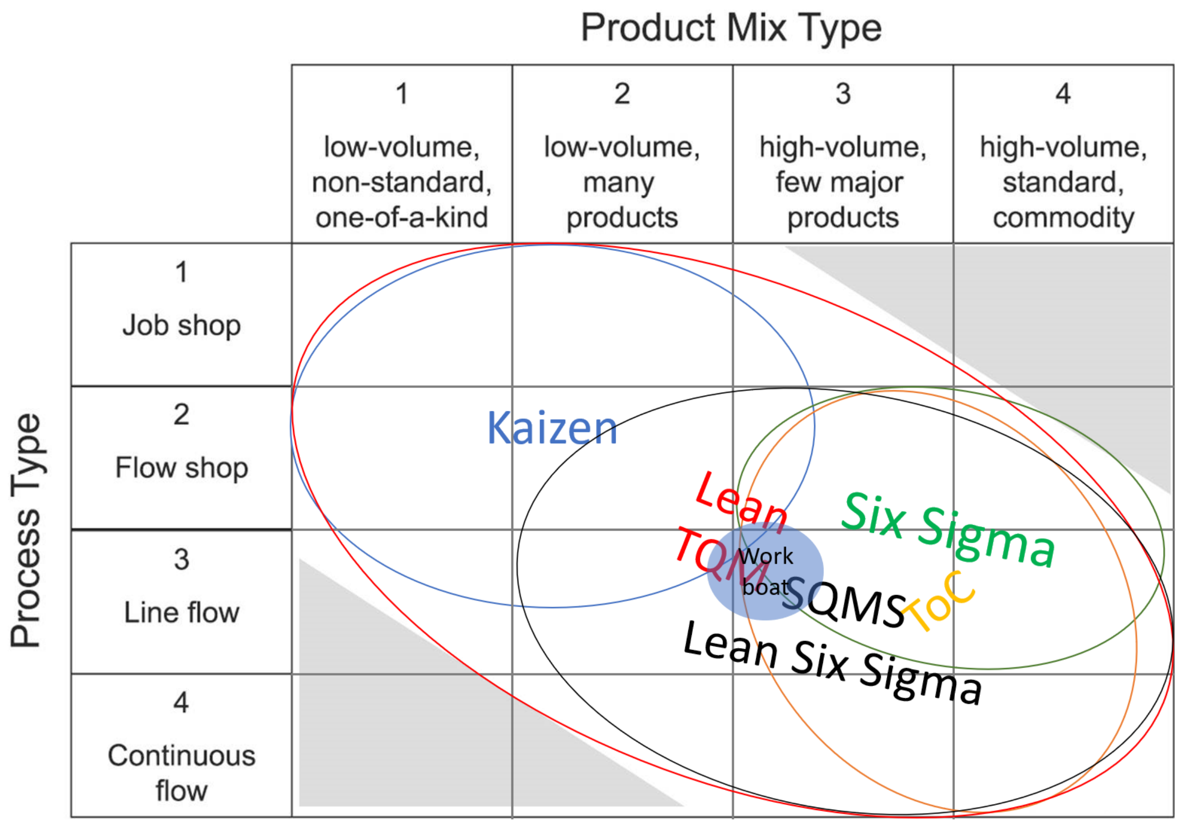


Figure 2.3: Strategies and workboats in product process matrix (Matrix from Hayes and Wheelwright (1985)).

Due to the uncertainties of how the workboats will perform in the process matrix, the workboats are displayed as an area instead of one point. The rating of the matching part will be based on the location of the workboat area in comparison with the strategy area. The more centred the workboat area is of the strategy area, the better. The rating is further elaborated in Table 2.4.

Table 2.4: The matching rating with description.

Score	Description
1	Not in the region
2	On the edge of the region
3	Near the edge of the region
4	Near the centre of the region
5	In the centre of the region

As can be seen in Figure 2.3, the workboat area is practically in the centre of the Lean and TQM area, which is also why both are rated with a 5. The area is just outside the centre of the SQMS and Six

Sigma, which leads to those strategies being rated with a 4. The workboat area is mostly inside the ToC area, so ToC is rated with a 3. Lastly, the workboat area is on the edge of both Kaizen and Six Sigma, which gives them both a rating of 2.

2.4.3. Focus

The objective of this research is to optimise voyages by analysing operational data. Since the goal is to optimise operations, there is no clear problem. Workboats sail, and there is no problem that needs to be solved. There now is a lot of untouched data available that can be used to further improve and optimise voyages. The goal is to find and remove waste and use this to improve operational efficiency. When using one of the strategies, it is important to have an aligned focus. To achieve this, the focus of the research is compared with the focus of the strategies. This will be done by comparing the focus, aim, and expected effects from section 2.3 with the objective of the research. The seven strategies will be rated on a scale of 1 to 5, which will subsequently be used to draw conclusions. The rating is further elaborated in Table 2.5.

Table 2.5: The focus, aim, and expected effects rating with description.

Score	Description
1	Different focus, aim and expected effects.
2	Minor similarities.
3	Focus, aim and expected effects are partly similar.
4	Similar focus, aim and expected effects.
5	Aligned focus, aim and expected effects.

The only strategy found to have an aligned focus, aim and expected effects with this research is LSS. LSS looks for waste to improve effectiveness and efficiency and keeps improving continuously. Therefore it is rated with a 5. Kaizen and Lean both have a similar focus as this research, but not as aligned as LSS, and are thus rated with a 4. ToC is rated with a 3 as it focuses mostly on the constraint, which might not be present in the case of workboat processes. Six Sigma is also rated with a 3 because there is no specific problem defined for this research, but the aim and effect do match. TQM is rated with a 2 because it mainly focuses on quality by changing management, which is difficult to translate to operational efficiency. The same accounts for SQMS, but on top of this, there is no standard for workboats yet. Therefore, SQMS is rated with a 1.

2.4.4. Literature

During the transportation-focused literature research, the authors gave different feedback on each of the BPM strategies. Some strategies were found to lead to better results and viability compared to others. As the objective of this research is not to invent a new strategy, it was decided to use a recognised strategy. The rating is further elaborated in Table 2.6.

Table 2.6: The literature rating with description.

Score	Description
1	Little to no indications strategy could work
2	Some research is done, but no clear indications strategy works
3	Research shows some indications strategy could work
4	Clear indications the strategy fits the objective
5	Papers showing the viability of the strategy and promising results

The findings from the literature study indicated that Lean and Six Sigma were proven to work in similar industries, so both were rated with a 5. TQM and LSS missed promising results but had clear indications that they could work, so they were rated with a 4. ToC and Kaizen gave some indications for being useful, but very convincing articles were lacking, leading to both strategies being rated with a 3. SQMS was discussed in very few papers, and there were no clear indications for the strategy to work in a workboat situation. As a result, SQMS was rewarded with a rating of 2.

2.4.5. Conclusion

The strategy used during this research will be the one that receives the highest average score. It was opted to consider all components to be of equal importance, which is also the reason why the selected strategy is chosen based on the average score. All scores are displayed in Table 2.7.

Table 2.7: Combined scores strategy selection.

	Data	Match	Focus	Literature	Average
Theory of Constraints	4	3	3	3	3,25
Lean Manufacturing	2	5	4	5	4
Six Sigma	5	2	3	5	3,75
Kaizen	1	2	4	3	2,5
Total Quality Management	2	5	2	4	3,25
Standardised Quality Management Systems	3	4	1	2	2,5
Lean Six Sigma	5	4	5	4	4,5

From Table 2.7, it becomes evident that the best strategy to be used for this research is LSS. The average score for LSS is higher than that of Lean, which ended second on the list. It is not surprising that LSS turned out to be the best-fitting strategy. Hamrol (2018) has previously stated that LSS is the solution with the highest potential when complementing it with some aspects from other strategies. Similarly, Chiarini and Kumar (2021) calls it *one of the best models belonging to the Operational Excellence*.

2.5. Model Building

In this section, a few papers will be selected to support the model building that will be done in Chapter 3. This section aims to find a way to combine LSS with the available data to create one data-based model. This will be done by learning from old research about LSS. The exact approach will not be determined. Instead, an overview of the possibilities will be provided, and the final choice will be made in Chapter 3.

2.5.1. Paper Selection

This section describes how research into LSS and logistics has been performed. Some papers were required to describe how to approach similar problems using LSS in logistics. These papers were also of value to learn from their encountered problems and mistakes.

The first search was performed on Google Scholar to find all research on the use of LSS in the maritime industry, which also mentioned digitalisation, Internet of Things, or Industry 4.0. This search resulted in 30 records. Review papers, papers on manufacturing, inaccessible papers, and papers with titles clearly not about LSS in the logistics sector were excluded. This resulted in 16 remaining records. After reading the abstracts and scanning the papers for Lean, Six Sigma, and LSS, two papers remained.

In order to say something useful, the inclusion of more than just two papers was required. Therefore, the search was expanded to multiple logistics sectors. Instead of exclusively the maritime sector, the following sectors were investigated; Maritime, shipping industry, road transport, aviation, and Freight transport. This resulted in over 1000 records in Google Scholar, which were far too many results to use for a proper selection. For that reason, it was decided to continue the search on *Scopus* and *Science Direct*. This gave three and 34 records, respectively. One of the three Scopus records was considered relevant, but it had already been found using Google Scholar. From the 34 Science Direct records, 12 seemed relevant. However, after reading the abstracts, four relevant records remained.

The topics of the papers differ, but they all seem relevant. Praharsi et al. (2021) and Besseris (2011) write about the shipping industry, Alsyouf et al. (2018) and Panagopoulos et al. (2017) discuss aviation, van den Bos et al. (2014) wrote about the implementation is construction companies, and Narkiniemi (2022) about the entire supply chain. After reading the papers Narkiniemi (2022) was also excluded from the review as the study focuses on applying strategies rather than on the results. Five papers are still enough to give an impression of how to proceed.

2.5.2. Comparison

Table 2.8 states all tools used in the research, the structure of the study, and the conclusion and discussion. This table gives a clear overview of how LSS is conducted and what results can be expected.

Table 2.8: Key takeaways of the LSS papers.

Paper	Tools	Structure	Conclusion and Discussion
Praharsi et al. (2021)	Critical to Quality (CTQ), defect per million opportunity (DPMO), sigma values, fishbone diagram, risk priority number (RPN) , failure mode effect analysis (FMEA)	DMAIC	CTQ's are: freight, vessel performance, communication and payment system. To support claims further research with empirical data can be carried out. A small study data wise.
Alsyouf et al. (2018)	project charter, SIPOC (supplier, input, process, output, and customer) diagram, CTQ, house-of-quality step, process flow chart, cause-and-effect diagrams, flow diagrams, histograms, Pareto charts, FMECA (critical), reliability centered maintenance (RCM), Strengths Weaknesses Opportunities Threats (SWOT) analysis, life-cycle cost analysis, multi-criteria decision making, system simulation	DMAIC	Identified most critical quality drivers and requirements. Analysing performance identified major problems. Effective communication and cooperation vital between stakeholders during implementation of LSS. Further research needs more data.
Besseris (2011)	Design of Experiments (DOE)	DMAIC	DOE needs limited resources. LSS not only useful in the manufacturing field but for any improvement project. Not always need for Gage R&R.
Panagopoulos et al. (2017)	Voice of the Customer (VOC), Voice of the Business (VOB), CTQ, Critical to Safety (CTS), Data Collection Planning (DCP), Hypotheses test, Control Chart, Measurement System Analysis (MSA), Capability analysis	DMAIC	Focuses on LSS and safety. Find outcomes within agreed specifications limits.
van den Bos et al. (2014)	FMEA, RPN, CTQs	DMAIC	This research focuses on how LSS is implemented. Often insufficient priority. planning and communication is important. Unravel problem into sub-issues.

2.5.3. Takeaways

It becomes clear from Table 2.8 that the DMAIC approach should be used when implementing LSS. A lot of tools are displayed in Table 2.8, and they are used during specific phases of the approach. To clarify, the tools will be divided into five DMAIC groups. Table 2.9 shows which tools can be used during each DMAIC step, which will help focus on the proper tools during the continuation of this research.

Table 2.9: LSS tools, sorted based on use in DMAIC.

Define	**Measure**	**Analyse**	**Improve**	**Control**
CTQ	DPMO	Fishbone diagram	SWOT	Case study
Project charter	Sigma values	FMEA	Life-cycle cost analysis	Control chart
SIPOC diagram	DCP	RPN	Multi-criteria decision making	
House-of-Quality	Fishbone diagram	Hypotheses test	System simulation	
Process flow chart	MSA	Flow chart	5 times why	
VOC	Capability analysis	Histograms	DOE	
VOB	Gage R&R	Pareto charts	Box plot	
CTS	Control Chart	RCM	Pareto chart	

Especially the conclusions and discussions from the papers provide important information for this research, but all findings will be considered in the continuation of this research. One issue that is addressed multiple times is the issue of gathering data. Fortunately, this should not pose a problem during this research due to the operational data collected by *Onboard*. The other findings are quite varied but can still help when kept in mind during the building of the model.

2.6. Discussion

The literature in this literature study was found in a systematic manner and led to unsurprising results. LSS turned out to be the best-fitting method compared to the other methods according to the grading system, and the literature found. Therefore, when answering the question *Which strategies suit the problem the best?*, it can be boldly stated that this is LSS. The question *What new data is available and what kind of data is this?* is answered in section 2.1. The question *What strategies to increase operational efficiency already exist?* is answered in section 2.2. The other research questions remain to be answered in Chapter 6. Though the results seem accurate, there are always some considerations that should be taken into account when drawing conclusions.

Firstly, the literature methodology, selectivity and amount of literature should be considered. The methodology for reviewing literature as described in subsection 1.6.4 and as described by Thorpe et al. (2005) might be too broad for the purpose of this research. A systematic review method can be used to read everything on a specific topic. However, the full potential of this method might not have been reached because of the way it was applied during this research. In addition to this, it was assumed during the literature study that the six BPM strategies as described in section 2.2, and the single combination made in subsection 2.2.3 were deemed sufficient. Logically, adding more strategies and combinations would give a broader picture and further expand the research. Section 2.5 shows five papers which performed a similar study, but Praharsi et al. (2021) found more papers than were found in this research. This indicates that there are likely more useful papers available, but the difference could also be due to the addition of data-based terms in the search for literature for this research. Expanding the search will presumably increase the number of records found. However, for the sake of time management, it was decided to stay with five papers as described in section 2.5.

Secondly, the operations described in subsection 2.4.2 are linked to production, and it is assumed that operations and production are comparable. This idea was based on studies that stated that the strategies could work in comparable situations. Further investigation into the comparison could be necessary to check whether the match made in this way is legitimate. Also, the definition of a workboat is quite broad due to the multiple types of vessels that are included. The assumption that one size fits all might be inconclusive, and the difference in vessels thus needs to be taken into account during this research.

Thirdly, as found in subsection 2.4.5, the average score might not be the perfect way to rate the different strategies, and the method should be critically reviewed. The score for LSS is noticeably higher than that of the other strategies when looking at the average score. Altering the weight of the four components according to their importance would have to be done in extreme manners for LSS not to be the highest-rated strategy. This would probably not give very realistic results for this research. Despite this consideration not being of too much importance for this research, it should be considered when e.g. applying this rating to other strategies.

Lastly, company management, communication and culture should be taken into account when implementing a strategy. The focus, aim, and expected effects of strategies were compared in subsection 2.4.3, but the implementation was not taken into account here. The involvement of management and the difficulties that can be encountered during implementation are stated in the strategy summaries, but these were not considered in the comparison of strategies. This was done on purpose as this research is very novel, and the strategies are unproven in this situation. It would be difficult to compare the change in company management, communication and culture when the impact of the strategies is not yet known. Apart from this, the importance of communication between stakeholders is also repeatedly highlighted during this research. Unfortunately, this can be of great difficulty because companies are not so keen on sharing information. Also, companies can have the tendency to be resistant when it comes to changing their culture. This can limit the guarantee of LSS working successfully as it largely depends on company culture changes.

Altogether, it can be concluded that to answer the main question, LSS is the best strategy. With a fair degree of certainty, it can be said that LSS is best suited to both analysing operational data and improving operational efficiency. Before the main question can be answered, first needs to find out which LSS tools can best be used, which will be done in Chapter 3. The findings will be tested in Chapter 4, and finally, the answer to the question will be given in Chapter 6.

3

Theoretical Background Model

The optimisation strategy chosen to improve operational efficiency is LSS. Knowing this, the question arises *Which tools suit the problem the best?* Numerous tools are available for the LSS strategy, as shown in Table 2.9. For this research, a selection of tools that can be used for the model will be made and substantiated in this chapter.

The tools are chosen with the *Onboard* data in mind and will focus on using data instead of interviews. Although the interviews could help improve operational efficiency, this research aims to provide a general approach to how to improve operational efficiency using operational data. Interviews can also lead to an opinionated result. The method should guide to new insights. The *Onboard* data is generated before and during the research. Only the definition of some of the data will be modified in particular cases. The aim is to reduce variation and not to identify errors. Identifying errors offshore is a problem because there is not necessarily something right or wrong. One solution is to set thresholds; label the data point as an error when data exceeds these thresholds. Determining the thresholds gives a new dimension to the research, which can be avoided by focusing on variation.

The define stage will be described in section 3.1. Section 3.2 will focus on the measure phase. The analysing process will be explained in section 3.3. The improvement methods will be described and explained in section 3.4. Section 3.5 will describe which control steps to take. The computations will be executed using the Python code attached in Appendix A.1. The five stages of the strategy are stated in the enumeration following this paragraph, and this chapter will be structured based on these five steps.

1. Define
2. Measure
3. Analyse
4. Improve
5. Control

3.1. Define

The goal of the define stage is to define the processes involved and identify the improvement opportunities. The define phase must result in all measured data being accommodated in a specific process. An activity is always active, so until a new activity is selected, all measured data is part of the activity. Defining the process is critical for the *Onboard* system because these defined processes form the basis of the measuring system. All measured components need to be defined as specifically as possible. The sensors on board a vessel constantly gather data which creates big data sets, and the *Onboard* system enables the crew to give this data meaning. The crew on board the vessel manually selects an activity which gives meaning to a specific part of the data. To give proper and useful meaning to the data, any activity that can take place must be clearly defined.

The data is given meaning manually, and because of this, there is a high chance of errors. Errors with a high probability will mainly consist of starting an activity too early or too late or selecting the wrong activity. Choosing an activity at the precise right moment is practically impossible, so there will always be a timing issue. When there are many activities with a short duration, being too late or early will have much more influence than when it comes to long-lasting activities, mainly because the average values of the activities are used. Often activities with similar characteristics follow each other up, and the impact of the errors can be reduced by combining activities. When the successive activities are lumped together, all the short activities that are very prone to errors become one activity that is less prone to errors. The quality of the longer-lasting activities compared to the single activities is then improved because it is less affected by mistakes. The disadvantage of merging the activities is that there are fewer analysis options. When there are many different activities, more activities can be compared with each other, but when activities are combined, possibilities are lost, so the quantity of options decreases.

3.1.1. Tools

Multiple usable tools define the operation of a production process, as shown in 2.5.3. The goal of the define stage is to accommodate all data in a process. The method needs to state what each activity means, when one activity is finished, and when the next one starts. This is important for LSS and especially for the *Onboard* system. The *Onboard* system benefits from having a clear step-by-step plan of which activity takes place, when, and which follows each other. Currently, onboard uses a flow chart to name all activities. A flow chart is a good fit due to the characteristics of the flow chart and the properties of the *Onboard* system. A flow chart combines the goals of identifying waste and defining operational processes. Although a flow chart does not recognise the importance of each process, the overall overview will create a clear resume and makes it easy to analyse the significant vessel processes in a later stage. To be able to produce a flow chart, an excellent process understanding is essential.

The other tools mentioned in Table 2.9 can have the same ability to identify improvement opportunities but focus less on the definition of the processes. VOC and VOB express what the customers and businesses want and need. What makes VOC and VOB useful is the clear insight into what is important and what is expected. VOC and VOB get everyone in line on what is important and needs to be done to improve the process. In order to use this method properly, interviews with people within the company and with the company's customers are important. The tools do not provide an overview of the processes, but they clearly show where the priorities lie. A project charter is valuable and, in a way, conducted in the previous chapters. When conducting this analysis, it could be beneficial to use a project charter, but this only works when the goal is to solve a specific problem. The project charter will not add much value when there is too much variation. For SIPOC, the entire process needs to be mapped out, from the supplier input, to what the customer gets, including the process. This is quite similar to a flow chart. The difference, however, is that the flowchart does not take the Supplier, Input, Output and Customer into account and only focuses on the process. CTQ and CTS are part of a few groups which are critical to the process. But just as Ted Hessing (2015) says, all these are customer-centric requirements. These tools focus on production and do not seem to fit the operational efficiency improvement task.

A flow chart is a clear tool where only the significance of each activity is missing. To solve this problem, VOC and VOB can be used. The other option is to create utility graphs that show where the resources are going and then determine what matters most. To use a method for this problem with interviews and going through the whole process seems a bit excessive because a utility graph together with a flow chart gives similar results. And to see what waste is, two flow charts are used. One is the current one, and the other is the optimal one, where the difference can be defined as waste. Another option is to extend the flow chart to a SIPOC. The SIPOC is somewhat irrelevant to the transport sector because the process is always slightly different and revolves around input and output. The process at workboats continues, and when the customers change, the process stays similar. These reasons are why it was decided to use the flowchart in the define stage.

A flow chart is created by starting at the beginning of a voyage and ending at the end. In between these two points, all possible activities should be described. The activities can be described by going through the process step by step. Not only is the current flowchart needed, but the optimal flowchart also needs to be created. With the current flow chart and the optimal flowchart, potential waste can be indicated. The flow chart might never be finished. In the improvement phase, it can be concluded that the process is a continuous improvement process requiring different activity sequences and a new flowchart. Figure 3.1 shows an example of a flow chart. What is shown in this figure is a round block which indicates the start and the end of a voyage, a square block which shows activity, and diamond-shaped blocks which indicate choices.

Creating a flow chart requires an in-depth understanding of the activities of the vessels. The flowchart will be the backbone of the procedure because everything measured is defined in the flowchart. For the analysis, an activity needs to be active at all times, and this is also how the *Onboard* system works. An activity can only be finished by starting the next activity. When creating the current flow chart, the first waste can be identified by comparing the flow chart to the optimal process flow chart.

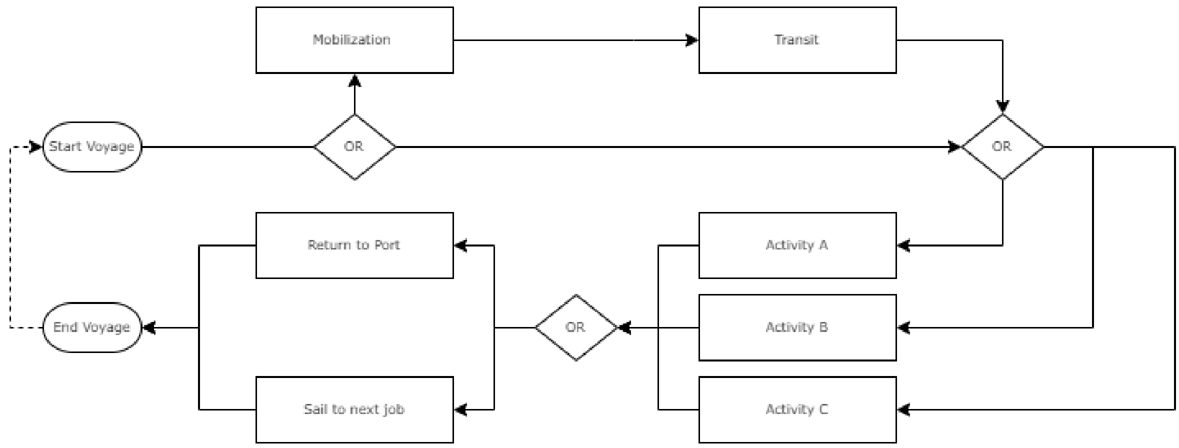


Figure 3.1: An example of a flowchart.

3.1.2. Procedure

The goal is to generalise all the voyages in one chart. A flow chart starts with a start point where the ”first” activity of a voyage begins. Often a voyage starts in port while the ship is on standby or idle or when the previous voyage is finished at the job site, from receiving the voyage to completing the voyage. The first step is selecting the start and end points of the chart.

After defining the start and end of a voyage, the intermediate activities have to be specified. An activity must be active during the entire voyage, so when the activity stops, the next starts. An activity always being operational needs to be taken into account when creating the flowchart. The crew on board the vessel needs to activate an activity when the previous activity ends, so waiting is also an activity. When creating the actual flow chart, there will be activities which do not add value to the operation. These activities can be removed from the optimal process flow chart’s subsequent flow chart. Only the value-adding activities are incorporated in the optimal process flow chart.

The result will be two flow charts where the one following the current process can be used to specify the measured activities. The one created with the optimal process can be compared to the current chart to identify the potential waste. With the flowchart, selections can be made that form groups. These groups can be visualised by placing a block over the grouped activities, which should be close to each other in the flowchart.

3.2. Measure

The measure phase is to express the system in numbers and determine the process’s current state. Critical is ensuring the correct data is collected and that this data is normally distributed and stable. Another part of the measure phase is to check what kind of errors the data can contain. The data errors will be used to exclude data during the analysis phase. During data collection, errors occur, and the data sets have errors. Errors need to be found and eliminated from the data set to increase the quality of the data. The reason for the errors must be found to identify the problems effectively. Identifying errors will also establish feedback on the measuring system and crew. To understand the problem, the reason for the errors will be identified. Increasing the quality of the data is outside the scope of this research. This research aims to show how the current data can improve operational efficiency.

Determining the state and extent of the processes is done by checking the measurements and identifying what to measure to get the best overview. This phase will start by identifying what to measure. The next step is determining whether the measured data is stable and normally distributed. The outliers and the known errors will be identified. This research will work with the data as it is. To conclude, the main goals of this phase are defining the KPIs, checking the stability, finding outliers and listing all the known errors in the data.

3.2.1. Tools

Expressing of the system is done using a DCP constructed based on the flow chart, the *Onboard* system, and the KPIs. In this study, the DCP is less critical because all the data is already being collected and only needs to be selected. Due to the assumption that the systems are correct and the sensors work properly, MSA is not conducted. A company could decide to perform an MSA to check whether the measurement system gives the required output, but during this research, the assumption is made that the sensors and measurement system are correct. In order to identify the errors in the data, a Fishbone diagram will be used. A Fishbone diagram is a tool to find a problem's root. By finding the roots of the errors in the data, the possibility of these errors occurring can be considered in the analysis phase. A fishbone diagram is also referred to as an Ishikawa or cause-and-effect diagram. Figure 3.2 shows a fishbone diagram with five categories, and the arrows indicate where the reasons for the errors are stated.

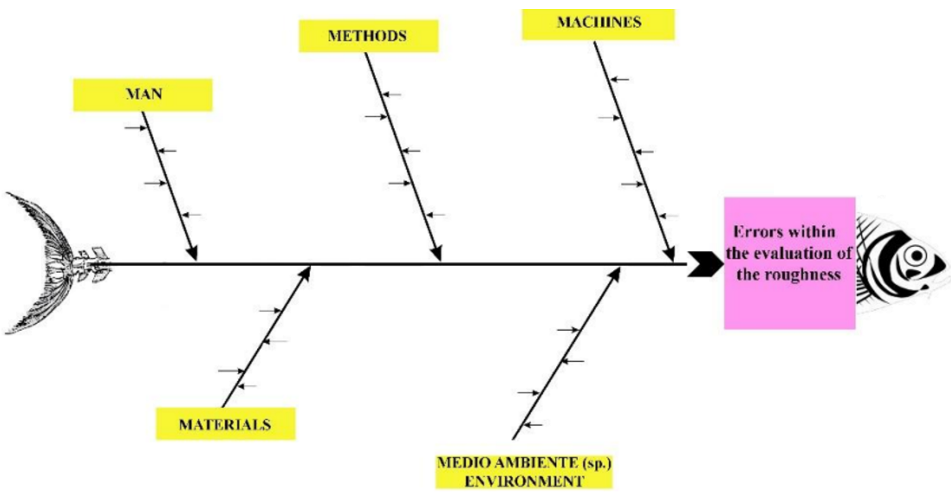


Figure 3.2: An example of a fishbone diagram by Liliana (2016).

Determining the current state of the process is done using a capability analysis. Doshi and Desai (2019) states that a capability analysis needs control charts, repeatability and reproducibility tests, Gage R&R, and part variation (PV). Repeatability tests, reproducibility tests, and PV are not used due to the lack of shifts, different measurements, and no two vessels are exactly the same. Gage R&R is used to test the measuring system. Gage R&R should include the people measuring or different measuring systems. The focus is aimed on variance and not at defects. Defects would be events which are unacceptable for the customer. In this case, determining what performances are unacceptable for the customer is out of the scope of the research. Not focusing on defects will exclude DPMO. Sigma values can be used when the measurements are stable and in control which is too big of an assumption.

3.2.2. KPIs

The key performance indicators are the indicators on which the processes are tested and compared. When a process is tested on stability and normality, the KPIs are the measurements which need to be stable and normal. For the vessel operators, fuel and time are essential as both need to be minimised. KPIs will differ per activity but contain the time or the fuel. The difference in KPIs is due to the difference in activities. For transit, the most important KPIs are litres of fuel per nm and time per nm, while fuel per hour is more relevant and time per activity completed during activities. Although the *Onboard* system measures all the KPIs, whether requested or not, for clarity, it is essential to establish all relevant KPIs early.

3.2.3. Process capability

Capability analysis is needed to check the process. Which analysis is correct can be established based on the properties of the data. The data gathered by *Onboard* is continuous data and numeric. The data is expected to be parametric because the data is collected while under the influence of nature, so the data is expected to be normally distributed. The process control phase can start after establishing whether the data is normally distributed. There are multiple ways to test if the data is normally distributed. Panagopoulos et al. (2017) has merged the most common hypothesis tests into categories. To give a clear overview of why the hypothesis tests are used, the choices will be made on the basis of the road map of Panagopoulos et al. (2017). The road map also shows options to test hypothesises for means and variance, which will be discussed in section 3.3. When following the road map, shown in Figure 3.3, there are three tests to check the normality. Which of the three methods is the best fit might be difficult to answer, so chosen is to conduct all three methods. When all three normality tests conclude with the same answer, there is no problem, but if one of the methods has a different conclusion, a histogram or Q-Q plot can be used to decide how to continue. An example of a Q-Q plot and histogram are shown in Figure 3.4 and 3.5.

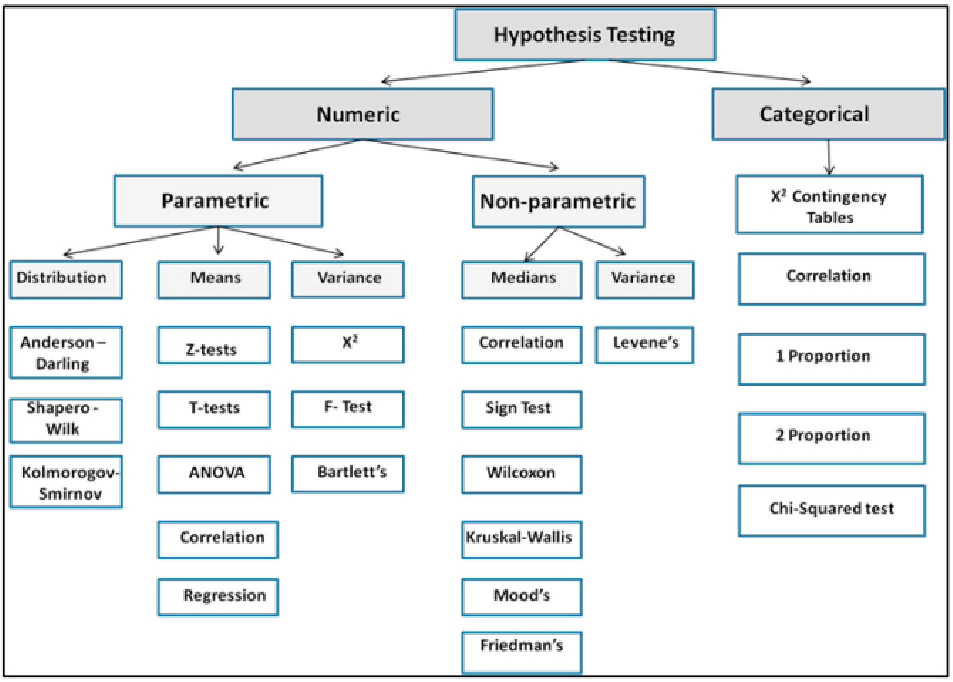


Figure 3.3: Hypothesis testing road map by Panagopoulos et al. (2017).

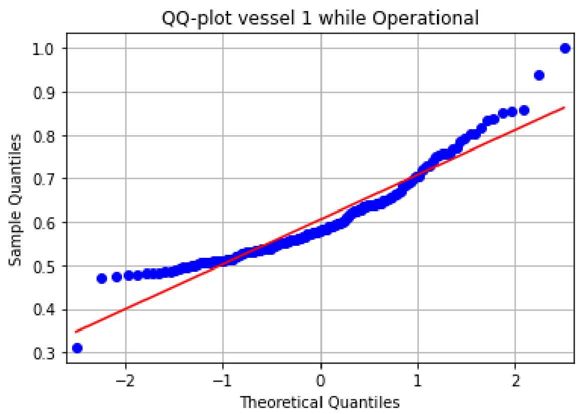


Figure 3.4: An example of a Q-Q plot.

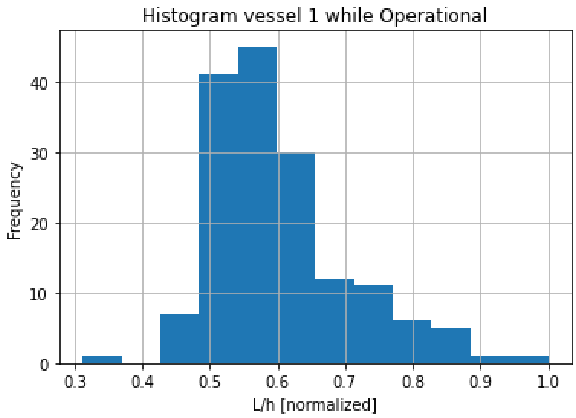


Figure 3.5: An example of a histogram.

The Statistical Process Control (SPC) Charts employed to control the stability of a process are also combined and mapped by Panagopoulos et al. (2017). The road map of Panagopoulos et al. (2017) is used to show the reasoning behind the choice of the charts. The first choice is whether the data will be viewed in groups, samples, or individually per data point. When looking at each data point, the graphs become very cluttered. It was decided to look at samples consisting of a fixed number of data points over a fixed period. A sample is randomly selected from a data set over a chosen time. The size of the sample must take into account the number of those activities per period. The period must consider that x samples are needed to get a good result. The samples will consist of a selection of the data points except for the outliers. The data points will then be randomly selected from the data.

Figure 3.6 shows a typical workboat timeline. This figure shows a random week for a workboat. The picture shows a crane when the vessel is in port, a boat when the vessel is sailing, a block of actions when the ship is active, and an anchor when the vessel is at anchor. The timeline shows that there are one or two activity groups per day of the week, that the vessel usually sails twice a day and that the vessel is anchored or in the harbour once a day. In order to obtain a significant sample size, it was decided to make one sample per week from five data points. The five points have been chosen to give some space so that a sample can still be made if nothing or less happens for a day or when the data points during a week contain outliers. A week has also been selected so that the measurement phase will not last longer than 20 weeks. With a larger number of groups, the samples can increase.

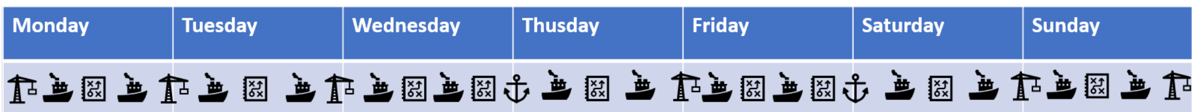


Figure 3.6: Workboat activities during a week.

When following the road map of Panagopoulos et al. (2017), shown in Figure 3.7, the X-bar and R-chart are the proper tools. These two charts show if the system is in control. The X-bar chart shows the averages of all samples and checks if all the sample means are within the control limits. The R-chart shows the range in the samples and whether the range exceeds the range limits. The limits of both the X-bar and R-chart are calculated and depend on the sample size. The calculations will be elaborated on in a later paragraph. Ted Hessing (2019) shows the same results with a different road map. According to Benneyan (2001), the S-chart is better than the R-chart. The R-chart is preferred when activities are combined in groups because of the small sample pool. When the sample size can increase above the nine samples, the S-chart can be used instead of the R-chart. An example of an X-bar and R-chart are shown in Figure 3.8 and 3.9. The X-bar and R-chart are considered reliable from twenty samples according to Montgomery (1985).

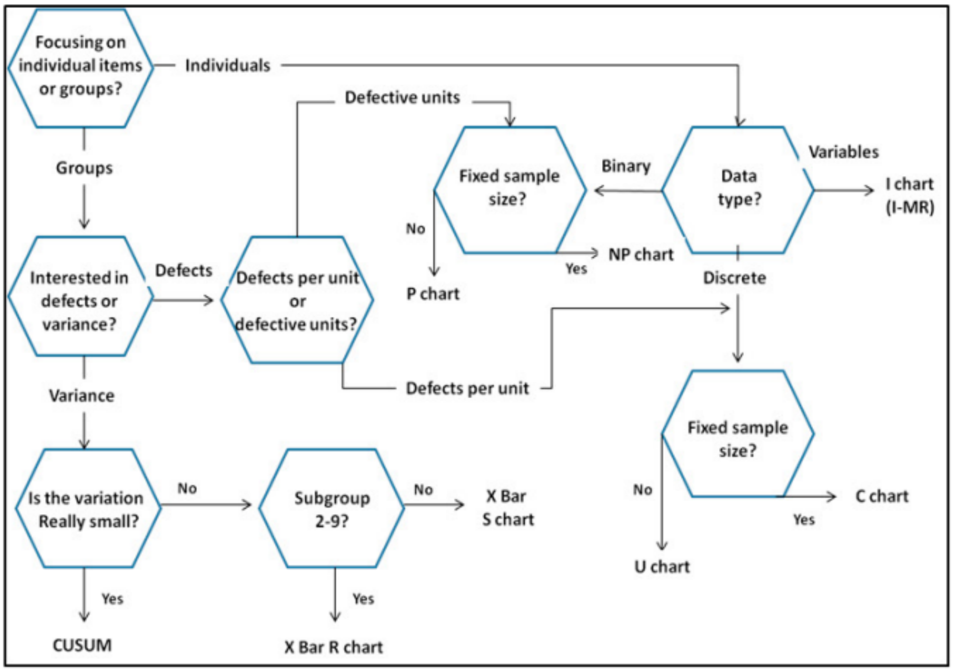


Figure 3.7: Control Chart selection road map by Panagopoulos et al. (2017).

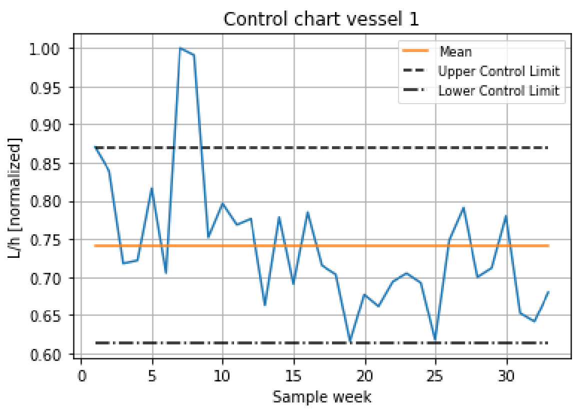


Figure 3.8: An example of an X-bar chart.

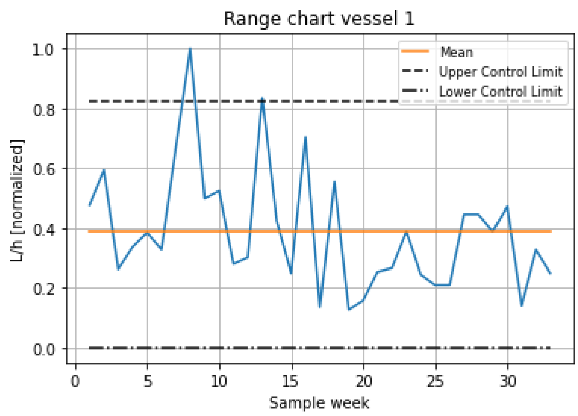


Figure 3.9: An example of an R-chart.

Chosen is to conduct Anderson-Darling, Shapiro-Wilk, and Kolmogorov-Smirnov tests to increase confidence in the results. All three tests expect the data to be normally distributed. When the tests indicate that the data is not distributed normally, the analysis phase needs to start by identifying the reason for this. Chosen is to conduct all the tests with the same null hypothesis. The null hypothesis (H_0) is the distribution is normally distributed. The alternative hypothesis is the data is not normally distributed. When the p-value is larger than 0.05, there is no evidence the data is not normally distributed, and H_0 will not be rejected. These tests have difficulties rejecting the null hypothesis with small data sets and confirming the null hypothesis test with large data sets. To be more confident, the Q-Q plot and the histogram of the dataset are reviewed when making a decision.

The Anderson-Darling, Shapiro-Wilk, and Kolmogorov-Smirnov tests are often used according to Das and Imon (2016), and Ghasemi and Zahediasl (2012). These are all similar tests but with a slight difference. Shapiro-Wilk tests the difference between data points with the difference in data points on the Q-Q plot. Kolmogorov-Smirnov, or the KS-test, checks the maximum difference from the normal distribution and states that if the distance is too big, it can not be assumed the sample distribution is the same as the normal distribution. The Anderson-Darling is similar to the Kolmogorov-Smirnov test but with more emphasis on the tails.

The X-bar shows whether the mean of the process samples is in control, and the R-chart is used to check if the range is in control. When the values of the process line in the X-bar and R-chart exceed the upper or lower limits, the system is out of control. When the system is out of control, the analysis should improve stability. The charts are formed by using samples from the data. Box plots make the samples more representative by excluding the outliers. The data is tested in subgroups of five samples to filter the first errors. The data is sampled to limit the influence of an individual value.

The X-bar and R-chart are constructed using the calculations and constants of Montgomery (1985). The X-bar chart has an upper control limit (UCL) and a lower control limit (LCL) based on the sample mean X-bar. The X-bar formulas for the UCL and LCL are equation 3.1 and 3.2. The R-chart is based on the samples' average range; the UCL and the LCL equations are 3.3 and 3.4. The constants A_2, D_4, and D_3 are used in the formulas. All these constants are from Table 3.1. The $\bar{X}$ is the average of the samples, and $\bar{R}$ is the average of the sample ranges.

$$UCL = \bar{X} + \bar{R} * A_2 \tag{3.1}$$

$$LCL = \bar{X} - \bar{R} * A_2 \tag{3.2}$$

$$UCL = \bar{R} * D_4 \tag{3.3}$$

$$LCL = \bar{R} * D_3 \tag{3.4}$$

The system is deemed in control when all points are between the limits, and there is no other pattern than a random walk. Indications of an out-of-control system are a run with more than seven increasing or decreasing points in a row, a system showing a nonrandom pattern, or a system having multiple points near the limits.

Table 3.1: Table of constants from Montgomery (1985).

Appendix VI Factors for Constructing Variables Control Charts

Observations in Sample, n	Chart for Averages: Factors for Control Limits			Chart for Standard Deviations: Factors for Central Line		Chart for Standard Deviations: Factors for Control Limits				Chart for Ranges: Factors for Central Line		Chart for Ranges: Factors for Control Limits				
	A	A_2	A_3	c_4	$1/c_4$	B_3	B_4	B_5	B_6	d_2	$1/d_2$	d_3	D_1	D_2	D_3	D_4
2	2.121	1.880	2.659	0.7979	1.2533	0	3.267	0	2.606	1.128	0.8865	0.853	0	3.686	0	3.267
3	1.732	1.023	1.954	0.8862	1.1284	0	2.568	0	2.276	1.693	0.5907	0.888	0	4.358	0	2.574
4	1.500	0.729	1.628	0.9213	1.0854	0	2.266	0	2.088	2.059	0.4857	0.880	0	4.698	0	2.282
5	1.342	0.577	1.427	0.9400	1.0638	0	2.089	0	1.964	2.326	0.4299	0.864	0	4.918	0	2.114
6	1.225	0.483	1.287	0.9515	1.0510	0.030	1.970	0.029	1.874	2.534	0.3946	0.848	0	5.078	0	2.004
7	1.134	0.419	1.182	0.9594	1.04230	0.118	1.882	0.113	1.806	2.704	0.3698	0.833	0.204	5.204	0.076	1.924
8	1.061	0.373	1.099	0.9650	1.0363	0.185	1.815	0.179	1.751	2.847	0.3512	0.820	0.388	5.306	0.136	1.864
9	1.000	0.337	1.032	0.9693	1.0317	0.239	1.761	0.232	1.707	2.970	0.3367	0.808	0.547	5.393	0.184	1.816
10	0.949	0.308	0.975	0.9727	1.0281	0.284	1.716	0.276	1.669	3.078	0.3249	0.797	0.687	5.469	0.223	1.777
11	0.905	0.285	0.927	0.9754	1.0252	0.321	1.679	0.313	1.637	3.173	0.3152	0.787	0.811	5.535	0.256	1.744
12	0.866	0.266	0.886	0.9776	1.0229	0.354	1.646	0.346	1.610	3.258	0.3069	0.778	0.922	5.594	0.283	1.717
13	0.832	0.249	0.850	0.9794	1.0210	0.382	1.618	0.374	1.585	3.336	0.2998	0.770	1.025	5.647	0.307	1.693
14	0.802	0.235	0.817	0.9810	1.0194	0.406	1.594	0.399	1.563	3.407	0.2935	0.763	1.118	5.696	0.328	1.672
15	0.775	0.223	0.789	0.9823	1.0180	0.428	1.572	0.421	1.544	3.472	0.2880	0.756	1.203	5.741	0.347	1.653
16	0.750	0.212	0.763	0.9835	1.0168	0.448	1.552	0.440	1.526	3.532	0.2831	0.750	1.282	5.782	0.363	1.637
17	0.728	0.203	0.739	0.9845	1.0157	0.466	1.534	0.458	1.511	3.588	0.2787	0.744	1.356	5.820	0.378	1.622
18	0.707	0.194	0.718	0.9854	1.0148	0.482	1.518	0.475	1.496	3.640	0.2747	0.739	1.424	5.856	0.391	1.608
19	0.688	0.187	0.698	0.9862	1.0140	0.497	1.503	0.490	1.483	3.689	0.2711	0.734	1.487	5.891	0.403	1.597
20	0.671	0.180	0.680	0.9869	1.0133	0.510	1.490	0.504	1.470	3.735	0.2677	0.729	1.549	5.921	0.415	1.585
21	0.655	0.173	0.663	0.9876	1.0126	0.523	1.477	0.516	1.459	3.778	0.2647	0.724	1.605	5.951	0.425	1.575
22	0.640	0.167	0.647	0.9882	1.0119	0.534	1.466	0.528	1.448	3.819	0.2618	0.720	1.659	5.979	0.434	1.566
23	0.626	0.162	0.633	0.9887	1.0114	0.545	1.455	0.539	1.438	3.858	0.2592	0.716	1.710	6.006	0.443	1.557
24	0.612	0.157	0.619	0.9892	1.0109	0.555	1.445	0.549	1.429	3.895	0.2567	0.712	1.759	6.031	0.451	1.548
25	0.600	0.153	0.606	0.9896	1.0105	0.565	1.435	0.559	1.420	3.931	0.2544	0.708	1.806	6.056	0.459	4.541

For $n > 25$

$$A = \frac{3}{\sqrt{n}},\ A_3 = \frac{3}{c_4\sqrt{n}},\ c_4 \simeq \frac{4(n-1)}{4n-3},$$

$$B_3 = 1 - \frac{3}{c_4\sqrt{2(n-1)}},\ B_4 = 1 + \frac{3}{c_4\sqrt{2(n-1)}},$$

$$B_5 = c_4 - \frac{3}{\sqrt{2(n-1)}},\ B_6 = c_4 + \frac{3}{\sqrt{2(n-1)}}.$$

3.2.4. Outliers

Within the data, there are errors which can result in differences in the values and are called outliers. Outliers can influence the samples, so the outliers need to be filtered from the data. There is a lot of variation in the offshore industry, so the filtering should not be too extreme. According to Schwertman et al. (2004), the box plot is too controversial, but for this application, that seems to fit. The outliers should be taken out of the samples but not from the data. The outliers are interesting to learn from due to their extreme properties. The outliers should, therefore, not be removed from the dataset. Figure 3.10 shows an example of two box plots.

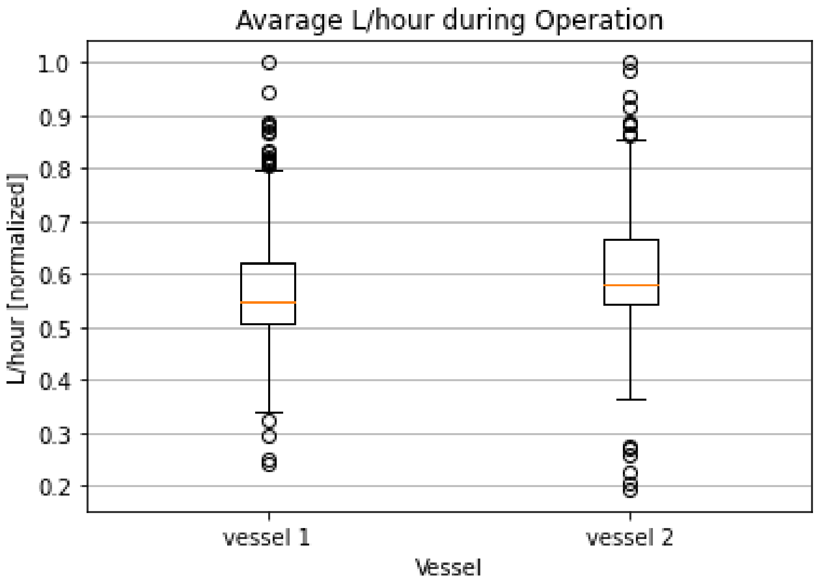


Figure 3.10: Example of two box plots.

3.2.5. Data errors

All data sets will contain identical types of errors due to the way the measuring system is created. The way the *Onboard* system works creates situations where some errors can occur. This section will focus on these errors and make the analyst aware of the potential errors. The errors are identified by a fishbone diagram which gets to the root of the problem. The fishbone diagram works with five general causes for errors: measurements, materials, personnel, environment, and methods. A fishbone diagram is there to find the reason for errors, but these can change over time. The diagram shows what can cause errors in the data. The fishbone diagram shown in Figure 3.11 was created using the knowledge of the *Onboard* staff and errors which came up during the research but may not contain all possible errors.

An error which can occur due to measurements is wrong data being collected. This can happen when a sensor is not correctly attached to the server. Material errors are when a server of sensors breaks down. Personnel creates errors by starting an activity late, not selecting an activity, or selecting the wrong activity. The environment can play a role when the vessel is in bad weather. And due to the methods, there can not be two activities simultaneously. When an activity is defined such that it can occur in different situations, it can create problems.

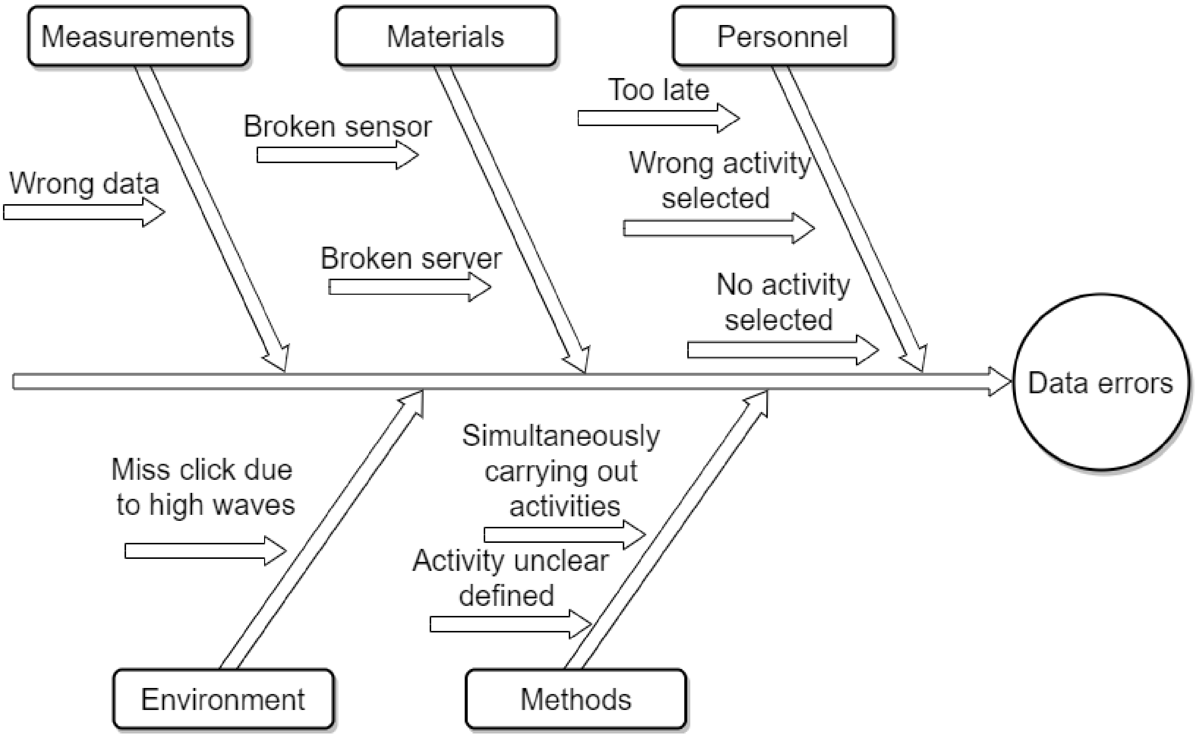


Figure 3.11: The possible reasons for errors in the data sets.

The results are incorrect. Due to the previously stated issues, the results will contain errors. Removing all these errors from the data is out of the scope of this research, and the goal is to show the potential of using the data and results as is. The fact that errors exist within the results must be kept in mind when analysing the processes. To decrease the influence of the data mistakes, the analysis starts by grouping the smaller activity groups, for example, the activities with DP active. An easy way to eliminate some small misclicks or wrong activities is by deleting the corrected ones. Assumed is that there are no activities that take less than a minute, so activities that take less than one minute will not be considered. The lost time will not be added to the next activity because this is deemed to be irrelevant when using groups.

3.2.6. Procedure

The measurement procedure is straightforward with the *Onboard* system. The crew starts activities every time they start to do something new, and all sensor data during this activity is stored automatically. Utilisation graphs will be created to decide what to analyse. The goal of this research is to analyse the data based on the activity of the data given by the crew on board the vessels. The fact that people manually add activities to the data creates room for errors in the datasets. Broken sensors are nothing new on board vessels, and this also is a reason for errors in the datasets. A fishbone diagram must be created to map out all possible errors in the data. An example of the fishbone diagram can be found in subsection 3.2.5.

After identifying the errors, the apparent errors need to be removed. An example of removing errors is removing activities which show to be misclicks. Decreasing the influence of the errors in the data is done by grouping activities performed in similar sequences. An example of this grouping is all the activities nearby an offshore platform or another vessel. By grouping activities, the influence of the errors due to being late declines. Small mistakes overall influence activities with a longer duration less. The groups formed in the first case are idle, in transit, performing offshore activities, and waiting.

The groups need to be tested on normality in the next step. *Python* functions conduct the statistical normality tests. The used function can be found in appendix A.1, and the details of these tests are outside the scope of this research. When the results are that the data is normally distributed, nothing needs to be done with these results. When it turns out the data is not normally distributed, the first thing to analyse is why it is not normally distributed.

The X-bar and R-chart are created to show the stability of the data. When the data exceeds the upper limit, something is wrong or bad, and if the data exceeds the lower limit, something is wrong or goes well, and in both cases, the reason needs to be analysed. The obvious outliers need to be examined and checked on data mistakes. If something is wrong with the data, the data can be cleared of those errors. The chart is created in *Python* using the formulas stated in subsection 3.2.1.

3.3. Analyse

The goal is to delve deeper into the measured data and show what influences the data. During the analyse phase, the differences between datasets need to be specified. If the data is unstable or not normal, the stability and, or normality must be increased by finding special cause variation or errors which cause the data to be formed the way it is.

When the X-bar or R-chart shows outliers, the first thing to do is check whether the outliers are errors in the data or outliers in the process. When multiple outliers seemingly have the same cause, a common data error can be removed, or a variable with a seemingly negative influence can be identified. The next step is to look for special cause variation. Removing the special cause variation can be done by normalising a variable, for example, the current.

The analysis phase will compare data sets when the data is stable and in control. Analysing data is done by comparing two situations and stating a significant difference between these two means. For example, two vessels that do the same job perform differently. When there can be shown that one of the two vessels is significantly better, the reason needs to be found why the performance differs.

The measurement phase needs to be redone if the analysis shows that the data is not measured correctly. To redo the measurements, the measurement equipment needs to be calibrated, the crew needs to be trained, the procedure needs to be updated, or a combination of these things.

3.3.1. Tools

So the goal is to go deeper into the measured data and show what influences the data. In order to analyse the trends in the data, the second Fishbone diagram will be used. The Fishbone diagram is used to identify the reasons for variation during the process. Creating this fishbone diagram explains why the data output is the way it is. The fishbone diagram used in this research is an example diagram, and within a company, probably more reasons for variation can be found. The Fishbone diagram was created to give an impression of how the fishbone diagram needs to look.

When the data is out of control or unstable, the errors must be compared. Chosen is to use a Pareto chart which shows the number of times an error occurs compared to the other errors. This results in an overview of what error influences the data most. Figure 3.12 shows an example of the Pareto chart. The RPN could replace or be combined with the Pareto chart. RPN is calculated by multiplying Severity, Frequency, and Discovery Probability. The disadvantage of the RPN is the difficulty of determining all the components and therefore is chosen not to include this in the analysis phase. The severity component of the RPN is something to keep in mind when using the Pareto chart.

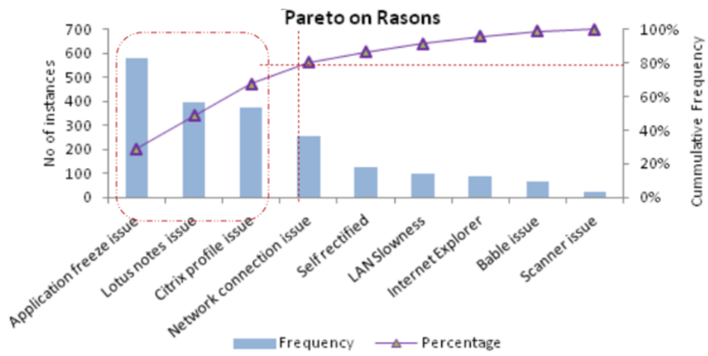


Figure 3.12: An example of a Pareto chart by Koripadu and Subbaiah (2014).

When the potential threats for the system are explored with the fishbone diagram, a way has to be found to reduce this variation positively. Because this research aims to decrease variation, not failures, FMEA does not fit this research. RCM aims to prevent errors, but again the aim is to reduce variation and not errors. By looking at two situations and seeing which situation is better, it is essential to compare the means. When returning to the road map of Panagopoulos et al. (2017) shown in Figure 3.3, tools which will help during the next phase are found. Because the data is still assumed to be numeric and parametric. The road map ends with five ways to assist in finding the differences. Correlation and regression are different in that correlation is more general. Regression looks for a trend line in the scatter plot because the objective is to determine the difference between two situations. A hypothesis test will show whether this was correct when a difference is indicated. This means regression is too advanced for this analysis in the first stage. The tool used during the correlation phase is a scatter plot. Figure 3.13 shows an example of a scatter plot. The hypothesis test which will be used is the t-test. The t-test is used due to the sample size. A z-test needs at least 30 samples which will take too much time to gather. But in the case of more similar vessels, the z-test could be considered. The Gage R&R ANOVA test compares two situations to measure if there is a significant statistical difference.

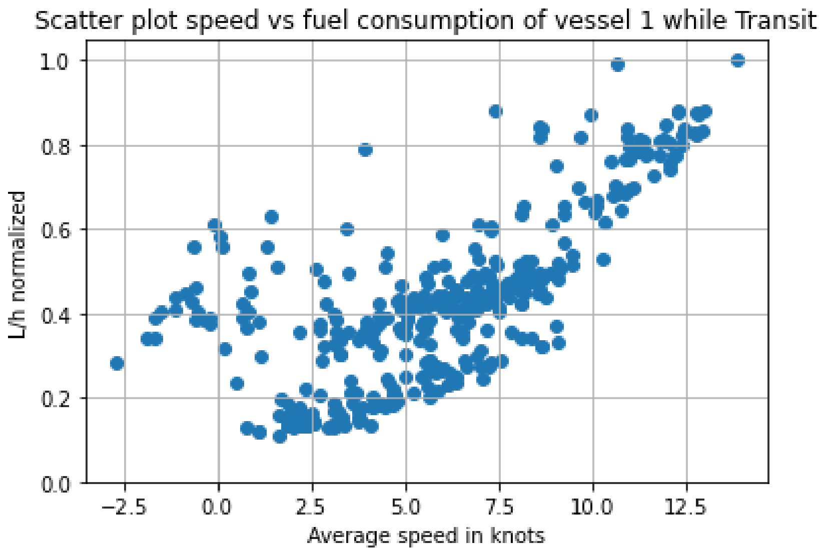


Figure 3.13: An example of a scatter plot.

When comparing two different vessels, the variance needs to be comparable. To test this, the road map of Panagopoulos et al. (2017) gives three options. The x^2 test compares the model output to real-world data. In the case of this system, real-world data is the only data. Because there is no difference in data, the x^2 test adds no value. Bartlett's and the F-test test if the variance is equal to another system. This needs to be done when comparing similar vessels before testing whether there might be a significant difference. Bartlett's and F-test tests will be used for the case of similar vessels and are needed when conducting ANOVA. The F-test looks specifically at two distributions, and Bartlett's test looks at multiple distributions. One problem with the F-test is that it is much more sensitive when the data is not normally distributed according to Hosken et al. (2018). Because it is assumed that the data is normally distributed, there is no problem, but if there is any doubt about the data distribution, it is better to use Levene's test. Levene's test is also for comparing two distributions but only suffers less when the data is not normally distributed. Vorapongsathorn et al. (2004) states that Bartlett's test is also sensitive to non-normal distributions, so this is something to keep in mind. When the goal is to compare two vessels, Bartlett's and Levene's-test will be conducted using *Python*.

3.3.2. Procedure

When the processes are mapped, it is time to decide what to analyse. The data error fishbone diagram, from 3.2.5, must be consulted to find the reason for the instability. When the data points seem incorrect, the points need to be eliminated from the dataset. If there is no error in the out-of-control data, a new fishbone diagram must be created with the reasons for variation. A fishbone diagram should lead to all possible causes for variation in a process. So a fishbone diagram gives all reasons for the difference between data points. Variation during the process originates in the variation of the process and are variables such as weather, crew, and machinery. These fishbone diagrams are case-dependent but will have some common ground. The goal of this fishbone diagram is to find reasons for variations based on variation reasons in Measurements, Materials, Personnel, Environment, Methods, and Machines. To create such a diagram, it is best to include multiple people involved in the vessel operation and create a complete diagram with as many reasons for variation as possible. The influence of these errors can be analysed, and a solution to decrease the variability of this problem can be identified.

If the data is not normally distributed, the reason for this needs to be found. The data not being normally distributed is at least one variable influencing the system in a non-random way. To properly analyse the data, all data needs to be normalised by the variable which forms the problem. When normalising is no option, the data must be grouped into smaller sub-groups. For example, the current is the biggest problem. The subgroups could exist between zero and two knots, two and four knots, etc. When the data shows normal behaviour, the next step can be taken.

Outliers might be present in the X-bar and R-chart from the measure phase. The system needs to be analysed when the X-bar or R-chart shows outliers or the system shows a non-random pattern or multiple points near the limits. The analysis should determine whether the data issues occurred due to an error in the data or a poor or excellent executed process. In both cases, common ground with other results needs to be checked. The main reasons for the data being out of control need to be found. When the data seems to be influenced by something, a scatter plot indicates if there is any correlation. A scatter plot of two variables of the data against each other. In this case, it will be one of the KPIs against something which seems to influence the data. The trend should be investigated when there seems to be a relationship between the variables.

When the system shows to be in control, the outliers from the box plots are the start of the research. These are the extremes and should show the differences between the positive and negative influences. When the measure phase shows no or very few outliers, a new X-bar control chart must be created using the golden standard. The control chart is similar to the one used in the measure phase but does not use a random sample but a golden one. The golden sample finds more outliers and takes the random samples from the central 50 % of the data. The golden sample decreases the variation and creates a better situation to strive for while showing the negative and positive outliers. The difference with the method from section 3.2 is that the X-bar chart will not use samples but all the single data points. After this, the same method should be applied, as stated in the previous paragraph.

When there seem to be correlations, a hypothesis test needs to be conducted on what to compare. This is done the same way as explained in the previous paragraph of this section. A hypothesis test compares two distributions and tests whether the difference is significant. When there seems to be a considerable difference between different vessels, use Gage R&R ANOVA. Gage R&R ANOVA is a comparison test which also takes the legitimacy of the comparison into account, which means that the differences in variance between the two vessels are also taken into account. The hypothesis can be vessel A performs better than vessel B on a certain level. When the hypothesis test is not refuted, the data sets may infer to be different. The improvement phase can start when the correlations are deemed to be founded.

3.3.3. Stable and Unstable data

The difference between the stable and unstable data approach is not significant. In the case of stable and normal data, the goal is to find something which creates variation. In the case of unstable data, the goal is to find causes that make the data either unstable and not normal or unstable or not normal. The procedure during the analyse phase is similar.

3.4. Improve

When the analysis phase states that current processes can be improved, the improvement phase is there to improve these processes. From the analysis phase, several improvement opportunities can arise, and to choose, each improvement's impact must be visualised. After visualising the improvements, the reason for the difference in this process must be determined by getting to the heart of the problem. The Improvement phase focuses only on one aspect at a time, so improving the most significant aspect results in more gain.

3.4.1. Tools

The improvement phase can either find the reason for the data not being stable and in control or improve operational efficiency. So the result is either the reason for a data error and a solution or a way to improve efficiency and why the process is inefficient. In the case of unstable data, there is a special cause variation in the process. This variation will be removed from the dataset to compare the data. According to Brooks (2014), 20 per cent of the causes often create 80 per cent of the problems. By visualising the causes of the issues in the data which make the data unstable, the problems which need to be attacked first can be determined. The visualisation is called a Pareto chart. The difference with the Pareto chart from the previous section is that this one shows the number of resources instead of the occurrences. The Pareto chart helps by choosing what to improve in the first place. When two different situations are compared to see which situation is better, two box plots show the mean and spreading of the results. The box plots give a visualisation of how the process is performed. Box plots after the improvement phase should clearly show a better performance than those before. If the new box plot improves, the improvement phase seems to be a success, and the system might not be improved if there is no clear improvement. The 5 times why method will find the root cause of the issue. With the 5 times method, an issue that causes the difference can be found. By asking why until the real issue shows. When the reason is known, the issue can be addressed, and the process can be improved.

The Pareto chart is similar to the one created in section 3.3 but more focused on resources and gains. To improve a process, the average and the variation have to decrease. The difference between the two situations can be visualised with a box plot to ensure the improvement has the needed result. 5 times why is a tool where the idea is to ask why five times a row. The analysis phase shows a difference, and the first step is to ask why there is a difference. The next step is to ask why again. Asking why continues until the real reason for the difference is found, which in most cases means asking why five times.

The tools chosen are Box plot, Pareto chart and 5 why, but there are more options. The SWOT analysis is not included in this research because the data does not give all information needed. The data does not show clear strengths or weaknesses. MCDM requires many interviews that will not be performed during this research. The interviews will give weight to the improvements, just like the SWOT analysis, but both take a lot of time and result in an opinionative conclusion. The Pareto chart results in numbers and shows the real potential. Life cycle cost is not relevant because the research needs to deliver results within a life cycle. Simulations and DOE take too much time to set up and execute. Simulations and DOE are also irrelevant to this research because no predictive model is created.

3.4.2. Procedure

After the analysis phase, multiple processes can seem imperfect. When this is the case, the potential gain needs to be calculated, which is the maximum amount of fuel or time which can be reduced. When the potential gain is calculated, a Pareto chart shows the difference between the improvements. From the Pareto chart, the optimisation gain influence is visualised compared to the other improvements. The difference in the flow charts explained in 3.1 results in waste, and eliminating waste is also a gain. The Pareto chart shows the potential gain of every improvement together with the percentage of the total potential improvement.

The Pareto chart shows which improvement to focus on. The reasons for the process's imperfections are found using the 5 times why method. After using this tool, the nature of the problem will become clear. When the core of the problem is known, a solution can be established.

3.5. Control

The control phase is all about controlling if improvements resolve the problem. The results need to show an improved and stable system. If the system is stable and in control, the system is improved. Otherwise, the issue is not resolved properly. After the process changes, a visual representation of the old and new situation is needed.

In the case of the data being unstable, not normal, or both, the control phase is practically the measure phase. The difference between the control phase and the measure phase is that when reaching the control phase, the process is improved, and only data is filtered when reaching the measure phase.

3.5.1. Tools

The control phase controls if the improvements of the previous phase improve the system. X-bar and R-charts will show if the system did improve stably. The control charts will be the same as in the measure phase, so the X-bar and the R-chart. When the system improves the mean, the UCL and the LCL of the X-bar chart will go down, and the variance in the R-chart will decrease.

3.5.2. Procedure

The first thing to do is split the data before and after the improvement. The control charts can be made when the difference between before and after is established. If the improvements enhance the process, the X-bar chart should show a lower mean and less variability and the X-bar and R-chart should stay in control. When either the X-bar chart shows no improvement or the R-chart shows no improvement, it can be concluded that during the improvement process, something went wrong, and the steps need to be retaken to find the reason. When it is concluded the improvements did work, the entire process can start over again to improve another imperfection.

3.6. Risks

The chosen method brings risks and potential problems that need to be considered. The chosen method needs time to work. There is a need for a certain amount of data over a certain period. When a system is improved, it will take time to see whether the improvements give the expected results. When conclusions are drawn too early, the findings could be false. The data can not easily be adapted, making it difficult to correct errors. When a flow chart shows an activity name used for two different activities, the name of one of the activities needs to be changed, and the raw data can not be adjusted, which leaves errors in the data. Fishbone diagrams are used due to the ability to find the root of a problem without extensive knowledge of a company. To construct the most inclusive fishbone diagram, interviews are also required, which are not conducted during this research. The control charts can also show non-random patterns which need to be removed according to Montgomery (1985). When clear patterns show, actions will be taken, but no effort will be put into actively finding patterns. When the data has no random walk as is assumed, the analysis might not be the most fitting one. The normality tests do not guarantee anything and are not perfect. The tests give proper indications when all the tests end up with the same results, but none are perfect.

3.7. Conclusion

This chapter answered the question *Which tools suit the problem the best?* The chapter clarified why the tools were chosen and what the added value of each tool was. A flowchart has been made to show all the tools mentioned in the previous section per phase. The flowchart indicates which phases follow each other and in which order the tools are used. The tools are numbered to indicate when the tools are used during a phase. The flowchart contains one moment of choice, which concerns whether the data is stable and in control, and the course of the process depends on the answer to this question. The flow chart, including all tools, can be seen in Figure 3.14.

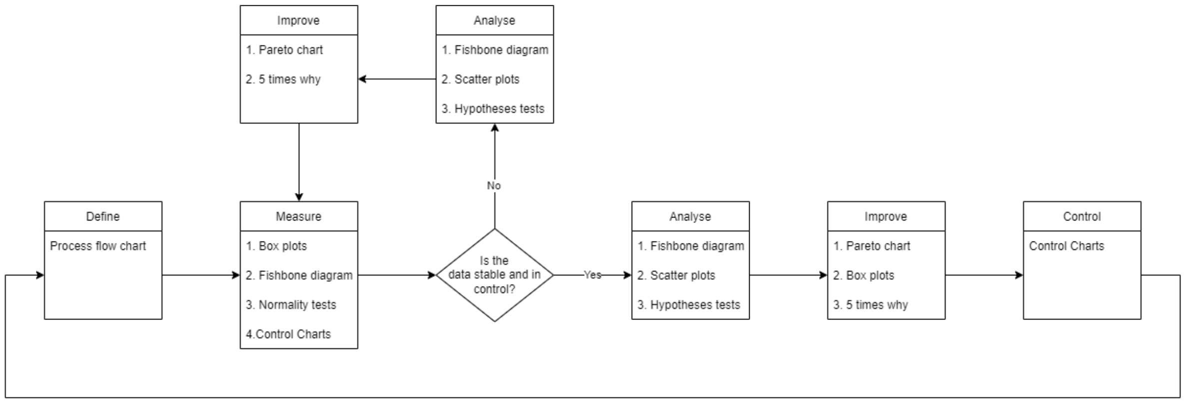


Figure 3.14: The process flow of optimisation project.

4

Case Studies

In this chapter, five vessels of three different companies will be analysed. The companies will be anonymised because it concerns potentially sensitive information. The first two companies are offshore supply companies, and the third company is a towage company. The first company has relatively few activities compared to the second company. In the second company, two sister vessels are compared. The third company will analyse two similar vessels but not the same one. This chapter should show that the method described in chapter 3 can be used for different companies, different but also similar vessels and that all activity groups can be improved.

4.1. Case 1

The first case is the case of *Vessel 1*, an offshore supply vessel of *Company 1*. This example shows a case in which the data is unstable and needs to be stabilised before the analysis phase can start.

4.1.1. Define

Figure 4.1 shows the flow chart of *Company 1*. The flowchart shows a schematic representation of a journey. A journey starts at the beginning, which in this case, Start new Voyage and is shown on the left of the flowchart. A journey starts with In transit at *Company 1*. In transit, it is sailing from one location to the next. The vessels either sail to another platform or sail to a port. The vessel can have two activities in a port: OTHER activities or Port Operations. After the activities in the port, a new voyage will be started when the activity is finished. When the vessel has sailed to a platform, the next step is either getting ready to perform activities at the platform or the vessel has to wait for the weather to get better, and the W.O. Weather (waiting on weather) activity is used. When activities near a platform need to be performed, this is done with the DP system active. The first activity near a platform is DP set-up or when the journey has started at a platform nearby, and the DP system is still active at DP Standby / Idle. When the DP set-up is completed, it can either go into DP Standby / Idle or immediately start the 500m entry, which means that the vessel enters the 500m to the platform where the DP system must be active. Arriving at the platform, the vessel will either lie on standby next to the platform, 500m Standby or the vessel will start performing an activity. The activities at the platform consist of OTHER activities, Platform crane where the crane from the platform puts something on or takes something off the vessel, MCC transfer when the vessel uses the Motion Compensated Crane, Liquid transfer when liquid needs to be transferred, or Gangway transfer when people come over to a platform or the vessel. After one of these activities, the vessel either goes to standby next to the platform, 500m standby, to wait for the next activity, or the vessel leaves the 500m zone, and the 500m exit becomes active. After the 500m exit, the vessel can end the voyage, lie down Standby / Idle or wait outside the 500m zone on DP, DP Standby / Idle. After Standby / Idle, the vessel first does a DP set-up before a new activity can start. After DP Standby / Idle, the vessel can immediately enter the 500m zone again.

The flow chart shows the groups in different colours. In yellow, the transit block is shown. The transit block only contains the In transit activity. The waiting group is blue. This group includes all activities which can be defined as waiting. Within the waiting group are W.O. Weather because a vessel has to wait until the weather gets better, and DP Standby / Idle. The Idle group is shown in the green block. The Idle activities are the activities in port and Standby / Idle because, during these activities, the vessel is inactive. The active block is red, containing all activities from the DP set-up to the 500m exit. This group includes activities while the DP is active. Four activities in the graph are red. These blocks occur in multiple groups and must be divided into numerous activities to use the activities properly.

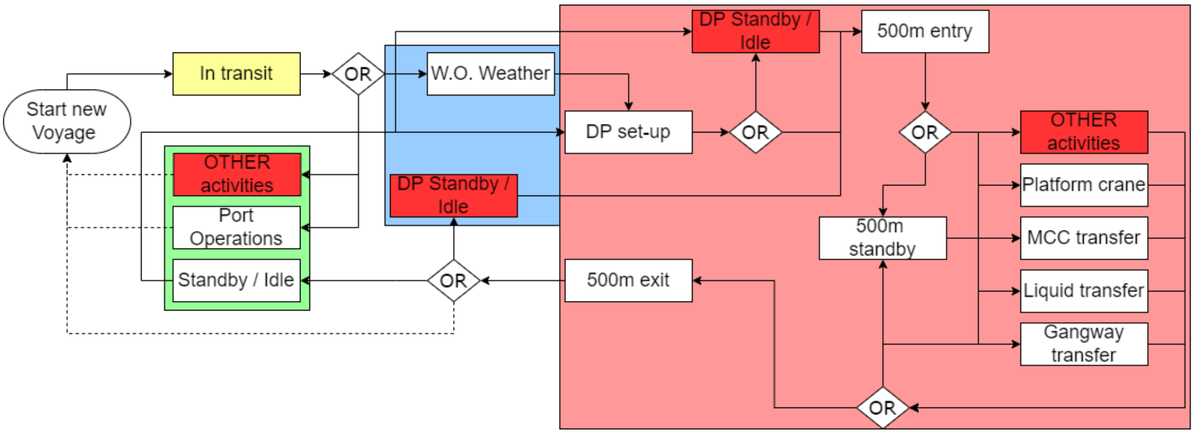


Figure 4.1: Flow chart Company 1.

The improved Flow chart shown in Figure 4.2 shows some minor differences from the current one. The most rigorous change is removing the waiting block, which in a perfect world would not be necessary, so it is all waste. W.O. weather is unfavourable, but to tackle this problem, weather prediction needs to be improved outside the data's possibilities. DP Standby / Idle can occur due to wrong timing or because the vessel has to wait, but this is not the best option. The considerations should be or stay in 500m standby or go Standby / Idle and, after this, a new DP set-up, but which one to choose depends on the available time. 500m standby is a timing issue after the 500m entry, so it should not happen either. The locations of OTHER activities are not all added because the flow chart would be too cluttered. In some cases, OTHER activities are used in moments during the active phase and sometimes in port. So OTHER activities depend on the situation and can be placed in many places in the flow chart but chosen is not to do this and only use the most frequent. To increase the use of this activity, it should be split into OTHER activities in port and OTHER activities operation.

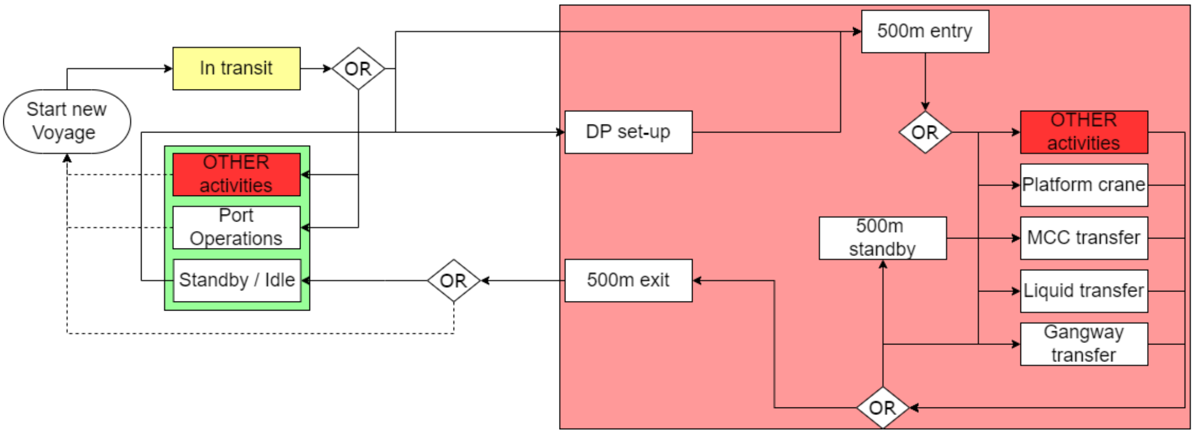


Figure 4.2: Flow chart in an optimal world Company 1.

In the flow charts are two problems, namely OTHER activities and DP Standby / Idle. These two activities have two blocks in the flowcharts which means the activities could be specified more accurately. Waiting is something which needs to be avoided as much as possible. Because the data can not be regenerated, the OTHER activities are split by a threshold, assuming OTHER activities during operation are consuming less time than the ones while waiting and by checking the previous and following activity.

DP Standby / Idle can be split by looking at the surrounding activities. The grouped activities are overviewed in Table 4.1.

Table 4.1: Table of groups.

Group	Activities
Idle	Standby / Idle
	PORT operations
	OTHER activities
Active	500m exit
	Gangway transfer
	500m standby
	Platform crane
	500m entry
	DP set-up
	OTHER activities
	MCC transfer
	Liquid transfer
	DP Standby / Idle
Transit	In transit
Waiting	DP Standby / Idle
	W.O. Weather

4.1.2. Measure

For companies, it is currently most important that costs go down and that the vessels are used as much as possible. Costs can be reduced by minimising fuel consumption, and Utility can be improved by minimising time. For this reason, it was decided to use fuel and time as KPIs. The utilisation graphs will show both time and fuel consumed. The rest of the analysis will use fuel per hour, making the activities more comparable. Figure 4.3 shows the utilisation graph, and 4.4 shows the grouped utilisation. In Figure 4.3, all the time and fuel used for the activities are shown as a percentage. In the figure, only a few activities seem to have a significant impact. To limit the influence of errors in the data, it was decided in Chapter 3 to combine the different activities. The groups are the coloured blocks shown in Figure 4.1. As long as several activities from one group follow each other, the activities are made into one large activity. After merging the activities in the group's Transit, Waiting, Idle, and Active, the utility graph looks as shown in Figure 4.4.

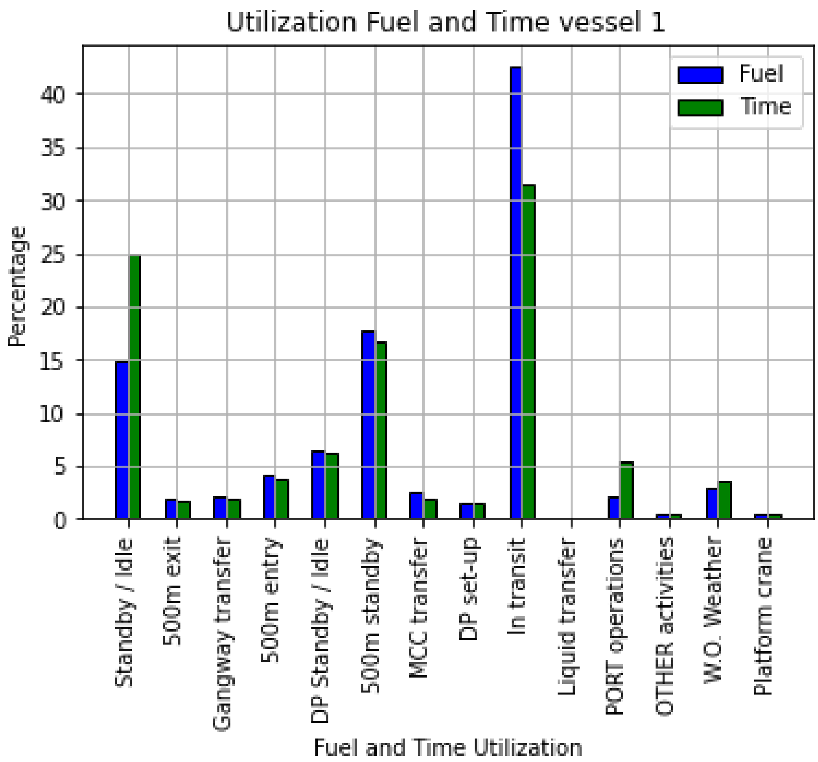


Figure 4.3: The utilisation graph of *Vessel 1* of *Company 1*, showing the time and fuel utilisation of all individual activities.

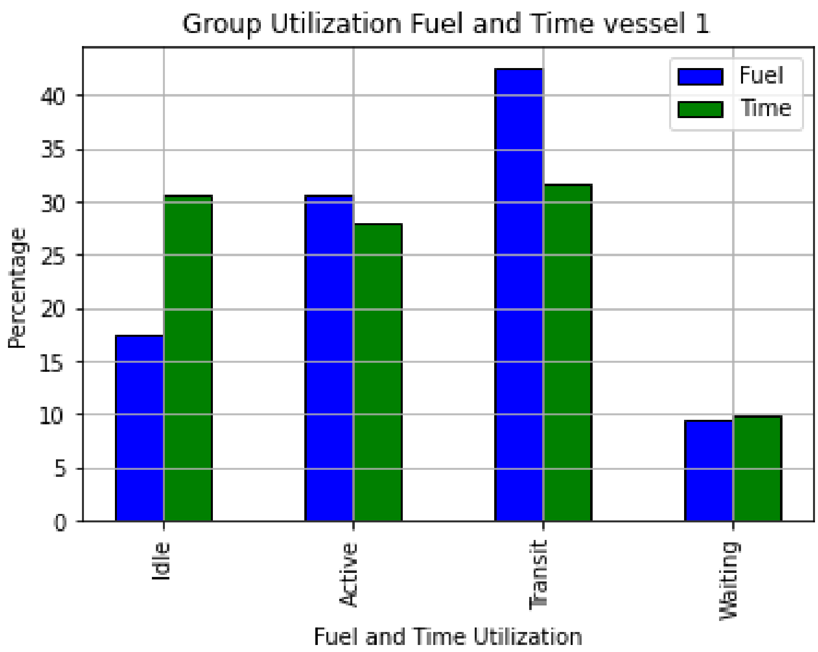


Figure 4.4: The grouped utilisation graph of *Vessel 1* of *Company 1* showing the time and fuel utilisation of all grouped activities.

Figure 4.5 shows the box plots of *Vessel 1*. These box plots are used to find the outliers. The outliers will not be considered during the sample creation. The box plots also visualise how much fuel is used per hour per activity group.

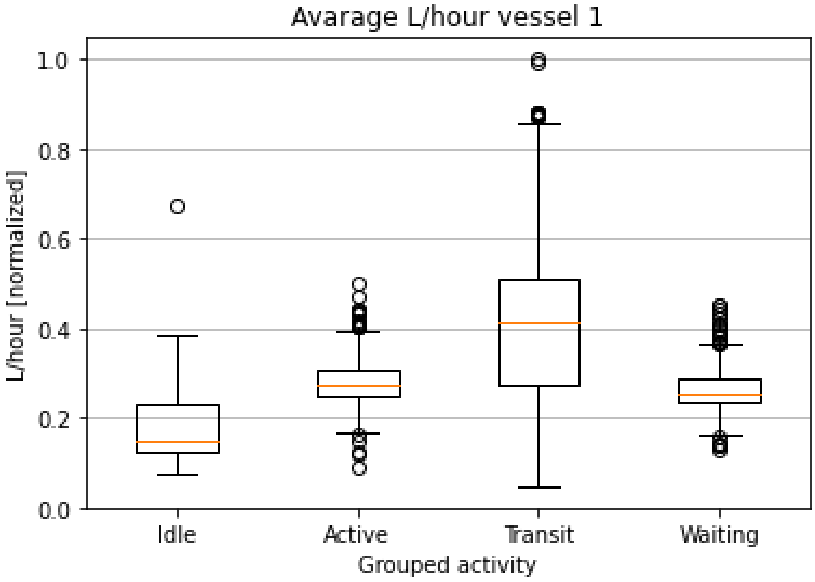


Figure 4.5: Box plots of *Vessel 1* from *Company 1*.

As stated in Chapter 3, a sample is a group of five data points taken from data over a week. The samples are needed to create an X-bar and R-chart and conduct statistical tests. A sample can be created if a group occurs more than 5 times a week. From the last 36 opportunities to create samples during Idle activities, 21 samples were created during Active activities 36, Transit 31, and Waiting activities 27. When not as many samples are created as weeks pass by during the period, some weeks had less than data points that week. For example, over the last 36 weeks, 31 transit samples have been created. The difference means that in five of those 36 weeks, the vessels measured less than five transit activity groups. The tests say the data, while active, does not seem normally distributed. The exception is the Kolmogorov-Smirnov test which does not conclude that the data is not normally distributed. The data while waiting does not seem normally distributed according to the p 15% Anderson test, but all other tests do not indicate that the data is not normally distributed. While idle and in transit, the data seems normally distributed according to all tests. The exact results of the statistical tests are shown in appendix B.1.1.

Idle is at the lower end of the number of samples, and when looking at the Q-Q plot shown in Figure 4.6 and the histogram shown in Figure 4.7, serious doubt can be raised towards the outcomes of the tests. The other issue with Idle is the number of samples which is not enough to create an X-bar or R-chart. The data is heavily skewed towards the right, as visible in the histogram. The idle data should not be considered normal and ready for the analyse phase.

While active, the data is not normally distributed according to the test. The Q-Q plot shown in Figure 4.8 and the histogram shown in Figure 4.9 show better results than the ones during Idle. In the histogram, quite a lot of data seems to be at the right off the centre, and the Q-Q plot also shows the data to be right skewed. The Active data should not be considered normal and ready for the analyse phase.

None of the test state that while in transit, the data is not normally distributed. When looking at the Q-Q plot shown in Figure 4.10 and the histogram shown in Figure 4.11, it does not become clear that the data is not normally distributed. Assumed will be the transit data is normally distributed.

According to almost all tests, there is no reason to assume the data is not normally distributed. When looking at the Q-Q plot shown in Figure 4.12 and the histogram shown in Figure 4.13, serious doubt can be raised about the outcomes of the tests. The Q-Q plot shows heavy tails, and the data can not be considered normally distributed.

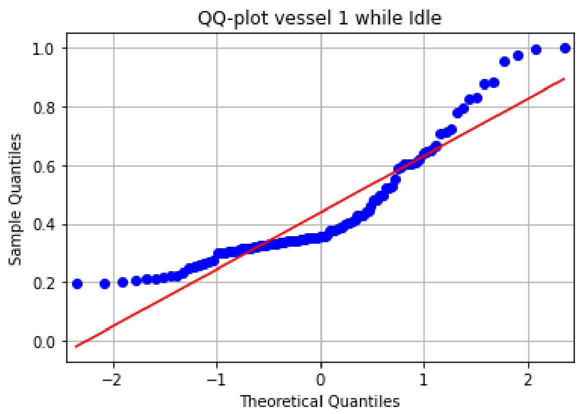


Figure 4.6: The Q-Q plot of the data from *Vessel 1* while Idle.

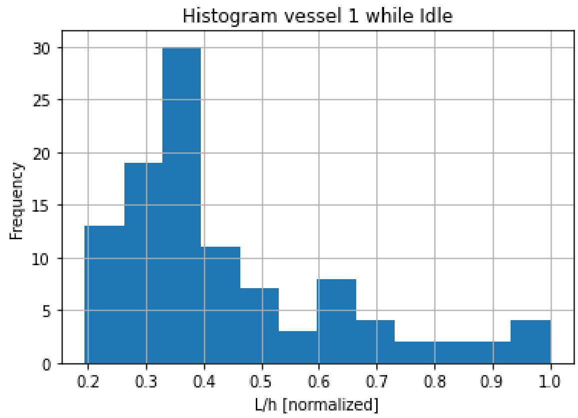


Figure 4.7: The Histogram of the data from *Vessel 1* while Idle.

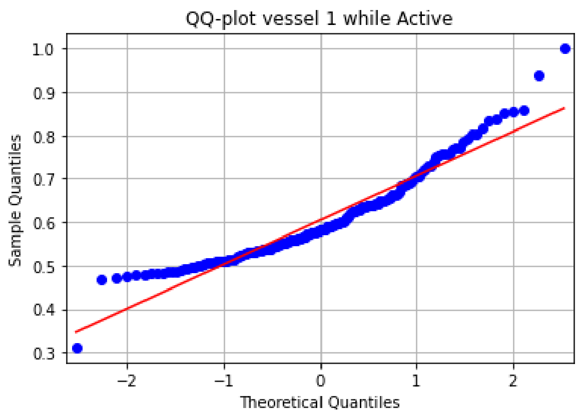


Figure 4.8: The Q-Q plot of the data from *Vessel 1* while Active.

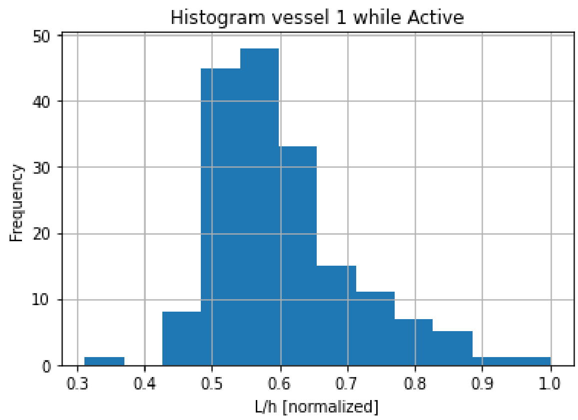


Figure 4.9: The Histogram of the data from *Vessel 1* while Active.

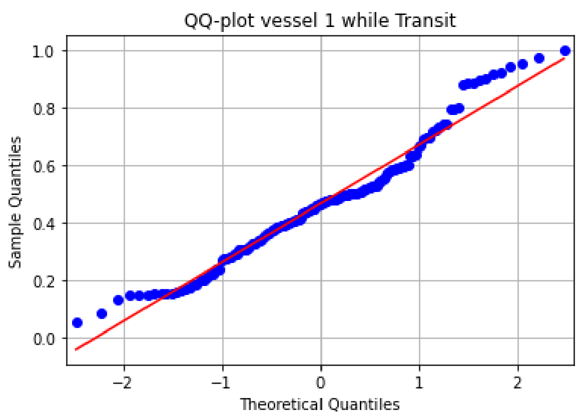


Figure 4.10: The Q-Q plot of the data from *Vessel 1* while in Transit.

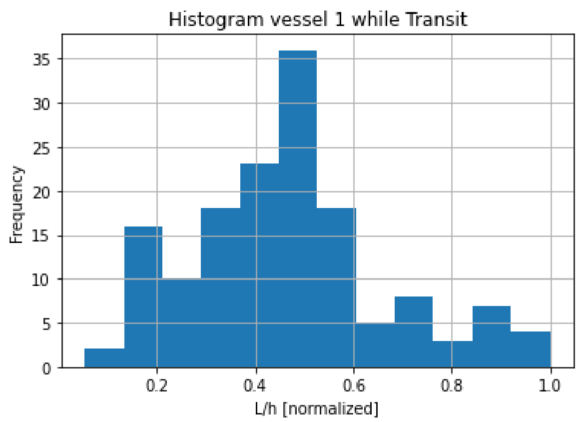


Figure 4.11: The Histogram of the data from *Vessel 1* while in Transit.

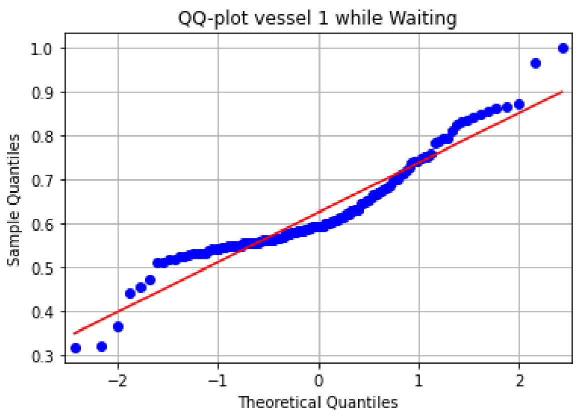


Figure 4.12: The Q-Q plot of the data from *Vessel 1* while Waiting.

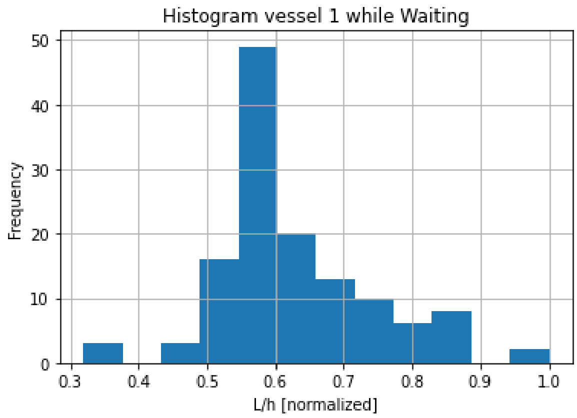


Figure 4.13: The Histogram of the data from *Vessel 1* while Waiting.

Because, at the moment, only the data while in transit is deemed to be normally distributed, only the X-bar and R-chart while in transit will be shown. The other X-bar and R-charts can be used when the data quality is increased. Figures 4.14 and 4.15 show the X-bar and R-chart while in transit. To determine if the data is in control, the limits should not be exceeded, no trend should be visible, and there should not be too many data points close to the limits. The figures show that the data does not exceed the UCL or LCL and has no clear trend or many data points near the limits. Some samples are missing, but overall the data seems in control.

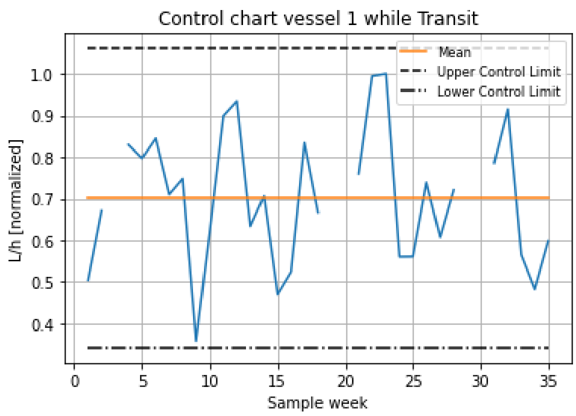


Figure 4.14: The X-bar chart of *Vessel 1* from *Company 1* while in Transit.

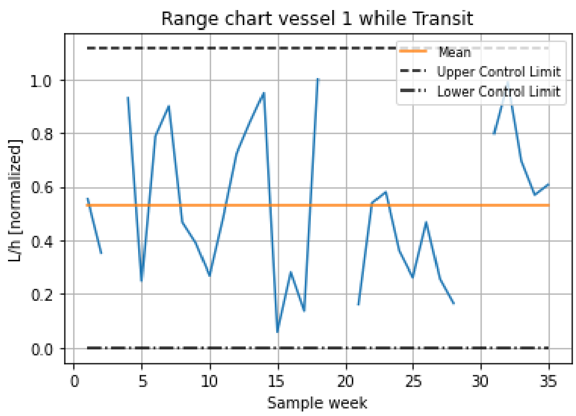


Figure 4.15: R-chart of *Vessel 1* from *Company 1* while in Transit.

4.1.3. Analyse

The first question is what to focus on. Because only one of the groups seems normally distributed, the in-transit data needs to be considered. The problem with the transit activity of *Company 1* is that there is only one transit activity with a lot of diversity, as becomes very clear when looking at Figure 4.5. The reason for this is assumed to be the correlation between speed and fuel consumption. Normally an exponential correlation would be expected. To see if there is an exponential relation, a scatter plot is created as shown in Figure 4.16. When looking at the scatter plot, it seems to show some indications of exponential growth.

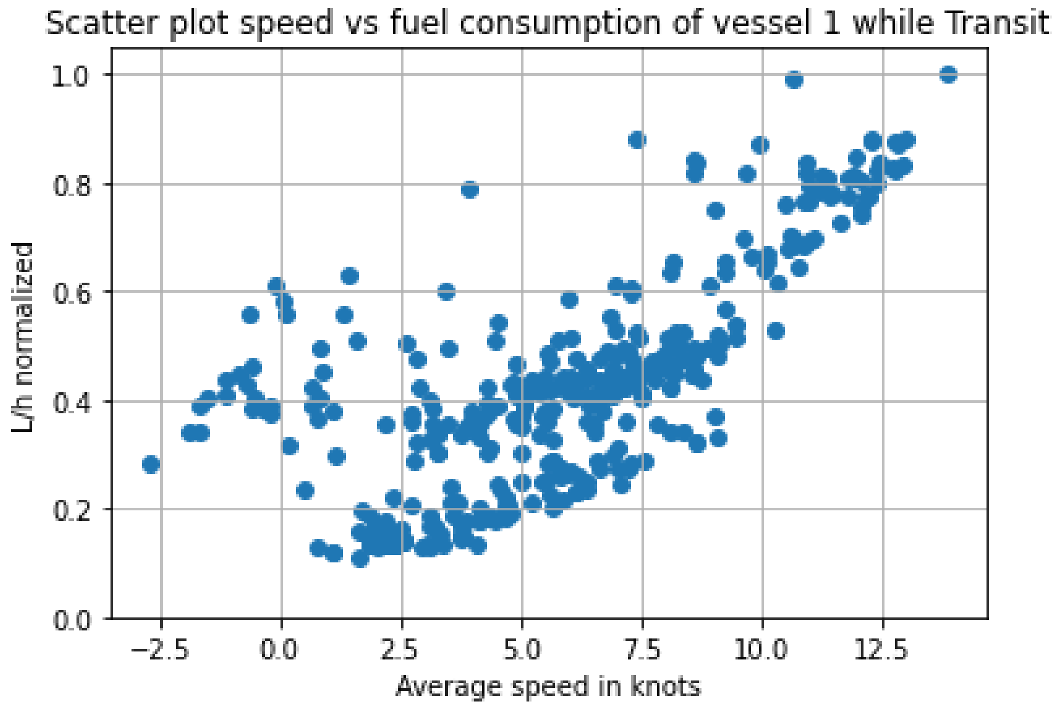


Figure 4.16: The scatter plot plotting speed against fuel consumption of *Vessel 1* from *Company 1* while in Transit.

A trend is visible in Figure 4.16, but mainly at a lower speed, there seems to be more noise. This becomes even clearer in Figure 4.17 and 4.18. The figures show travailing less and more than 5 miles. Figure 4.17 shows the data points where the vessels sails more than 5 miles, and the data shows an abundantly clear exponential trend. Looking at Figure 4.18, the transits from less than 5 miles show no clear trend. The data over short distances seems highly influenced by accelerating and decelerating.

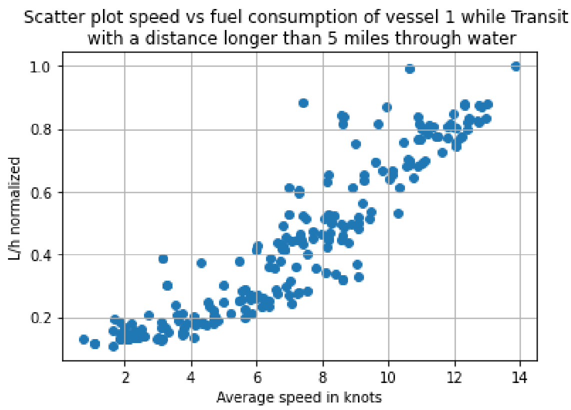


Figure 4.17: The scatter plot plotting speed against fuel consumption of *Vessel 1* from *Company 1* while in Transit only shows the journeys where more than 5 miles were travelled.

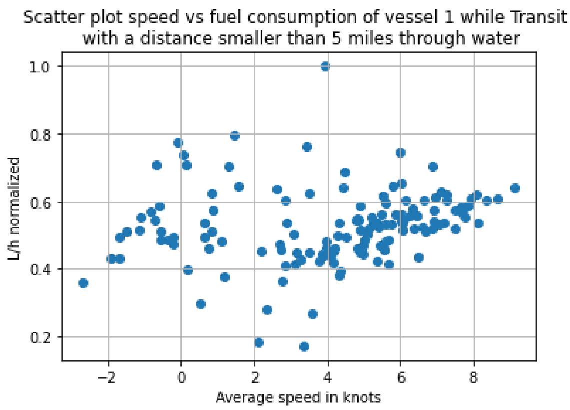


Figure 4.18: The scatter plot plotting speed against fuel consumption of *Vessel 1* from *Company 1* while in Transit only shows the journeys where less than 5 miles was travelled.

The difficulty with activities while in transit is the lack of knowledge schedule-wise. If a deadline has to be met, the vessel must sail at a certain speed, no matter the conditions. What is known is that when a vessel arrives and after the DP set-up goes to DP Standby / Idle, the vessel is waiting, and with planning, this could be avoided. What can be seen is that the short distance journeys take a significantly smaller amount of time. When the sailing time is short, the start-up phase of the engine has relatively more influence.

While active, the data from the vessel does not seem to be normally distributed. The first thing to do is to check for errors in the data. Going from point to point through the data errors fishbone diagram displayed in Figure 3.11 will help locate errors. Two problems seem to occur: Wrong activities selected and unclearly defined activities. This becomes visible because the activities are grouped, and the grouping will not go as expected when an activity falls out of line. All activities should start with either a DP set-up or 500m entry and end with a 500m exit, but this is far from true. Only in 475 cases of the 745 opportunities is the last activity 500m exit. After examining the flow chart, it becomes clear some activities are not detailed enough. OTHER activities and DP Standby / Idle are most probably influencing the grouping. OTHER activities happen either during the vessel is active or while in port. The DP Standby / Idle needs to be split into a waiting and an active part and is often wrongly used instead of 500m standby.

4.1.4. Improve

A way to improve the transit data would be by dividing the transit activity into two different modes. One transit mode is for sailing steadily toward another location, and the other is for moving towards another location over a short distance. The scatter plot is shown with all data points in Figure 4.19. At the moment, 5 miles is chosen to be the cutoff point but to increase the analysis options. The difference should be specified on more than only the distance travelled. Something to consider is that the influence on starting up is bigger when the journey takes shorter, but the data does not show clear differences other than sailing short distances through water. Something to dive into deeper is why the fuel consumption is higher when the vessel sails slower than the current, so when the speed through water is negative. This should be discussed with the company to get a better understanding. A reason could be that the measurements are wrong.

The exponential growth of fuel consumption becomes very clear from the data from sailing more than 5 miles. This shows vessels must try to sail as slowly and steadily as possible. At this moment, there is waiting involved in the process. The first step would be to try and plan the journey better so the vessel can sail slower.

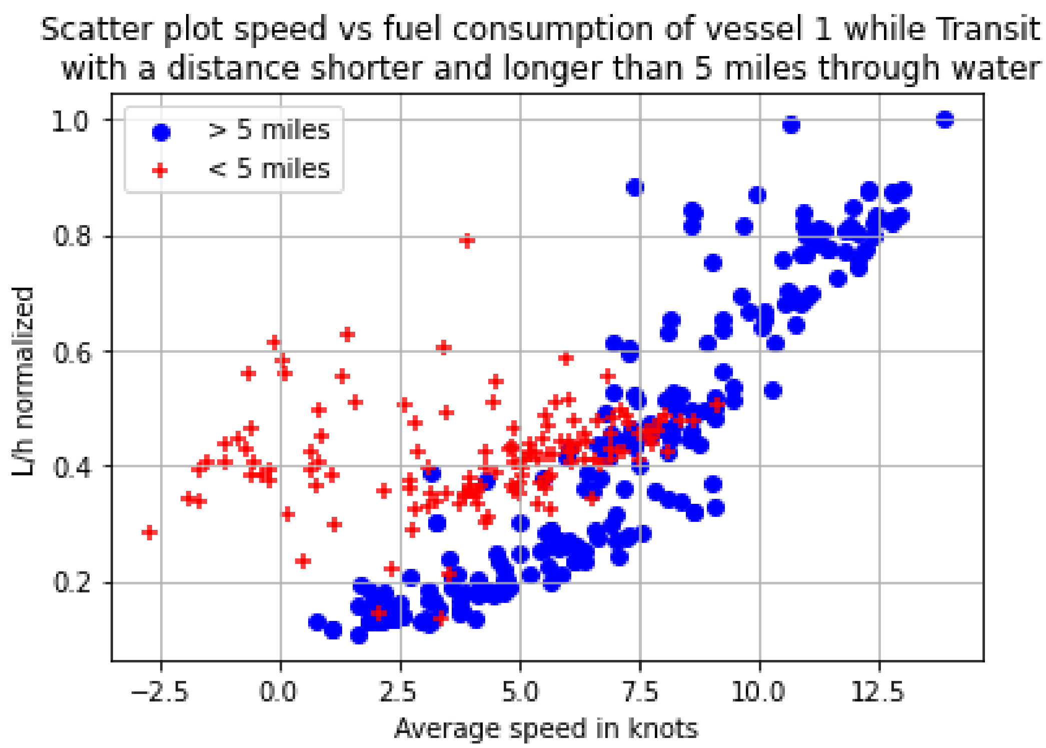


Figure 4.19: The scatter plot plotting speed against fuel consumption of *Vessel 1* from *Company 1* while in Transit shows the difference between short and long-distance transits.

Before a Pareto chart can be made, the options for active activities need to be analysed, and the quality needs to be increased. To improve the data quality, the first focus lies on the OTHER activities and DP standby / idle activities. The OTHER activities will be split by determining that when the OTHER activity occurs before or after a port operation, the OTHER activity is not during an operation. The DP standby / idle activities are split into three groups, misclicks, DP standby, and the original DP standby / idle. In the first group, the misclicks are defined by the DP standby / idle activities, which happen between two offshore activities and should have been 500m standby. Those activity names are changed to 500m standby. The DP standby group is the group of DP standby / idle activities that happen after the DP set-up. This is still waiting but needs to be named differently for grouping purposes. The DP standby / idle activities not changed before are deemed correct. Another improvement could be to increase the quality of the data further. This can be done by setting limitations. For example, a 500m exit should take approximately 500 m over ground, not way more. First is tested whether the earlier implied improvements have a positive effect. A way to improve the data in the *Onboard* system could give some limitations, such as if you entered the 500 m area, the next activity can not be DP standby / idle because, in this case, you would first need to exit the 500m area.

4.1.5. Control

To control if the improvements improved the quality, the number of times the final activity is correct is compared to the old situation. In the first case, 475 of the 745 opportunities, 64%, had as the last activity 500m exit. After the data improvements, this goes up to 400 out of 460, 87%. This also shows 75 cases of the DP standby / idle activity between 500m exit and 500m entry which have been changed to 500m Standby which is incorrect. When adjusting this error by excluding the DP standby / idle activity between 500m exit and 500m entry, the amount of seemingly proper activity groups goes up to 474 out of 534 opportunities, a percentage of 89%.

The updated system now needs to go through the measure phase again, giving improved statistical test results. The new data, while active, does not seem normally distributed according to the p 15% and p 10% Anderson test. Still, all other tests do not indicate that the data is not normally distributed as is shown in Table B.5 of appendix B.1.2. The Q-Q plot, shown in Figure 4.20, and the histogram shown in Figure 4.21, do not give clear reasons not to see the data as normally distributed.

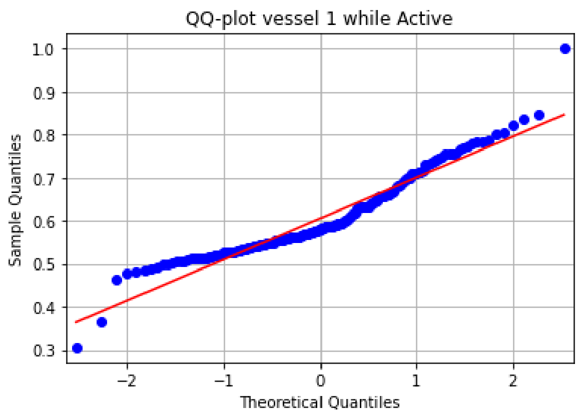


Figure 4.20: The Q-Q plot of the data from *Vessel 1* while Active.

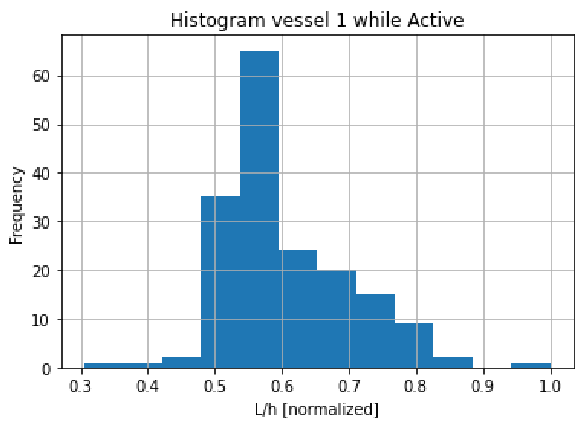


Figure 4.21: The Histogram of the data from *Vessel 1* while Active.

Because, at the moment, only the data while active is deemed to be normally distributed, the X-bar and R-chart while active will be shown. Figures 4.22 and 4.23 show the X-bar and R-chart while active. To determine if the data is in control, the limits should not be exceeded, no trend should be visible, and there should not be too many data points close to the limits. The figures show the data does exceed the UCL or LCL, mainly in the first weeks. In week 8, both the X-bar and R-chart reach the maximum value which exceeds the UCL. The X-bar chart exceeds the UCL in weeks 1, 7, 8, and 12 and the LCL in weeks 13 and 19. The R-chart only exceeds the UCL in week 8. The X-bar and R-chart show out of control, whereas the X-bar chart seems more out of control than the range.

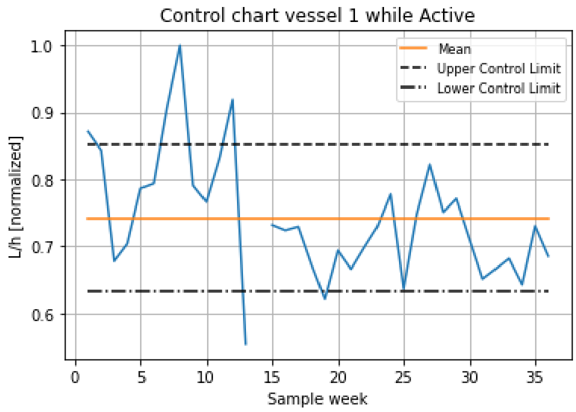


Figure 4.22: The X-bar chart of *Vessel 1* from *Company 1* while Active.

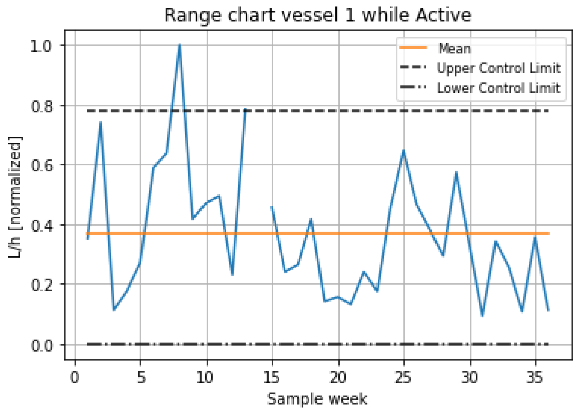


Figure 4.23: R-chart of *Vessel 1* from *Company 1* while Active.

4.1.6. Analyse

When diving deeper into the X-bar, Figure 4.22 and R-chart, Figure 4.23, some things stand out. At the two most prominent peaks of the R-chart, the mean is at the top and its lowest. The outliers are filtered out of the sample, so the sample will probably not contain outliers. The next step is to consult the fishbone diagram shown in Figure 4.24. There is still inaccurate grouped data which could be an issue, but there is no reason to expect this to cause an out-of-control system. The different cargo is not taken into account in this case. The personnel may have created some variation but not enough to get the system out of control. While improving the data quality, there was some doubt about carrying out activities. DP Standby / Idle doe not seem to be an improvement of 500m standby, so the vessels could better stay in the 500m zone. But staying in the 500m zone is also not the best option. A vessel could better go Idle for a while to save fuel. These imperfect activities did anyways not seem to cause the peaks. Data about waves, wind and currents are missing when looking at the environment. When conducting some weather research on the dates of the outliers becomes clear that the two out-of-control points in weeks 8 and 12 were weeks where a storm came by. Weather data is unavailable within the *Onboard* data, and will be, due to time limitations, out of the scope of this research. To increase the data quality adding weather data seems necessary. Looking for improvements will continue without solving the issues in the control chart because the data would be stable if chosen only to take the last twenty samples. For further research, it would be wise to look into either seasonality or weather.

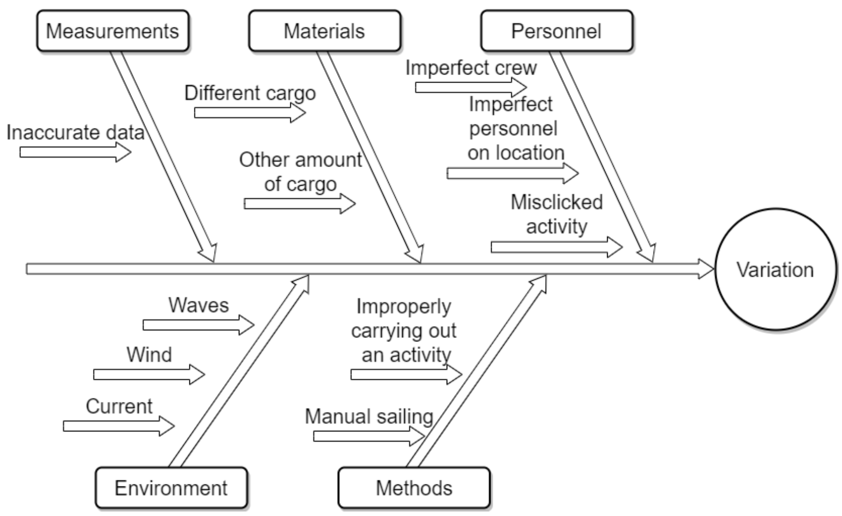


Figure 4.24: The possible reasons for variation in the data sets.

The statement made earlier about 500m Standby being better than DP Standby / Idle because there is less sailing involved, and when outside the 500m zone, Standby / Idle is better than DP Standby / Idle.

To test the hypothesis of 500m Standby being better than DP Standby / Idle, the activities should be equal to each other, or 500m Standby needs to be better than DP Standby / Idle. Two random samples from the activities are taken and compared to test the hypothesis—both the F and the Bartlett's-test result in the conclusion that both activities have similar variations. A t-test concludes there is no reason to assume that the mean of both activities is different, as shown in Figure 4.25.

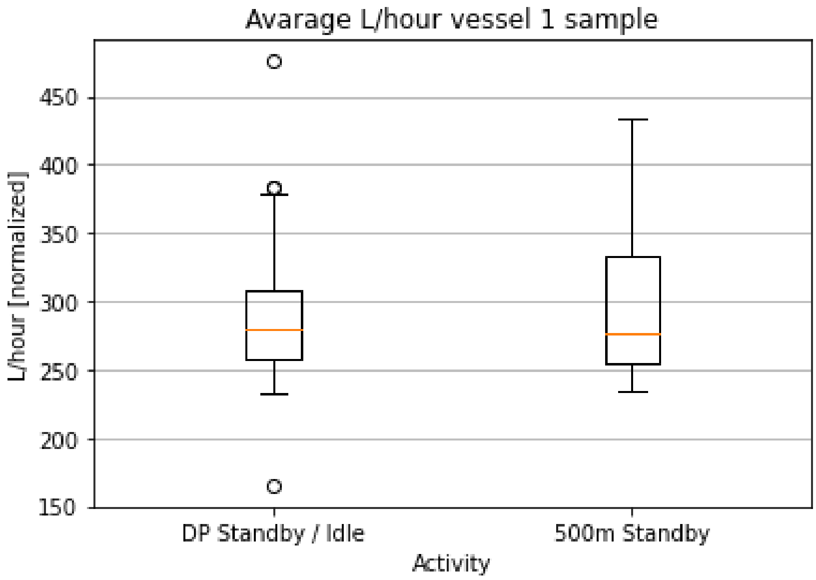


Figure 4.25: Two box plots showing 500m Standby and DP Standby / Idle samples.

If 500m Standby takes longer than 500m exit, 500m entry, and DP set-up, it could be an idea to go Standby / Idle instead of staying in the 500m zone. A histogram, shown in Figure 4.26, is created to get familiar with the time 500m Standby takes. The histogram shows a non-normal distribution with quite a few activities taking longer than the average time to do a DP set-up, exit, and enter the 500m zone. To illustrate how long the 500m Standby can take in Figure 4.26, a red vertical line is plotted, indicating the average time it takes to do a DP set-up and exit and enter the 500m zone.

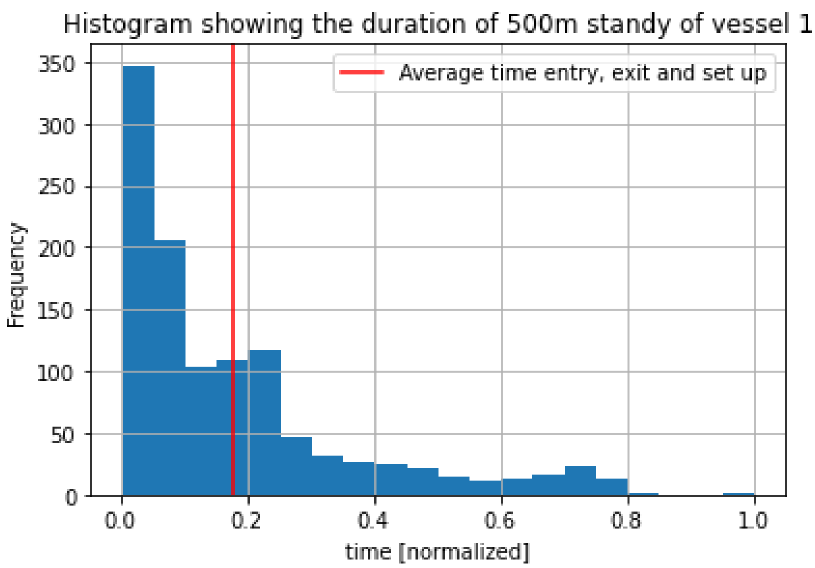


Figure 4.26: Histogram showing the time 500m Standby takes.

4.1.7. Improve

During the analyse phase, four improvement opportunities came up. The first one was to improve planning to sail slower. The waiting time can not all be redressed due to unpredictable events or external influences but assumed when planning strictly. With proper communication with the platform, the waiting time could be brought to a minimum. The second one tries not to sail out when there is a storm. As visible in the data, fuel consumption increases significantly, but the lack of data will not allow it to be considered during the improvement phase. When weather data is included, this could be something to consider and plan maintenance around, for example. The third improvement opportunity was exiting the 500m zone and going Idle instead of staying on 500m Standby. And the fourth and last is going Idle instead of staying on DP Idle / Standby in between exiting and entering the 500m zone.

Choosing which opportunity to improve is made based on the potential gain. The potential gain is an estimation of how much fuel could be saved. For the transit improvement is assumed all DP Standby / Idle after the DP set-up is waiting time, and waiting time can be used to sail slower. Extra time was calculated by summing up all waiting time. The newly available time is equally split over all the transit activities which sailed more than 5 miles, and a new speed is calculated by dividing the distance by the time plus the extra time. The scatter plot plotting speed against fuel consumption while in transit longer than 5 miles is shown in Figure 4.27 but this time including a trend line. The trend line is used to calculate the new fuel consumption per hour. The function calculates the actual fuel consumption with the function and the new consumption with the hypothetical new speed. Transit improvement is simplified, and more components need to be included, which is why the fuel used while at DP is not subtracted. The calculated hypothetical gain is almost 10% of the total fuel consumption while sailing further than 5 miles. This 10% would mean almost 3.5% of the total fuel consumption.

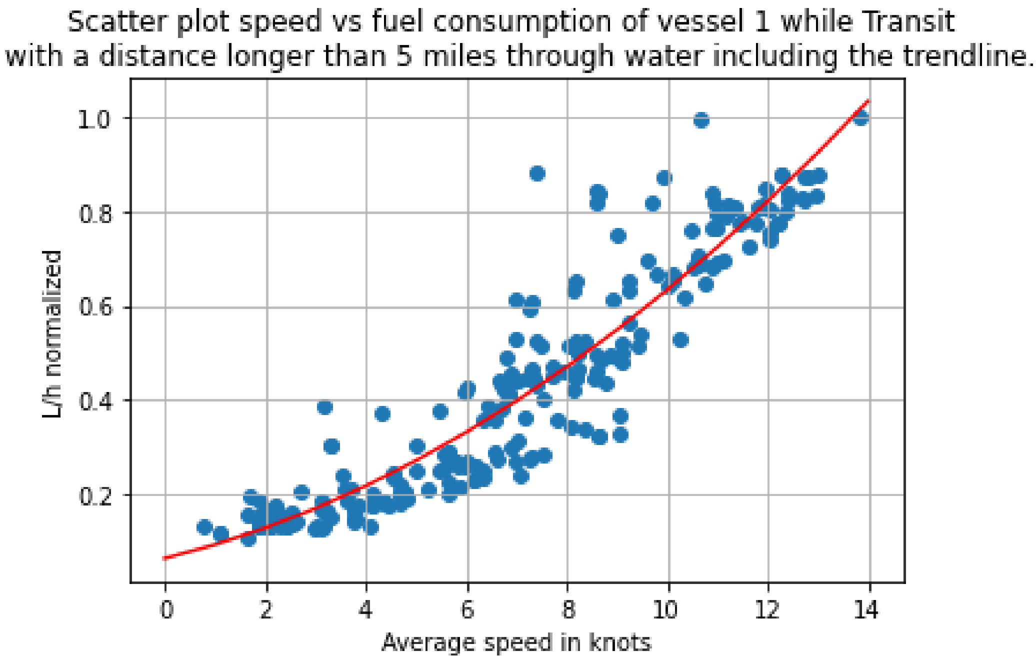


Figure 4.27: The scatter plot plotting speed against fuel consumption of *Vessel 1* from *Company 1* while in transit longer than 5 miles showing the trend line.

The DP Standby / Idle activities frequently happen between the 500m exit and the 500m entry activity. Going idle would decrease fuel consumption if this activity takes longer than the time to set up the DP system. The potential gain is calculated by subtracting the average time of the DP set-up activity from the DP Standby / Idle activities between 500m exit and entry. When DP Standby / Idle is longer than the average DP set-up time, the time difference is multiplied by the average Standby / Idle fuel consumption. This improvement means a 23% decrease in the fuel consumption of these activities, which would result in an 0.5% reduction overall. If 500m Standby takes longer than the time for 500m exit DP set-up and 500m entry, the same thing as the DP Standby / Idle activities between 500m exit and entry is true. The calculations are similar but include the average time and fuel consumption of the 500m exit and entry. The 500m Standby calculation results in a decrease of 14%, which is 2% of total fuel consumption. All the gains are summarized in the Pareto chart displayed in Figure 4.28.

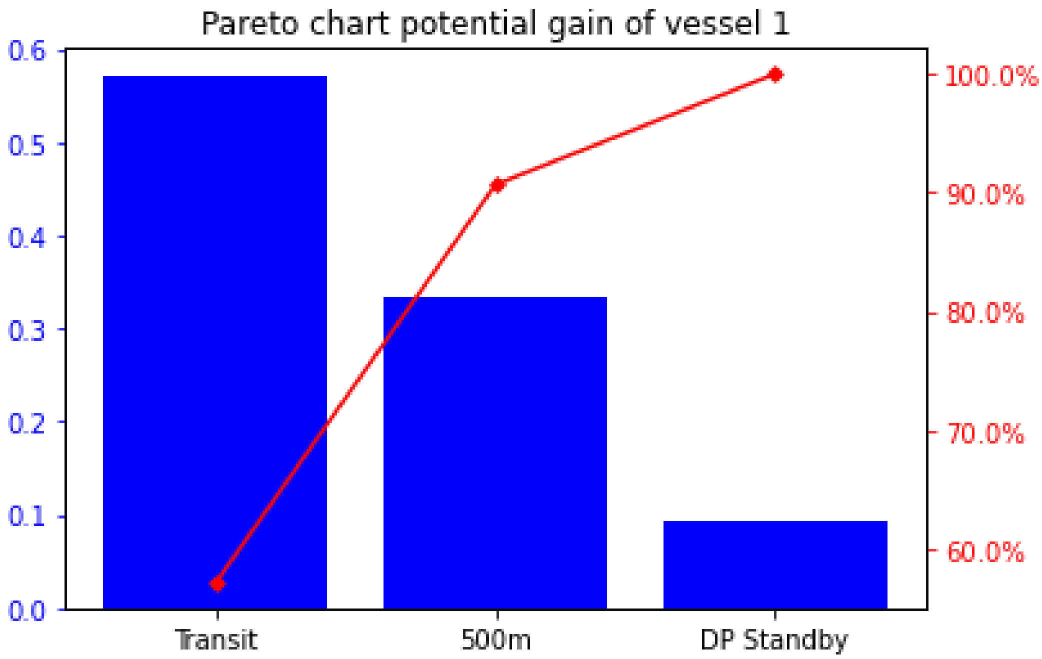


Figure 4.28: The Pareto chart of *Vessel 1* from *Company 1* shows the potential gain of the proposed improvements.

When looking at the Pareto chart, the Transit improvement seems to be the most apparent to tackle first. The Improvement plan to sail slower is based on the waiting time after the DP set-up. What is not clear is the cause of the waiting time. During the analyse phase is seemingly assumed that the reason was a planning issue, but the problem can have multiple origins. The first question which needs to be asked in order to start the 5 times why is, Why do you have to wait when arriving? This question needs to be answered to be able to tackle the problem. The next question could be, Why is the planning imperfect? Is it maybe not the planning but a platform where the vessel has to wait too long? In that case, why not arrive later? Or why is the platform making the vessel wait? These questions will eventually end up in a clear understanding of the problem.

4.1.8. Control

The control phase will consist of an X-bar and R-charts but will need more time to show results.

4.2. Case 2

The second case is the case of *Vessel 2* and *Vessel 3* of *Company 2*. *Company 2* has just like *Company 1* offshore supply vessels, but the vessels of *Company 2* are more focused on cargo than human transfers. This example shows two cases of two identical vessels. *Vessel 2* is gathering data for a while, and *Vessel 3* is active for roughly 20 weeks.

4.2.1. Define

The define phase starts by composing the company's flow chart. The Flow chart contains all company activities, but in the case of *Company 2*, not all activities are included. The flow chart does not include every activity because some rarely occur at the used vessels. These activities are not included in the graph because there is no real influence on the entire process. This is also shown in Figures 4.29 and 4.30, which show the utility graphs with all activities. As activity names, the abbreviation of every activity is used because not all abbreviations are immediately apparent. The full names are displayed in table 4.2. These graphs show never or seldom-executed activities, which are not included in the Flow charts. The activities not used in the flow charts will not be elaborated.

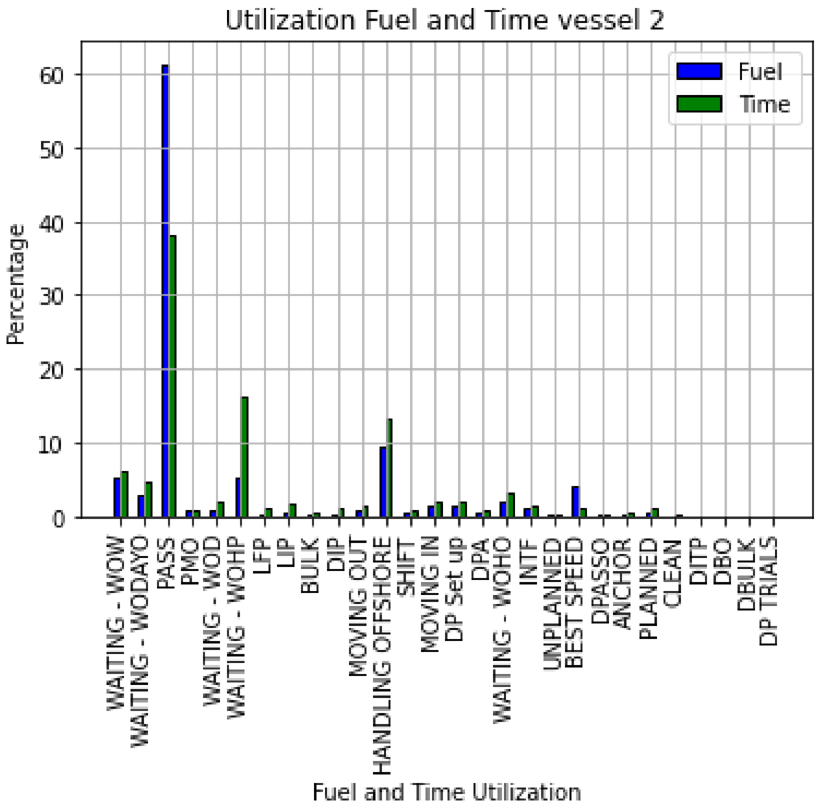


Figure 4.29: The utility graph of all activities of *Vessel 2*.

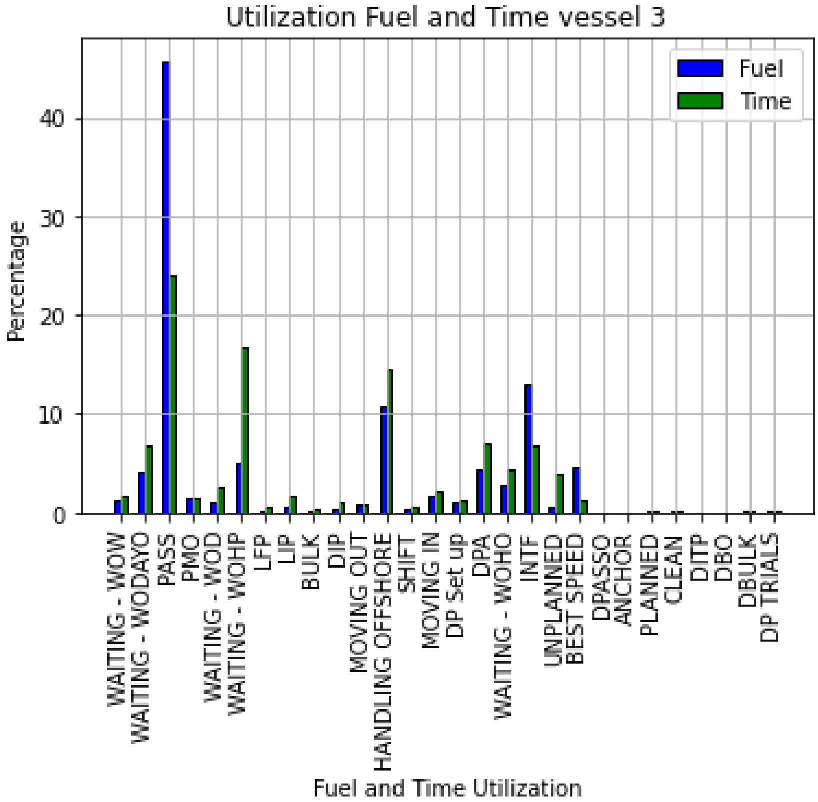


Figure 4.30: The utility graph of all activities of *Vessel 3*.

Table 4.2: Table of activities and groups of *Company 2*.

Group	Activity	Full name
Active	**DP Set up**	Set up DP
	DP TRIALS	DP trials
	HANDLING OFFSHORE	Off- and Backload
	MOVING IN	Moving in
	MOVING OUT	Moving out
Idle	**ANCHOR**	Awaiting orders
	BULK	Loading or discharging of bulk in port
	CLEAN	Cleaning bulk tanks
	DBO	Delayed by operator
	DBULK	Dedicated bulk loading
	DHO	Dedicated Offshore Handling
	DIP	Discharge cargo in port
	DITO	Dedicated idle time offshore
	DITP	Dedicated idle time in port
	LFP	Loading fuel or POT water in port
	LIP	Loading cargo in port
	PLANNED	Planned maintenance
	PTC	Potable water tank cleaning
	WAITING - WOD	Waiting on departure
	WAITING - WOHO	Waiting on handling offshore
	WAITING - WOHP	Waiting on handling port
	WAITING - WOW	Waiting on weather
Transit	**BEST SPEED**	Sailing to locations, at maximum speed
	DPASSO	Dedicated passage offshore
	DPASSP	Dedicated Pass in port
	INTF	Sailing between offshore installations
	PASS	Passage to and from Port
	PMO	Port movement
	SHIFT	Shifting vessel
Waiting	**DPA**	Dynamic positioning anchoring
	FLEXO	Idle time to fit schedule offshore
	FLEXP	Idle time to fit schedule Port
	UNPLANNED	Unplanned maintenance
	WAITING - WODAYO	Waiting on day shift

Figure 4.31 shows the flow chart of *Company 2*. The flowchart shows a schematic representation of a journey. A journey of a vessel of *Company 2* starts either while in port, between port operations, or after finishing an operation at a platform. When a new journey starts in the port, one of the port activities is finished, and the next begins. The significant port activities are LIP loading cargo in port, DIP discharge cargo in port, WAITING - WHOP waiting on handling port, BULK loading or discharging of bulk in port, LFP loading fuel or POT water in port, and WAITING - WOD waiting on departure. After a port operation, the vessels sometimes need to shift to another location in or outside the port to go on anchorage during the DP Anchorage activity. After DPA, the vessel will SHIFT back to port and start a new port activity. When the port activities are finished, and the vessel starts moving towards an offshore location, the vessel first manoeuvres out of the port, which starts activity PMO. After the vessel sailed out of the port, the vessel sails towards an offshore location and this sailing activity is named PASS. After passing, the vessel arrives at a platform with two possibilities, either the vessel directly starts an activity, or the vessel has to wait before setting up DP. The waiting activities which can accrue before the offshore activities are WODAYO Waiting on the day shift, WOHO Waiting on handling offshore, and WOW Waiting on the weather. When the waiting is finished, the offshore activities start. The offshore activities start with DP Set up followed by the vessel moving towards the platform, MOVING IN. After moving in, cargo is transferred during HANDLING OFFSHORE and the vessel sails away from the platform during MOVING OUT. Between DP Set up and MOVING IN, the vessel occasionally has to

wait until it can go to the platform and has to wait for handling offshore. And now and then, the vessel has to change its position next to a platform. This special manoeuvre is indicated with DPASSO and sometimes with INTF. After the offshore activity, the vessel will either immediately proceed to another location, indicated with the activity name INTF, PASS, DPASSO, or SHIFT, or a new voyage is first started and then sailed to another site or back to the port. When sailing to another site, the sequence begins again, so wait first or go straight to the DP Set up. Pass is activated first when sailing back to the port, after which the vessel near the port starts PMO. Now it may be that before the vessel enters the port, the vessel must wait and goes for DP Anchorage and then SHIFT into the port. When the vessel is back in port, a port activity is activated, and everything starts all over again.

Figure 4.31 shows the flow chart of *Company 2*. There are four groups. The first group is Idle, which includes all activities while in port. The second group, transit, consists of all activities while sailing. The third group Waiting is the group where the activities are waiting for something. The last and fourth group is Active, and in this group are all activities around offshore handling. The flow chart shows the groups in different colours. The transit blocks are yellow, the waiting groups blue, the Idle group green, and Active has the colour red. The reason behind the multiple blocks is that sailing directly between activities is defined differently. And entering and exiting the port are split into two groups to make the diagram neater. SHIFT is marked in red because it causes some ambiguity. When the vessel is in the port, there is a SHIFT activity sailing inside the port. This SHIFT needs to be kept separate to keep transit clear. SHIFT is sometimes used offshore, which seems like the wrong activity chosen. From Idle, there is transit to an offshore activity or waiting before activities can start. After the offshore activity, the vessel transits back to port or sails to another offshore activity. BEST SPEED is not included because BEST SPEED is PASS but on maximum speed.

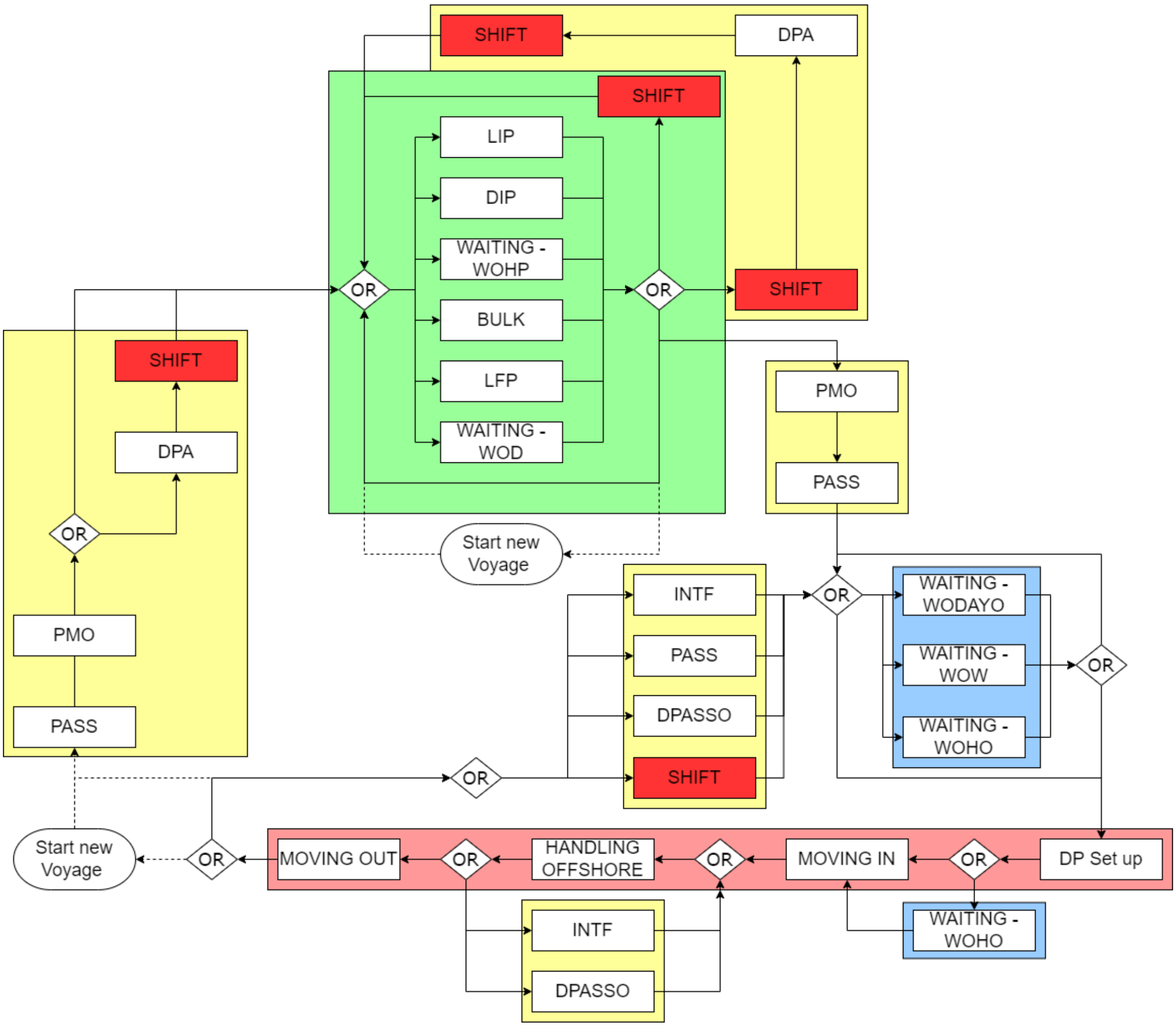


Figure 4.31: Flow chart *Company 2*.

The improved flow chart shown in Figure 4.32 shows some differences from the current one. The most rigorous change is the removal of the waiting blocks, which in a perfect world would not be necessary, so waiting is considered waste. DPA and SHIFT are removed from the flow chart because sailing into the port without waiting would be better. SHIFT in the port is not included in the new diagram because it would be optimal if all port activities were in one spot. And during the transit in between the activities, one is selected to clarify the transit, which should already work this way. SHIFT is marked red in the optimal diagram because SHIFT is the name of different activities and not only the one indicated in the flowchart. The SHIFT activity is still an activity where the naming needs to be improved.

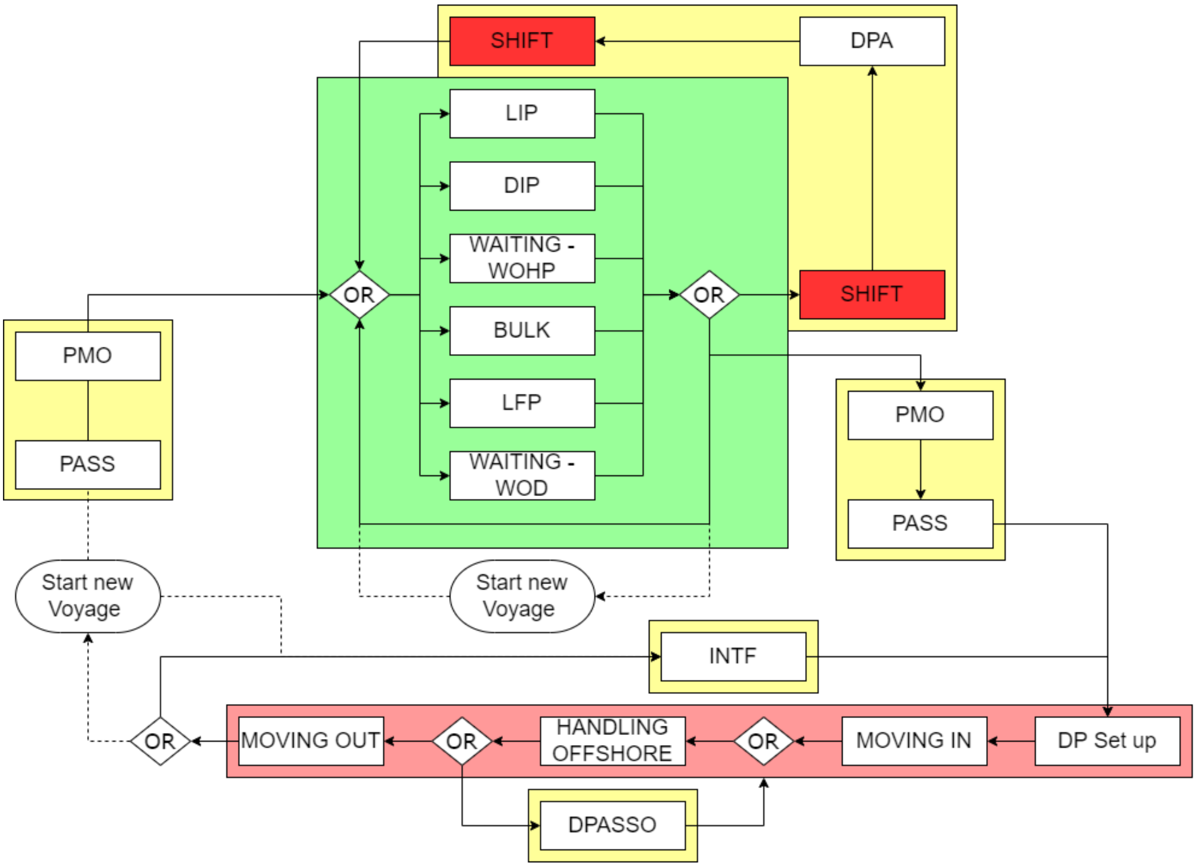


Figure 4.32: Flow chart in an optimal world *Company 2*.

4.2.2. Measure

The chosen KPIs are fuel and time because these are the most important for the vessel owners at the moment. The utilisation graphs will show both time and fuel consumed. The rest of the analysis will use fuel per hour to make the activities more comparable. Figure 4.33 and 4.34 show the grouped utilisation. In Figure 4.29 and 4.30 all the activities showed time and fuel used as a percentage. In the figures, only a few activities seem to have an impact. These insignificant activities can form a more significant factor when grouped, as shown in Figure 4.33 and 4.34.

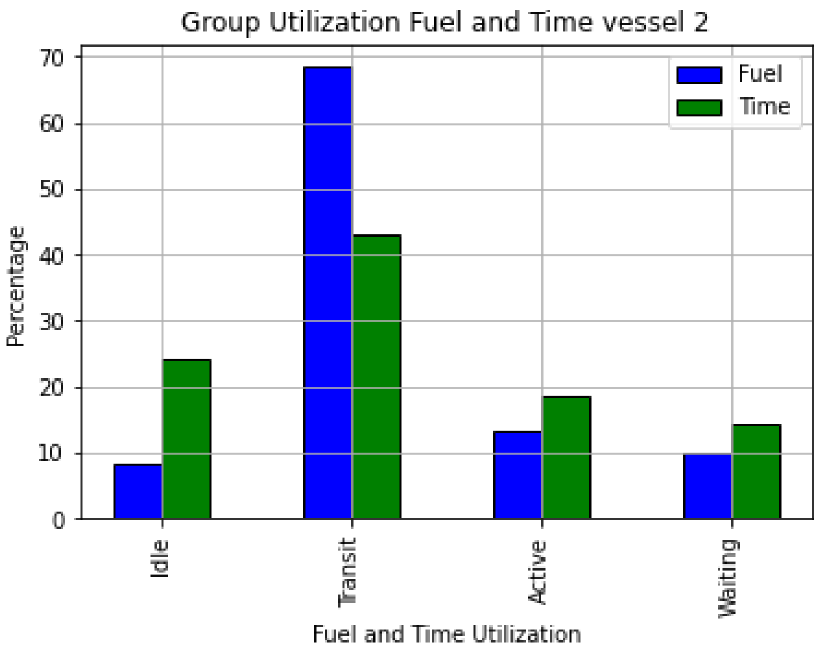


Figure 4.33: The grouped utilisation graph of *Vessel 2* of *Company 2* showing the time and fuel utilisation of all grouped activities.

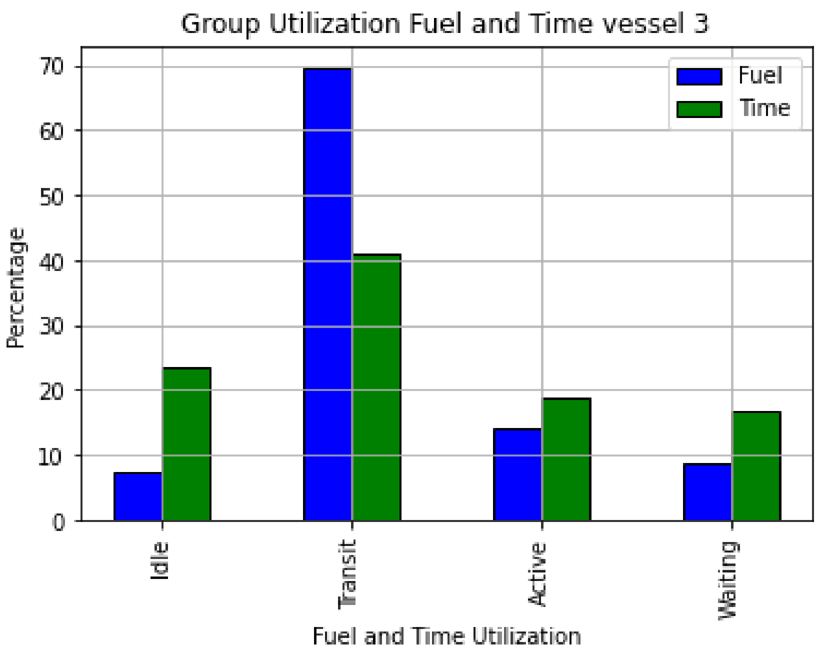


Figure 4.34: The grouped utilisation graph of *Vessel 2* of *Company 2* showing the time and fuel utilisation of all grouped activities.

Figure 4.35 shows the box plots of *Vessel 2*, and Figure 4.36 shows the box plots of *Vessel 3*. These box plots show the outliers in the samples and how the activities behave in comparison to each other. Outliers are excluded during the sample creation. The box plots visualize the fuel consumption per hour per activity group.

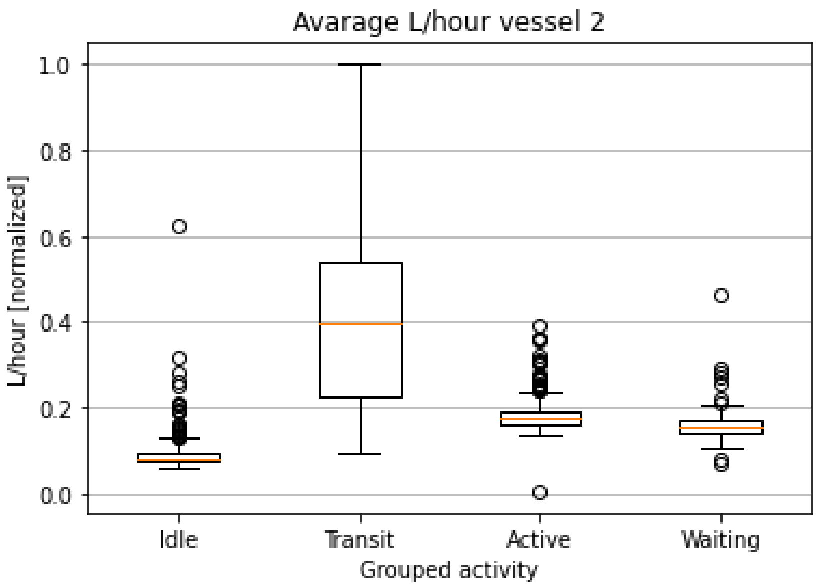


Figure 4.35: Box plots of *Vessel 2* from *Company 2*.

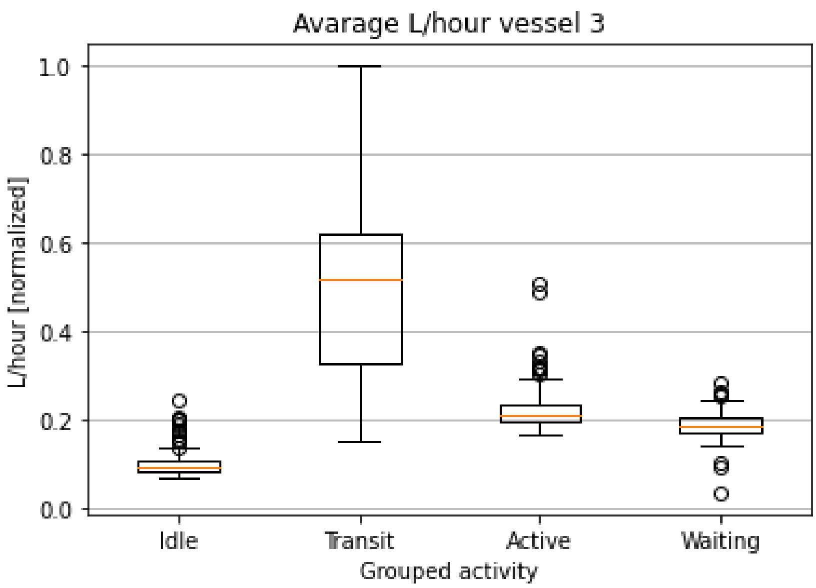


Figure 4.36: Box plots of *Vessel 3* from *Company 2*.

This case will consider two sister vessels, so Figure 4.37, 4.38, 4.39, and 4.40 show the box plot of every activity group next to each other. When looking at the box plots, the two vessels seem indeed similar.

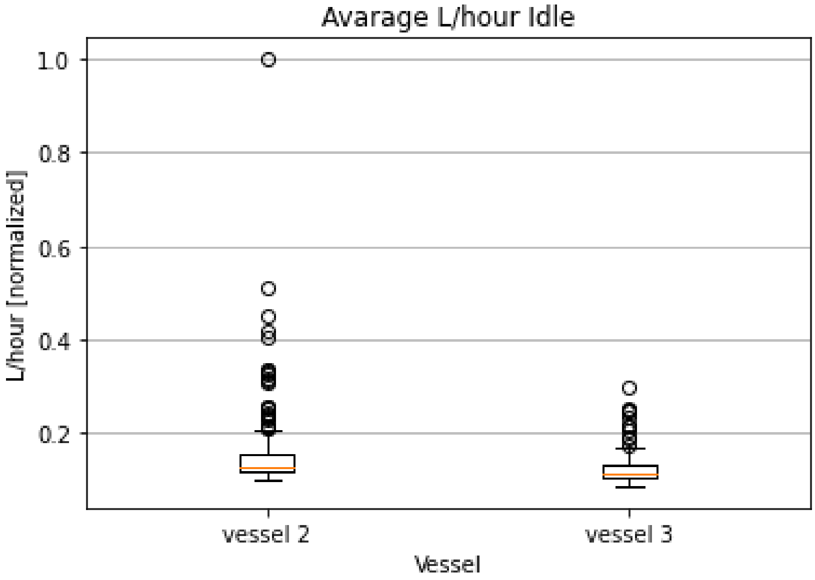


Figure 4.37: Box plot of *Vessel 2* and *Vessel 3* from *Company 2* while idle.

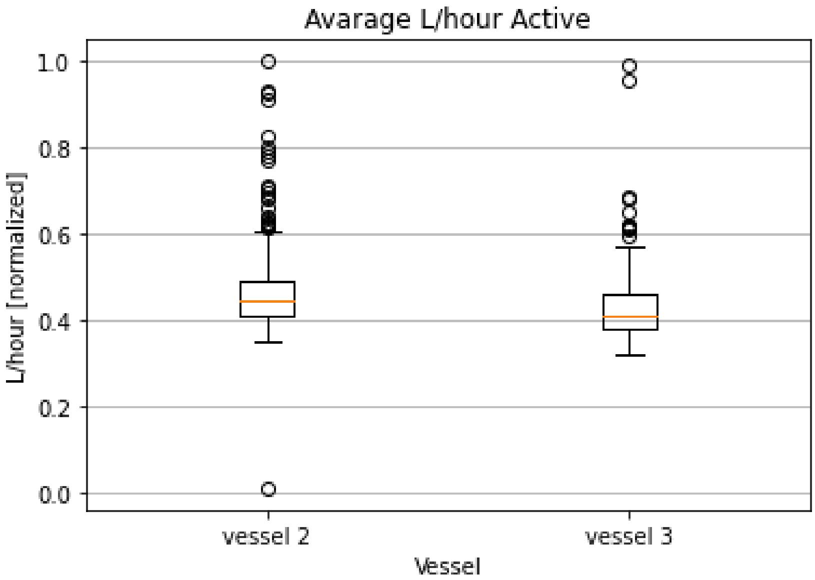


Figure 4.38: Box plot of *Vessel 2* and *Vessel 3* from *Company 2* while active.

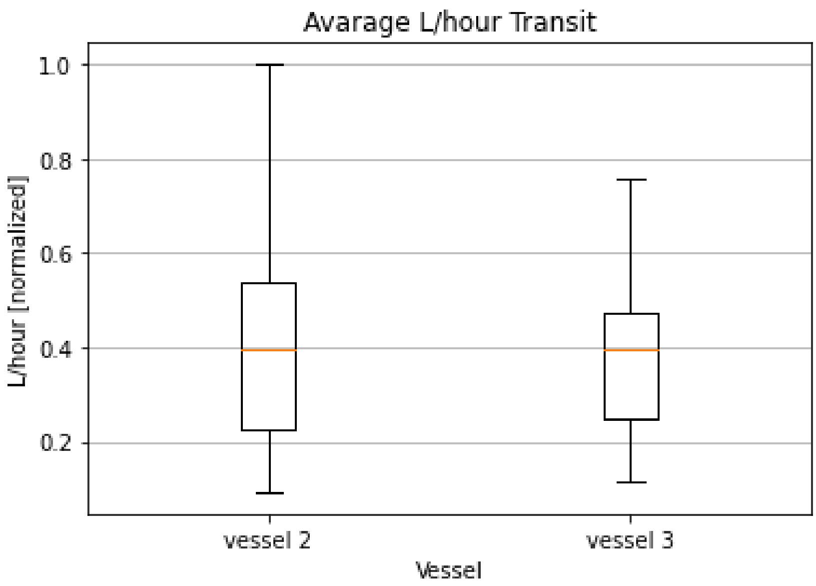


Figure 4.39: Box plot of *Vessel 2* and *Vessel 3* from *Company 2* while in transit.

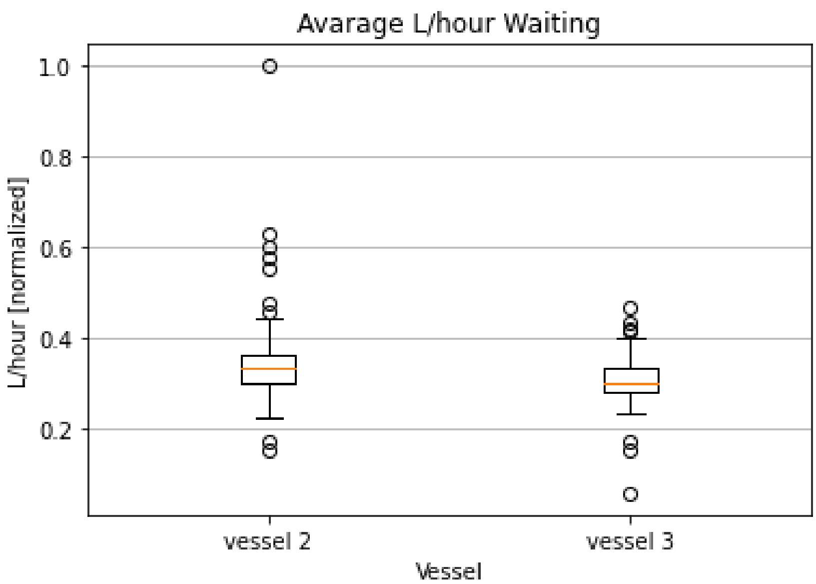


Figure 4.40: Box plot of *Vessel 2* and *Vessel 3* from *Company 2* while waiting.

The results of *Vessel 2* from *Company 2* will be discussed. The data needs to contain at least 20 samples. A sample is created if a group occurs more than five times in one week. The last 37 weeks are included in these tests. During these weeks, 17 groups considered idle are formed, 25 samples for active, 36 samples for when in transit and 6 for waiting. The results of the statistical tests are summarized in this paragraph, and the complete results are stated in appendix C.1.1. The test results of the idle, active, transit and waiting data point out that there is no reason to reject the null hypothesis, and the data looks normally distributed.

Idle has too few samples to conduct analyses properly. The Q-Q plot shown in Figure 4.41 and the histogram shown in Figure 4.42, the data is skewed towards the right. The tests consider the data to be normally distributed, but the Q-Q plot and histogram do not consolidate the conclusion. The idle data should not be considered normal.

While active, the data is normally distributed according to the statistical tests. The Q-Q plot shown in Figure 4.43 and the histogram shown in Figure 4.44 show the data to be a bit skewed to the right and show a hole in the distribution. The active data should not be considered normal and ready for the analysis phase.

None of the tests states that while in transit, the data is not normally distributed. When looking at the Q-Q plot shown in Figure 4.45 and the histogram shown in Figure 4.46, it becomes clear that the data is not normally distributed. The histogram and Q-Q plot clearly show two peaks in the data. This data should not be considered normally distributed and needs to be improved.

According to all tests done for waiting, there is no reason to assume the data is not normally distributed. The Q-Q plot shown in Figure 4.47 and the histogram shown in Figure 4.48, doubt can be raised about the outcomes of the tests. The data consisted of only six samples, which is too little to be analysed, and the statistical tests can not be deemed useful in this case.

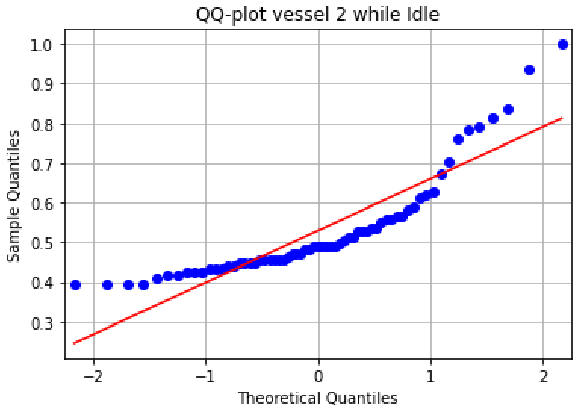


Figure 4.41: The Q-Q plot of the data from *Vessel 2* while Idle.

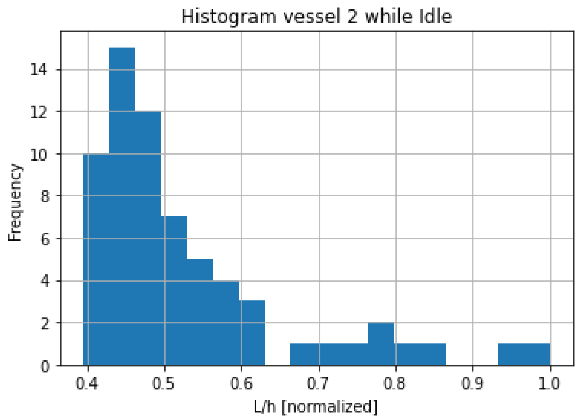


Figure 4.42: The Histogram of the data from *Vessel 2* while Idle.

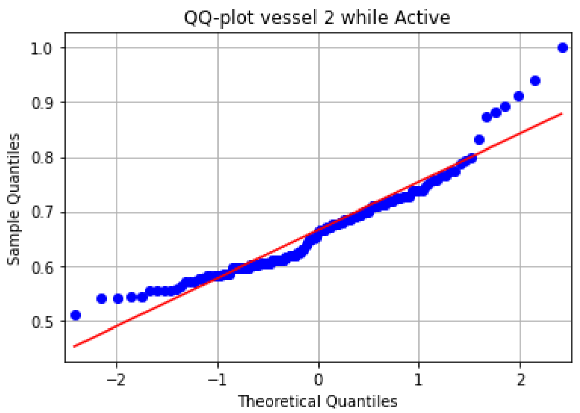


Figure 4.43: The Q-Q plot of the data from *Vessel 2* while Active.

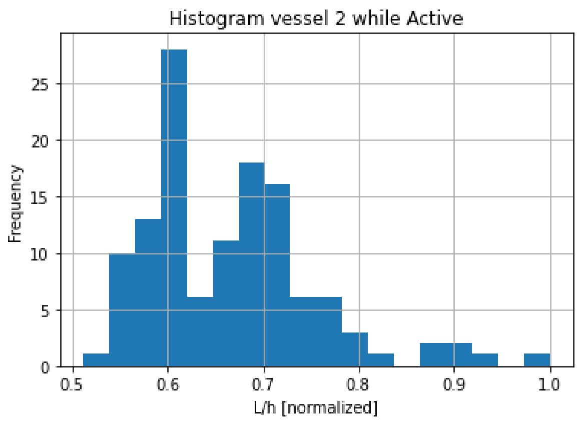


Figure 4.44: The Histogram of the data from *Vessel 2* while Active.

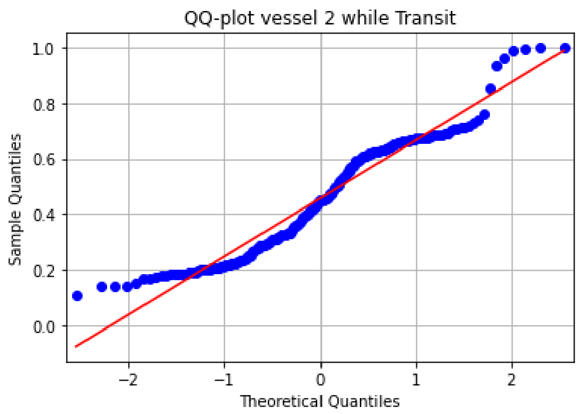


Figure 4.45: The Q-Q plot of the data from *Vessel 2* while in Transit.

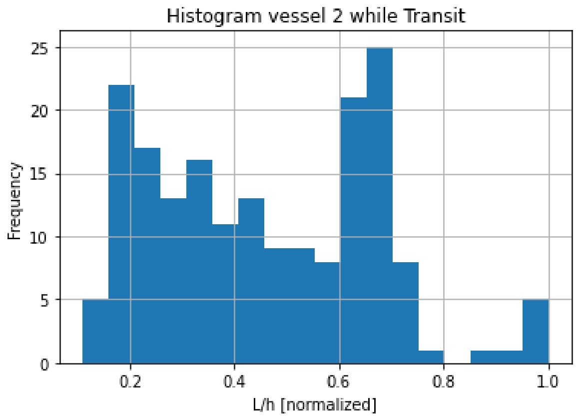


Figure 4.46: The Histogram of the data from *Vessel 2* while in Transit.

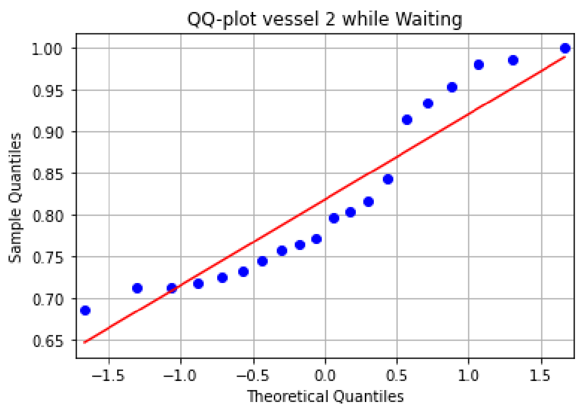


Figure 4.47: The Q-Q plot of the data from *Vessel 2* while Waiting.

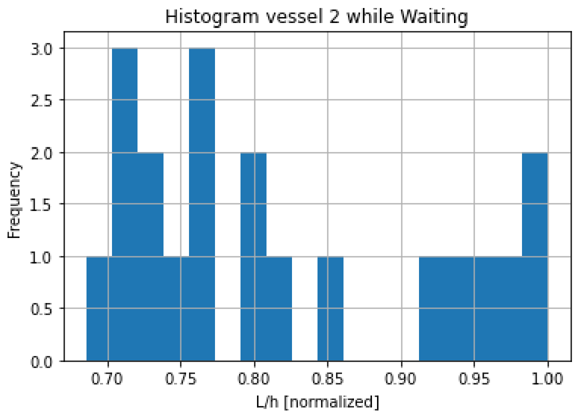


Figure 4.48: The Histogram of the data from *Vessel 2* while Waiting.

in these paragraphs the results of *Vessel 3* from *Company 2* will be discussed. The data needs to contain at least 20 samples. A sample is created if a group occurs more than five times in one week. The last 20 weeks are included in these tests, so the samples must be created weekly. During these weeks, 8 groups, considered Idle, are formed, 19 samples for Active, 20 for when in transit and 10 for waiting. The results of the statistical tests are summarized in this paragraph, and the complete results are stated in appendix C.1.2. The test results of the Idle and Transit data suggest there is no reason to reject the null hypothesis, and the data looks normally distributed. The test results of the active data do not show unanimous results. Only the Anderson test with p at 15% rejects the null hypothesis and states the data is not normally distributed. The tests, while waiting, almost unanimously agree that the data is not normally distributed. The Anderson test with p at 1% and the Kolmogorov-Smirnov tests fail to reject the null hypothesis.

Idle has too few samples to conduct analyses properly. When looking at the Q-Q plot shown in Figure 4.49 and the histogram shown in Figure 4.50, the data is skewed towards the right and far from normal. The tests consider the data to be normally distributed, but the Q-Q plot and histogram do not consolidate the conclusion. The idle data should not be considered normal.

While active, the data is normally distributed according to some tests. The Q-Q plot shown in Figure 4.51 and the histogram shown in Figure 4.52 show the data to be a bit skewed to the right but no big inconsistencies. There are no obvious reasons to assume the Active data is not normal and ready for the analyse phase.

None of the tests states that the data is not normally distributed while in transit. But just like *Vessel 2* when looking at the Q-Q plot shown in Figure 4.53 and the histogram shown in Figure 4.54, it becomes clear that the data is not normally distributed. The histogram and Q-Q plot clearly show at least two peaks in the data. This data should not be considered normally distributed and needs to be improved.

According to most tests, there are reasons to assume the data is not normally distributed. When looking at the Q-Q plot shown in Figure 4.55 and the histogram shown in Figure 4.56, it does not become clear the data is not normally distributed. The data consisted of only ten samples, which is too little to be analysed, and the statistical tests can not be deemed use full in this case.

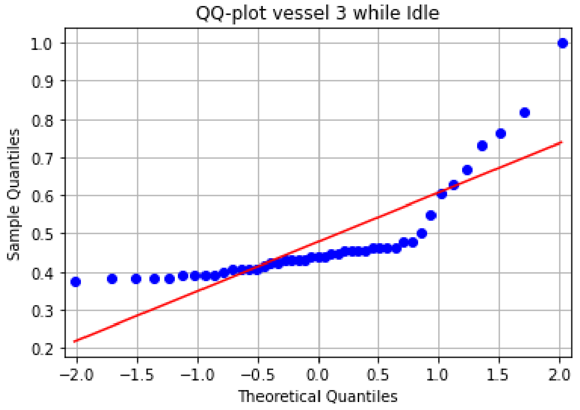


Figure 4.49: The Q-Q plot of the data from *Vessel 3* while Idle.

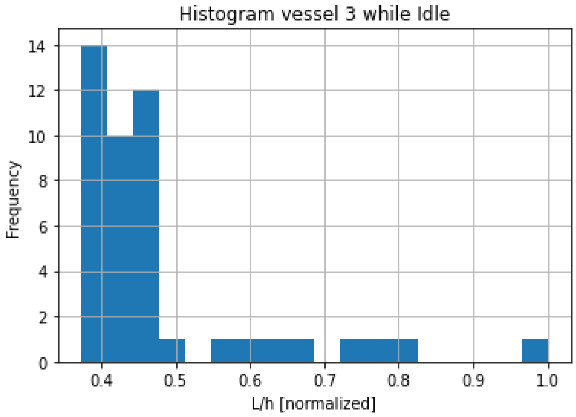


Figure 4.50: The Histogram of the data from *Vessel 3* while Idle.

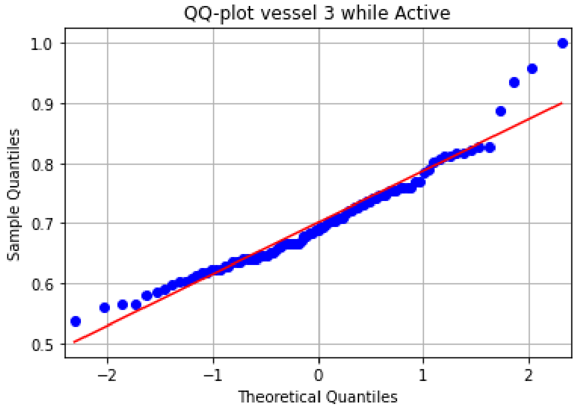


Figure 4.51: The Q-Q plot of the data from *Vessel 3* while Active.

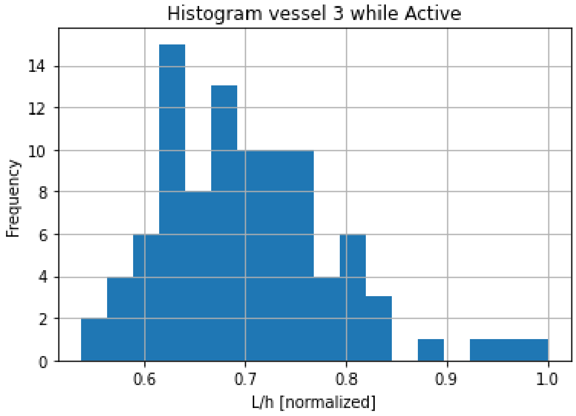


Figure 4.52: The Histogram of the data from *Vessel 3* while Active.

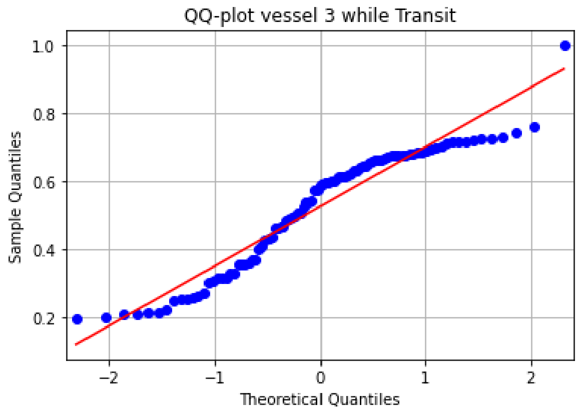


Figure 4.53: The Q-Q plot of the data from *Vessel 3* while in Transit.

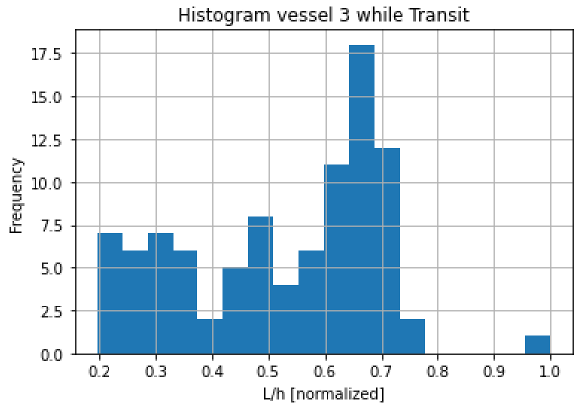


Figure 4.54: The Histogram of the data from *Vessel 3* while in Transit.

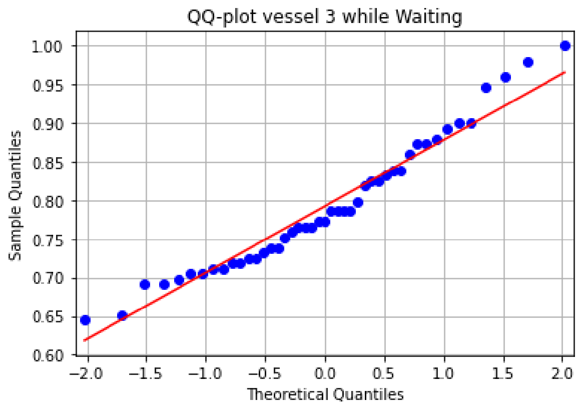


Figure 4.55: The Q-Q plot of the data from *Vessel 3* while Waiting.

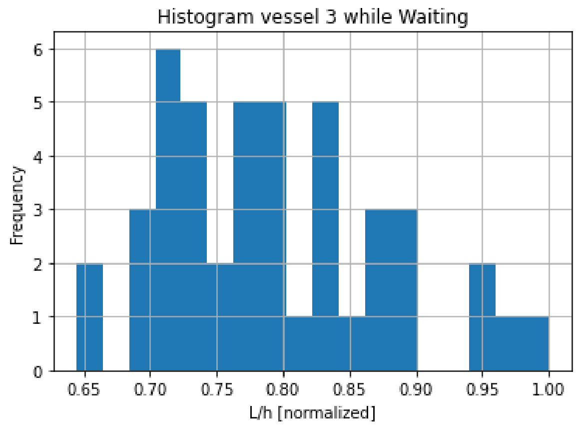


Figure 4.56: The Histogram of the data from *Vessel 3* while Waiting.

Because at the moment, only the data from *Vessel 3* while active is deemed to be normally distributed, only the X-bar and R-chart while in active of *Vessel 3* will be shown. The other X-bar and R-charts can be used when the data quality is increased. Figures 4.57 and 4.58 show the X-bar and R-chart. The Control chart shows a stable and in-control system, but the Range chart demonstrates an out-of-control point and one very close to the edge. The quality of the data from *Vessel 3* while active seems to be on the verge of being stable and in control, but if the active activity needs to be monitored, it can be improved.

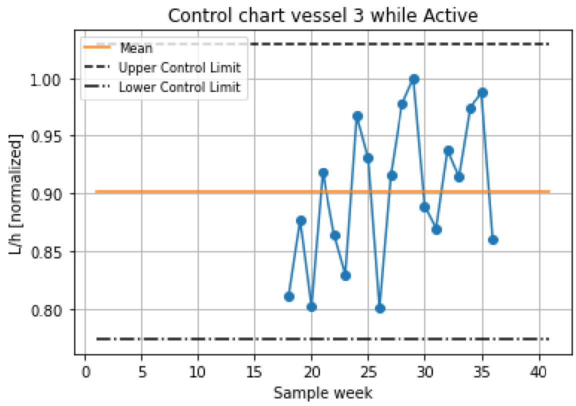


Figure 4.57: The X-bar chart of *Vessel 3* from *Company 2* while active.

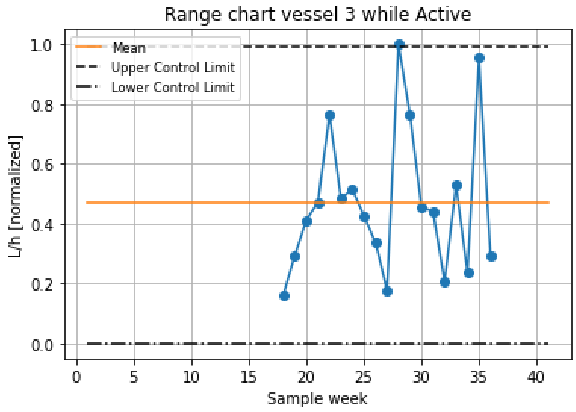


Figure 4.58: R-chart of *Vessel 3* from *Company 2* while active.

4.2.3. Analyse

The first question is where to focus. The utilisation graphs, displayed in Figure 4.33 and 4.34, show almost 70% of fuel is used while in transit while the number two, while active, does not even use 15% of the fuel. Due to the influence of transit, the transit data needs to be further analysed. For the transit, enough data is available. The active group data has almost enough input and will also be included in the analysis phase.

The transit group consist of seven different transit modes. To find a reason for the data not being normally distributed, all different modes are plotted in Figure 4.59 and 4.60. The scatter plots show the fuel consumption versus the average speed in knots over ground. Using speed through water instead of speed over ground would be preferred, but the speed sensor does not work consistently. In both scatter plots in the lower left corner, DPA, DPASSO and SHIFT are located. In the upper right corner is a cluster of BEST SPEED, the fastest speed. PMO, PASS and INTF show an exponentially increasing trend through the centre.

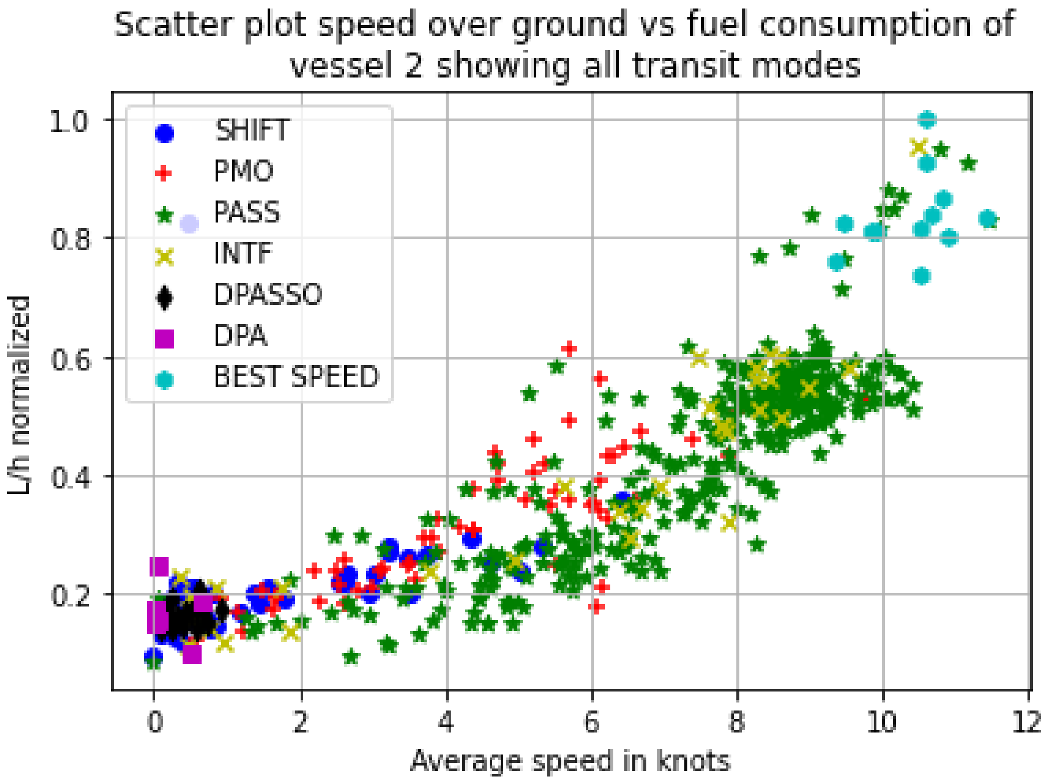


Figure 4.59: The scatter plot plotting speed against fuel consumption of *Vessel 2* from *Company 2* while in Transit.

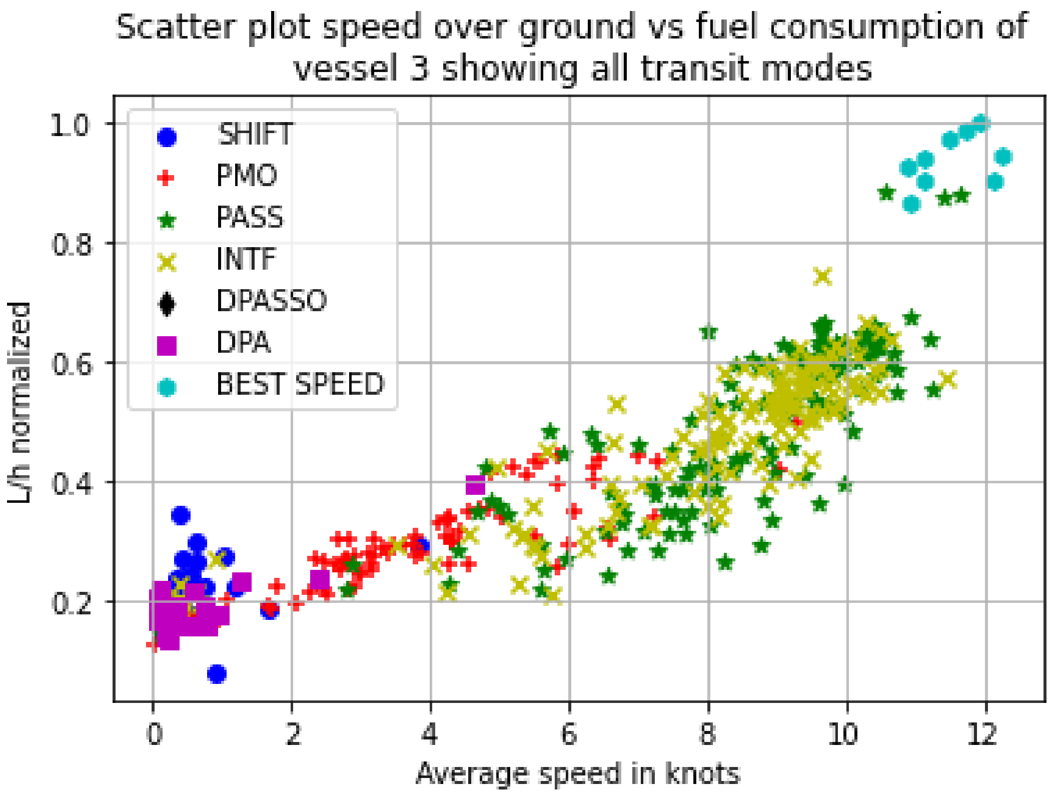


Figure 4.60: The scatter plot plotting speed against fuel consumption of *Vessel 3* from *Company 2* while in Transit.

In Figure 4.61, 4.62, 4.63, and 4.64 are the DPA, DPASSO and SHIFT split from the PMO, PASS, BEST SPEED and INTF. When the two groups split up, the data is neater and better observations are possible. Looking for mistakes is done by following the fishbone diagram displayed in Figure 3.11. Errors in the measurements seem to show while analysing the speed through water data. Speed through water data is calculated using the distance through water data which is full of holes and unrealistic values. The reason for the errors could be a broken sensor. When looking at the scatter plots, there could be some wrong-selected activities, but the reason could be that activities are unclear. For example *Vessel 2* used SHIFT in a different way than *Vessel 3* as is visible in Figure 4.62 and Figure 4.64. In those figures, DPASSO is only used by *Vessel 2*, which could mean *Vessel 3* uses the wrong activity. Another difference is the number of times *Vessel 3* used INTF, which could indicate either the vessel is used differently or the activity is unclear defined. The wrong activities will be selected when the crew on board a vessel is unaware of when to use what activities. When looking at Figure 4.61 and 4.63 both vessels show a similar trend.

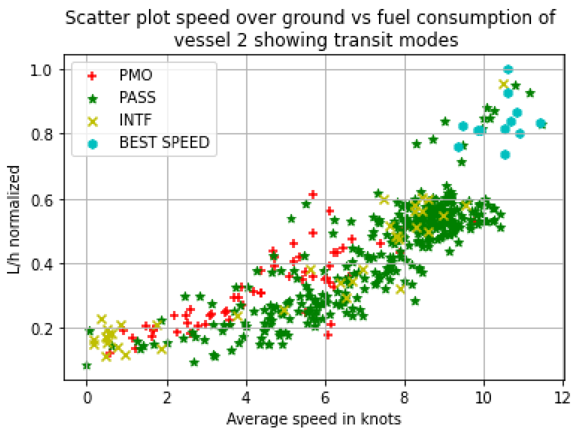


Figure 4.61: The scatter plot plotting speed against fuel consumption of *Vessel 2* from *Company 2* while in transit only shows PMO, PASS, INTF, and BEST SPEED.

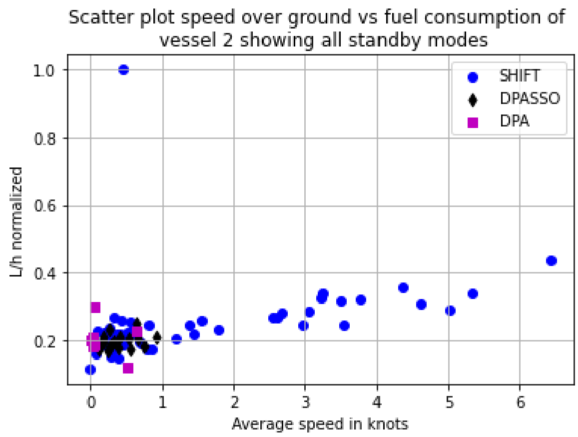


Figure 4.62: The scatter plot plotting speed against fuel consumption of *Vessel 2* from *Company 2* while in transit only showing SHIFT, DPASSO, and DPA.

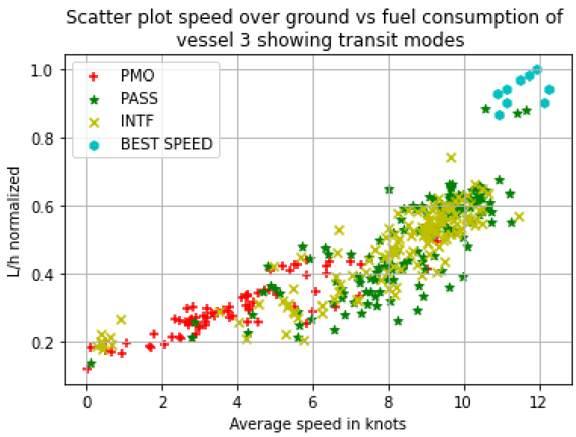


Figure 4.63: The scatter plot plotting speed against fuel consumption of *Vessel 3* from *Company 2* while in transit only shows PMO, PASS, INTF, and BEST SPEED.

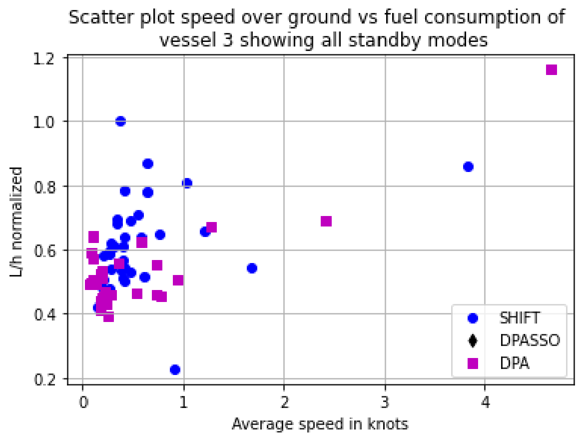


Figure 4.64: The scatter plot plotting speed against fuel consumption of *Vessel 3* from *Company 2* while in transit only showing SHIFT, DPASSO, and DPA.

Before analysing the activities, the quality has to be improved. The grouped activities from *Vessel 2* are not normally distributed enough, and *Vessel 3* seems slightly out of control. The data will be checked for errors by consulting the fishbone diagram from section 3.2.5 shown in Figure 3.11. Assumed is that the data is accurate and the materials are correct. The personnel has probably been late, but this should not have a significant impact due to the grouping. Wrong activities might have been selected, but no examples have been found. It seems in between activities, activities such as waiting and shifting take place. By excluding these activities from the active group, the other activities will split the active group. When analysing the out-of-control data of *Vessel 3* displayed in Figure 4.57 and 4.58, one thing gets clear the highest average samples seem to contain no errors in the sequence. The lower average samples do seem to have multiple errors. The number of times the last activity is not moving out is 309 out of 381, 81% for *Vessel 2* and 205 out of 299, 69% for *Vessel 3*.

4.2.4. Improve

This improve phase will focus on improving the quality of the data. The phase will start by finding the problem of the transit modes. The next step will describe how the problem is going to be addressed. The second part of the section will take the same steps but will focus on the active modes. No Pareto chart is needed because all known errors will be taken care of.

The problem is the transit data is not normally distributed, so the first question we should ask is, Why is the transit not normally distributed? The answer to this question seems to be the different transit modes. Why is it going wrong with the different modes? The transit modes have different profiles, PASS is sailing from a port to a platform, and SHIFT is moving inside the port. Due to the different kinds of transit, the data will show multiple peaks. Why do the transfer modes in Figure 4.59 and 4.60 seem to have another appearance? It seems that due to a large number of different transfer modes, the personnel on board the vessels is not aware of which activity when to use. Why not decrease the options and remove doubles? All modes, but for BEST SPEED, have their sequence and specifics.

Because all modes have a specific sequence, the data can be updated and split into groups. Updating the data will be done by describing clear sequences for the transit modes and changing the names of the activities with the wrong transit mode. The sequences used will be the ones from the improved flow chart shown in Figure 4.32. The sequence for DPASSO is defined as all transits near a platform, so after DP Set up and before MOVING OUT. INTF is all transit between offshore locations. Pass is the transfer from or to an offshore location from or to a port. In between PASS and port operation, there is PMO. And SHIFT is in between port operations or between port operations and DPA. The data will be split into the new Transit group containing PMO, PASS, INTF, and BEST SPEED. The other three transit modes will be in the other group. It would also be an improvement to either drive the staff to better indicate the activities or to clarify the activity names.

During activities, a transit relatively close to the platform often takes place. A vessel has to wait after DP Set up. These activities cause the grouping process to be cut off. The goal is to group activities next to the platform; these inconsistencies work against this. To improve the grouping phase, everything within the DP Set up and MOVING OUT needs to be included in the activity group. DPASSO is more similar to moving in and out than the other transit modes, so it is included in the active group. Waiting between DP Set up and MOVING OUT is also included to improve the grouping process and the normality.

4.2.5. Control

The first indication of whether the improvements worked the number of times MOVING OUT was the last activity is compared to the period before. the number used to be 309 out of 381, 81% for *Vessel 2* and 205 out of 299, 69% for *Vessel 3*. After the upgrades, the number went up to 290 out of 331, 88% for *Vessel 2* and 192 out of 220, 88% for *Vessel 3*.

The results of *Vessel 2* from *Company 2* will be discussed. Idle and Waiting are excluded due to the number of samples, which is too little for the analysis. The number of samples went down by one due to the data improvements, and the transit samples went down by 4 to 32. The results of the statistical tests are summarized in this paragraph, and the complete results are stated in appendix C.2.1. The test results of the Active and Transit data mean there is no reason to reject the null hypothesis, and the data looks normally distributed.

The statistical tests conducted on the active data conclude the data is normally distributed. The Q-Q plot shown in Figure 4.65 and the histogram shown in Figure 4.66 show the data to be a bit skewed to the right and seems to miss some data in the middle. Doubt can be raised about whether the active data should be considered normal and ready for analysis.

None of the tests states that while in transit, the data is not normally distributed. The Q-Q plot shown in Figure 4.67 and the histogram shown in Figure 4.68 both show the data is not normally distributed. The histogram and Q-Q plot clearly show a peak in the data. The different peak is in the data due to the most sailed speed. Figure 4.61 shows a cluster of data points around the 9 knots with fuel consumption of around 0.6, as shown in the histogram.

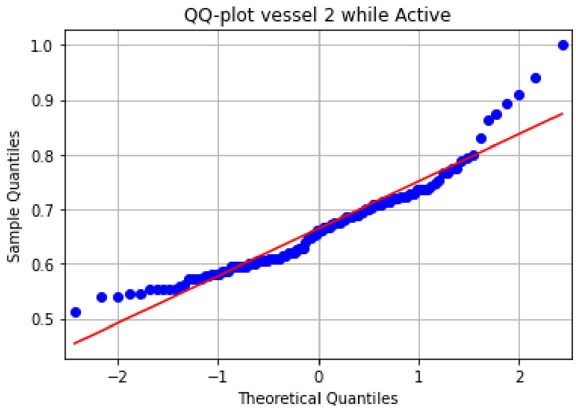


Figure 4.65: The Q-Q plot of the data from *Vessel 2* while Active.

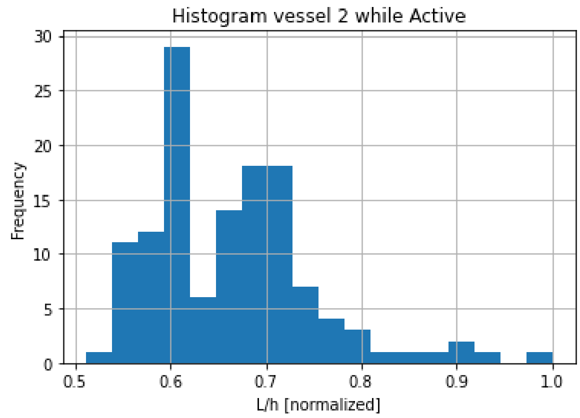


Figure 4.66: The Histogram of the data from *Vessel 2* while Active.

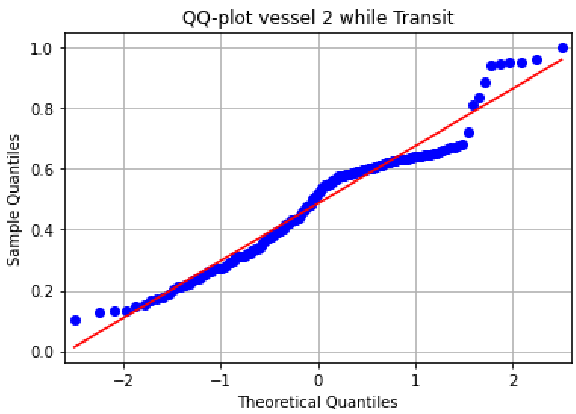


Figure 4.67: The Q-Q plot of the data from *Vessel 2* while in Transit.

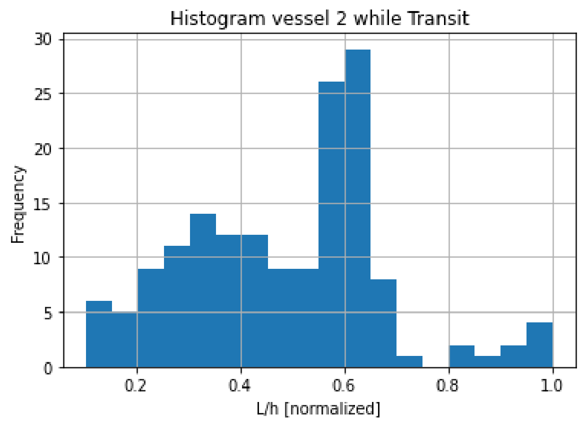


Figure 4.68: The Histogram of the data from *Vessel 2* while in Transit.

in these paragraphs the results of *Vessel 3* from *Company 2* will be discussed. The transit samples remained at 20, but the active samples went down to 17. Although there are too few active samples, the analysis will continue, but extra care must be taken with the results. The results of the statistical tests are summarised in this paragraph, and the complete results are stated in appendix C.2.2. The test results of the Active and Transit data show no reason to reject the null hypothesis, and the data looks normally distributed.

While active, the data seems normally distributed according to the statistical tests. The Q-Q plot shown in Figure 4.69 and the histogram shown in Figure 4.70 show the data to be a bit skewed to the right and rather divided. The low number of samples makes the histogram quite capricious, which makes it hard to tell if the data is normally distributed. There are no clear reasons to assume the active data is not normal and ready for the analyse phase, and in this case, the analyses will be conducted.

None of the tests states that the data is not normally distributed while in transit. But just like *Vessel 2* when looking at the Q-Q plot shown in Figure 4.71 and the histogram shown in Figure 4.72, it seems like there are multiple peaks. The peak is less clear than the peak of *Vessel 2* but still needs to be considered.

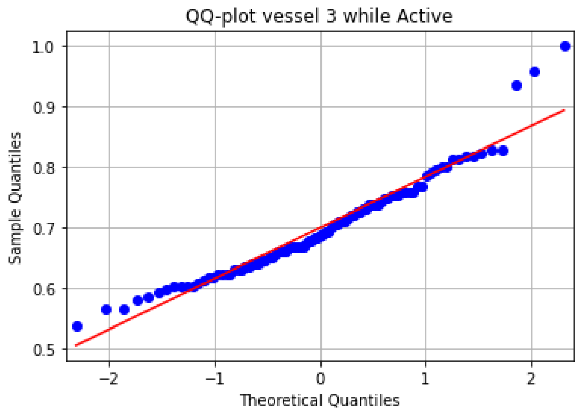


Figure 4.69: The Q-Q plot of the data from *Vessel 3* while Active.

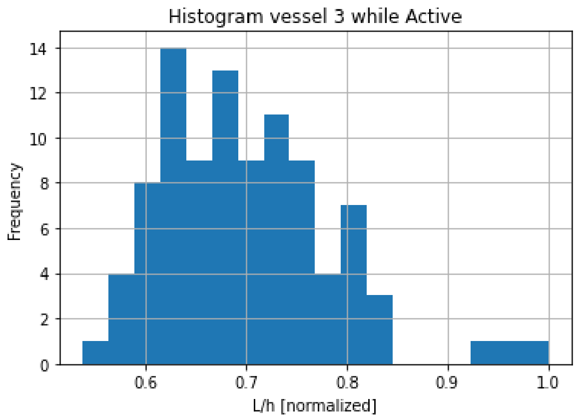


Figure 4.70: The Histogram of the data from *Vessel 3* while Active.

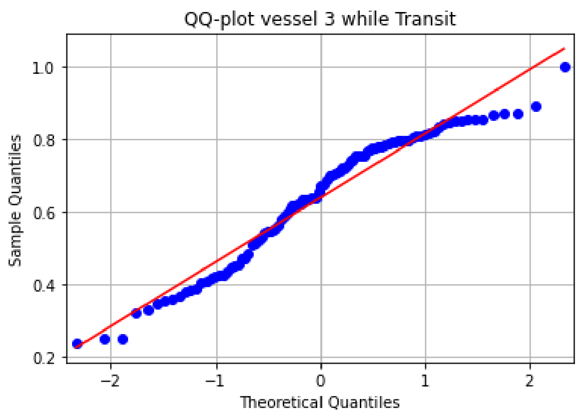


Figure 4.71: The Q-Q plot of the data from *Vessel 3* while in Transit.

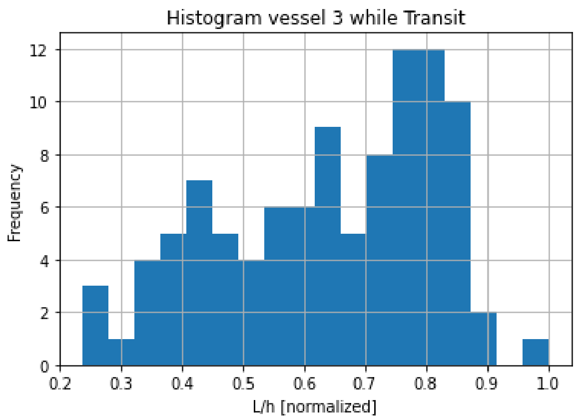


Figure 4.72: The Histogram of the data from *Vessel 3* while in Transit.

The X-bar and R-charts of both vessels while active and in transit are shown. The active control chart of *Vessel 2*, Figure 4.73, is out of control. The R-chart of *Vessel 2*, Figure 4.74, also shows to be out of control. The active control and range chart of *Vessel 3* seem to be in control but seem a bit capricious, just like the histogram.

The transit control chart of both *Vessel 2*, Figure 4.77, and *Vessel 3*, Figure 4.79, show to be different. Where *Vessel 2* is again capricious and a few times out of control *Vessel 3* shows stably in control. The R-charts from *Vessel 2*, Figure 4.78, and *Vessel 3*, Figure 4.80, seem to reinforce the claim made about the control graphs. *Vessel 3* seems to be in control while *Vessel 2* seems out of control.

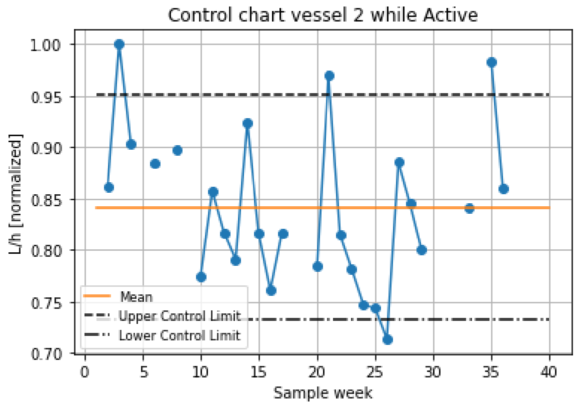


Figure 4.73: The X-bar chart of *Vessel 2* from *Company 2* while active.

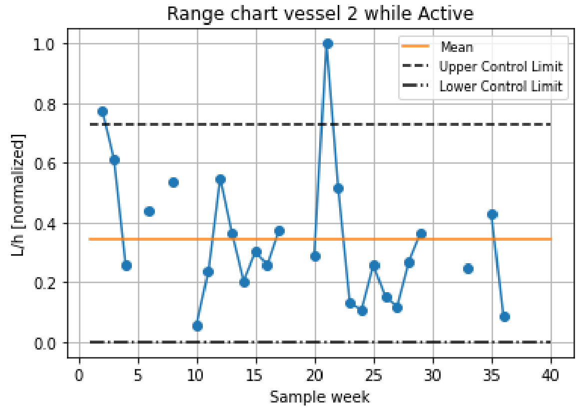


Figure 4.74: The R-chart of *Vessel 2* from *Company 2* while active.

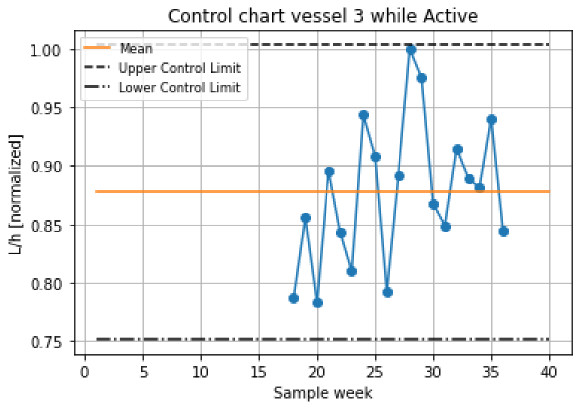


Figure 4.75: The X-bar chart of *Vessel 3* from *Company 2* while active.

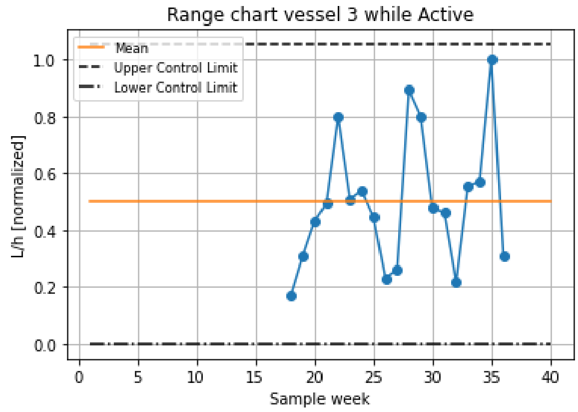


Figure 4.76: The R-chart of *Vessel 3* from *Company 2* while active.

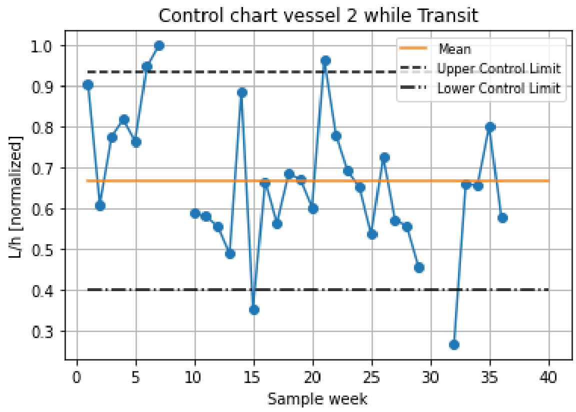


Figure 4.77: The X-bar chart of *Vessel 2* from *Company 2* while active.

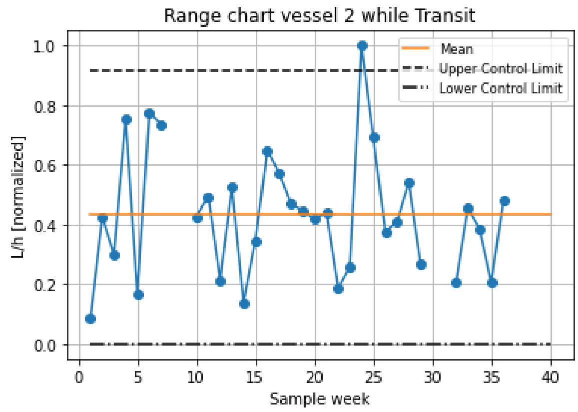


Figure 4.78: The R-chart of *Vessel 2* from *Company 2* while active.

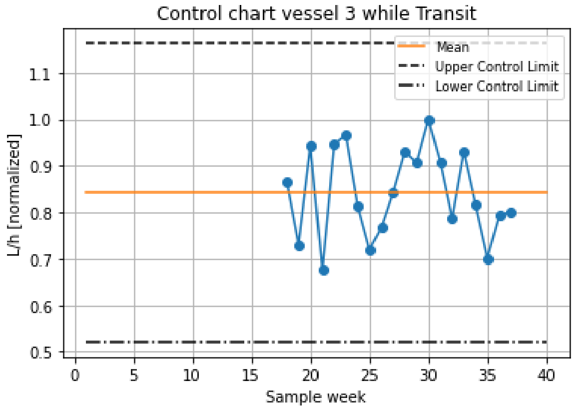


Figure 4.79: The X-bar chart of *Vessel 3* from *Company 2* while active.

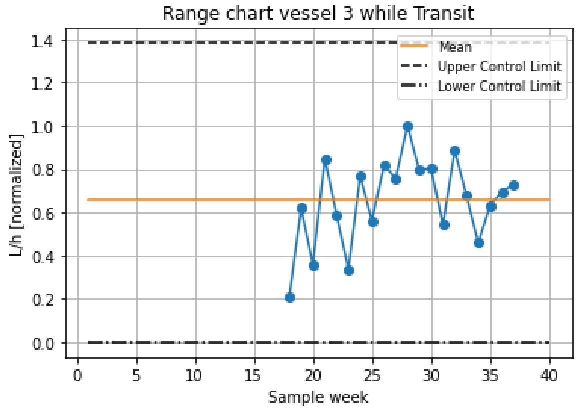


Figure 4.80: The R-chart of *Vessel 3* from *Company 2* while active.

4.2.6. Analyse

With the updated data, the grouped utility graphs changed as well. The updated Utility graphs are displayed in Figure 4.81 and 4.82. In these updated graphs, transit is still the most dominant component. The main focus will lay on improving the efficiency of transit because of the influence of the fuel used during transit on the total fuel consumption.

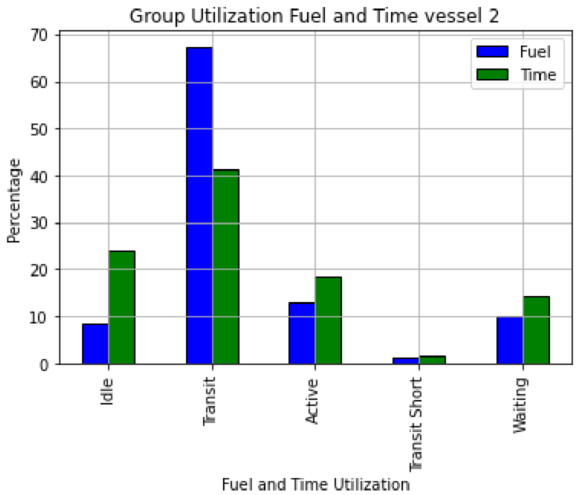


Figure 4.81: The updated utility graph of *Vessel 2* from *Company 2*.

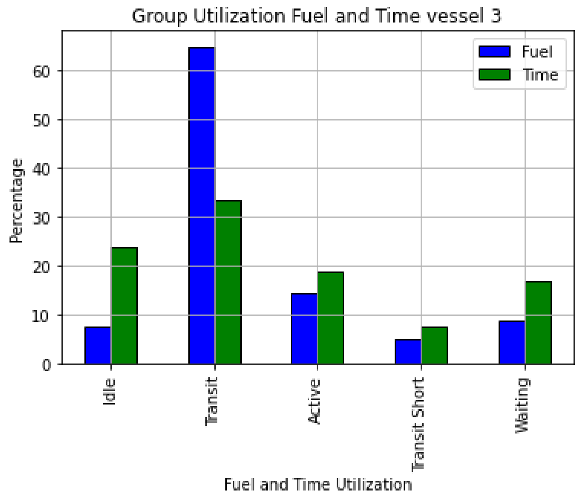


Figure 4.82: The updated utility graph of *Vessel 3* from *Company 2*.

When looking at the box plots of active and transit data, shown in Figure 4.83 and 4.84, *Vessel 3* seems to outperform *Vessel 2* in both cases. A T-test is needed to state that the mean of *Vessel 3* is lower than the mean of *Vessel 2*. A T-test can only be performed on two data sets with equal variance. Because *Vessel 3* and *Vessel 2* are the same vessels doing the same activities, the variation is assumed to be equal. The null hypothesis will be *Vessel 2*, and *Vessel 3* have the same variance. Bartlett's and Levene's tests are conducted to test the null hypothesis. When the p-value is lower than 0.05, it can be assumed the variance of the two vessels is different. The results of Bartlett's and Levene's tests for the active and transit data are shown in Table 4.3. This results in p-values, while active, of 0.314 and 0.685, both above 0.05, so the null hypothesis is not rejected. The p-values of the transit modes are 4.45E-07 and 0.001, below 0.05, so this null hypothesis will be rejected. The results mean that the variation of the active data of both vessels is similar, and a T-test can be conducted. This does not apply to the transit data. What this means for the transit data is that the variance differs, which has probably to do with the out-of-control system of *Vessel 2*.

The T-test will be done for the active data only. The null hypothesis will be *Vessel 2*, and *Vessel 3* have the same mean. The T-test is conducted to test the null hypothesis. When the p-value is lower than 0.05, the mean of the two vessels is assumed to be different. The T-test results are also shown in Table 4.3. The p-value found by the T-test is 0.025, which is smaller than 0.05. The p-value of 0.025 means the means of the two vessels while active are probably different.

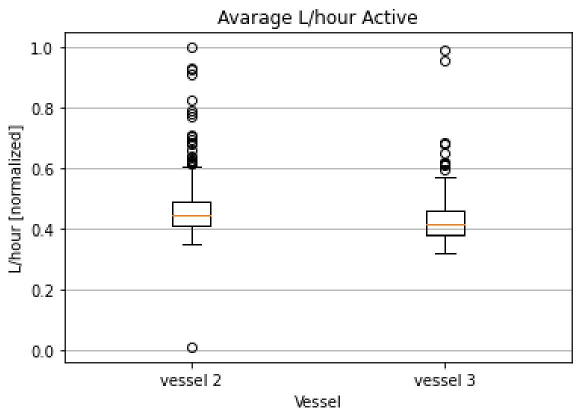


Figure 4.83: The updated box plots from *Company 2* while active.

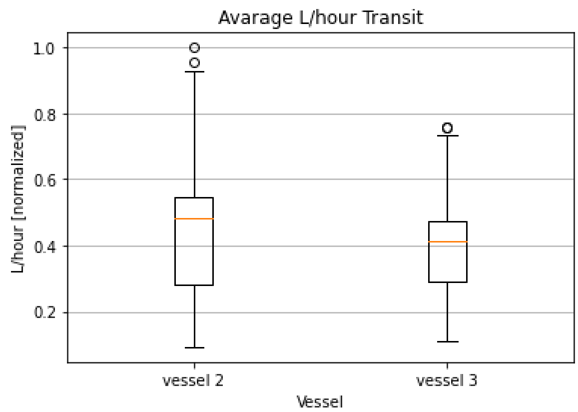


Figure 4.84: The updated box plots from *Company 2* while in transit.

Table 4.3: The Bartlett's, F, and T-tests were conducted for *Vessel 2* and *Vessel 3* for active and transit.

		Bartlett's test	Levene's test	T-test
Active	Statistic	1.013	0.164	2.246
	p-value	0.314	0.685	0.025
Transit	Statistic	25.488	34.211	
	p-value	4.45E-07	0.001	

The reason for the difference between the activities of *Vessel 2* and *Vessel 3* needs to be in the data. The fishbone diagram shown in Figure 4.85 will assist by offering possible reasons. When looking at the speed through water, incorrect data does not seem impossible. Inaccurate data could be checked but will not be included in this analysis. The cargo the vessels are carrying and handling might be different, but the vessels themselves do not handle the load, so this is out of the picture. The vessels are the same, and their jobs are the same, so the cargo should be similar either way. The two crews might have different ways of working. All environmental issues and imperfect personnel on location need research into the vessel destinations. The improperly carrying out of activities might be an issue but research deeper into the data is necessary to figure this out.

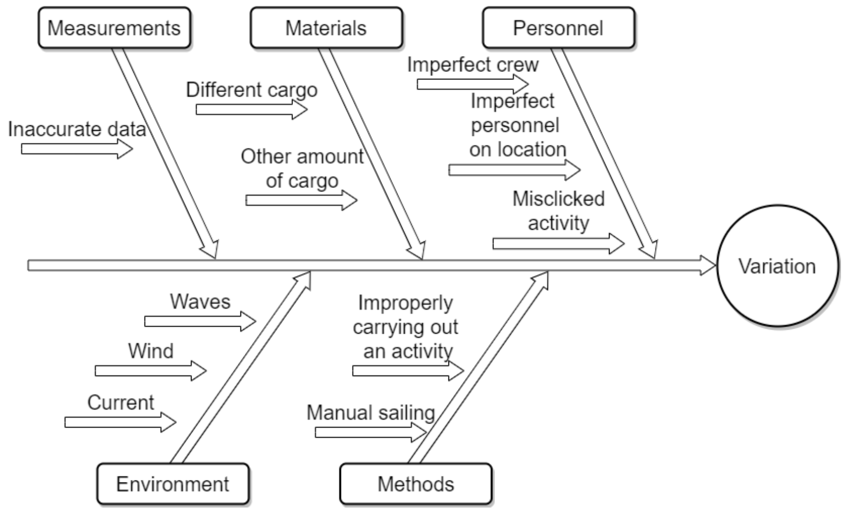


Figure 4.85: The possible reasons for variation in the data sets.

Analysing the transit with statistical analysis showed the difference in variance. Figure 4.86 is plotted to show what this means. The data of *Vessel 2* is indicated with blue stars and a yellow trend line, and the data of *Vessel 3* with red crosses and a green trend line. In the scatter plot, the difference between the vessels is clear. In the most common speed area, *Vessel 3* outperforms *Vessel 2*. The trend lines are estimations but give a good indication overall.

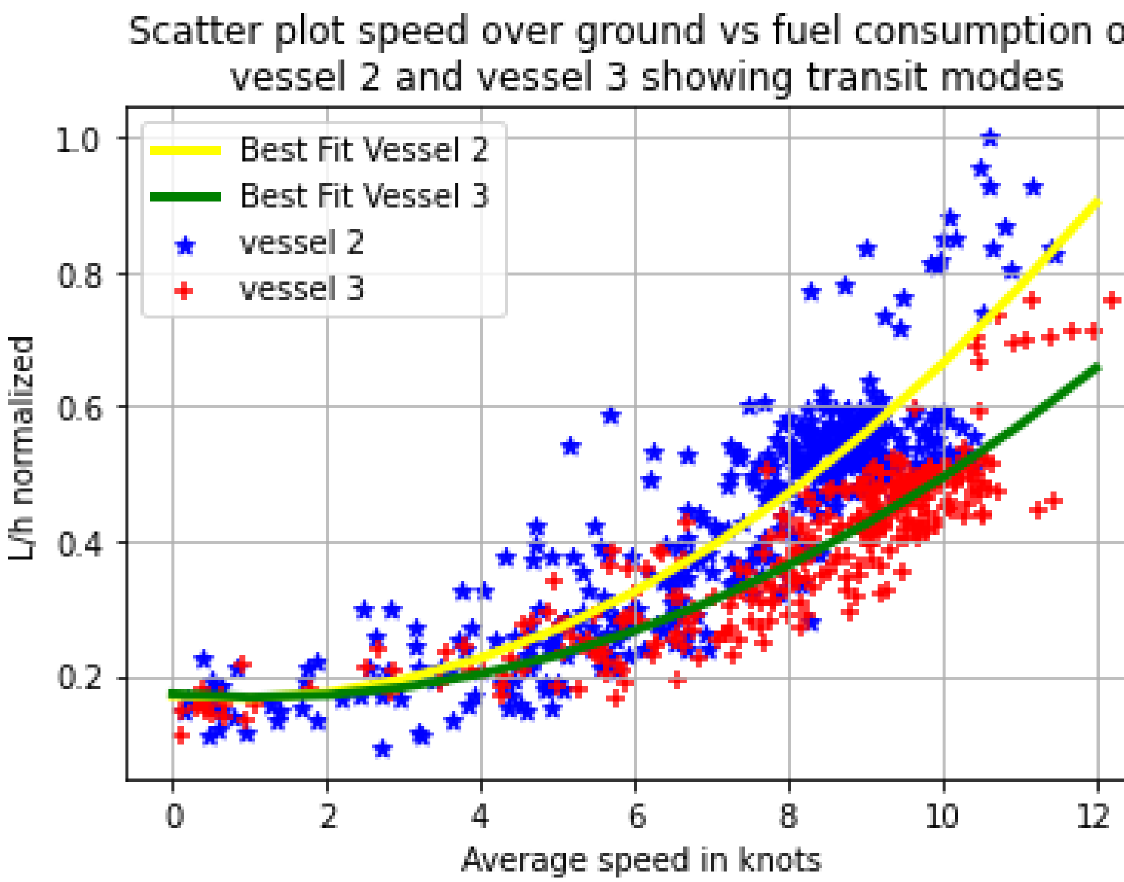


Figure 4.86: *Vessel 2* and *Vessel 3* showing the transit mode including trend lines.

4.2.7. Improve

The possible improvements are improving the active activities, the transit, or by removing the waiting activities and waste. During the active phase, the vessels should be able to perform the same way. Statistical tests showed the mean of *Vessel 3* was lower than the one of *Vessel 2*. To calculate the potential gain, the averages of both vessels will be compared, and the improvement which *Vessel 2* possibly could make would be the potential gain. The improvement could result in a 6.6% gain for the activities while active for *Vessel 2*. When the waiting is dissolved, all waste from waiting will be eliminated.

The question if the speed is correct arises from Figure 4.86, does the *Vessel 2* sail at the proper speed? The most common speed for *Vessel 2* is around 8.5 knots. By dividing the most common speed by other speeds and using those speeds and the trend line to find the fuel consumption per hour of those speeds, the litres used per journey, relative to the most common speed, can be determined. The trend line function is used to calculate the potential gain, and other speeds have been interpolated to find the answer. When sailing around 5.5 knots, *Vessel 2* uses 11% less fuel over a trip. The calculations are visualised in Figure 4.87. In this figure, the black lines are cutting the trend lines of *Vessel 2* and *Vessel 3* at 8.5 knots. It shows *Vessel 3* sailing at almost the perfect speed, but *Vessel 2* seems to sail too fast. The black line of *Vessel 2* shows that 5.5 knots would be better fuel-wise than the most occurring speed but does not include the fact that 5.5 knots will take the vessel way longer to arrive. When the vessel starts sailing slower, the utilisation will be negatively influenced. The black and grey lines show fuel used per trip compared to where the lines cut the yellow and green trend lines. The black and grey lines can only be used to find a better speed for the vessel and say nothing about the fuel per hour, which stays in line with the trend lines.

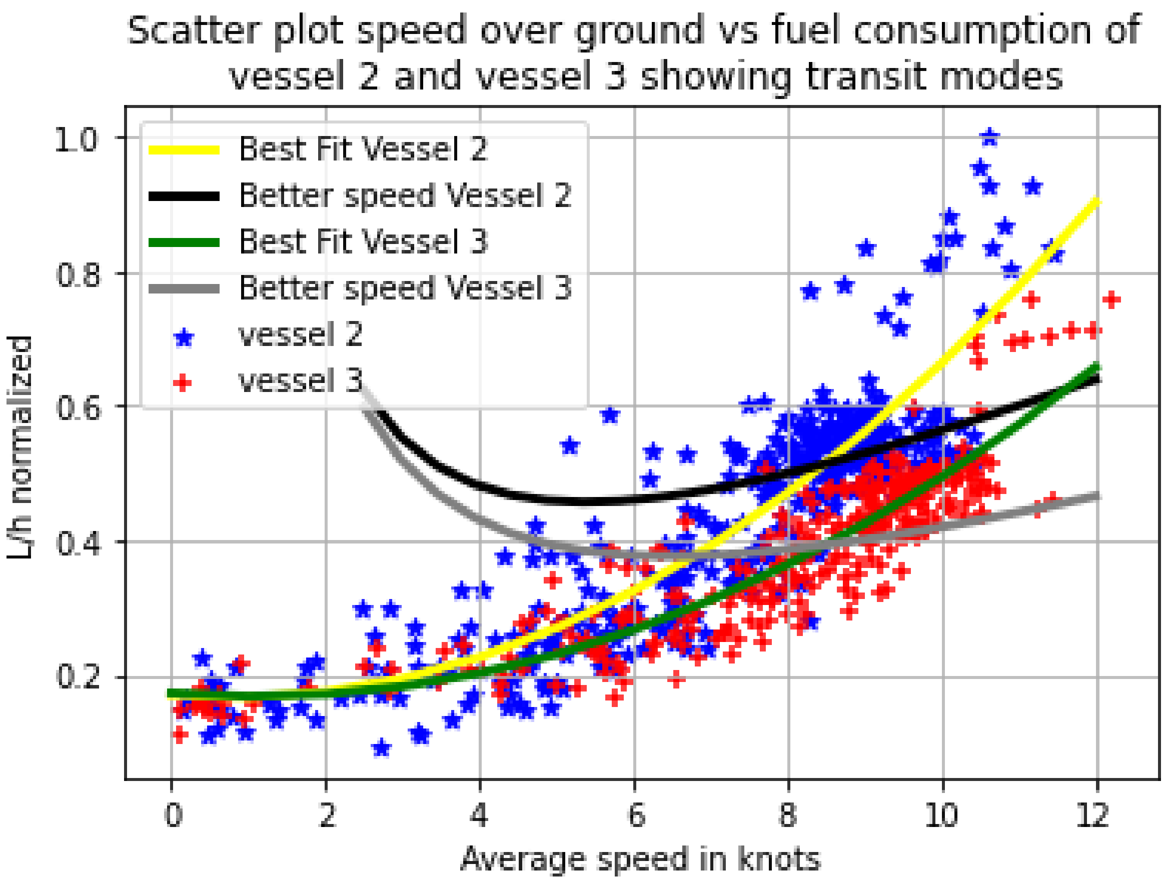


Figure 4.87: *Vessel 2* and *Vessel 3* showing the transit mode, including trend lines and lines indicating the fuel consumption per trip at another speed.

All these improvements and the potential gains are shown in the Pareto chart 4.88. Improving the transit speed of *Vessel 2* needs to be of the highest priority. By sailing slower, the waiting time reduces as well. *Vessel 3* could also reduce waiting time by sailing slower it is possible, see 4.87. When it turns out the sailing speed was perfect, speed losses are compensated by waiting less because the litres used during waiting go down. This seems like two birds with one stone, but the planning and communication with the platforms need to be improved.

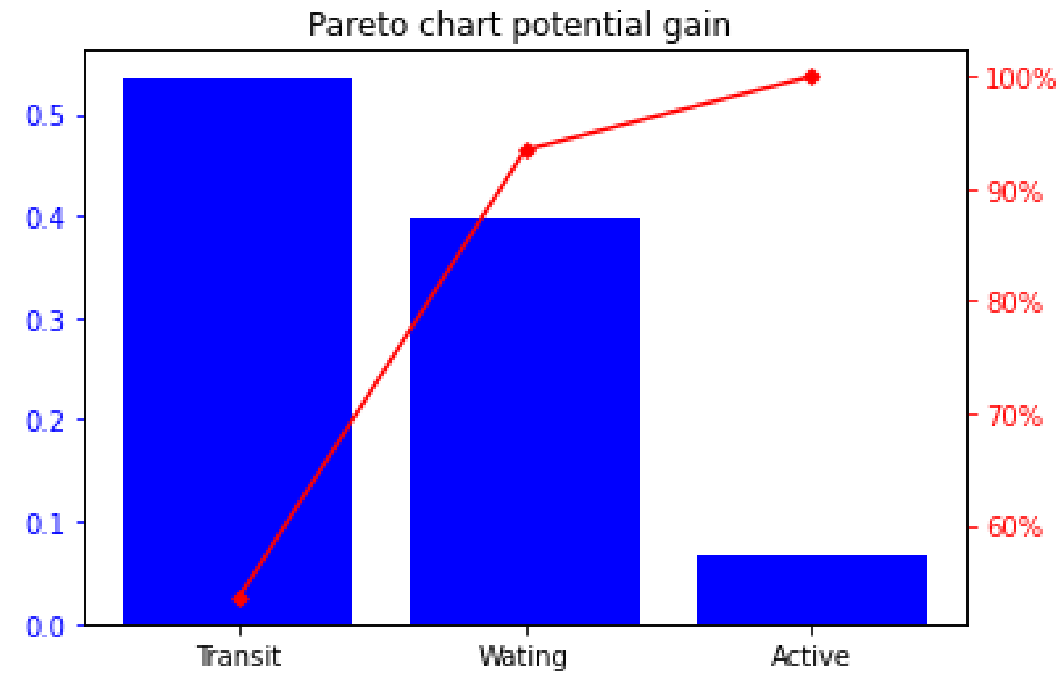


Figure 4.88: The Pareto chart of *Company 1* shows the potential gain of the proposed improvements.

The root of the speed problem needs to be found to improve sailing. Why is the difference in fuel per vessel so high? Because the vessels seem to have another optimal speed. Why is the speed of *Vessel 2* not sailing at its perfect speed? And why can the speed not be changed? Why is this not tested? When answers to all these answers are available, the operations of *Vessel 2* can be improved.

4.2.8. Control

The control phase will consist of an X-bar and R-chart but will need more time to show results. And in this case, the control phase will need to include a scatter plot with the speed of both vessels.

4.3. Case 3

The second case is the case of *Vessel 4* and *Vessel 5* of *Company 3*. *Company 3* is a towage company operating multiple tugs. This example shows two cases of two similar vessels. Both have used the *Onboard* system for more than nine months.

4.3.1. Define

Figure 4.89 shows the flow chart of *Company 3*. When a new voyage starts, the first activity is mobilisation. Mobilisation is sailing to the location where the job will take place. After this, either the vessel must wait, drift, or is on-site on the spot where the job starts. After arriving on the spot and waiting, the actual job can start. A job is one of five activities: fire watch, line to bow, line to stern, pushing to berth, and towing. Fire watch means being on standby when a fire breaks out. Line to bow represents the situation where the tug escorts a vessel with a line connected to the vessel's bow. Line to stern is the same as Line to bow, but in this case, with the line connected to the stern. Pushing to berth stands for the situation where the tug is pushing a vessel to the quay when a ship's ropes are fastened. Towing indicates when the towing started and is part of either Line to bow or line to stern. After the job is done, the vessel sails back to berth, is moored and goes Idle until a new voyage starts, or immediately sails to another job and sails free or drifts for a moment till the new voyage starts.

Within the flow chart are four groups, all shown in Figure 4.89 with their unique colour. The first group is Idle, which includes only the Moored activity. Moored is the only activity where the vessel is idle. The second group, transit, consists of all activities while sailing. The transit group includes mobilization, drifting, sailing free, job to job, and sail to berth. The third group waiting is the group where the activities are waiting for something to start, including drifting, on-site, and waiting. The last and fourth group is active, and within this group fall all activities for which the vessels were designed: fire watch, line to bow, line to stern, pushing to berth, and towing. The transit block is yellow, the waiting group blue, the idle group green, and the active group red. Drifting and waiting are marked in red because the activities are in the activity list but are barely or not used by the vessels.

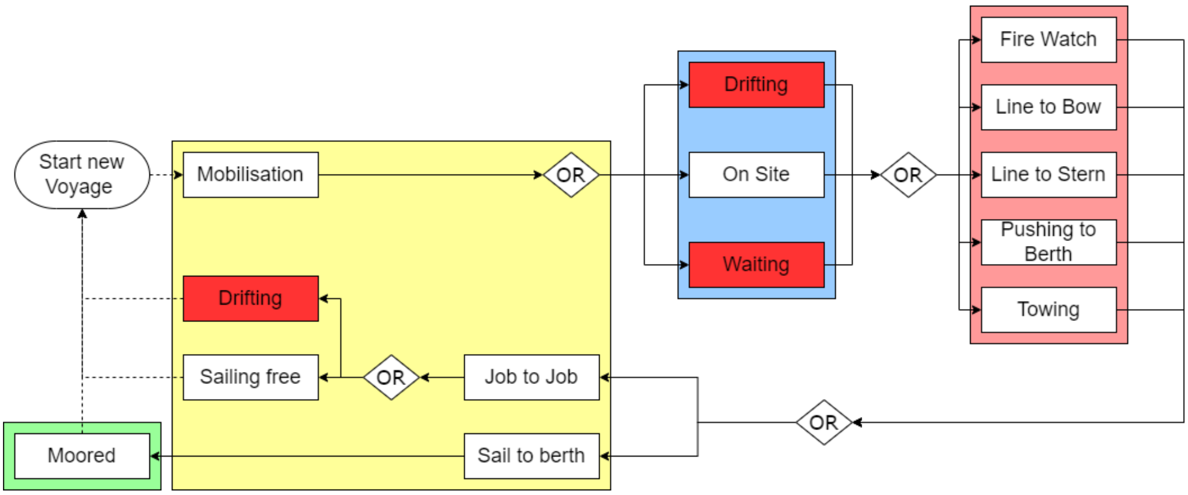


Figure 4.89: Flow chart *Company 3*.

The flow chart does include every activity, even though some rarely or never occur. Figures 4.90 and 4.91 show the utility graphs with all activities. Waiting is barely used, which shows in the graphs, and the graphs do not show the drifting activity because the activity does not occur. Because these activities rarely happen, the activities are removed from the optimal flowchart.

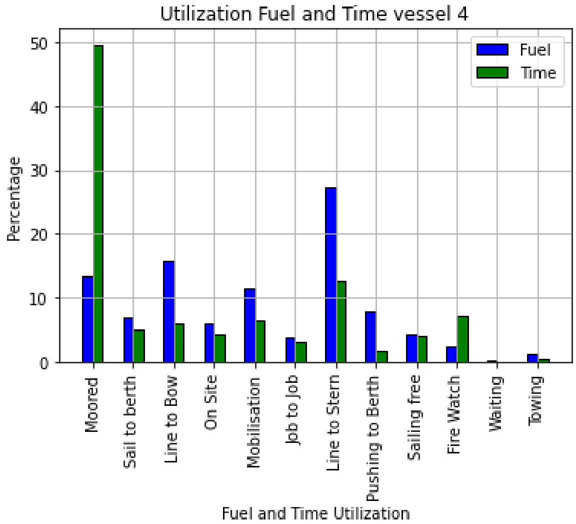


Figure 4.90: The utility graph of all activities of *Vessel 4*.

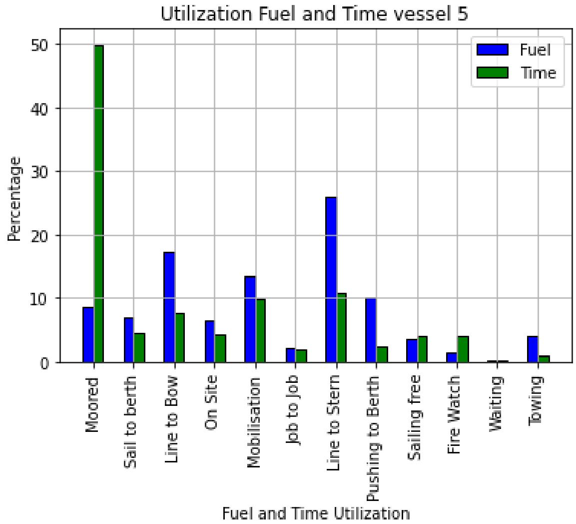


Figure 4.91: The utility graph of all activities of *Vessel 5*.

The improved flow chart shown in Figure 4.92 shows some differences from the current one. The Drifting blocks are removed because they are unused. The waiting block is removed because waiting is a waste of resources. Although On site is in the waiting group, it is not removed because the on-site activity also includes the time it takes to connect a line to a vessel, for example. Both flow charts are smooth and straightforward compared to the other two cases.

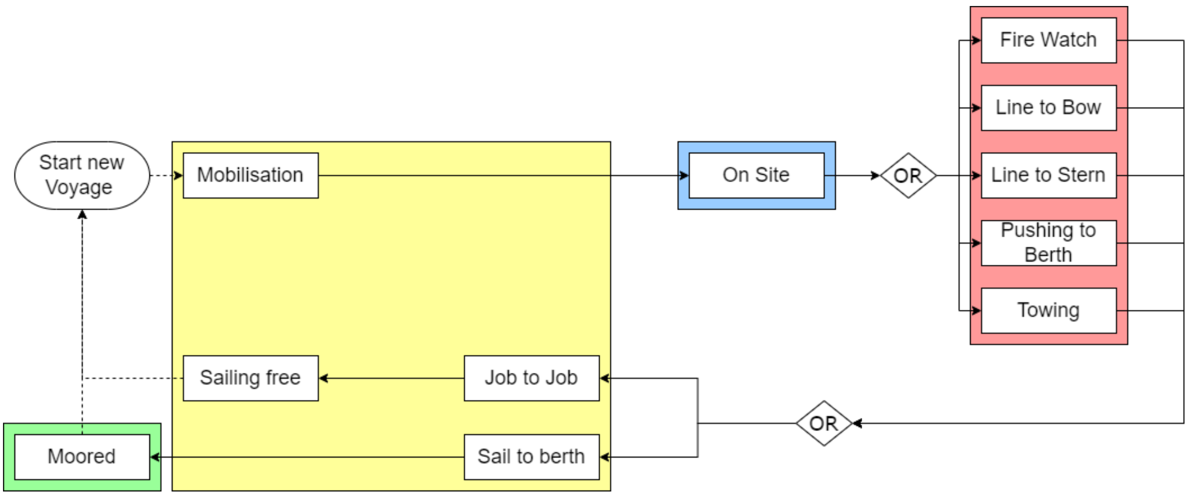


Figure 4.92: Flow chart in an optimal world *Company 3*.

4.3.2. Measure

The chosen KPIs are fuel and time because, at the current moment, these are the most important for the vessel owners. The utilisation graphs will show both time and fuel consumed. The rest of the analysis will use fuel per hour to make the activities more comparable. Figure 4.93 and 4.94 show the grouped utilisation. In Figure 4.90 and 4.91 all the activities showed time and fuel used as a percentage. In the figures, the impact of the activities differs from very to little influential. These insignificant activities can form a more significant factor when grouped, as shown in Figure 4.93 and 4.94. The utilisation graphs show more than half of the fuel used during activities. The utilisation graphs also show the vessels moored almost half the time.

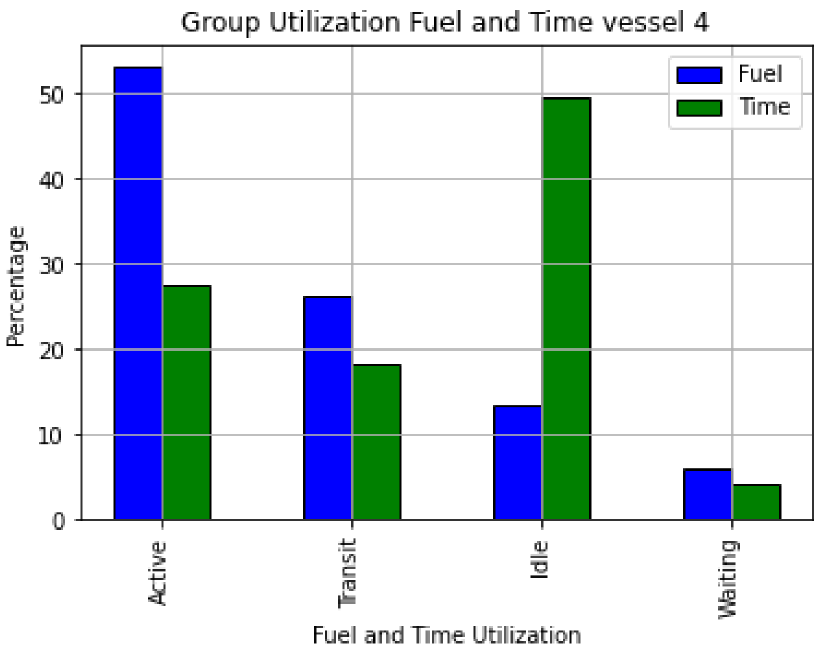


Figure 4.93: The grouped utilisation graph of *Vessel 4* of *Company 3* showing the time and fuel utilisation of all grouped activities.

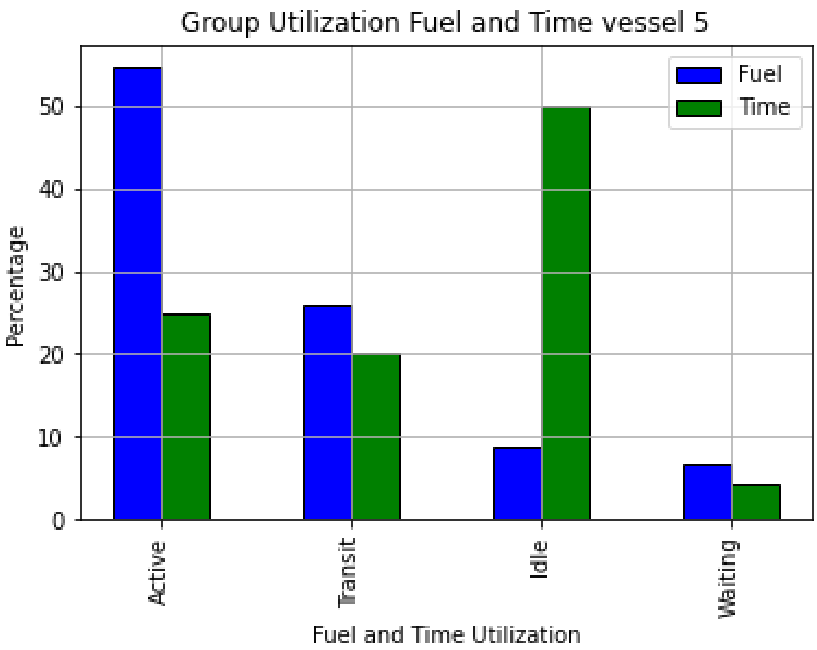


Figure 4.94: The grouped utilisation graph of *Vessel 4* of *Company 3* showing the time and fuel utilisation of all grouped activities.

The vessels were equipped with the onboard systems and when looking at X-bar and R-chart displayed in Figure 4.95 and 4.96, the change in fuel consumption while in transit becomes clear. *Company 3* set a goal for the fuel consumption while in transit to try to sail at a specific value the fuel consumption. And without changing anything to the vessel or way of working, the crew on board started sailing with lower fuel consumption. The R-chart does also show how way more stable the vessel is performing. After ten weeks, the goal seems to be set, and after ten more weeks, the results become apparent.

This research aims to increase the system's efficiency as it is now, which means the first data will not be included, and only the last 20 weeks will be considered.

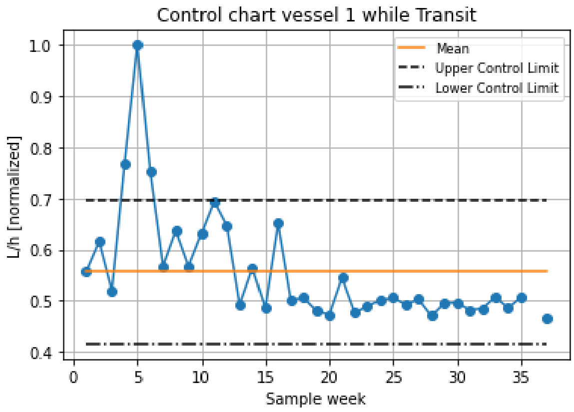


Figure 4.95: The X-bar chart of *Vessel 4* from *Company 3* while in transit.

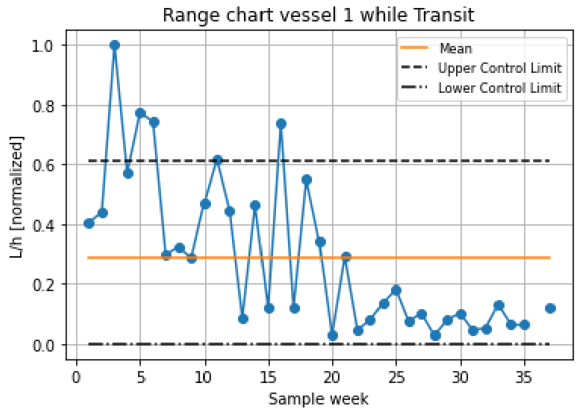


Figure 4.96: R-chart of *Vessel 4* from *Company 3* while in transit.

Figure 4.97 shows the box plots of *Vessel 4*, and Figure 4.98 shows the box plots of *Vessel 5*. These box plots show the outliers in the samples and how the activities behave in comparison to each other. Outliers are excluded during the sample creation. The box plots visualize the fuel consumption per hour per activity group. Most apparent from these box plots is the number of outliers shown in the figures, which makes the data hard to read. Because the captains have been given goals to achieve, the captains have started sailing more focused on those goals. The goals were not immediately reached. During the transition period, there were spikes in the data. Lately, much more has been accomplished in the way the goals dictate. When striving for goals, it will affect the average and the median. Many outliers occur when combining this with the more extreme values from the transition period.

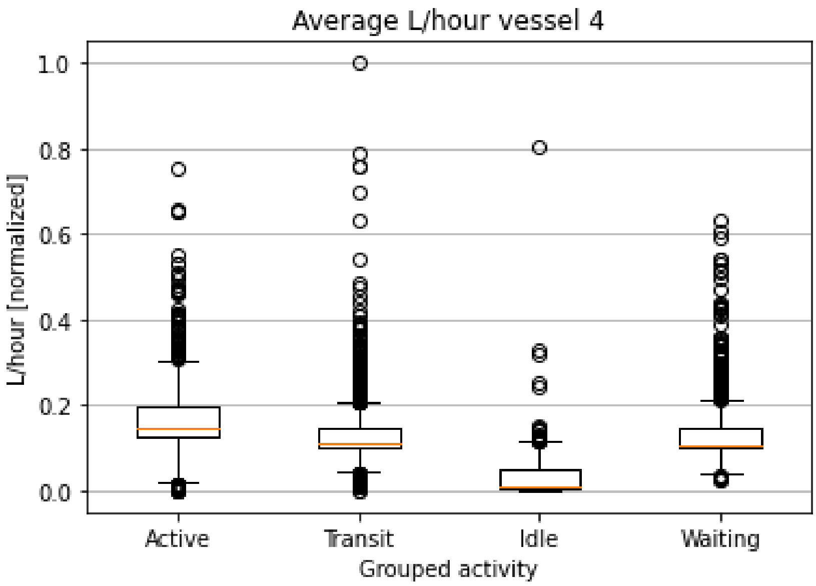


Figure 4.97: Box plots of *Vessel 4* from *Company 3*.

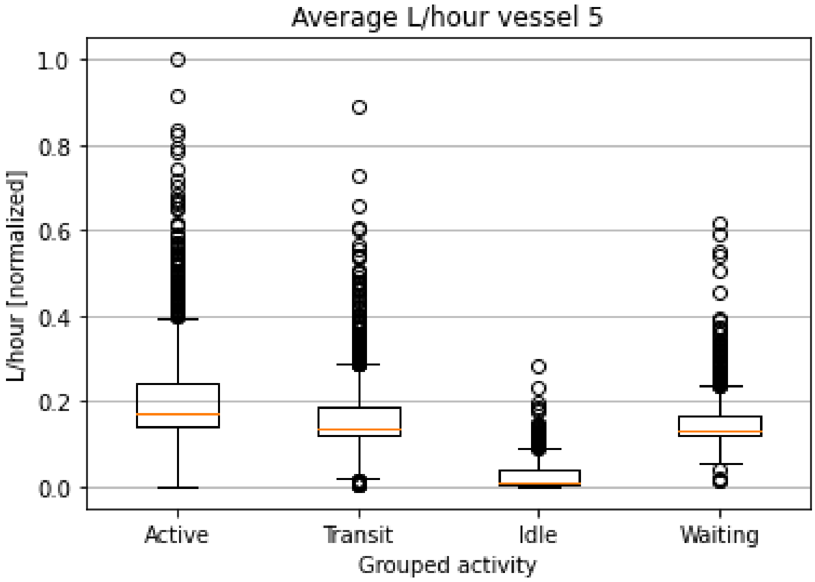


Figure 4.98: Box plots of *Vessel 5* from *Company 3*.

The grouped box plots can also visualize the difference in the forty weeks. This case will consider two of the same vessels, so Figure 4.99, 4.101, 4.103, and 4.105 show the box plot of every activity group next to each other over all 40 weeks. Figure 4.100, 4.102, 4.104, and 4.106 show the box plot of every activity group next to each other over the last 20 weeks. *Vessel 5* is a bigger vessel than *Vessel 4*, which shows in the figures. Although unclear, the box plots over the last 20 weeks show fewer outliers than the box plots of all 40 weeks, while the relative box spread is bigger.

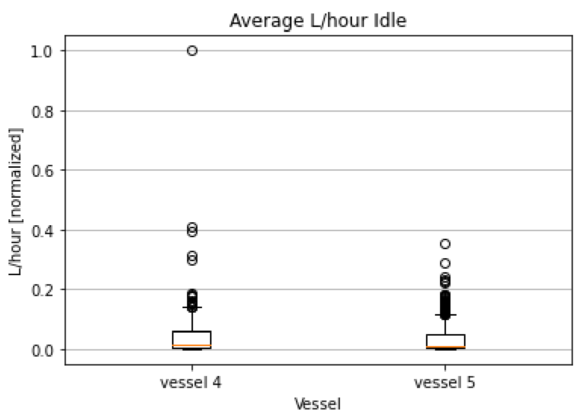


Figure 4.99: Box plot of *Vessel 4* and *Vessel 5* from *Company 3* while idle over the last 40 weeks.

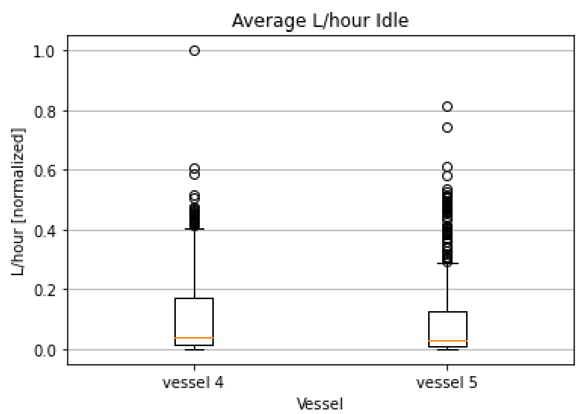


Figure 4.100: Box plot of *Vessel 4* and *Vessel 5* from *Company 3* while idle over the last 20 weeks.

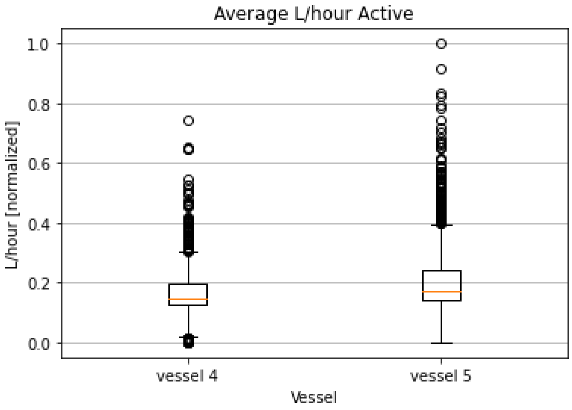


Figure 4.101: Box plot of *Vessel 4* and *Vessel 5* from *Company 3* while active over the last 40 weeks.

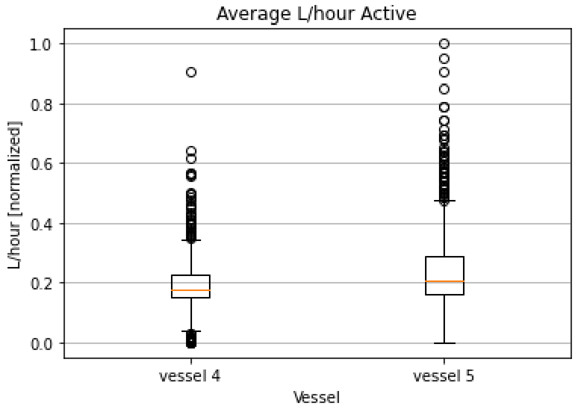


Figure 4.102: Box plot of *Vessel 4* and *Vessel 5* from *Company 3* while active over the last 20 weeks.

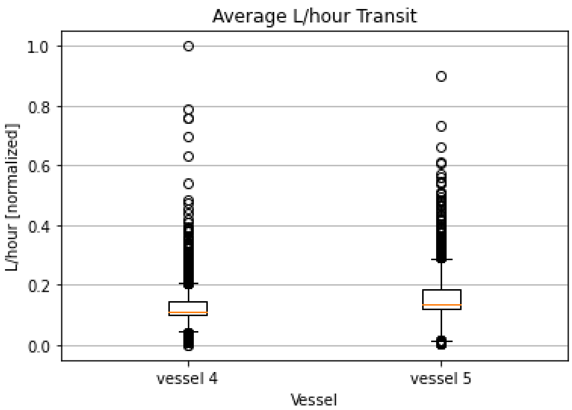


Figure 4.103: Box plot of *Vessel 4* and *Vessel 5* from *Company 3* while in transit over the last 40 weeks.

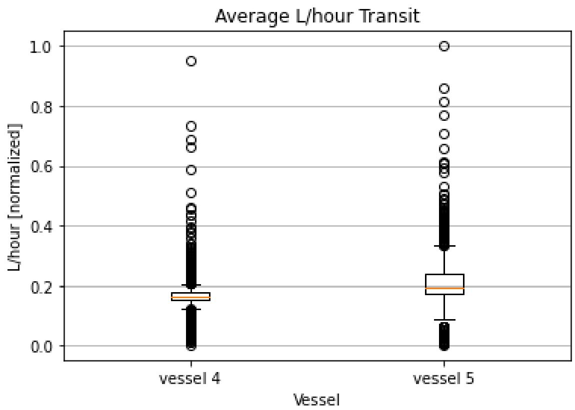


Figure 4.104: Box plot of *Vessel 4* and *Vessel 5* from *Company 3* while in transit over the last 20 weeks.

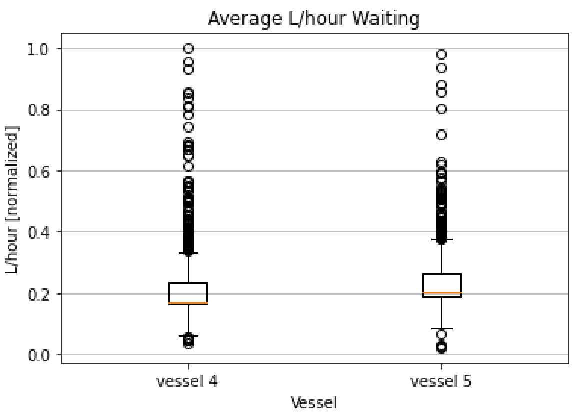


Figure 4.105: Box plot of *Vessel 4* and *Vessel 5* from *Company 3* while waiting over the last 40 weeks.

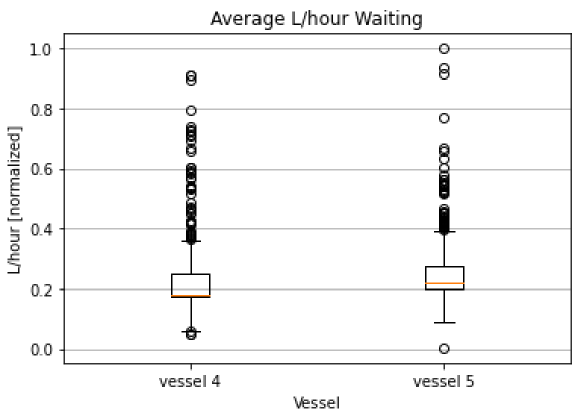


Figure 4.106: Box plot of *Vessel 4* and *Vessel 5* from *Company 3* while waiting over the last 20 weeks.

The results of *Vessel 4* from *Company 3* will be discussed. In this section, the results of the forty-week data will also be briefly discussed. The last 21 weeks are included in these tests. During these weeks, 18 groups considered idle formed, 20 samples for Active, 21 when in transit and 18 for waiting. The results of the statistical tests are summarized in this paragraph, and the complete results of the forty weeks are stated in appendix D.1.1 and the last 21 weeks in D.1.3. For the forty-week tests, the results show the data not to be normally distributed. Only the active data seems normally distributed. When only the data from 20 weeks is used, the test outcomes are dissimilar. The idle data could be normally distributed, but the p at 15, 10, and 5 per cent of the Anderson test indicates that the data is not normally distributed. The test results of the Active, Transit, and Waiting data show no reason to reject the null hypothesis, and the data looks normally distributed.

The idle Q-Q plot shown in Figure 4.107, and the histogram shown in Figure 4.108, show the data is very skewed towards the right. The tests raise doubt about the data being normally distributed, but when looking at the Q-Q plot and histogram, concluded can be the data is not normally distributed. The reason for this could be the different kinds of being moored. Sometimes, being moored means nothing happens, and the fuel consumption is close to zero, and sometimes before mobilization, the fuel consumption goes up significantly.

While active, the data is normally distributed according to the statistical tests. The Q-Q plot shown in Figure 4.109, and the histogram shown in Figure 4.110, show the data to be skewed to the right. There is some reason the active data should not be considered normal and ready for the analyse phase. In this case, the data will be deemed appropriate.

None of the tests states that while in transit, the data is not normally distributed. When looking at the Q-Q plot shown in Figure 4.111 and the histogram shown in Figure 4.112, it does not become clear that the data is not normally distributed. The histogram and Q-Q plot might show two peaks in the data. For now, the data is considered to be fitting.

According to all tests done for waiting, there is no reason to assume the data is not normally distributed. The Q-Q plot shown in Figure 4.113, and the histogram shown in Figure 4.114, doubt can be raised about the outcomes of the tests. The histogram shows a steep peak, and the Q-Q plot is angular. The data can not be deemed normally distributed.

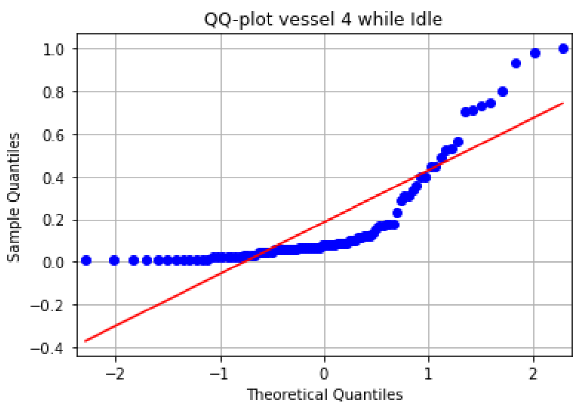


Figure 4.107: The Q-Q plot of the data from *Vessel 4* while Idle.

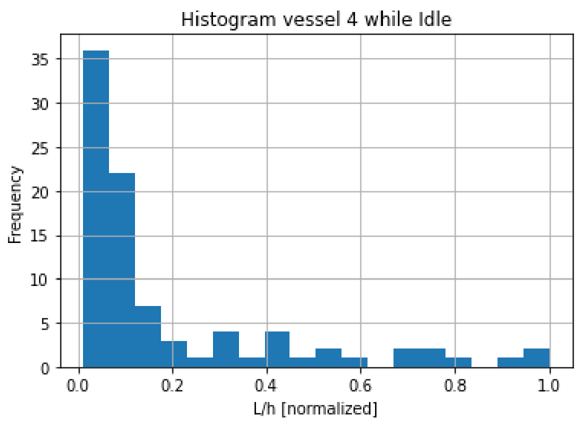


Figure 4.108: The Histogram of the data from *Vessel 4* while Idle.

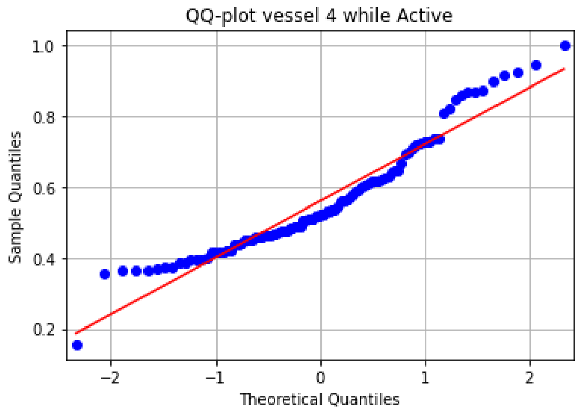


Figure 4.109: The Q-Q plot of the data from *Vessel 4* while Active.

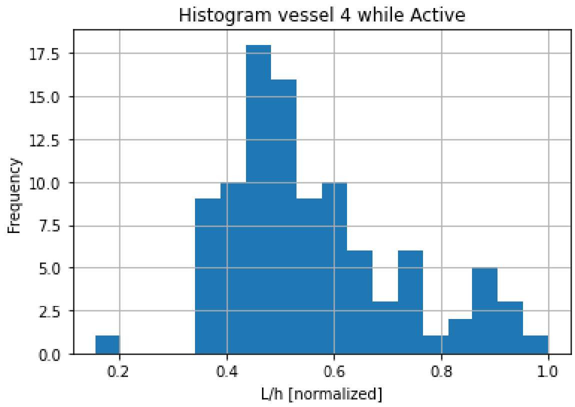


Figure 4.110: The Histogram of the data from *Vessel 4* while Active.

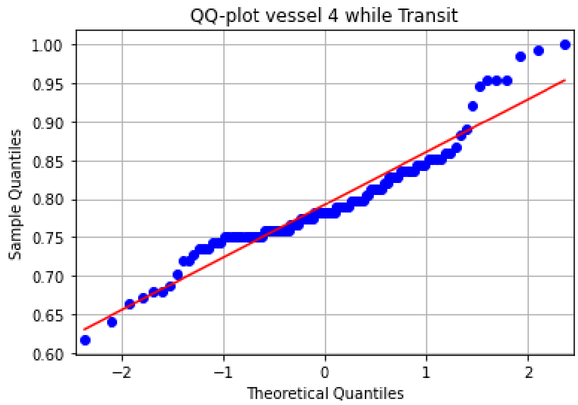


Figure 4.111: The Q-Q plot of the data from *Vessel 4* while in Transit.

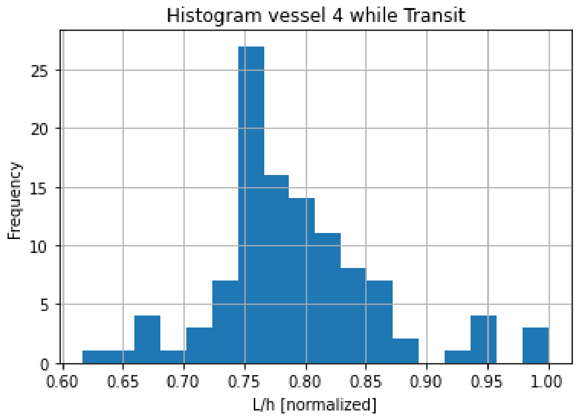


Figure 4.112: The Histogram of the data from *Vessel 4* while in Transit.

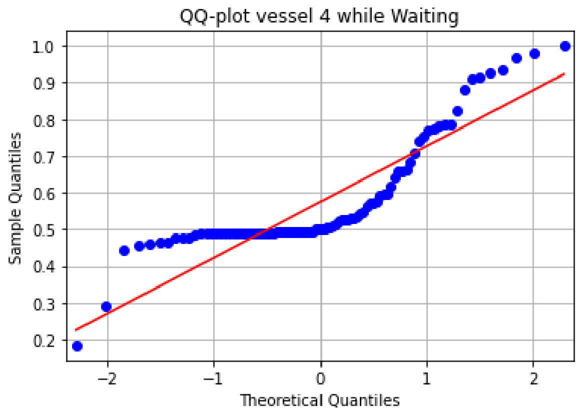


Figure 4.113: The Q-Q plot of the data from *Vessel 4* while Waiting.

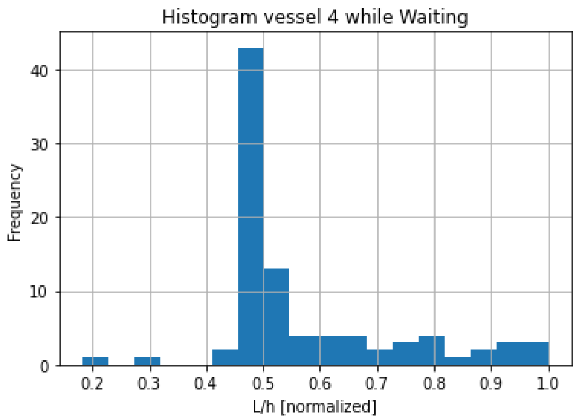


Figure 4.114: The Histogram of the data from *Vessel 4* while Waiting.

The results of *Vessel 5* from *Company 3* will be discussed in these paragraphs. In this section, the results of the forty-week data will also be briefly discussed. The last 21 weeks are included in these tests. During these weeks, 19 groups considered idle formed, 19 samples for Active, 20 when in transit and 19 for waiting. The results of the statistical tests are summarized in this paragraph, and the complete results of the forty weeks are stated in appendix D.1.2 and the last 21 weeks in D.1.4. For the forty-week tests, the results show the data not to be normally distributed. Only the active and transit data show some indication of a normal distribution. When only the data from 21 weeks is used, the test outcomes are dissimilar. The idle data could be normally distributed, but the p at 15 and 10 per cent of the Anderson test indicates that the data is not normally distributed. And while in transit, the p at 15 of the Anderson test indicates that the data is not normally distributed. The test results of the active and waiting data show no reason to reject the null hypothesis, and the data looks normally distributed.

Idle has the same issue as *Vessel 4*. When looking at the Q-Q plot shown in Figure 4.115 and the histogram shown in Figure 4.116 show the data is very skewed towards the right. The tests raise doubt about the data being normally distributed, but when looking at the Q-Q plot and histogram, it can be concluded the data is not normally distributed.

While active, the data is normally distributed according to some tests. The Q-Q plot shown in Figure 4.117 and the histogram shown in Figure 4.118 show the data to be a bit skewed to the right, and a small peak seems to show at the lower and higher end. There seem to be some reasons to assume the active data is not normal and ready for the analyse phase but in this case, the analyse phase will continue with this data.

The tests state some doubt about the data not being normally distributed while in transit. But just like *Vessel 4* when looking at the Q-Q plot shown in Figure 4.119 and the histogram shown in Figure 4.120, it does not become clear that the data is not normally distributed. The histogram and Q-Q plot might show two peaks in the data. For now, the data is considered to be fitting.

According to the tests, the data can be assumed to be normally distributed. When looking at the Q-Q plot shown in Figure 4.121 and the histogram shown in Figure 4.122, doubt can be raised about the outcomes of the tests. The histogram clearly shows a steep peak, and the Q-Q plot is too angular. The data can not be deemed normally distributed.

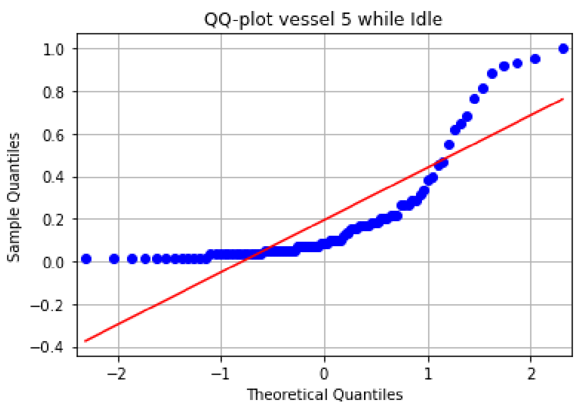


Figure 4.115: The Q-Q plot of the data from *Vessel 5* while Idle.

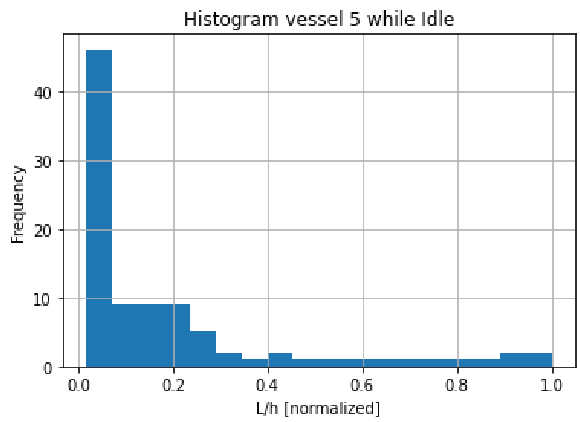


Figure 4.116: The Histogram of the data from *Vessel 5* while Idle.

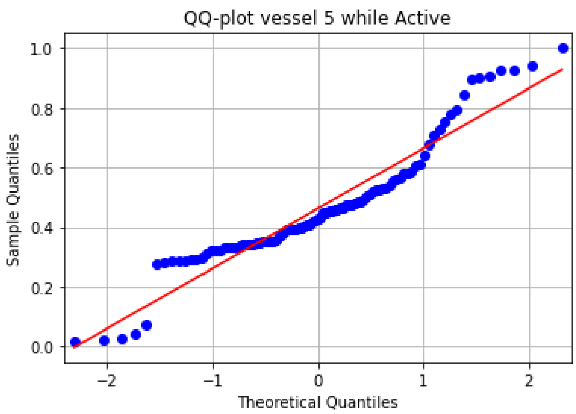


Figure 4.117: The Q-Q plot of the data from *Vessel 5* while Active.

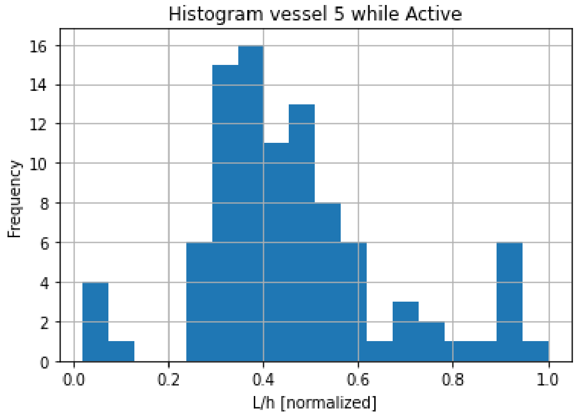


Figure 4.118: The Histogram of the data from *Vessel 5* while Active.

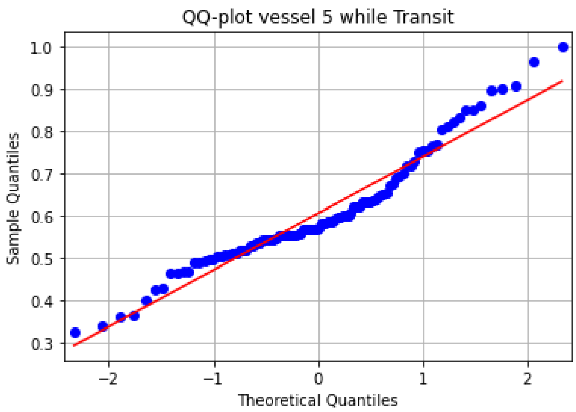


Figure 4.119: The Q-Q plot of the data from *Vessel 5* while in Transit.

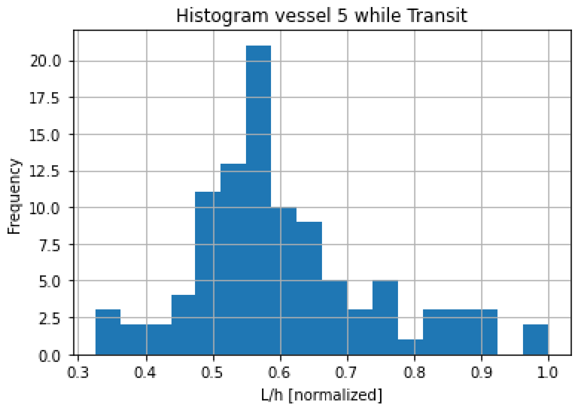


Figure 4.120: The Histogram of the data from *Vessel 5* while in Transit.

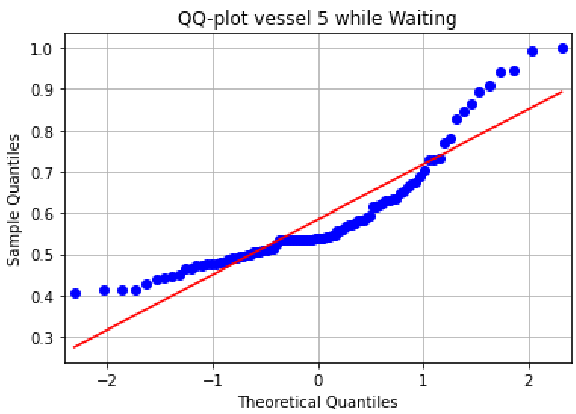


Figure 4.121: The Q-Q plot of the data from *Vessel 5* while Waiting.

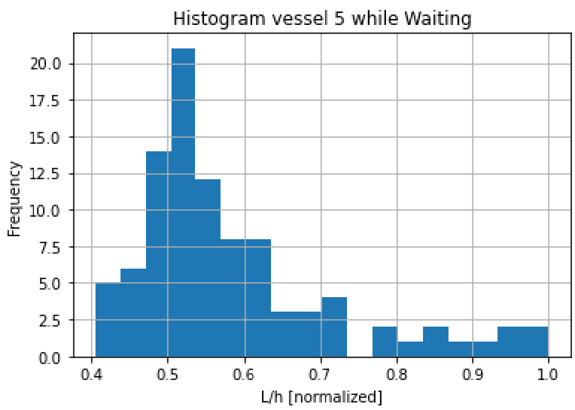


Figure 4.122: The Histogram of the data from *Vessel 5* while Waiting.

Active and transit data from both vessels are assumed to be normally distributed. This means the control and range charts of the data while active and the data while in transit of both vessels will be shown. The control chart and the range chart of *Vessel 4* while active are displayed in Figure 4.123 and 4.124. When looking at the control chart and the range chart of *Vessel 4* while active, the data shows to be in control. The only thing which shows are the two missing data points at weeks 19 and 21, which might indicate something happened one of those weeks. Figures 4.125 and 4.126 show the X-bar and R-chart while in transit. When looking at the figures, some samples are close to the UCL of either the control chart or the range chart, but only one of the data points in the R-chart is out of control. The out-of-control point is the first data point of the new period, which is deemed a consequence of the transit period.

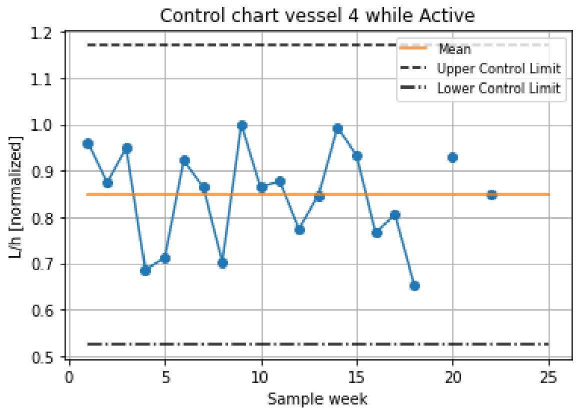


Figure 4.123: The X-bar chart of *Vessel 4* from *Company 2* while in transit.

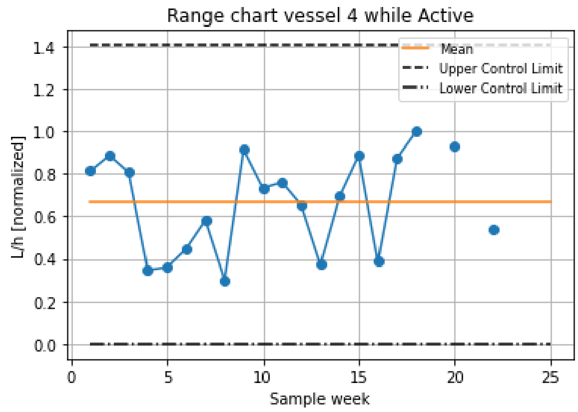


Figure 4.124: R-chart of *Vessel 4* from *Company 2* while in transit.

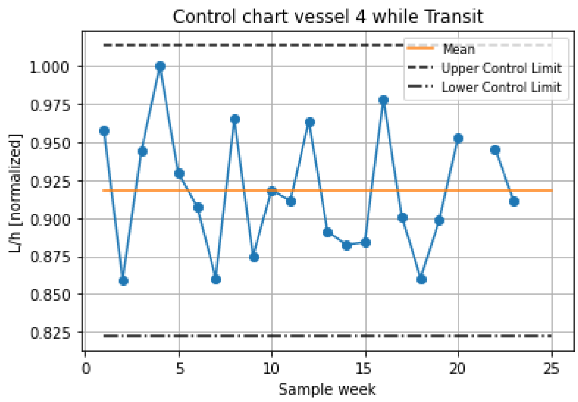


Figure 4.125: The X-bar chart of *Vessel 4* from *Company 2* while in transit.

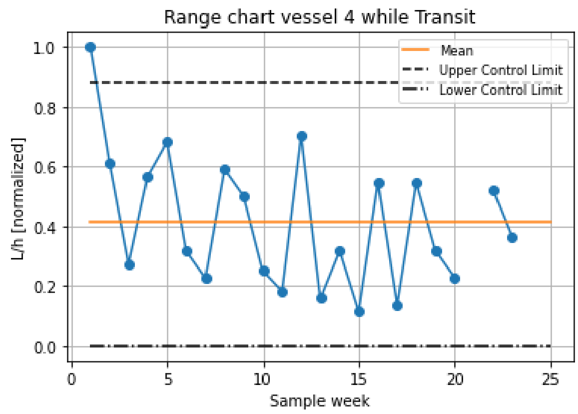


Figure 4.126: R-chart of *Vessel 4* from *Company 2* while in transit.

The control chart and the range chart of *Vessel 5* while active are displayed in Figure 4.127 and 4.128. When looking at the control chart and the range chart of *Vessel 5* while active, the data shows to be in control. The R-chart shows the vessel to be almost out of control in weeks 10 and 11, but overall the system seems to be in control. The data while in transit shows to be out of control in weeks 3, 5 and 6. Figures 4.129 and 4.130 show the X-bar and R-chart while in transit. The out-of-control points can still be a consequence of the transit period.

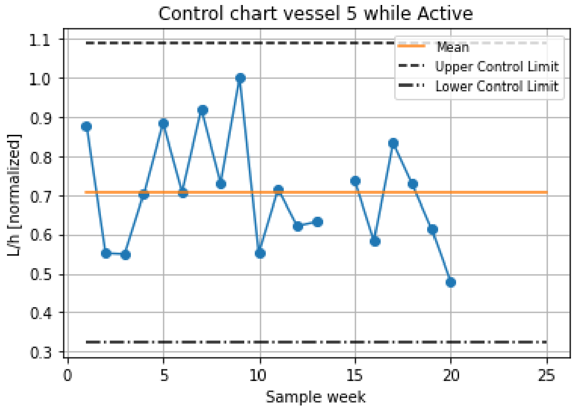


Figure 4.127: The X-bar chart of *Vessel 5* from *Company 3* while in transit.

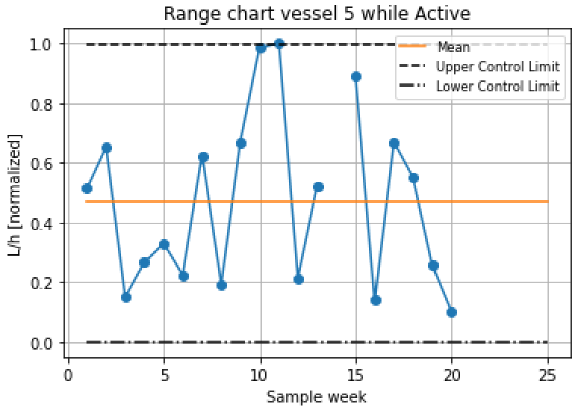


Figure 4.128: R-chart of *Vessel 5* from *Company 3* while in transit.

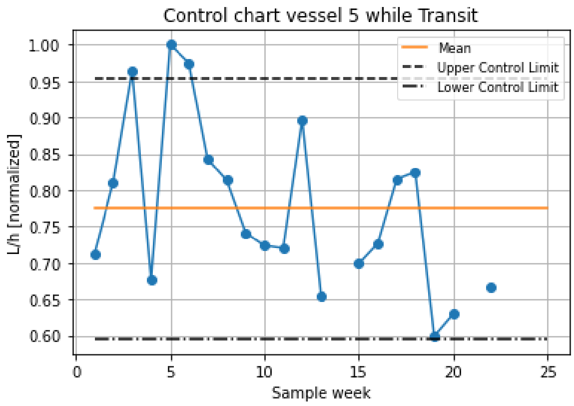


Figure 4.129: The X-bar chart of *Vessel 5* from *Company 3* while in transit.

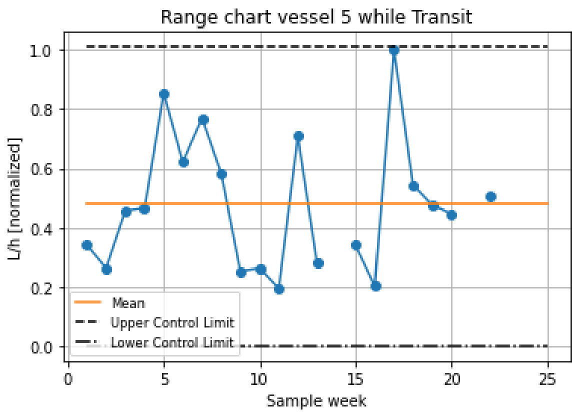


Figure 4.130: R-chart of *Vessel 5* from *Company 3* while in transit.

4.3.3. Analyse

The first question is where to focus. The utilisation graphs, displayed in Figure 4.93 and 4.94, show almost 80% of fuel is used while active or in transit. Due to the influence of active and transit, and active and transit having the most normally distributed data, only these two datasets will be analysed.

To find optimisation opportunities for *Vessel 4* and *Vessel 5* needed is to dive deep into the data. The fishbone diagram shown in Figure 4.131 will assist by offering possible reasons for variation. The measurement system sometimes does not work, which shows in the X-bar and R-charts. The data gaps in the X-bar and R-chart are due to missing data. Tugs do not carry cargo. Knowing which vessels are pushed or pulled can be interesting. The difference in personnel can be checked by comparing captains, which might make a difference. Environmental data is not available but does not seem too important in this case, but it could be an improvement to take into account. Improperly carrying out activities can be tested by comparing the performance of different vessels.

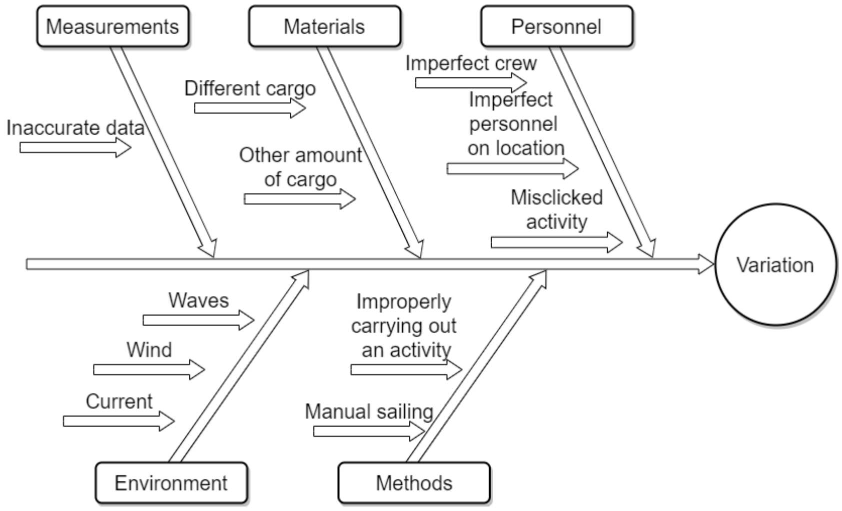


Figure 4.131: The possible reasons for variation in the data sets.

The variability of the active activities seems relatively higher than the transit activities. *Vessel 4* has a range of transit from 1 to 0.85, and active has a range from 1 to 0.65. *Vessel 5* has a range while in transit of 1 to 0.6 and a range of 1 to 0.45 while active. The variability also seems higher for *Vessel 5* than *Vessel 4*. This could mean two things, either *Vessel 5* is not pushing enough, or the strive values for *Vessel 4* are too high. Looking at the differences between outliers during active activities, the time of good outliers is longer than bad outliers. The Fire watch activities are almost all the good outliers. When diving deeper into the active activities, they seem pretty different. Figure 4.132 and 4.133 show how different the activities are. Within the data, also no indications are found of differences between vessels, captains or locations while active. The reason for this seems to be the significant difference in activities. Grouping activities does not make sense for this specific case because no activities follow up, and the activities differ too much. According to the statistical test and the box plots, non of the active activities have a similar variance. Doing all tests between the vessels and activities only showed the line-to-bow activity of *Vessel 4* and *Vessel 5* coming close to having similar variance. The active activities need to be analysed individually to improve the analysis. Box plots show the spreading of the activities, which are too different from being seen as one group. To improve the analysis, the activity group need to be rolled back.

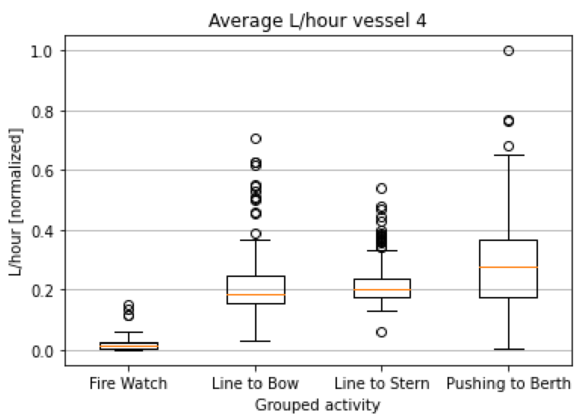


Figure 4.132: The box plots from *Company 3* show the different activities in the active group of *Vessel 4*.

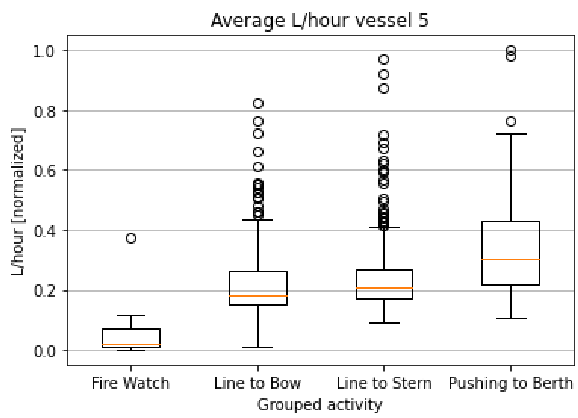


Figure 4.133: The box plots from *Company 3* show the different activities in the active group of *Vessel 5*.

While active, the data shows no indication of improvement opportunities. When the vessels are in transit, there are indications on how to improve efficiency. The indications show in Figures 4.134 and 4.135. Locations 26 and 27 and 8 and 9 are similar. As the box plots in Figure 4.134 show, the locations also have an equivalent fuel consumption for *Vessel 4*. When looking at 4.135 the fuel consumption of *Vessel 5* the box plot shows a similar fuel consumption for locations 26 and 27, but the difference between 8 and 9 seems significant.

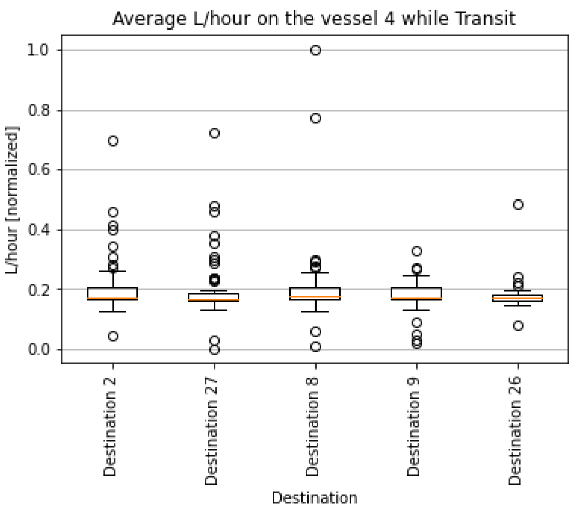


Figure 4.134: The box plots show the difference in fuel consumption of activities with as location the ones shown, from *Company 3* of *Vessel 4* while in transit.

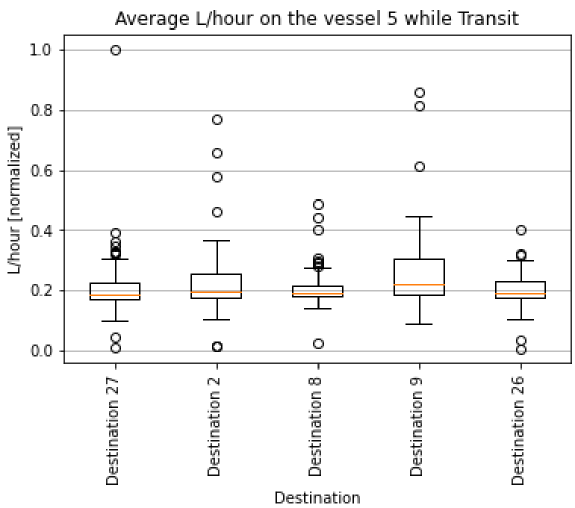


Figure 4.135: The box plots show the difference in fuel consumption of activities with as location the ones shown, from *Company 3* of *Vessel 5* while in transit.

Bartlett's and Levene's tests are conducted to test the statements made in the previous paragraph. Similar locations 26 and 27 are compared. Assumed destinations 26 and 27 have similar fuel consumption because the destinations are located next to each other. The null hypothesis, in this case, will be that the means and variance of the transits are equal for both destinations. Bartlett's tests indicate that the null hypothesis for the variance needs to be rejected, while Levene's tests conclude not to reject the null hypothesis. The results of both tests are displayed in Table 4.4. The two tests show different outcomes. Bartlett's test shows the variance to be unequal in the case of *Vessel 4* and *Vessel 5*, while Levene's test shows both vessels to have equal variance. Whether to assume an equal variance or not, the box plot is consulted. *Vessel 4* seems more stable than *Vessel 5*. The number of outliers *Vessel 4* can indicate why the results are worse. The outliers are part of the sample to check whether the data is stable, which could lead to data that is not normally distributed. A non-normal distribution influences Bartlett's test more, so the results from Bartlett's tests are possibly influenced too much by the non-normality of the data. According to Vorapongsathorn et al. (2004) Bartlett's test is less robust when the data is not normally distributed than Levene's test. After consulting the box, plots the results from Bartlett's tests, assuming the data has an equal variance. Because the data has an assumed equal variance, the T-test is conducted. The null hypothesis of the equal means can not be rejected in both cases. Both the T-test show the data has an equal mean.

Table 4.4: Bartlett's, Levene's, and T-tests were conducted for *Vessel 4* while in transit with 26 and 27 as destinations.

		Bartlett's test	**Levene's test**	**T-test**
Vessel 1	Statistic	43.300	2.224	-1.134
	p-value	4.696E-11	0.140	0.261
Vessel 2	Statistic	5.030	1.539	0.235
	p-value	0.025	0.219	0.815

The second statement about the destinations was about *Vessel 5*. *Vessel 5* seems to have a different fuel consumption at destinations 8 and 9, while the two destinations are similar. The null hypothesis is the means and variance of the transit activities are equal for both destinations. Bartlett's tests indicate that the null hypothesis for the variance needs to be rejected, while Levene's test suggests that for *Vessel 4*, the destinations have a similar variance, as shown in Table 4.5. When looking at the box plots, Levene's test and the tests of destinations 26 and 27 look similar. Still, Bartlett's tests indicated differently chosen to ignore the outcomes of Bartlett's test again and conduct a T-test. The conducted tests conclude *Vessel 4* has a similar fuel profile for the two locations. *Vessel 5*, on the other hand, has a different variance which also clearly shows in the box plot of Figure 4.135. Although the spread of location also spreads lower than destination 8, the mean is lower.

Table 4.5: Bartlett's, Levene's, and T-tests were conducted for *Vessel 4* while in transit with 8 and 9 as destinations.

		Bartlett's test	**Levene's test**	**T-test**
Vessel 1	Statistic	38.896	0.650	0.808
	p-value	4.470E-10	0.422	0.421
Vessel 2	Statistic	61.001	13.460	
	p-value	5.703E-15	0.396E-03	

All vessels of *Company 3* have multiple captains. The captains have different ways of sailing, which could influence fuel consumption. To compare, the captains chosen is only to include the captains who have been sailing during the last month. The captains sailing more than a month ago and not in the last month are not included in this analysis. The captains not included in this analysis could be utilised to check if they were sailing better than the captains are sailing now. The captain data is taken over 21 weeks. *Vessel 4* had three captains the last month and *Vessel 5* six captains. The three captains who sailed on *Vessel 4* seem relatively similar, as shown in Figure 4.136. The captains of *Vessel 5* are shown in Figure 4.137 and do seem to show differences. *Vessel 5* will be further analysed. Assumed is that all captains sail with similar fuel consumption, so this will be the null hypothesis. As a basis, captains 16 and 4 will be compared to check if captains sail similarly and after this, captains 7 and 10.

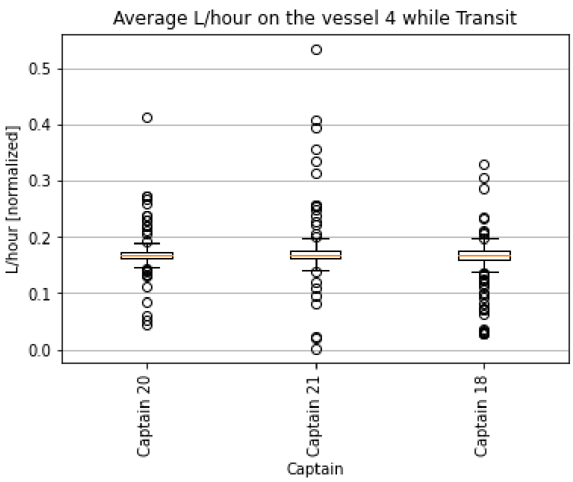


Figure 4.136: The box plots show the difference in fuel consumption of activities with as captain the ones shown, from *Company 3* of *Vessel 4* while in transit.

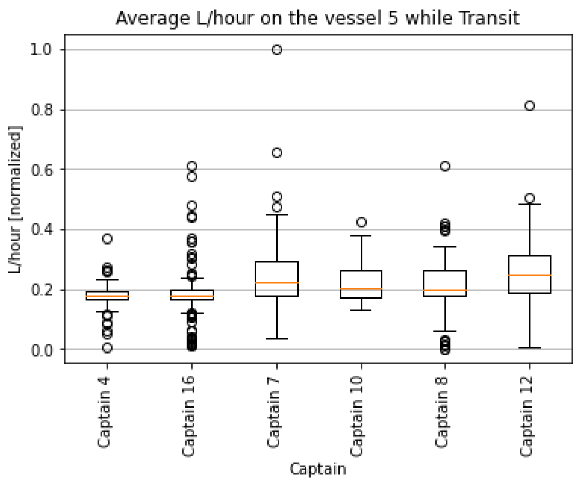


Figure 4.137: The box plots show the difference in fuel consumption of activities with as captain the ones shown, from *Company 3* of *Vessel 5* while in transit.

Tests will try to show captains 4 and 16 sailing with similar fuel consumption and whether 7 and 10 have a similar profile. Assuming all captains sail with similar fuel consumption, the null hypothesis is all variances and means are equal. Bartlett's test of captains 4 and 16 concludes the null hypothesis needs to be rejected, and Levene's test tells the null hypothesis needs not to be rejected. After consulting the box plot, chosen is to assume the captains have the same variance. The T-test does not reject the null hypothesis, which shows captains 4 and 16 probably have an equal mean. The variance tests of captains 7 and 10 show a different picture. Bartlett's test and Levene's test reject the null hypothesis. This means captains 7 and 10 sail differently. The difference between the other captains will be analysed. All test results are shown in Table 4.6.

Table 4.6: Bartlett's, Levene's, and T-tests were conducted for *Vessel 5* while in transit with captains 4, 16, 7, and 10.

		Bartlett's test	Levene's test	T-test
Captain 4 vs 16	Statistic	4.596	0.354	0.948
	p-value	0.032	0.552	0.344
Captain 7 vs 10	Statistic	42.140	9.401	
	p-value	8.499E-11	0.237E-02	

Because 4 and 16 are deemed equal, the distribution of 7 and 10 will only be tested compared to captain 16. Captain 16 is chosen for the comparison because this captain has the most sailing data. Assuming all captains have the same variance and means, this will be the null hypothesises. Bartlett's tests reject the null hypothesises. Levene's test for captain 16 versus 7 also rejects the null hypothesis. Levene's test for captains 16 versus 10 does not reject the null hypothesis. The T-test for captains 16 and 10 clearly shows a difference between the means. All test results are shown in Table 4.7.

Table 4.7: Bartlett's, Levene's, and T-tests were conducted for *Vessel 5* while in transit with captain 16 in comparison to 7 and 10.

		Bartlett's test	Levene's test	T-test
Captain 16 vs 7	Statistic	28.788	13.078	
	p-value	8.077E-08	0.351E-03	
Captain 16 vs 10	Statistic	9.107	0.094	-2.837
	p-value	0.255E-03	0.759	0.553E-02

The tests result in a couple of observations. The first two clear observations are that *Vessel 5* needs to sail more efficiently to destination 9, and captains 7 and 10 need to sail more efficiently. As earlier shown, *Vessel 4* seems to sail more stable than *Vessel 5*. The difference in vessel efficiency could be the number of different captains as *Vessel 4* had 3 different captains last month and *Vessel 5* six. What also became apparent from the tests was the result of the statistical test. Bartlett's tests give poor outcomes, which could indicate a non-normal distributed distribution of the samples. The box plots show the test probably results in a correct conclusion, but the outputs of Bartlett's test indicate a problem. The reason for this non-normal distribution could again lie within the later set goals. The goals give the data a lot of outliers and steep spikes.

Figure 4.138 and 4.139 show the fuel consumption against the speed. As is visible in the graphs, *Company 3* set a goal for the amount of fuel per hour. This is why the litre per hour stays relatively constant over speed. The data is now based on the maximum amount of litre fuel per hour, as shown in the figures, but this might not be optimal fuel-wise. Idle is better than sailing fuel-wise, so it is sometimes better to be moored faster than to use less fuel per hour but sailing longer. This matters less when waiting is the next activity, but in the case of sailing to berth and mobilization, it is something to keep in mind.

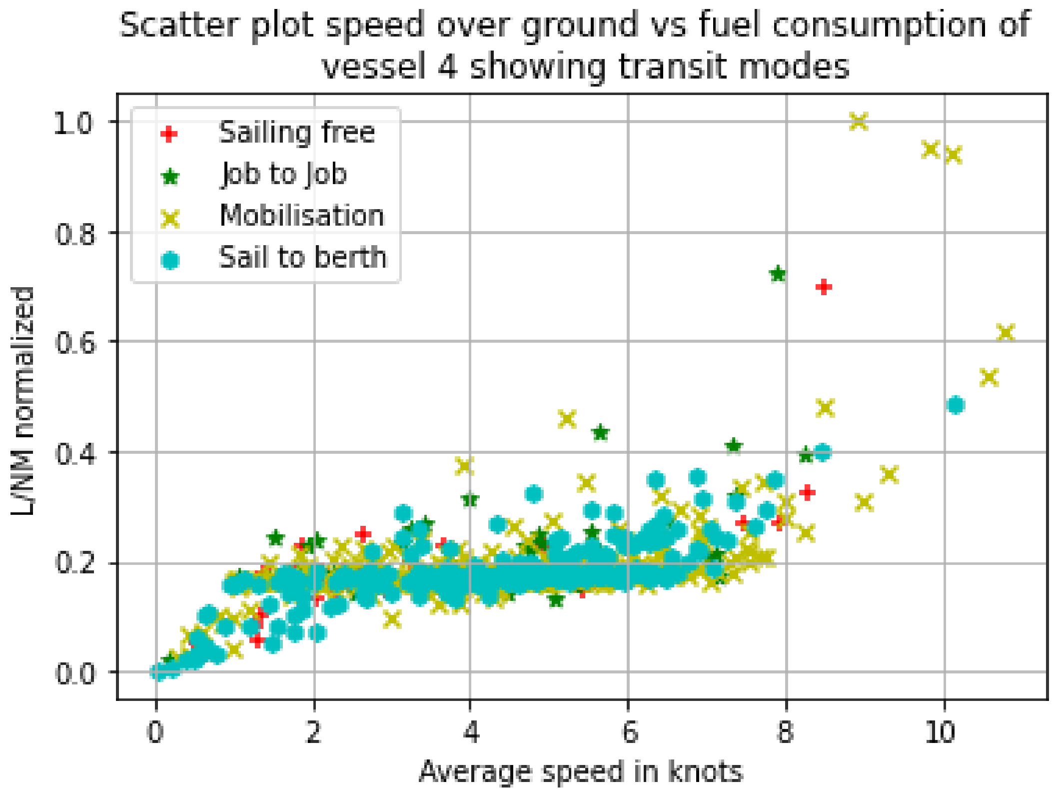


Figure 4.138: The scatter plot plotting speed against fuel consumption of *Vessel 4* from *Company 3* while in Transit.

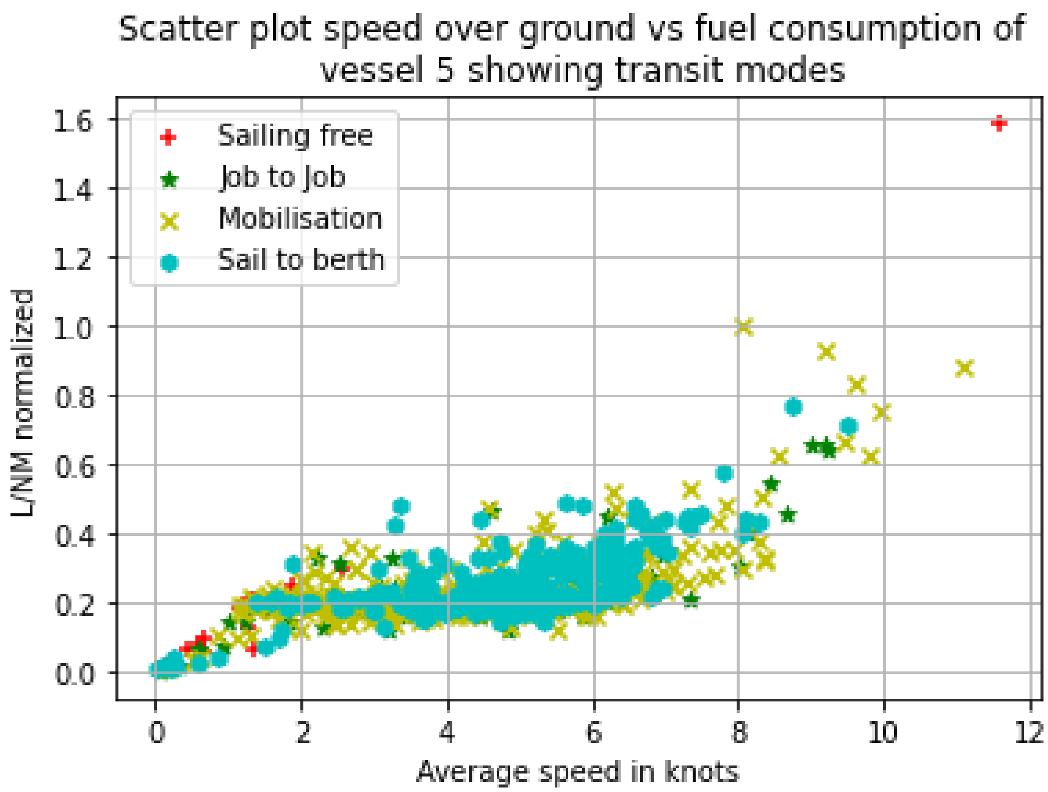


Figure 4.139: The scatter plot plotting speed against fuel consumption of *Vessel 5* from *Company 3* while in Transit.

Figure 4.140 and 4.141 show a different picture. These two graphs show the litres per nautical mile. The sailing influences the data used in these graphs at the prescribed speed. Now around six or seven knots, the amount of fuel per NM is the lowest, and the arrival time is faster. The problem with this graph is that all data seems to be at the border due to the set goal.

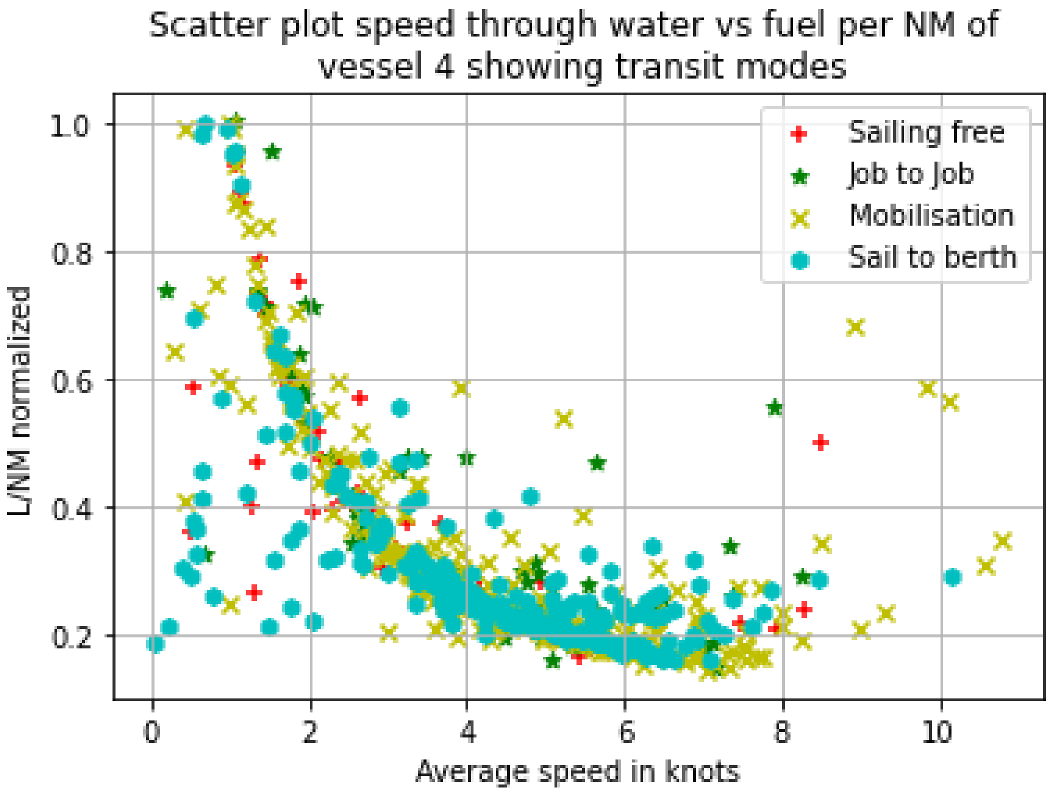


Figure 4.140: The scatter plot plotting speed against fuel consumption of *Vessel 4* from *Company 3* while in Transit.

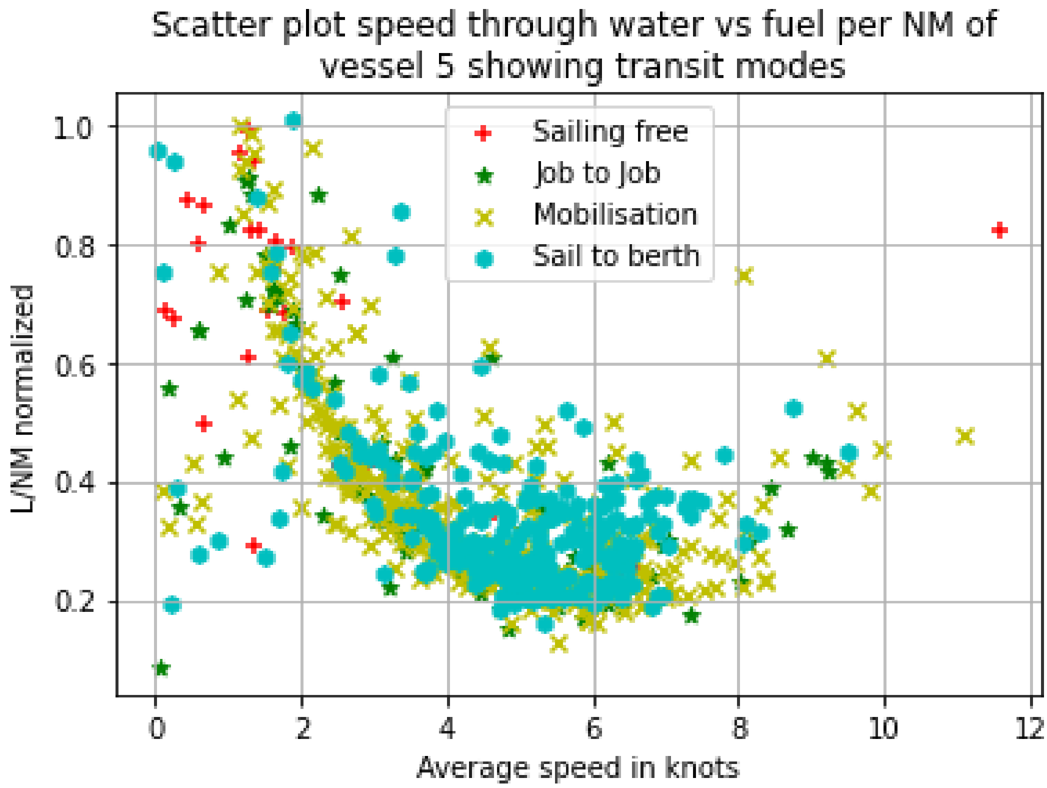


Figure 4.141: The scatter plot plotting speed against fuel consumption of *Vessel 5* from *Company 3* while in Transit.

4.3.4. Improve

While most fuel is consumed while the vessels are active, the active activities are not included in the improvement phase. The entire cycle needs to be redone for the active activities. This will not be done during this research but should be conducted the same way the transit activity analysis is now. At the moment, the transit goals are set in litres per hour. According to the analyse phase, it seems like the goals do not consider litres per NM which could indicate the goals increase the total fuel used. The goal of litres per hour needs to be revised, but the original data before any goals were set needs to be selected to find speed curves. This is outside this research's scope but seems useful for new projects.

The investigation into the captains and locations showed potential, but for now, only three results. This research was done for two vessels using two variables, potentially leading to more gain. The Potential gain for the three improvements is calculated by the percentage difference between the better captain or destination and the worst captain or destination. With the calculated percentage improvement, the absolute fuel used can be calculated. When improving the performance of Captain 7, the potential gain is almost 1 per cent. The improvement of destination 9 has a potential gain of 0.4 per cent, and optimising the performance of Captain 10 could lead to a potential gain of 0.3 per cent. The Pareto chart, shown in Figure 4.142, is created with these potential gains.

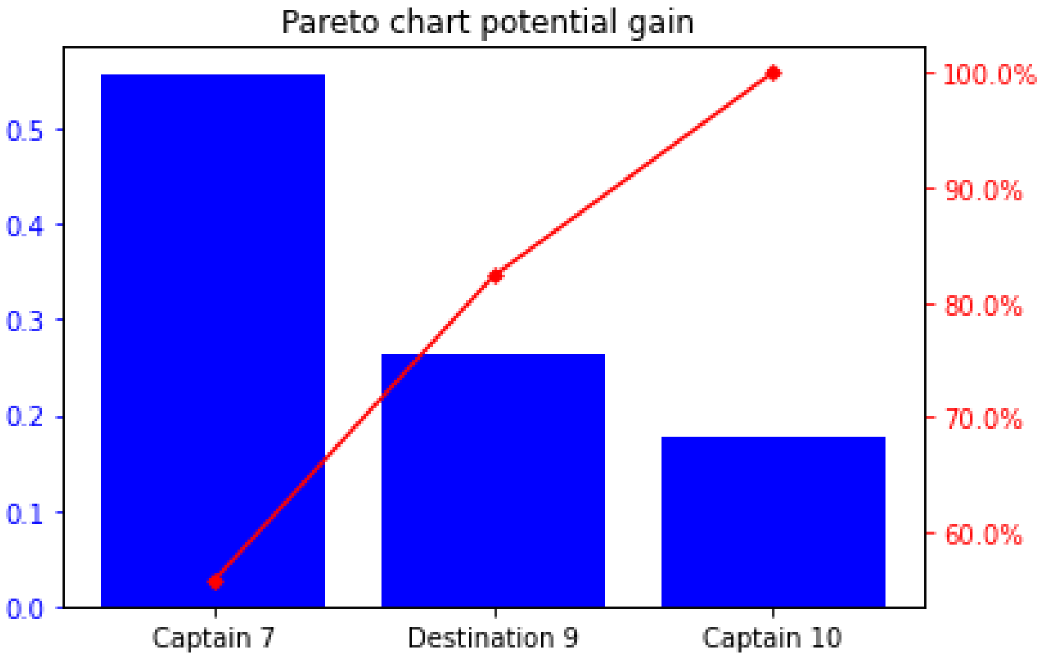


Figure 4.142: The Pareto chart of *Company 1* shows the potential gain of the proposed improvements.

The improvement phase will start with improving the performance of Captain 7. Five times why is used to find the root of Captain 7's problems. Why is captain 7 not performing as well as the other captains? The difference with the other captains is the number of times the captain has been captain of *Vessel 5*. Why is the number of times an influence? The Captains seem to need some time to get used to the vessel. Why do the captains need time? This could be due to training or because the captains are unfamiliar with the situation. The following questions will lead further into the company's foundations and will not be answered in this research. The following questions will have to be stated: why is the training program not preparing the new captains enough, or why are there so many new captains?

4.3.5. Control

The control phase will consist of an X-bar and R-chart but will need more time to show results.

5 Discussion

The research aims to find the answer to the question, can the data be used to improve vessel operations? The way the answer is formed is by conducting a literature study, executed in chapters 2 and 3, and after the literature study, testing the conclusions followed by conducting three case studies in chapter 4. This chapter will discuss the assumptions and whether the beliefs match the results, case by case. The discussion will contain all findings of the cases and, after this, the general discussion issues.

5.1. Case 1

The first case is the case of *Vessel 1*, an offshore supply vessel of *Company 1*. This case showed how LSS could stabilise a process by removing errors from the data. The case also demonstrated how to optimise an operation by looking at the process of one vessel. *Vessel 1* has quite a lot of offshore activities but limited options to choose from in the *Onboard* system. The transit and port operations showed little specific data. After some adaptions, the data was improved, but more data activities in the *Onboard* system can increase the analysis options, as shown in the case. The case establishes that the method can show results when the data is still quite raw, so nothing has been done to optimise the operation.

In Chapter 3 was assumed the flow chart was an excellent tool for identifying waste and defining operational processes. Case 1 illustrated the operational processes became clear when all activities were connected and placed in a flow chart. At a glance, a vessel's complete process is straightforward, and the issues in the system immediately surface. When the optimised flow chart is added, most improvement points come up. All potential improvements can be traced back to the flow charts. Although the waste comes up immediately after creating the flow charts, the importance of each improvement remains unknown. The question remains if the improvements were reachable. For example, the arrival time and which platform to arrive at were used as a constant, but are these constants? VOB or VOC could be used for this question, but this research lacks testing on whether this would improve the method.

In case 1, Anderson-Darling, Shapiro-Wilk, and Kolmogorov-Smirnov tests were used to show normality. All three tests showed weird results when analysing the idle and waiting data. Although the tests resulted in a normal distribution for both groups, the histogram and Q-Q plot clearly showed something else. This indicates a weakness of the three chosen tests. This could have something to do with the 50 samples, which is, for most tests, the bare minimum. The idle and waiting data are not further analysed after being deemed not normally distributed. Further investigation into these groups can find why the tests work improperly.

Samples are randomly selected to construct an X-bar and R-chart. When selecting random data, the outcomes can differ. In this case, the one clear outlier is shown with every seed change, which indicates the apparent outliers will display in the graphs.

In Chapter 3, all errors need to be found in the data, and a Pareto chart needs to be created to decide which error to resolve first. In case 1, the most apparent errors found were removed simultaneously. Removing all errors improved the data quality without needing a Pareto chart. The approach of eliminating all obvious errors also makes more sense because looking for all errors in the data and calculating the potential influence seems inadvisable when another option is to remove all errors which show up.

Chapter 3 states that a scatter plot can be used to find the correlation during the analysis phase. Case 1 showed that a scatter plot is unnecessary when looking into the improvement of data. This implies that the analysis phase for improving data quality and operational efficiency are not as closely correlated as stated in Chapter 3.

Case 1's processes were not structured and neat enough to conduct hypothesis tests. The case is mainly devoted to mapping the processes and improving the sequences of activities. Also, there was not too much to compare during the case because only one vessel was analysed, and no different crews were recorded in the logbook. Because the case has a lot of similar activities, the most gain seems to be in changing the activity sequence. When the optimisation is optimising activity sequences, box plots do not make sense. When an activity sequence is better than another, box plots will show an optimised box plot, which is better than the original box plot.

The improvement section of case 1 shows a total of six per cent potential gain. What needs to be kept in mind is the Lean concept of striving for perfection. The potential gain is more a strive value than a gain to expect. Although the method seems promising, the results need to be verified before a definite conclusion can be drawn, but the expected results will be less than six per cent.

5.2. Case 2

The second case is the case of *Vessel 2* and *Vessel 3* of *Company 2*. *Company 2* has just like *Company 1* offshore supply vessels, but the vessels of *Company 2* are more focused on cargo than human transfers. This example shows two cases of two identical vessels. *Vessel 2* has been gathering data for a while, and *Vessel 3* has been active for roughly 20 weeks. The case showed two sister vessels with fewer activities than the vessels of case one. Although there were fewer activities, the number of options to choose from in the *Onboard* system was more than two times higher than in case 1. The different vessels did not perform the same according to the data. Still, the analysis resulted in insights on decreasing the difference in vessel performance and increasing the efficiency of the worse-performing vessel.

As the introduction indicates, the crew has many options to tell what the vessel is doing. When a flow chart is put together, it becomes clear how many of these activities overlap. *Company 2* has a total of 36 identical activities to choose from. Many of these activities are rarely used and have not been included in the flow chart creation, shown in figure 4.31. The activities that are used are also often confused with each other. For example, there are seven different activities of sailing. When analysed, it also becomes clear that this is used interchangeably. Analysing becomes more manageable with more activities because it can be brought up more specifically when things go wrong on board the vessel. Still, the crew does not quickly know which activity to select. What probably also plays a role in this situation is that the abbreviations used are unclear. So, where there were too few activities in case one, there seem to be too many in this case, and a middle ground between the activities of these two companies seems to be the right way. When creating an optimal flow chart, it becomes clear where the crew is going amiss. So, in addition to determining where the waste is in the process, the optimal flow chart also clarifies which activities need to be cleaned up or what each activity entails should be made more explicit. Because *Company 2* has many activities, having one spot in the flow chart where a journey stops and starts are not enough. After all, a new voyage can start at *Company 2* between two activities in the port or after carrying out an activity offshore. When creating a flowchart, it must therefore be kept in mind that there is not always just one starting point in a flowchart.

The data must be normally distributed to use X-bar and R-charts, as the literature prescribes. For

Vessel 3, transit seems at least more stable than the active activity. The question is, therefore, how important it is that the data is normally distributed and to what extent this can deviate. Determining how normal the data is is again a problem here; this is clearly shown in the normality tests of case 2. Initially, all data of *Vessel 2* is seen as normally distributed, while this is not the case. The difference between the normality tests, histograms, and Q-Q plots becomes apparent here. One reason may be that the statistical tests are performed with the average sample value, and the histograms and Q-Q plots are made with the five data points from the samples. The small data size is a problem for most statistical tests states Mishra et al. (2019). Mishra et al. (2019) state that only the Shapiro–Wilk test can be used for data samples smaller than 50, which indicates the Shapiro–Wilk test should give accurate results, but in this case, the test also seems to lack the power to test for normality. Further research could test whether using all sample data would increase the tests' results. Further improvement of the error fishbone diagram also seems necessary since the reason for not normally distributed transit activities is that several activities are grouped. So, the possibility that the grouping of activities is not done correctly must also be considered.

In this case, it was decided to use an X-bar and R-chart with data that is not with certainty normally distributed. At the later stage of the research, this does not seem to cause any problems. The same is true for the 20 samples that are required. In the case the research was conducted while active had only 17 samples, this does also not seem to cause any problems at a later stage. What could be a problem is a situation where two vessels are compared with each other, and both have a different period. In case 2, *Vessel 2* uses the data of 37 weeks and *Vessel 3* the data of 21 weeks. It has not been tested in this case, but seasonality could impact the comparison outcome. For example, if the weather in the nonidentical weeks was worse than that in the corresponding weeks, this could give biased results. To determine whether the biased outcomes are a problem, whether seasonality is a problem must be determined, and weather data is, therefore, also needed.

The case study can continue without meeting all the requirements may have more consequences. The question then becomes, should a step back always be taken in non-normally distributed processes? In this case, the action continued while the step-by-step plan returned to the measure phase. Not taking a step back did not seem to have significant consequences. A consequence does seem to emerge during hypothesis testing. Bartlett's and Levene's tests were performed to compare the same situations. It is known that Bartlett's test is made for more than two data sets to be compared, which may be why the test results are very different from the results of Levene's test. The data not being normally distributed could also be a good cause of the abnormal results of Bartlett's test, but this still needs to be investigated. For now, the result of Levene's test seems better than Bartlett's test in any situation. In case 3, comparable results are found.

The last thing that needs to be said about this case has to do with the Pareto chart. It has been decided to use the Pareto chart based on the KPI fuel. When, as suggested, the vessel has to slow down by 3 knots per hour, much more time is needed for each leg of sailing. Before this improvement can be implemented, the time's influence must be considered.

5.3. Case 3

The third case is the case of *Vessel 4* and *Vessel 5* of *Company 3*. *Company 3* is a towage company operating multiple tugs. This example shows two cases of two similar vessels. Both have used the *Onboard* system for more than nine months. *Company 3* started improving operational efficiency a couple of months ago by setting fuel-per-hour targets. This case shows how the method works when the first optimisations have already been implemented. The improvements now affect all data, and the data with the goal value is the most frequent. The optimisations found mainly consist of several small improvements. When all improvements combine, the potential is one % of a vessel's fuel consumption.

The flow chart of case 3 was clear, and with the optimal flow chart, little waste was found. The groups that have been created are questionable. Later in the research, it also became clear that the activities differ quite a lot. When it is considered that all the activities differ from each other and belong to a different group, the comparison with the offshore supply ships also becomes more difficult.

Looking back to the matching in Chapter 2, some rethinking is needed. Figure 2.3 shows an area where workboats operate, but when looking at a tug, a Flow shop seems to have more similarities than a mixed-model assembly line, which would also result in a larger area where the workboat would have to be placed. The increase in the workboat area would not be a significant problem as the area is still within the LSS range.

The chosen KPIs were fuel and time, but fuel per hour is not always the proper KPI. In this case, goals were set a few months ago, and these goals are set to an X number of litres per hour. This generally works well when an activity is being carried out. Still, it becomes more complicated when more time is required due to lower fuel consumption, which becomes apparent during transit. When a specific target of X fuel per hour is maintained, the speed may decrease, and the vessel takes longer to reach the destination. When less fuel is used per hour for longer, the total fuel consumption can still increase, which is reflected in this case. This raises the question of whether the KPIs fuel and time have been the correct KPIs and whether the results are the same when they are compared, for example, to fuel per NM.

In all cases, the Kolmogorov-Smirnov tests gave poor results. Still, during one of the tests while in transit which was very clearly not normally distributed, the Kolmogorov-Smirnov test rejected the null hypothesis. Because the data were not normally distributed, the question becomes does the test add anything to the research results, or can the test be eliminated from the method? Mishra et al. (2019) stated below 50 samples, Shapiro-Wilk is the only statistical test to test normality which works well. This could also mean that if the method uses less than 50, it only makes sense to use the Shapiro-Wilk test. Another result related to research done by Mishra et al. (2019) is when the number of samples went down, the statistical test results improved. Because most tests used work worse with small data sets, a possibility is the quality of the test just decreased. More tests with small sample sizes are needed to gain confidence in the test outcomes and the normality of the data.

The tug situation differs a bit from the offshore supply vessel situation. In this case, the same variance fishbone diagram is used as the one from the offshore supply vessels. The method states every company needs to create their fishbone diagram. This case did not take things into account which are more relevant for this situation, for example, swerving for other vessels. The tug fishbone diagram should be customised to be more focused on the issues tugs encounter.

When analysing the operations, in this case, it became clear that more in dept knowledge is needed. When the optimisations are started, more obvious improvements can no longer be found, which means that more specific things have to be analysed and requires more data. In the cases used, only the most superficial analysis has been done, and, as case 3 showed, several minor improvements have already popped up. The downside of the minor improvements is the time it takes to control them. When a slight improvement is tested, which takes three months before results can be seen, optimisation will take a very long time before actual results show. A solution is to improve several things simultaneously. Still, the risk is that some of these improvements will weaken or enhance the effect of each other, making it unclear which of the improvements has an impact.

5.4. General

Firstly, the aim throughout this entire research has been to eliminate waste to increase operation efficiency and decrease pollution. However, pollution was barely mentioned during the research, and all efforts went into reducing fuel consumption. Sometimes while making something leaner, it does not become greener according to Norton (2007), which is something to keep in mind during optimising. In this case, all pollution, CO_2 emission, is calculated by the amount of fuel used, which means when using less fuel, the pollution decreases.

It can be said that the choice for LSS was the right choice. Looking back at Chapter 2, one thing needs to be reconsidered: matching the workboat processes with the BPM strategies. The original location, as shown in Figure 2.3, corresponds well to offshore supply vessels but does not cover the load when looking at tugs. The workboat area has to cover a more extensive area in the *Flow shop* row, and a lower volume of products needs to be included. An improved, more inclusive version of the workboat process in the product process matrix is shown in Figure 5.1. If the choice had to be made again, the outcome of LSS would not change.

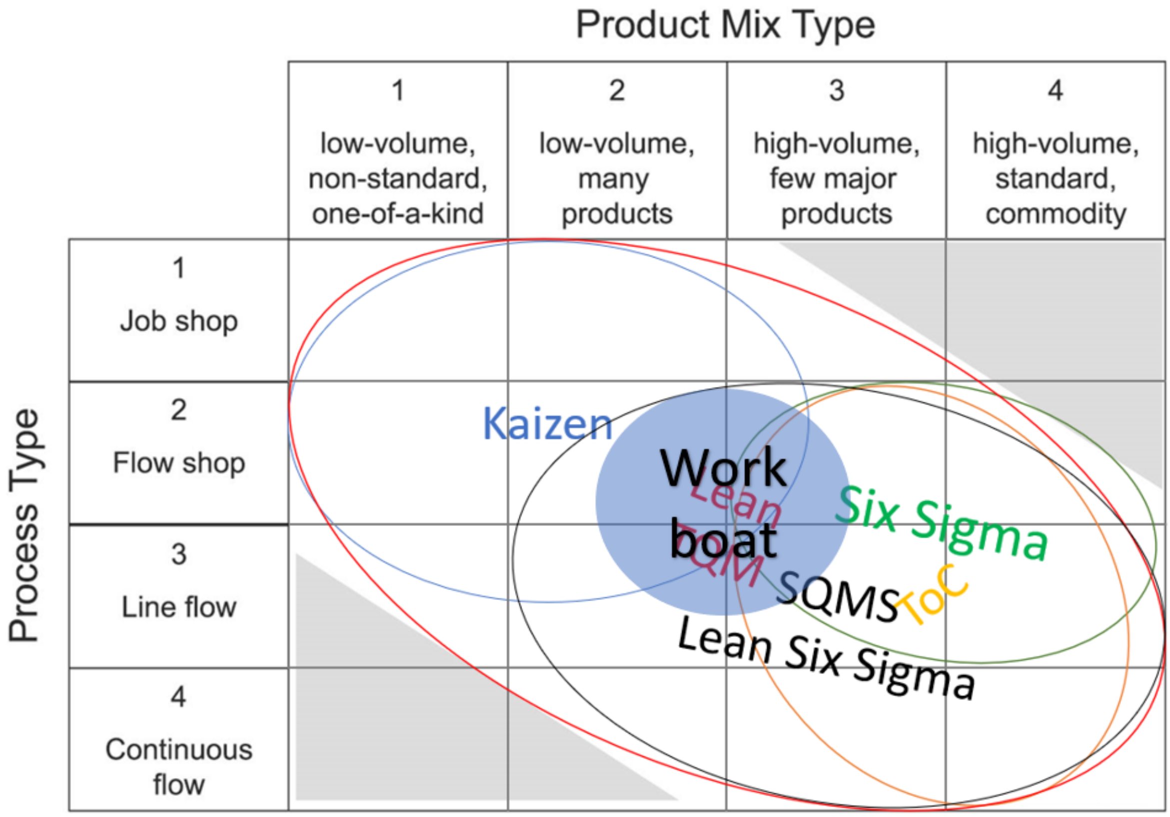


Figure 5.1: BPM strategies and workboat process in the product process matrix (Matrix from Hayes and Wheelwright (1985)).

After testing all the tools, it seems that some things can be crossed off the list. The stat tests that test normality do not seem to give correct results. One option is to improve the tests by increasing the sample size; another option is to delete the tests and work only with histograms and Q-Q plots. The Pareto chart should be used to determine which error to solve first is unnecessary. When errors are found, they are often immediately rectified. Making a Pareto chart is extra work. Bartlett's test is also superfluous when comparing two things. Bartlett's test would only become relevant again if several data had to be compared simultaneously. Also, the box plots in the improvement phase are not showing new things, so it is better when the box plots are left out. When these tools are not used, the analysis still appears successful. The scatter plot also seems unnecessary for analysing an out-of-control or not normal distribution. For clarity, Figure 5.2 is the updated image from the conclusion of section 3. In the figure, the tools deemed unnecessary after performing the case studies have been omitted. And VOC and VOB have been added to improve the define stage.

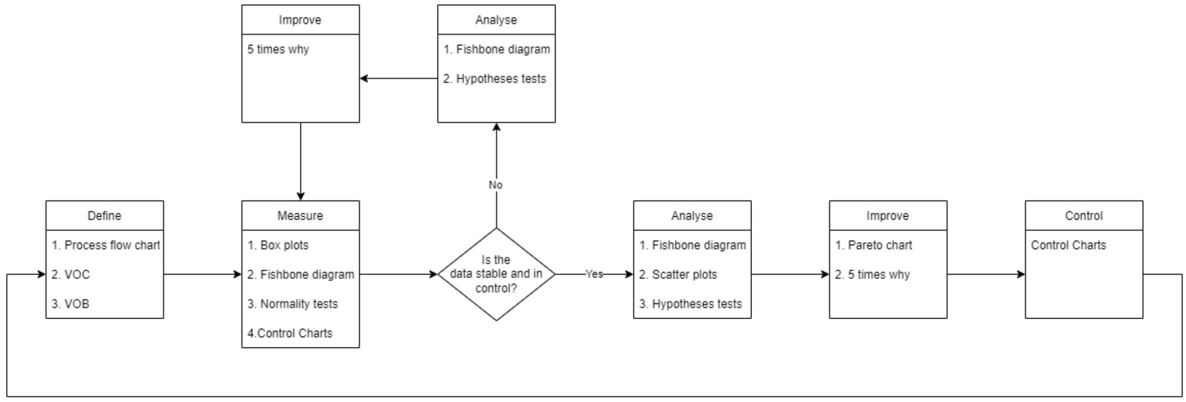


Figure 5.2: The process flow of optimisation project.

6

Conclusions, and Recommendations

6.1. Conclusion

The research contains six research questions and the main question. The main question is, *How can operational data be used to improve the operational efficiency of workboat operations?* The other research questions of this thesis are stated in the following enumeration.

- What new data is available, and what kind of data is this?
- What strategies which increase operational efficiency already exist?
- Which strategies suit the problem the best?
- Which tools suit the problem the best?
- Is the available data sufficient to increase operational efficiency?
- What data could further improve operational efficiency?

This chapter will answer all research questions one by one. The chapter will finish by answering the main question.

6.1.1. What new data is available, and what kind of data is this?

Initially, the idea of *Onboard* was to research how to improve operational efficiency when using the data collected by *Onboard*. *Onboard* collects vessel data from the vessels and makes it transparent for the vessel owner. The collected data includes location, time, distance, speed, fuel consumption, and logbook data. Log data consists of the captain, destination, etc. The data is collected as time series data, but the crew immediately gives meaning to the data with the *Onboard* system. When the crew selects an activity, the time series data until the next activity starts becomes part of that activity, and all activities are grouped into voyages. The data is collected every 10 seconds and yields large data sets. Due to the onboard system that divides the data directly under activities and voyages, the *Onboard* data will not be considered big data.

6.1.2. What strategies which increase operational efficiency already exist?

Improving operational efficiency has been important for quite some time, especially in the production industry. The strategies used in the manufacturing industry, business process management (BPM) strategies, have also found their way into other sectors. The most forthcoming BPM strategies in literature are considered for this application, according to Hamrol (2018). The seven strategies considered are the Theory of Constraints, Lean Manufacturing, Six Sigma, Kaizen, Total Quality Management, Standardized Quality Management Systems and Lean Six Sigma (LSS).

6.1.3. Which strategies suit the problem the best?

The seven BPM strategies found to answer the previous question were compared to reach the answer. The BPM strategies were compared based on how data is used in the strategy, how the strategy matches the workboat activities, the focus of strategies, the aim, and the approximated effects, and the application in the transport industry. The comparison has shown that LSS is the most suitable method. The method emphasises the use of operational data. The production area in which LSS operates corresponds to the area in which workboats operate. The focus, aim and expected effects of LSS are aligned with this research's focus, aim and expected effects. And finally, the literature provides clear indications that the strategy has potential in the workboat situation. This research has come to this conclusion, and other research reaches the same result. According to Hamrol (2018), LSS is the highest potential solution when complementing it with aspects of other strategies. Chiarini and Kumar (2021) calls LSS *one of the best models belonging to the Operational Excellence*.

LSS is structured in five phases; Define, Measure, Analyse, Improve, and Control. In the define phase, defined is how the process is structured. During the measure phase, the process is quantified. While analysing, the source of the problem or variation has to be found. In the improvement phase, a way to improve the process needs to be uncovered. The control phase checks whether the improvement works and whether the process is enhanced stably.

6.1.4. Which tools suit the problem the best?

LSS has many tools, and a selection has been made to improve these specific workboat processes with data. A flow chart shows during the define phase the structure of the process. The measure phase uses a fishbone diagram to determine the inconsistencies in the data, box plots to compare the distributions and means, and capability analysis, including Control Charts and Normality tests, which ensure the data is normally distributed and in control. A fishbone diagram helps by finding the reason for the variation, while scatter plots help to analyse variables showing correlation and to construct a null hypothesis. The hypotheses tests check whether the null hypothesis formulated in the analysis phase needs to be rejected. In the improvement phase, a Pareto chart helps to decide which improvement to implement first, while the 5 times why tool gets to the root of the problem. Finally, when an improvement is implemented, the control phase controls the improvements on improving operational efficiency and stably doing this. All tools are summarised and presented in the following enumeration, indicating in which phase the tools are used.

- **Define**, Process flow chart
- **Measure**, Fishbone diagram, Capability analysis, Control Charts, Normality tests, Box plots
- **Analyse**, Fishbone diagram, Scatter plots, Hypotheses tests
- **Improve**, Pareto chart, 5 why
- **Control**, Control charts

6.1.5. Is the available data sufficient to increase operational efficiency?

The data is sufficient to demonstrate operational efficiency issues. This research has shown that ideas emerged about how the efficiency of workboats can be improved in three cases. Unfortunately, the whole sequence was never completed due to a lack of time. Since the control phase has never been completed, it cannot be said with certainty that the method works and that the data is sufficient to improve operational efficiency. When looking for improvements to increase operational efficiency, the data seems promising. For this research, not all data is used, and more data is available, and even without all data used, the method shows good potential. The question is whether the data is enough to improve operational efficiency and can be answered with a cautious yes.

6.1.6. What data could further improve operational efficiency?

Because LSS has a continuous improvement philosophy that strives for perfection, more data can be utilised. Missing data which came to the surface during the case studies was weather data. In Case 1, there was a data point that was not within the limits of a control chart, so the system was out of control. When looking at why the fuel consumption was much higher, there was no data implying anything was wrong. A small weather study showed a storm in that area during that period. Nothing gave a reason for the higher fuel consumption in the data, but these issues can also be tackled when weather data is added.

During this research, the focus was on the litres of fuel per hour. The KPIs were fuel and time, but in the end, the Pareto chart was only produced using fuel. In all these cases, time has not been taken into account. The reason that time is not included is that the importance of time is unknown. Therefore, tracking how important it is to arrive at a particular time is essential. Indicating whether there is a hard deadline is, therefore, an addition to the data. It is also challenging to determine how long an activity should last. When, for example, one container or ten containers have to be transferred, or whether a small vessel has to be guided into the port or a RoRo vessel. An addition would therefore be the cargo of the vessel. With the cargo information, times can also be better compared.

6.1.7. How can operational data be used to improve the operational efficiency of workboat operations?

The data can help understand what is happening during the vessel process and why this is happening. It can also help show that an improvement is not the best in a particular situation. Vessels, crews, and locations can all be compared to each other, and the best one can be found. It can help focus on what has the most significant potential. But the main question can not be fully answered because there was not enough time to test the improvements. Because all conducted cases showed that there is indeed a lot of potential in the method used, it will be assumed to answer this question, that even if these improvements do not lead to an improved process, other improvements can be found which do improve the system and can improve a workboat process.

The question remaining is the main question of this research, how can operational data be used to improve the operational efficiency of workboat operations? The method presented in this research uses the activities of workboats, which are grouped and compared with each other. These activity groups were analysed based on a selection of LSS tools. These analyses indicate options for improving the general process and finding differences in components. The improvements will also help clarify the processes, ultimately benefiting operational efficiency. The potential to expose problems in the measurement of data and the potential solutions to improve efficiency give confidence that this LSS method is a way to use novel operational data to improve the operational efficiency of workboat operations.

6.2. Recommendations

6.2.1. Practical Recommendations

The practical recommendations will recommend *Onboard* and the companies using the *Onboard* IoT gateway on what they can do to increase the quality of operational data of workboat operations. The recommendations will consist of things encountered during this research.

In case 2, graphs are made using the amount of fuel per nautical mile over ground. If it had been possible, the amount of fuel per nautical mile through water would have been used. The problem is that there seem to be many problems when measuring speed through water. The data of the distance through water is not always stable enough to form stable results. Because this misses good opportunities, a recommendation is to ensure these sensors work.

As stated earlier in this conclusion, weather data and sub-activities for cargo would be a valuable improvement of the data. In case 1, the weather causes the data to be out of control, and analysing the time of activities is difficult during all cases because the cargo is not, or difficult, accessible. Instead of adding the weather data, it is also possible to determine whether the current can be calculated based on speed through water, speed over land, and the vessel's heading.

When making the flow chart during case 2, it became clear that some activities were mixed up and that there was little structure in the activities selected by the crew. Making a flowchart makes it clear to everyone what needs to be done, so a recommendation is also to give the crew a flowchart to know which activity should be used. Another option would be to automatically generate a flow chart to clarify how activities are going or what is going wrong with the activity selection. A flow chart can also help to suggest when an activity should be selected. Where one activity always follows another activity, this can also be suggested by the system.

6.2.2. Further Research

Finally, there are a few things that need further investigation. This research is just the tip of the iceberg, and more research into the *Onboard* data and operational efficiency can be performed.

The tests of the proposed improvements are missing. Improvements have been proposed, and those improvements need to be implemented. After implementing the improvements, new data has to be collected, and it has to be controlled whether the improvements work. During this research, it can be determined whether there are other possibilities to improve the operation of workboats.

At the moment, it can be concluded that there are errors in the data. One of the things that can still be investigated is whether improving the data quality increases or improves the data analysis option. This can be done using time series data. It can also be checked whether other things can be optimised with the time series data.

Finally, something to investigate further are the requirements for the statistic tests. For example, 20 samples are required, but are these enough or too few? Another question is, does the data need to be normally distributed? By testing this, the method can be adapted to lead to better results.

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A

Python Code

A.1. Code

This appendix contains the main code with all the functions created. The file GetAccessToken was not added to the appendix because it contains passwords.

A.1.1. The main code

```
import matplotlib.pyplot as plt
from General.queries import queries
import datetime
import numpy as np
from General.Golden_sample import Golden_sample
from General.Sorting import Sorting
from General.Utility import Utility
from General.Groups import Groups
import sys
from General.Statistical import statistical_group
from General.Find_Outliers import Find_Outliers
from General.Group_data import Group_data

#%% ################## Importing data ##################
# Set the start date (year, month, day)
start_date = datetime.date( ,  ,  )

# Columns 0 = start Time, 0 = end Time,
# 2 = avgLitersPerHour, 3 = Duration, 4 = activity ID,
# 5 = Distance over ground, 6 = Distance through water, 7 = final activity name,
# 8 = Category name, 9 = voyage ID, 10 = destination, 11 = Captian name,
# 12 = Liter per NM through water, 13 = current in knots, 14 = liters fuel used,
# 15 = Liter per NM OG, 16 = start activity, 17 = number of activities
df_array, vessel = queries(start_date)

#%% ################### Define ##########################
# Retriving data names
Groups_Activities, Groupnames = Groups()
Activities, Destinations, Groups_test, Captains = Sorting(vessel, df_array)

# Test if correct
Test_activities = []
```

```
for y in range(len(Groups_Activities)):
    Test_activities = np.append(Test_activities, Groups_Activities[Groupnames[y]]
    , axis = 0)

if len(Test_activities) != len(Activities):
    print('Refresh Activity file !!!')
    sys.exit()

#%% Data sorting
df_array_Group = Group_data(vessel, df_array, Groupnames, Groups_Activities)

Vessels_used = list(df_array_Group.keys())

vessel_norm = []
for x in range(len(Vessels_used)):
    vessel_norm.append("vessel {}".format(x+4))
#%% Plotting
# Utility
Utility_Fuel_Time, Utility_string, Utility_Group = Utility(df_array, Vessels_used
, Activities, Groups_Activities, vessel_norm)

# Create boxplot
Max_boxplot = {}
for z in range(len(vessel_norm)):
    Max_vessel = []
    for y in range(len(Groupnames)):
        Max_vessel.append(max(df_array_Group[Vessels_used[z]][Groupnames[y]][:,2]))
    Max_boxplot[Vessels_used[z]] = max(Max_vessel)

for z in range(len(vessel_norm)):
    Box = []
    for y in range(len(Groupnames)):
        Box.append(df_array_Group[Vessels_used[z]][Groupnames[y]][:,2]
        /Max_boxplot[Vessels_used[z]])

    fig, ax = plt.subplots()
    ax.boxplot(Box)
    ax.set_xticklabels(Groupnames)
    plt.title("Average L/hour {}".format(vessel_norm[z]))
    plt.xlabel("Grouped activity")
    plt.ylabel("L/hour [normalized]")
    plt.grid(axis = 'y')
    plt.show()


# Grouped boxplots
# Find maximum
Max_boxplot = {}
for y in range(len(Groupnames)):
    Max_vessel = []
    for z in range(len(vessel_norm)):
        Max_vessel.append(max(df_array_Group[Vessels_used[z]][Groupnames[y]][:,2]))
    Max_boxplot[Groupnames[y]] = max(Max_vessel)

# Create boxplot
for y in range(len(Groupnames)):
```

```
    Box = []
    for z in range(len(vessel_norm)):
        Box.append(df_array_Group[Vessels_used[z]][Groupnames[y]][:,2]
        /Max_boxplot[Groupnames[y]])

    fig, ax = plt.subplots()
    ax.boxplot(Box)
    ax.set_xticklabels(vessel_norm)
    plt.title("Average L/hour {}".format(Groupnames[y]))
    plt.xlabel("Vessel")
    plt.ylabel("L/hour [normalized]")
    plt.grid(axis = 'y')
    plt.show()

# Get the sample values and limits
Golden, Mean_overall, Total_sample, std_overall, Mean, Range, range_overall,
sample, Limmits_outside = Golden_sample(df_array_Group, start_date, vessel_norm)

# Conduct statistical analysis
Length_Sample = statistical_group(Mean_overall, Total_sample, Mean, Range,
vessel_norm, df_array_Group, start_date, range_overall, Vessels_used)

# Get the outliers
Outliers_Bad, Outliers_Good, Bad_Outliers_mean, Good_Outliers_range, Bad_Outliers_range,
Difference_Good_Bad = Find_Outliers(df_array_Group, Limmits_outside, Vessels_used)
```

A.1.2. AddOperation

```
import numpy as np

def AddOperation(A):
    # Import accessToken and url from GetAccessToken
    i = 0

    array = np.copy(A)
    array[:] = np.NaN
    for x in range(len(A)):
        Delta = (abs(A[x-1,0] - A[x,1])).total_seconds()
        if A[x,9] in array[:,9] and Delta < 120:
            array[i-1,0] = A[x,0]
            array[i-1,3] = array[i-1,3] + A[x,3]
            array[i-1,5] = abs(array[i-1,5]) + abs(A[x,5])
            array[i-1,6] = abs(array[i-1,6]) + abs(A[x,6])
            array[i-1,13] = (array[i-1,6]-array[i-1,5])/(array[i-1,3]/3600)
            array[i-1,14] = array[i-1,14] + A[x,14]
            if array[i-1,6] == 0:
                array[i-1,12] = np.NaN
            else:
                array[i-1,12] = array[i-1,14]/array[i-1,6]
            array[i-1,2] = array[i-1,14] / (array[i-1,3]/3600)
            array[i-1,17] = array[i-1,17] + A[x,17]
            array[i-1,16] = A[x,16]
        else:
            array[i,:] = A[x,:]
            i = i + 1
```

```
        # if i > 1:
        #     Extra_column1 = np.append(Extra_column1, A[i-1,7])
        #     Extra_column2 = np.append(Extra_column2, A[i-1,7])

    # Extra_columns =
    #
    # removing nan
    arrayB = array[0:i,:]
    return arrayB
```

A.1.3. DataToMatrix

```
import json
import pandas as pd
import numpy as np
import dateutil.parser

def DataToMatrix(r):
    # Json data to text
    json_data = json.loads(r.text)

    # Sort data
    df = pd.json_normalize(json_data['data']['activities'], ['fuelConsumption',
    'combined'], ['durationSeconds', 'type', 'voyage', 'id', 'shift']
    , errors='ignore')

    # Check if there is data
    if df.size == 0:
        df_array = []
    else:
        df_sOG = pd.json_normalize(json_data['data']['activities'],
        ['speedOverGround', 'speed'], ['id'], errors='ignore')
        df_sTW = pd.json_normalize(json_data['data']['activities'],
        ['speedThroughWater', 'speed'], ['id'], errors='ignore')

        # Create array from data frame
        df = df[pd.notnull(df)]
        df_array = df.to_numpy()


        # Json data to text
        Kind = pd.json_normalize(df_array[:,4])
        Kind_array = Kind.to_numpy()

        # Replace empty values with nan
        Voyage_raw = df_array[:,5]
        for i in range(len(Voyage_raw)):
            if type(Voyage_raw[i]) == float:
                Voyage_raw[i] = {'id': 'nan'}

        # Replace empty values with nan
        Voyage_raw_dest = df_array[:,5]
        for i in range(len(Voyage_raw_dest)):
            if type(Voyage_raw_dest[i]) == float:
                Voyage_raw_dest[i] = {'id': 'nan'}
```

```
# Json data to text
Voyage = pd.json_normalize(Voyage_raw)
Voyage_array = Voyage.to_numpy()



# Creating empty array for speed's
Speed = np.empty((len(df_array[:,5]),2))
Speed[:] = np.NaN

# Json data to text
df_sOG_array = df_sOG.to_numpy()
df_sTW_array = df_sTW.to_numpy()


# Linking the speed arrays to the df array by ID
for i in range(len(df_sOG)):
    sOG_ID = df_sOG.iloc[i,1]
    loc = df.index[df['id'] == '{}'.format(sOG_ID)].tolist()
    Speed[loc,0] = df_sOG_array[i,0]

for i in range(len(df_sTW)):
    sTW_ID = df_sTW.iloc[i,1]
    loc = df.index[df['id'] == '{}'.format(sTW_ID)].tolist()
    Speed[loc,1] = df_sTW_array[i,0]

# Json data to text
Captain = pd.json_normalize(df_array[:,7])
Captain_array = Captain.to_numpy()



# Delete wrong columns
df_array = np.delete(df_array,[4, 5, 7] ,1)

# Adding correct columns
# Columns 0 = start Time, 0 = end Time,
# 2 = avgLitersPerHour, 3 = Duration, 4 = activity ID,
# 5 = Distance over ground, 6 = Distance through water, 7 = activity name,
# 8 = Category name, 9 = voyage ID, 10 = Captian name
df_array = np.append(df_array, Speed, axis = 1)
df_array = np.append(df_array, Kind_array, axis = 1)
df_array = np.append(df_array, Voyage_array, axis = 1)

# Add name of captain
df_array = np.append(df_array, Captain_array, axis = 1)


# Sort for activities below 60 seconds and fuel of 0 (unrealistic values)
df_array = df_array[(df_array[:,3] >= 60) & (df_array[:,2] > 0)]

# calculate knots current
df_liter = np.empty((len(df_array),1))
df_liter[:] = np.NaN
for i in range(len(df_array)):
    df_liter[i,0] =  df_array[i,2]*df_array[i,3]/3600
```

```
        #Add Liter per NM
        df_literNM = np.empty((len(df_array),1))
        for i in range(len(df_array)):
            df_literNM[i,0] = df_liter[i,0]/df_array[i,6]

        # calculate knots current
        df_current = np.empty((len(df_array),1))
        df_current[:] = np.NaN
        for i in range(len(df_array)):
            if abs(df_array[i,5]-df_array[i,6]) != df_array[i,5] or
            abs(df_array[i,5]-df_array[i,6]) != df_array[i,6]:
                df_current[i,0] =  (df_array[i,6]-df_array[i,5])
                /(df_array[i,3]/3600)

        #Add Liter per NM
        df_literNMOG = np.empty((len(df_array),1))
        for i in range(len(df_array)):
            if df_array[i,5] != 0:
                df_literNMOG[i,0] = df_liter[i,0]/df_array[i,5]
            else:
                df_literNMOG[i,0] = np.NaN

        # Adding correct columns
        df_array = np.append(df_array, df_literNM, axis = 1)
        df_array = np.append(df_array, df_current, axis = 1)
        df_array = np.append(df_array, df_liter, axis = 1)
        df_array = np.append(df_array, df_literNMOG, axis = 1)

        # Add activities and number of activities during activity
        Start_Acticity = np.copy(df_array[:,7])
        Start_Acticity_array = np.array(Start_Acticity[:], copy=False,
        subok=True, ndmin=2).T
        Number_activities = np.ones(len(df_array))
        Number_activities_array = np.array(Number_activities[:],
        copy=False, subok=True, ndmin=2).T

        df_array = np.append(df_array, Start_Acticity_array, axis = 1)
        df_array = np.append(df_array, Number_activities_array, axis = 1)


        # string to time stamp
        for i in range(len(df_array)):
            df_array[i,0] = dateutil.parser.isoparse(df_array[i,0])
            df_array[i,1] = dateutil.parser.isoparse(df_array[i,1])

        for i in range(len(df_array[:,10])):
            if type(df_array[i,10]) == float:
               df_array[i,10] = 'nan'

    return df_array
```

A.1.4. Find Outliers

```
import numpy as np
```

```python
def Find_Outliers(df_array_Group, Limmits_outside, Vessels_used):
    Groupnames = list(df_array_Group[Vessels_used[0]].keys())

    # Create dicts with outliers
    Outliers_Bad = {}
    Outliers_Good = {}

    for x in range(len(Vessels_used)):
        Outliers_Bad_temp = {}
        Outliers_Good_temp = {}
        for z in range(len(Groupnames)):
            Outliers_Bad_temp[Groupnames[z]] = df_array_Group
            [Vessels_used[x]][Groupnames[z]][(df_array_Group
            [Vessels_used[x]][Groupnames[z]][:,2] >=
            Limmits_outside[Vessels_used[x]][Groupnames[z]][1])]
            Outliers_Bad[Vessels_used[x]] = Outliers_Bad_temp
            Outliers_Good_temp[Groupnames[z]] = df_array_Group
            [Vessels_used[x]][Groupnames[z]][(df_array_Group
            [Vessels_used[x]][Groupnames[z]][:,2] <=
            Limmits_outside[Vessels_used[x]][Groupnames[z]][0])]
            Outliers_Good[Vessels_used[x]] = Outliers_Good_temp

    # Calculate mean and range of the outliers
    Good_Outliers_range = {}
    Good_Outliers_mean = {}
    Bad_Outliers_mean = {}
    Bad_Outliers_range = {}
    Difference_Good_Bad = {}
    for x in range(len(Vessels_used)):
        Good_Outliers_mean_temp = {}
        Good_Outliers_range_temp = {}
        Bad_Outliers_mean_temp = {}
        Bad_Outliers_range_temp = {}
        Difference_Good_Bad_temp = {}
        for z in range(len(Groupnames)):
            if len(Outliers_Good[Vessels_used[x]][Groupnames[z]]) == 0:
                print('{} has no good outliers while {}'
                .format(Vessels_used[x], Groupnames[z]))
            else:
                Good_mean = np.zeros(len(Outliers_Good[Vessels_used[x]]
                [Groupnames[z]][0,:]))
                Bad_mean = np.zeros(len(Outliers_Bad[Vessels_used[x]]
                [Groupnames[z]][0,:]))
                Good_range = np.zeros(len(Outliers_Good[Vessels_used[x]]
                [Groupnames[z]][0,:]))
                Bad_range = np.zeros(len(Outliers_Bad[Vessels_used[x]]
                [Groupnames[z]][0,:]))
                # Check if there are outliers
                if len(Outliers_Bad[Vessels_used[x]][Groupnames[z]]) == 0:
                    print('{} has no Bad outliers while {}'
                    .format(Vessels_used[x], Groupnames[z]))
                elif len(Outliers_Good[Vessels_used[x]][Groupnames[z]]) == 0:
                     print('{} has no Good outliers while {}'
                     .format(Vessels_used[x], Groupnames[z]))
                else:
                    for y in range(len(Outliers_Bad[Vessels_used[x]]
```

```
[Groupnames[z]][0 ,:])):
    if type(Outliers_Bad[Vessels_used[x]]
    [Groupnames[z]][0 ,y]) == float or
    type(Outliers_Bad[Vessels_used[x]]
    [Groupnames[z]][0 ,y]) == int:
        Temp_bad = Outliers_Bad[Vessels_used[x]]
        [Groupnames[z]][: ,y]
        Temp_bad = [m for m in Temp_bad if
        np.isnan(m) == False]
        Bad_mean[y] = np.mean(Temp_bad)
        if len(Temp_bad) == 0:
            Bad_range[y] = 0
        else:
            Bad_range[y] = max(Temp_bad)
            − min(Temp_bad)

Bad_mean[5] = Bad_mean[5]*3600/Bad_mean[3]
Bad_mean[6] = Bad_mean[6]*3600/Bad_mean[3]

# Data in dict
Bad_Outliers_mean_temp[Groupnames[z]]
= Bad_mean
Bad_Outliers_mean[Vessels_used[x]]
= Bad_Outliers_mean_temp
Bad_Outliers_range_temp[Groupnames[z]]
= Bad_range
Bad_Outliers_range[Vessels_used[x]]
= Bad_Outliers_range_temp

for n in range(len(Outliers_Good[Vessels_used[x]]
[Groupnames[z]][0 ,:])):
    if type(Outliers_Good[Vessels_used[x]]
    [Groupnames[z]][0 ,n]) == float
    or type(Outliers_Good[Vessels_used[x]]
    [Groupnames[z]][0 ,n]) == int:
        Temp_Good = Outliers_Good[Vessels_used[x]]
        [Groupnames[z]][: ,n]
        Temp_Good = [m for m in Temp_Good
        if np.isnan(m) == False]
        Good_mean[n] = np.mean(Temp_Good)
        if len(Temp_Good) == 0:
            Good_range[n] = 0
        else:
            Good_range[n] = max(Temp_Good)
            − min(Temp_Good)

Good_mean[5] = Good_mean[5]*3600/Good_mean[3]
Good_mean[6] = Good_mean[6]*3600/Good_mean[3]

# Data in dict
Good_Outliers_mean_temp[Groupnames[z]]
= Good_mean
Good_Outliers_mean[Vessels_used[x]]
= Good_Outliers_mean_temp

Good_Outliers_range_temp[Groupnames[z]]
```

```
                    = Good_range
                    Good_Outliers_range[Vessels_used[x]]
                    = Good_Outliers_range_temp

                    Good_Bad_dif = np.zeros((2,len(Outliers_Good
                    [Vessels_used[x]][Groupnames[z]][0,:])))
                    for n in range(len(Outliers_Good[Vessels_used[x]]
                    [Groupnames[z]][0,:])):
                        if Bad_mean[n] != 0 and Good_mean[n] != 0:
                            Good_Bad_dif[0,n] = Bad_mean[n]-Good_mean[n]
                            Good_Bad_dif[1,n] = Bad_mean[n]/Good_mean[n]

                    Difference_Good_Bad_temp[Groupnames[z]]
                    = Good_Bad_dif
                    Difference_Good_Bad[Vessels_used[x]]
                    = Difference_Good_Bad_temp

    return Outliers_Bad, Outliers_Good, Bad_Outliers_mean,
    Good_Outliers_range, Bad_Outliers_range, Difference_Good_Bad
```

A.1.5. GetVesselData

```
from queries import queries
import datetime
from Sorting import Sorting
import csv


#%% Set the start date (year, month, day)
start_date = datetime.date( ,  ,  )

#%% Importing data
df_array, vessel = queries(start_date)

#%% Activities

Activities, Destinations, Groups = Sorting(vessel, df_array)

good_contracts = {}

good_contracts['Activity'] = Activities
good_contracts['Group'] = Groups

# write contracts to csv file
with open('Activity.csv', mode='w', newline='') as csv_file:
    fieldnames = list(good_contracts.keys())
    writer = csv.DictWriter(csv_file, delimiter=";", fieldnames=fieldnames)

    writer.writeheader()
    for i in range(len(good_contracts['Activity'])):
        d = {}
        for j in range(len(fieldnames)):
            d[fieldnames[j]] = good_contracts[fieldnames[j]][i]
        writer.writerow(d)
```

A.1.6. Golden sample

```
import matplotlib.pyplot as plt
import datetime
from datetime import date
import numpy as np
import random


def Golden_sample(df_array_Group, start_date, vessel_norm):
    Golden = {}
    Total_sample = {}
    Limmits_outside = {}
    x = 0
    Vessels_used = list(df_array_Group.keys())
    for x in range(len(Vessels_used)):
        Temp_dict_Golden = {}
        Temp_dict_Total = {}
        Groupnames = list(df_array_Group[Vessels_used[x]].keys())
        Limmits_outside_temp = {}
        for m in range(len(Groupnames)):
            start = start_date
            end_date = start + datetime.timedelta(days=7)
            n = 0
            sample_section = {}
            Total_sample_vessel = np.empty(0)
            Total_sample_array = np.empty((len(Vessels_used)))
            while end_date < date.today():
                z = 0
                sample = {}
                # Divide data by dates and put in dict
                for y in range(len(df_array_Group["{}".format(Vessels_used[x])]
                ["{}".format(Groupnames[m])])):
                    if df_array_Group["{}".format(Vessels_used[x])]
                    ["{}".format(Groupnames[m])][y,0].date() >= start
                    and df_array_Group[Vessels_used[x]]["{}"
                    .format(Groupnames[m])][y,0].date() < end_date:
                        sample[z] = df_array_Group[Vessels_used[x]]
                        ["{}".format(Groupnames[m])][y,:]
                        z += 1


                # Take an array out of the dict
                Fuel_array = np.empty((len(sample)))
                for q in range(len(sample)):
                    Fuel_array[q] = int(sample[q][2])

                # Find limits boxplot to fid sample
                B2 = plt.boxplot(df_array_Group[Vessels_used[x]]
                [Groupnames[m]][:,2])
                # Limmits_inside = [item.get_ydata()[0] for item
                in B2['whiskers']]
                Limmits_outside_temp[Groupnames[m]] = [item.get_ydata()[1]
                for item in B2['whiskers']]
                Limmits_outside[Vessels_used[x]] = Limmits_outside_temp
                plt.clf()
```

```
            # Select only the centralised data
            if len(Fuel_array) > 6:
                Fuel_array = Fuel_array[(Fuel_array
                >= Limmits_outside[Vessels_used[x]][Groupnames[m]][0])
                & (Fuel_array <= Limmits_outside[Vessels_used[x]]
                [Groupnames[m]][1])]
                if len(Fuel_array) < 5:
                    Fuel_array = np.empty((len(sample)))
                    Fuel_array[:] = np.NaN
                    for z in range(len(sample)):
                        Fuel_array[z] = int(sample[z][2])

                    Fuel_array = Fuel_array[(Fuel_array
                    >= Limmits_outside[Vessels_used[x]][Groupnames[m]][0])
                    & (Fuel_array <= Limmits_outside[Vessels_used[x]]
                    [Groupnames[m]][1])]

            else:
                 Fuel_array = np.empty(1)
                 Fuel_array[:] = np.NaN

            if len(Fuel_array) > 5:
                random.seed(3)
                Fuel_array = random.sample(list(Fuel_array), 5)
            else:
                Fuel_array = list(Fuel_array)

            sample_section[n] = Fuel_array
            Total_sample_vessel = np.concatenate((Total_sample_vessel,
            Fuel_array))
            start = end_date
            end_date = end_date + datetime.timedelta(days=7)
            n += 1

        nan_array_tot = np.isnan(Total_sample_vessel)
        not_nan_array_tot = ~ nan_array_tot
        Total_sample_array = Total_sample_vessel[not_nan_array_tot]

        Temp_dict_Golden["{}".format(Groupnames[m])] = sample_section
        Temp_dict_Total["{}".format(Groupnames[m])] = Total_sample_array

        Golden[Vessels_used[x]] = Temp_dict_Golden
        Total_sample[Vessels_used[x]] = Temp_dict_Total
        # Golden[vessel[0,2]][0][0]

# Calculate the mean
Mean_overall = {}
std_overall = {}
range_overall = {}

Mean = {}
Std = {}
Range = {}
for x in range(len(Vessels_used)):
    Mean_temp = {}
    Std_temp = {}
```

```
Range_temp = {}

Mean_overall_temp = {}
std_overall_temp = {}
range_overall_temp = {}
for m in range(len(Groupnames)):
    Mean_temp_temp = {}
    Std_temp_temp = {}
    Range_temp_temp = {}
    for i in range(len(Golden[Vessels_used[x]]["{}"
    .format(Groupnames[m])])):
        Mean_temp_temp[i] = np.mean(Golden[Vessels_used[x]]
        ["{}".format(Groupnames[m])][i])
        Mean_temp["{}".format(Groupnames[m])] = Mean_temp_temp
        Mean["{}".format(Vessels_used[x])] = Mean_temp

        Std_temp_temp[i] = np.std(Golden["{}".format(Vessels_used[x])]
        ["{}".format(Groupnames[m])][i])
        Std_temp["{}".format(Groupnames[m])] = Std_temp_temp
        Std["{}".format(Vessels_used[x])] = Std_temp

        Range_temp_temp[i] = max(Golden["{}".format(Vessels_used[x])]
        ["{}".format(Groupnames[m])][i])
        - min(Golden["{}".format(Vessels_used[x])]["{}"
        .format(Groupnames[m])][i])
        Range_temp["{}".format(Groupnames[m])] = Range_temp_temp
        Range["{}".format(Vessels_used[x])] = Range_temp


    # Dict back to array
    Mean_array = np.array(list(Mean[Vessels_used[x]]
    [Groupnames[m]].items()))
    #Calculating mean and put back in dict
    nan_array_mean = np.isnan(Mean_array[:,1])
    not_nan_array_mean = ~ nan_array_mean
    array_mean = Mean_array[:,1][not_nan_array_mean]
    Mean_overall_temp["{}".format(Groupnames[m])]
    = np.mean(array_mean[:])
    Mean_overall["{}".format(Vessels_used[x])]
    = Mean_overall_temp

    # Dict back to array
    Std_array = np.array(list(Std["{}"
    .format(Vessels_used[x])]["{}".format(Groupnames[m])].items()))
    #Calculating mean and put back in dict
    nan_array_std = np.isnan(Std_array[:,1])
    not_nan_array_std = ~ nan_array_std
    array_std = Std_array[:,1][not_nan_array_std]
    std_overall_temp["{}".format(Groupnames[m])]
    = np.std(array_std[:])
    std_overall["{}".format(Vessels_used[x])]
    = std_overall_temp

    # Dict back to array
    Range_array = np.array(list(Range["{}"
    .format(Vessels_used[x])]["{}".format(Groupnames[m])].items()))
```

```
            #Calculating mean and put back in dict
            nan_array_range = np.isnan(Range_array[:,1])
            not_nan_array_range = ~ nan_array_range
            array_range = Range_array[:,1][not_nan_array_range]
            range_overall_temp["{}".format(Groupnames[m])] = np.mean(array_range[:])
            range_overall["{}".format(Vessels_used[x])] = range_overall_temp

    # Output
    return Golden, Mean_overall, Total_sample, std_overall,
    Mean, Range, range_overall, sample, Limmits_outside
```

A.1.7. Group data

```
from General.AddOperation import AddOperation
import numpy as np


def Group_data(vessel, df_array, Groupnames, Groups_Activities):
    df_array_sorted = {}
    for x in range(len(vessel)):
        if type(df_array[vessel[x,2]]) != list:
            Temp_dict = {}
            for n in range(len(Groupnames)):
                Temp_tot = np.copy(df_array[vessel[x,2]])
                Temp_tot[:] = np.NaN
                q = 0
                for i in range(len(df_array[vessel[x,2]])):
                    if  df_array[vessel[x,2]][i,7] in
                    Groups_Activities[Groupnames[n]]:
                        Temp_tot[q,:] = df_array[vessel[x,2]][i,:]
                        q += 1
                Temp_dict[Groupnames[n]] = Temp_tot[0:q,:]
            df_array_sorted[vessel[x,2]] = Temp_dict

    # Add groups
    df_array_Group = {}
    for x in range(len(vessel)):
        if type(df_array[vessel[x,2]]) != list:
            Temp_dict = {}
            for y in range(len(Groupnames)):
                Temp_dict[Groupnames[y]]
                = AddOperation(df_array_sorted[vessel[x,2]][Groupnames[y]])
                df_array_Group[vessel[x,2]] = Temp_dict

    return df_array_Group
```

A.1.8. Groups

```
import csv
import numpy as np

def Groups():
    Activities = open('Activity.csv', 'r')
    reader = csv.reader(Activities, delimiter=";")

    # put data from file in var
```

```
    values = []
    for row in reader:
      values.append(row)
    Activities.close()

    Activities = np.array(values)

    Groups = {}
    q = np.delete(Activities, (0), axis=0)
    for n in range(len(q)):
        Groups["{}".format(q[n,1])] = q[:,0][(q[:,1] == q[n,1])]

    Groupnames = list(Groups.keys())
    return Groups, Groupnames
```

A.1.9. queries

```
import requests
from General.DataToMatrix import DataToMatrix
from get_access_Token import GetAccessToken
from General.GetVesselData import GetVesselData
from datetime import date
import datetime
import numpy as np


def queries(Begin):
    # Import accessToken and url from GetAccessToken
    Token, url = GetAccessToken()

    # Import vessel data, 0 = id, 1 = key, 2 = name
    vessel = GetVesselData()

    # Query for required data
    #                     activityType : {nameIn: ["In transit"]}
    query = """query VesselName($vessel : [String!], $FromTime : DateTime!,
    $UntillTime : DateTime!) {
      activities(where: { ship: { nameIn: $vessel }
      between: {from: $FromTime
      until: $UntillTime }
      }
      ) {
        voyage {
            id
            destinationLocation
          }
        durationSeconds
        id
        type {
            name
            category {
                name
                }
          }
        fuelConsumption {
          combined {
```

```
          start
          stop
          avgLitersPerHour
        }
      }
      speedOverGround {
        speed {
          nauticalMiles
        }
      }
      speedThroughWater {
        speed {
          nauticalMiles
        }
      }
      shift {
        captain {
            fullName
            }
      }
    }
  }"""

  df_array = {}
  #month = "{0:0=2d}".format(today.month)
  for x in range(len(vessel)):
      start_date = Begin
      end_date = start_date + datetime.timedelta(days=1)
      df_array_tot = []
      while end_date <= date(2022, 9, 21):
          # Sending request to graphqL
          r = requests.post(
              url,
              json={'query': query,
                    "operationName": "VesselName", "variables":
                          {"vessel": "{}".format(vessel[x,2]) ,
                           "FromTime": "{}-{}-{}T00:00:00Z".format(
                           start_date.year, "{0:0=2d}"
                           .format(start_date.month),
                           "{0:0=2d}".format(start_date.day)),
                          "UntillTime": "{}-{}-{}T00:00:00Z"
                          .format(end_date.year, "{0:0=2d}"
                          .format(end_date.month), "{0:0=2d}"
                          .format(end_date.day))}},
              headers={'Authorization': 'Bearer {}'.format(Token)}
              , timeout=100
              )

          df_array_temp = DataToMatrix(r)
          if type(df_array_temp) == list:
              df_array_temp = []
          elif len(df_array_temp) == 0:
              df_array_temp = []
          elif len(df_array_temp[0]) != 18:
              df_array_temp = []
          elif len(df_array_temp[0]) == 18 and len(df_array_tot) == 0:
```

```
                df_array_tot = df_array_temp
            else:
                df_array_tot = np.append(df_array_temp, df_array_tot, axis = 0)

            start_date = end_date
            end_date = end_date + datetime.timedelta(days=7)

        # Adding correct columns
        if len(df_array_tot) != 0:
            unique = np.copy(df_array_tot)
            n=0
            for z in range(len(df_array_tot)):
                if df_array_tot[z,4] != df_array_tot[z-1,4]:
                    unique[n,:] = df_array_tot[z,:]
                    n += 1
            df_array_new = unique[0:n,:]

        df_array["{}".format(vessel[x,2])] = df_array_new
    return df_array, vessel
```

A.1.10. Sorting

```
def Sorting(vessel, df_array):
    Activities = []
    Groups = []
    for x in range(len(vessel)):
        if type(df_array[vessel[x,2]]) != list:
            q = df_array["{}".format(vessel[x,2])][:,7]
            q_group = df_array["{}".format(vessel[x,2])][:,8]
            for n in range(len(q)):
                if q[n] not in Activities:
                    Activities.append(q[n])
                    Groups.append(q_group[n])

    # Get all unique destinations
    Destinations = []
    for x in range(len(vessel)):
        if type(df_array[vessel[x,2]]) != list:
            q = df_array["{}".format(vessel[x,2])][:,10]


            # Remove all double spaces
            for i in range(len(q)):
                q[i] = q[i].replace("␣␣", "␣")


            # Only select new inputs
            for n in range(len(q)):
                if q[n] not in Destinations:
                    Destinations.append(q[n])

    # Get all unique destinations
    Captains = []
    for x in range(len(vessel)):
        if type(df_array[vessel[x,2]]) != list:
            q = df_array["{}".format(vessel[x,2])][:,11]
```

```
            # Remove all capital letters
            for i in range(len(q)):
                q[i] = q[i].replace("□□", "□")

            # Only select new inputs
            for n in range(len(q)):
                if q[n] not in Captains:
                    Captains.append(q[n])

    # Sort destinations
    Destinations = sorted(Destinations)
    Captains = sorted(Captains)

    return Activities, Destinations, Groups, Captains
```

A.1.11. Statistical

```
import statsmodels.api as sm
import pylab
from scipy.stats import shapiro
from scipy.stats import anderson
from scipy.stats import kstest
from scipy.stats import norm
import datetime
import numpy as np
import matplotlib.pyplot as plt
import matplotlib.dates as mdates


def statistical_group(Mean_overall, Total_sample, Mean, Range, vessel_norm,
df_array_Group, start_date, range_overall, Vessels_used):
    vessel = Vessels_used
    Groupnames = list(df_array_Group[vessel[0]].keys())
    date_list = [start_date + datetime.timedelta(days=7*n) for n in range
    (len(Range["{}".format(vessel[0])]["{}".format(Groupnames[0])]))]
    week_list = list(range(1, len(date_list)+1))
    A2 = 0.577
    D3 = 0
    D4 = 2.114
    Length_Sample = {}
    for x in range(len(vessel)):
        Length_Sample_temp = {}
        for y in range(len(Groupnames)):
            # plot control chart
            mean_line = np.ones(len(df_array_Group[vessel[x]]
            [Groupnames[y]][:,2]))*Mean_overall[vessel[x]][Groupnames[y]]
            /max(df_array_Group[vessel[x]][Groupnames[y]][:,2])
            ulc = mean_line + range_overall[vessel[x]][Groupnames[y]]*A2
            /max(df_array_Group[vessel[x]][Groupnames[y]][:,2])
            llc = mean_line - range_overall[vessel[x]][Groupnames[y]]*A2
            /max(df_array_Group[vessel[x]][Groupnames[y]][:,2])
            plt.gca().xaxis.set_major_formatter(mdates.DateFormatter('%U'))
            plt.gca().xaxis.set_major_locator(mdates.DayLocator(interval=10))
            plt.plot(df_array_Group[vessel[x]][Groupnames[y]][:,0]
```

```
    -df_array_Group[vessel[x]][Groupnames[y]][:,0][-1]
    +datetime.date(2022, 1, 1),df_array_Group[vessel[x]]
    [Groupnames[y]][:,2]/max(df_array_Group[vessel[x]]
    [Groupnames[y]][:,2]))
    plt.plot(df_array_Group[vessel[x]][Groupnames[y]][:,0]
    -df_array_Group[vessel[x]][Groupnames[y]][:,0][-1]
    +datetime.date(2022, 1, 1),mean_line, label = 'Mean')
    plt.plot(df_array_Group[vessel[x]][Groupnames[y]][:,0]
    -df_array_Group[vessel[x]][Groupnames[y]][:,0][-1]
    +datetime.date(2022, 1, 1),ulc,'k--',
    label = 'Upper Control Limit')
    plt.plot(df_array_Group[vessel[x]][Groupnames[y]][:,0]
    -df_array_Group[vessel[x]][Groupnames[y]][:,0][-1]
    +datetime.date(2022, 1, 1),llc,'k-.',
    label = 'Lower Control Limit')
    plt.title("Control chart {} while {}".format(vessel_norm[x]
    , Groupnames[y]))
    plt.xlabel("Sample week")
    plt.ylabel("L/h [normalized]")
    plt.grid()
    plt.legend(fontsize = 'xx-small')
    plt.show()

    if len(Total_sample["{}".format(vessel[x])][Groupnames[y]]) == 0:
        print('{} has no inputs while {}'.format(vessel[x],
        Groupnames[y]))
    else:
        # Histogram
        plt.hist(Total_sample["{}".format(vessel[x])][Groupnames[y]]
        /max(Total_sample["{}".format(vessel[x])][Groupnames[y]]), bins=18)
        plt.title("Histogram {} while {}".format(vessel_norm[x]
        , Groupnames[y]))
        plt.ylabel("Frequency")
        plt.xlabel("L/h [normalized]")
        plt.grid()
        plt.show()

        # QQ-plot
        sm.qqplot(Total_sample["{}".format(vessel[x])][Groupnames[y]]
        /max(Total_sample[vessel[x]][Groupnames[y]]), line='s')
        plt.title("QQ-plot {} while {}".format(vessel_norm[x],
        Groupnames[y]))
        plt.grid()
        pylab.show()


        # Dict back to array
        Mean_array = np.array(list(Mean[vessel[x]][Groupnames[y]]
        .items()))
        #Calculating mean and put back in dict
        nan_array_mean = np.isnan(Mean_array[:,1])
        not_nan_array_mean = ~ nan_array_mean
        array_mean = Mean_array[:,1][not_nan_array_mean]
        Length_Sample_temp[Groupnames[y]] = len(array_mean)
        Length_Sample[vessel[x]] = Length_Sample_temp
```

```
Range_array = np.array(list(Range["{}".format(vessel[x])]
["{}".format(Groupnames[y])].items()))
#Calculating mean and put back in dict
nan_array_range = np.isnan(Range_array[:,1])
not_nan_array_range = ~ nan_array_range
array_range = Range_array[:,1][not_nan_array_range]

# Display what vessel
print('############ Normality test {} while {}
                ##############\n'.format(vessel_norm[x], Groupnames[y]))
if len(array_mean) < 3:
    print('Data must be at least length 3 to conduct
                    Shapiro test. \n')
else:
# normality test sharpio
    stat, p = shapiro(array_mean)
    print('Shapiro test {} while {}'.format(vessel_norm[x],
    Groupnames[y]))
    print('Statistics=%.3f, p=%.3f' % (stat, p))
    # interpret
    alpha = 0.05
    if p > alpha:
        print('Sample looks Gaussian (fail to reject H0) \n')
    else:
        print('Sample does not look Gaussian (reject H0) \n')


# Anderson-Darling test
result = anderson(array_mean)
print('Anderson test {} while {}'.format(vessel_norm[x],
Groupnames[y]))
print('Statistic: %.3f' % result.statistic)
p = 0
for i in range(len(result.critical_values)):
        sl, cv = result.significance_level[i], result
 .critical_values[i]
        if result.statistic < result.critical_values[i]:
         print('%.3f: %.3f, data looks normal
                          (fail to reject H0)' % (sl, cv))
         print('\n')
        else:
         print('%.3f: %.3f, data does not look normal
                          (reject H0)' % (sl, cv))
         print('\n')

# Kolmorogov-Smirnov test
loc, scale = norm.fit(array_mean)
n = norm(loc=loc, scale=scale)

stat, p = kstest(array_mean, n.cdf)
print('Kolmogorov-Smirnov test {} while {}'
.format(vessel_norm[x], Groupnames[y]))
print('Statistics=%.3f, p=%.3f' % (stat, p))
# interpret
alpha = 0.05
```

```
                if p > alpha:
                        print('Sample looks Gaussian
                                (fail to reject H0)\n')
                else:
                        print('Sample does not look Gaussian
                                (reject H0)\n')

                mean_line = (np.ones(len(Mean_array[:,1]))
                *Mean_overall[vessel[x]][Groupnames[y]])/max(array_mean)
                ulc = mean_line + (range_overall[vessel[x]]
                [Groupnames[y]]*A2)/max(array_mean)
                llc = mean_line - (range_overall[vessel[x]]
                [Groupnames[y]]*A2)/max(array_mean)
                plt.plot(week_list, Mean_array[:,1]
                /max(array_mean), marker='o')
                #plt.gcf().autofmt_xdate()
                plt.plot(week_list, mean_line, label
                = 'Mean')
                plt.plot(week_list, ulc,'k--', label
                = 'Upper Control Limit')
                plt.plot(week_list, llc,'k-.', label
                = 'Lower Control Limit')
                plt.title("Control chart {} while {}"
                .format(vessel_norm[x], Groupnames[y]))
                plt.xlabel("Sample week")
                plt.ylabel("L/h [normalized]")
                plt.grid()
                plt.legend(fontsize = 'small')
                plt.show()


                Range_line = np.ones(len(Range_array[:,1]))
                *range_overall[vessel[x]][Groupnames[y]]/max(array_range)
                ulc_Range = np.ones(len(Range_array[:,1]))
                *range_overall[vessel[x]][Groupnames[y]]*D4/max(array_range)
                llc_Range = np.ones(len(Range_array[:,1]))
                *range_overall[vessel[x]][Groupnames[y]]*D3/max(array_range)
                plt.plot(week_list, Range_array[:,1]
                /max(array_range), marker='o')
                #plt.gcf().autofmt_xdate()
                plt.plot(week_list, Range_line, label = 'Mean')
                plt.plot(week_list, ulc_Range,'k--',
                label = 'Upper Control Limit')
                plt.plot(week_list, llc_Range,'k-.',
                label = 'Lower Control Limit')
                plt.title("Range chart {} while {}"
                .format(vessel_norm[x], Groupnames[y]))
                plt.xlabel("Sample week")
                plt.ylabel("L/h [normalized]")
                plt.grid()
                plt.legend(fontsize = 'small')
                plt.show()

    return Length_Sample
```

A.1.12. Utility

```
import copy
import matplotlib.pyplot as plt
import numpy as np


def Utility(df_array, Vessels_used, Activities, Groups_Activities, vessel_norm):
    Utility = {}
    Utility_Group = {}
    vessel_number = 0
    for x in range(len(Vessels_used)):
        if type(df_array[Vessels_used[x]]) != list:
            Utility_array = np.zeros((len(Activities)+1, 2))
            for n in range(len(Activities)):
                Fuel = 0
                Time = 0
                for i in range(len(df_array[Vessels_used[x]][:,7])):
                    if df_array[Vessels_used[x]][i,7] == Activities[n]:
                        Fuel += df_array[Vessels_used[x]][i,14]
                        Time += df_array[Vessels_used[x]][i,3]
                Utility_array[n,0] = Fuel
                Utility_array[n,1] = Time
            Utility_array[len(Activities),0] =
            np.sum(df_array[Vessels_used[x]][:,14])
            Utility_array[len(Activities),1] =
            np.sum(df_array[Vessels_used[x]][:,3])

            Utility_string = copy.copy(Activities)
            Utility_string.append("Total")
            Utility[Vessels_used[x]] = Utility_array

            # Ulitity per group
            Groupnames = list(Groups_Activities.keys())
            Utility_group_array = np.zeros((len(Groupnames), 2))

            # Grouping the utilisation
            loc = {}
            for y in range(len(Groupnames)):
                loc_temp = np.empty((len(Groups_Activities[Groupnames[y]]),1))
                loc_temp[:] = np.NaN
                Fuel_group_temp = 0
                Time_group_temp = 0
                for z in range(len(Groups_Activities[Groupnames[y]])):
                    loc_temp[z] =
                    Utility_string.index(Groups_Activities[Groupnames[y]][z])
                    Fuel_group_temp +=
                    Utility[Vessels_used[x]][int(loc_temp[z]),0]
                    Time_group_temp +=
                    Utility[Vessels_used[x]][int(loc_temp[z]),1]
                Utility_group_array[y,0] = Fuel_group_temp
                Utility_group_array[y,1] = Time_group_temp

                Utility_Group[Vessels_used[x]] = Utility_group_array
                loc["{}".format(Groupnames[y])] = loc_temp
```

```
        # Plot all utilities
        r = np.arange(len(Activities))
        width = 0.25
        plt.bar(r, Utility_array[0:len(Activities),0]
        /Utility_array[len(Activities),0]*100, color = 'b',
                width = width, edgecolor = 'black',
                label='Fuel')
        plt.bar(r + width, Utility_array[0:len(Activities),1]
        /Utility_array[len(Activities),1]*100, color = 'g',
                width = width, edgecolor = 'black',
                label='Time')
        plt.xlabel('Fuel and Time Utilization')
        plt.ylabel('Percentage')
        plt.title('Utilization Fuel and Time {}'
        .format(vessel_norm[vessel_number]))
        # plt.grid(linestyle='--')
        plt.xticks(r + width/2,
        Utility_string[0:len(Activities)],rotation='vertical')
        plt.legend()
        plt.grid()
        plt.show()


        # Show Group Utility
        r = np.arange(len(Groupnames))
        width = 0.25
        plt.bar(r, Utility_group_array[:,0]
        /Utility_array[len(Activities),0]*100, color = 'b',
                width = width, edgecolor = 'black',
                label='Fuel')
        plt.bar(r + width, Utility_group_array[:,1]
        /Utility_array[len(Activities),1]*100, color = 'g',
                width = width, edgecolor = 'black',
                label='Time')
        plt.xlabel('Fuel and Time Utilization')
        plt.ylabel('Percentage')
        plt.title('Group Utilization Fuel and Time {}'
        .format(vessel_norm[vessel_number]))
        # plt.grid(linestyle='--')
        plt.xticks(r + width/2,Groupnames,rotation='vertical')
        plt.legend()
        plt.grid()
        plt.show()

        vessel_number += 1
    return Utility, Utility_string, Utility_Group
```

A.1.13. The activity download file

```
from queries import queries
import datetime
from Sorting import Sorting
import csv


#%% Set the start date (year, month, day)
```

```
start_date = datetime.date(2022, 4, 1)

#%% Importing data
df_array, vessel = queries(start_date)

#%% Activities

Activities, Destinations, Groups = Sorting(vessel, df_array)

good_contracts = {}

good_contracts['Activity'] = Activities
good_contracts['Group'] = Groups

# write activities to csv file
with open('Activity.csv', mode='w', newline='') as csv_file:
    fieldnames = list(good_contracts.keys())
    writer = csv.DictWriter(csv_file, delimiter=";", fieldnames=fieldnames)

    writer.writeheader()
    for i in range(len(good_contracts['Activity'])):
        d = {}
        for j in range(len(fieldnames)):
            d[fieldnames[j]] = good_contracts[fieldnames[j]][i]
        writer.writerow(d)
```

B

Case 1

B.1. Statistical Tests

B.1.1. First Analysis

Table B.1: The results of the statistical test of *Vessel 1* from *Company 1* while Idle.

Shapiro test		**Result**
Statistics	0.930	Fail to reject H0
p	0.138	Data looks Gaussian
Anderson test		
Statistics	0.492	
p @15%	0.508	Fail to reject H0 Data looks normal
p @10%	0.579	Fail to reject H0 Data looks normal
p @5%	0.694	Fail to reject H0 Data looks normal
p @2.5%	0.810	Fail to reject H0 Data looks normal
p @1%	0.963	Fail to reject H0 Data looks normal
Kolmogorov-Smirnov test		
Statistics	0.161	Fail to reject H0
p	0.592	Data looks Gaussian

Table B.2: The results of the statistical test of *Vessel 1* from *Company 1* while active.

Shapiro test		**Result**
Statistics	0.892	Reject H0
p	0.002	Data does not look Gaussian

Anderson test		
Statistics	1.033	
p @15%	0.528	Reject H0 Data does not look normal
p @10%	0.601	Reject H0 Data does not look normal
p @5%	0.721	Reject H0 Data does not look normal
p @2.5%	0.841	Reject H0 Data does not look normal
p @1%	1.000	Reject H0 Data does not look normal

Kolmogorov-Smirnov test		
Statistics	0.165	Fail to reject H0
p	0.254	Data looks Gaussian

Table B.3: The results of the statistical test of *Vessel 1* from *Company 1* while in transit.

Shapiro test		**Result**
Statistics	0.986	Fail to reject H0
p	0.948	Data looks Gaussian

Anderson test		
Statistics	0.127	
p @15%	0.522	Fail to reject H0 Data looks normal
p @10%	0.595	Fail to reject H0 Data looks normal
p @5%	0.713	Fail to reject H0 Data looks normal
p @2.5%	0.832	Fail to reject H0 Data looks normal
p @1%	0.990	Fail to reject H0 Data looks normal

Kolmogorov-Smirnov test		
Statistics	0.068	Fail to reject H0
p	0.997	Data looks Gaussian

Table B.4: The results of the statistical test of *Vessel 1* from *Company 1* while Waiting.

Shapiro test		**Result**
Statistics	0.956	Fail to reject H0
p	0.301	Data looks Gaussian
Anderson test		
Statistics	0.574	
p @15%	0.517	Reject H0 Data does not look normal
p @10%	0.589	Fail to reject H0 Data looks normal
p @5%	0.707	Fail to reject H0 Data looks normal
p @2.5%	0.824	Fail to reject H0 Data looks normal
p @1%	0.980	Fail to reject H0 Data looks normal
Kolmogorov-Smirnov test		
Statistics	0.165	Fail to reject H0
p	0.408	Data looks Gaussian

B.1.2. Second Analysis

Table B.5: The second results of the statistical test of *Vessel 1* from *Company 1* while Active.

Shapiro test		**Result**
Statistics	0.943	Fail to reject H0
p	0.070	Data looks Gaussian
Anderson test		
Statistics	0.636	
p @15%	0.527	Reject H0 Data does not look normal
p @10%	0.600	Reject H0 Data does not look normal
p @5%	0.719	Fail to reject H0 Data looks normal
p @2.5%	0.839	Fail to reject H0 Data looks normal
p @1%	0.998	Fail to reject H0 Data looks normal
Kolmogorov-Smirnov test		
Statistics	0.127	Fail to reject H0
p	0.577	Data looks Gaussian

C

Case 2

C.1. Statistical Tests

C.1.1. First Analysis *Vessel 1*

Table C.1: The results of the statistical test of *Vessel 1* from *Company 2* while Idle.

Shapiro test		**Result**
Statistics	0.966	Fail to reject H0
p	0.772	Data looks Gaussian
Anderson test		
Statistics	0.194	
p @15%	0.500	Fail to reject H0 Data looks normal
p @10%	0.569	Fail to reject H0 Data looks normal
p @5%	0.683	Fail to reject H0 Data looks normal
p @2.5%	0.797	Fail to reject H0 Data looks normal
p @1%	0.948	Fail to reject H0 Data looks normal
Kolmogorov-Smirnov test		
Statistics	0.110	Fail to reject H0
p	0.978	Data looks Gaussian

Table C.2: The results of the statistical test of *Vessel 1* from *Company 2* while active.

Shapiro test		**Result**
Statistics	0.956	Fail to reject H0
p	0.340	Data looks Gaussian

Anderson test		
Statistics	0.430	
p @15%	0.514	Fail to reject H0 Data looks normal
p @10%	0.586	Fail to reject H0 Data looks normal
p @5%	0.703	Fail to reject H0 Data looks normal
p @2.5%	0.820	Fail to reject H0 Data looks normal
p @1%	0.975	Fail to reject H0 Data looks normal

Kolmogorov-Smirnov test		
Statistics	0.125	Fail to reject H0
p	0.788	Data looks Gaussian

Table C.3: The results of the statistical test of *Vessel 1* from *Company 2* while in transit.

Shapiro test		**Result**
Statistics	0.977	Fail to reject H0
p	0.632	Data looks Gaussian

Anderson test		
Statistics	0.352	
p @15%	0.528	Fail to reject H0 Data looks normal
p @10%	0.601	Fail to reject H0 Data looks normal
p @5%	0.721	Fail to reject H0 Data looks normal
p @2.5%	0.841	Fail to reject H0 Data looks normal
p @1%	1.000	Fail to reject H0 Data looks normal

Kolmogorov-Smirnov test		
Statistics	0.123	Fail to reject H0
p	0.600	Data looks Gaussian

Table C.4: The results of the statistical test of *Vessel 1* from *Company 2* while waiting.

Shapiro test		**Result**
Statistics	0.916	Fail to reject H0
p	0.475	Data looks Gaussian
Anderson test		
Statistics	0.320	
p @15%	0.592	Fail to reject H0 Data looks normal
p @10%	0.675	Fail to reject H0 Data looks normal
p @5%	0.809	Fail to reject H0 Data looks normal
p @2.5%	0.944	Fail to reject H0 Data looks normal
p @1%	1.123	Fail to reject H0 Data looks normal
Kolmogorov-Smirnov test		
Statistics	0.229	Fail to reject H0
p	0.851	Data looks Gaussian

C.1.2. First Analysis *Vessel 2*

Table C.5: The results of the statistical test of *Vessel 2* from *Company 2* while Idle.

Shapiro test		**Result**
Statistics	0.917	Fail to reject H0
p	0.367	Data looks Gaussian
Anderson test		
Statistics	0.325	
p @15%	0.507	Fail to reject H0 Data looks normal
p @10%	0.578	Fail to reject H0 Data looks normal
p @5%	0.693	Fail to reject H0 Data looks normal
p @2.5%	0.808	Fail to reject H0 Data looks normal
p @1%	0.961	Fail to reject H0 Data looks normal
Kolmogorov-Smirnov test		
Statistics	0.181	Fail to reject H0
p	0.880	Data looks Gaussian

Table C.6: The results of the statistical test of *Vessel 2* from *Company 2* while active.

Shapiro test		**Result**
Statistics	0.913	Fail to reject H0
p	0.083	Data looks Gaussian
Anderson test		
Statistics	0.527	
p @15%	0.505	Reject H0 Data does not look normal
p @10%	0.575	Fail to reject H0 Data looks normal
p @5%	0.690	Fail to reject H0 Data looks normal
p @2.5%	0.804	Fail to reject H0 Data looks normal
p @1%	0.957	Reject H0 Data looks normal
Kolmogorov-Smirnov test		
Statistics	0.136	Fail to reject H0
p	0.830	Data looks Gaussian

Table C.7: The results of the statistical test of *Vessel 2* from *Company 2* while in transit.

Shapiro test		**Result**
Statistics	0.950	Fail to reject H0
p	0.396	Data looks Gaussian
Anderson test		
Statistics	0.347	
p @15%	0.505	Fail to reject H0 Data looks normal
p @10%	0.575	Fail to reject H0 Data looks normal
p @5%	0.690	Fail to reject H0 Data looks normal
p @2.5%	0.804	Fail to reject H0 Data looks normal
p @1%	0.957	Fail to reject H0 Data looks normal
Kolmogorov-Smirnov test		
Statistics	0.113	Fail to reject H0
p	0.945	Data looks Gaussian

Table C.8: The results of the statistical test of *Vessel 2* from *Company 2* while Waiting.

Shapiro test		**Result**
Statistics	0.801	Reject H0
p	0.015	Data does not looks Gaussian
Anderson test		
Statistics	0.876	
p @15%	0.501	Reject H0 Data does not look normal
p @10%	0.570	Reject H0 Data does not look normal
p @5%	0.684	Reject H0 Data does not look normal
p @2.5%	0.798	Reject H0 Data does not look normal
p @1%	0.950	Fail to reject H0 Data looks normal
Kolmogorov-Smirnov test		
Statistics	0.280	Fail to reject H0
p	0.348	Data looks Gaussian

C.2. Statistical Tests

C.2.1. Second Analysis *Vessel 1*

Table C.9: The results after updates of the statistical test of *Vessel 1* from *Company 2* while active.

Shapiro test		**Result**
Statistics	0.976	Fail to reject H0
p	0.823	Data looks Gaussian
Anderson test		
Statistics	0.176	
p @15%	0.513	Fail to reject H0 Data looks normal
p @10%	0.584	Fail to reject H0 Data looks normal
p @5%	0.701	Fail to reject H0 Data looks normal
p @2.5%	0.817	Fail to reject H0 Data looks normal
p @1%	0.972	Fail to reject H0 Data looks normal
Kolmogorov-Smirnov test		
Statistics	0.082	Fail to reject H0
p	0.993	Data looks Gaussian

Table C.10: The results after updates of the statistical test of *Vessel 1* from *Company 2* while in transit.

Shapiro test		**Result**
Statistics	0.972	Fail to reject H0
p	0.564	Data looks Gaussian
Anderson test		
Statistics	0.381	
p @15%	0.523	Fail to reject H0 Data looks normal
p @10%	0.596	Fail to reject H0 Data looks normal
p @5%	0.715	Fail to reject H0 Data looks normal
p @2.5%	0.834	Fail to reject H0 Data looks normal
p @1%	0.992	Fail to reject H0 Data looks normal
Kolmogorov-Smirnov test		
Statistics	0.104	Fail to reject H0
p	0.843	Data looks Gaussian

C.2.2. Second Analysis *Vessel 2*

Table C.11: The results after updates of the statistical test of *Vessel 2* from *Company 2* while active.

Shapiro test		**Result**
Statistics	0.944	Fail to reject H0
p	0.363	Data looks Gaussian
Anderson test		
Statistics	0.320	
p @15%	0.501	Fail to reject H0 Data looks normal
p @10%	0.571	Fail to reject H0 Data looks normal
p @5%	0.685	Fail to reject H0 Data looks normal
p @2.5%	0.799	Fail to reject H0 Data looks normal
p @1%	0.951	Reject H0 Data looks normal
Kolmogorov-Smirnov test		
Statistics	0.115	Fail to reject H0
p	0.960	Data looks Gaussian

Table C.12: The results after updates of the statistical test of *Vessel 2* from *Company 2* while in transit.

Shapiro test		**Result**
Statistics	0.973	Fail to reject H0
p	0.819	Data looks Gaussian
Anderson test		
Statistics	0.242	
p @15%	0.506	Fail to reject H0 Data looks normal
p @10%	0.577	Fail to reject H0 Data looks normal
p @5%	0.692	Fail to reject H0 Data looks normal
p @2.5%	0.807	Fail to reject H0 Data looks normal
p @1%	0.960	Fail to reject H0 Data looks normal
Kolmogorov-Smirnov test		
Statistics	0.104	Fail to reject H0
p	0.843	Data looks Gaussian

D

Case 3

D.1. Statistical Tests

D.1.1. First Analysis *Vessel 1* Over 40 Weeks

Table D.1: The results of the statistical test of *Vessel 1* from *Company 3* while Idle.

Shapiro test		**Result**
Statistics	0.903	Reject H0
p	0.006	Data does not look Gaussian
Anderson test		
Statistics	1.052	
p @15%	0.524	Reject H0 Data does not look normal
p @10%	0.597	Reject H0 Data does not look normal
p @5%	0.717	Reject H0 Data does not look normal
p @2.5%	0.836	Reject H0 Data does not look normal
p @1%	0.994	Reject H0 Data does not look normal
Kolmogorov-Smirnov test		
Statistics	0.145	Fail to reject H0
p	0.445	Data looks Gaussian

Table D.2: The results of the statistical test of *Vessel 1* from *Company 3* while active.

Shapiro test		**Result**
Statistics	0.962	Fail to reject H0
p	0.306	Data looks Gaussian
Anderson test		
Statistics	0.290	
p @15%	0.523	Fail to reject H0 Data looks normal
p @10%	0.596	Fail to reject H0 Data looks normal
p @5%	0.715	Fail to reject H0 Data looks normal
p @2.5%	0.834	Fail to reject H0 Data looks normal
p @1%	0.992	Fail to reject H0 Data looks normal
Kolmogorov-Smirnov test		
Statistics	0.096	Fail to reject H0
p	0.899	Data looks Gaussian

Table D.3: The results of the statistical test of *Vessel 1* from *Company 3* while in transit.

Shapiro test		**Result**
Statistics	0.728	Reject H0
p	0.000	Data does not look Gaussian
Anderson test		
Statistics	3.137	
p @15%	0.528	Reject H0 Data does not look normal
p @10%	0.601	Reject H0 Data does not look normal
p @5%	0.721	Reject H0 Data does not look normal
p @2.5%	0.841	Reject H0 Data does not look normal
p @1%	1.000	Reject H0 Data does not look normal
Kolmogorov-Smirnov test		
Statistics	0.257	Reject H0
p	0.014	Data does not look Gaussian

Table D.4: The results of the statistical test of *Vessel 1* from *Company 3* while waiting.

Shapiro test		**Result**
Statistics	0.902	Reject H0
p	0.008	Data does not look Gaussian
Anderson test		
Statistics	1.033	
p @15%	0.522	Reject H0 Data does not look normal
p @10%	0.595	Reject H0 Data does not look normal
p @5%	0.713	Reject H0 Data does not look normal
p @2.5%	0.832	Reject H0 Data does not look normal
p @1%	0.990	Reject H0 Data does not look normal
Kolmogorov-Smirnov test		
Statistics	0.172	Fail to reject H0
p	0.286	Data looks Gaussian

D.1.2. First Analysis *Vessel 2* Over 40 Weeks

Table D.5: The results of the statistical test of *Vessel 2* from *Company 3* while Idle.

Shapiro test		**Result**
Statistics	0.778	Reject H0
p	0.000	Data does not looks Gaussian
Anderson test		
Statistics	2.906	
p @15%	0.524	Reject H0 Data does not look normal
p @10%	0.597	Reject H0 Data does not look normal
p @5%	0.717	Reject H0 Data does not look normal
p @2.5%	0.836	Reject H0 Data does not look normal
p @1%	0.994	Reject H0 Data does not look normal
Kolmogorov-Smirnov test		
Statistics	0.262	Reject H0
p	0.017	Data does not look Gaussian

Table D.6: The results of the statistical test of *Vessel 2* from *Company 3* while active.

Shapiro test		**Result**
Statistics	0.913	Reject H0
p	0.010	Data does not look Gaussian

Anderson test		
Statistics	0.836	
p @15%	0.526	Reject H0 Data does not look normal
p @10%	0.599	Reject H0 Data does not look normal
p @5%	0.718	Reject H0 Data does not look normal
p @2.5%	0.838	Fail to reject H0 Data looks normal
p @1%	0.996	Fail to reject H0 Data looks normal

Kolmogorov-Smirnov test		
Statistics	0.167	Fail to reject H0
p	0.270	Data looks Gaussian

Table D.7: The results of the statistical test of *Vessel 2* from *Company 3* while in transit.

Shapiro test		**Result**
Statistics	0.925	Reject H0
p	0.019	Data does not look Gaussian

Anderson test		
Statistics	0.987	
p @15%	0.527	Reject H0 Data does not look normal
p @10%	0.600	Reject H0 Data does not look normal
p @5%	0.719	Reject H0 Data does not look normal
p @2.5%	0.839	Reject H0 Data does not look normal
p @1%	0.998	Fail to reject H0 Data looks normal

Kolmogorov-Smirnov test		
Statistics	0.159	Fail to reject H0
p	0.308	Data looks Gaussian

Table D.8: The results of the statistical test of *Vessel 2* from *Company 3* while Waiting.

Shapiro test		**Result**
Statistics	0.890	Reject H0
p	0.003	Data does not look Gaussian
Anderson test		
Statistics	1.179	
p @15%	0.526	Reject H0 Data does not look normal
p @10%	0.599	Reject H0 Data does not look normal
p @5%	0.718	Reject H0 Data does not look normal
p @2.5%	0.838	Reject H0 Data does not look normal
p @1%	0.996	Reject H0 Data does not look normal
Kolmogorov-Smirnov test		
Statistics	0.168	Fail to reject H0
p	0.261	Data looks Gaussian

D.1.3. Second Analysis *Vessel 1* Over 20 Weeks

Table D.9: The results of the statistical test of *Vessel 1* from *Company 3* while Idle.

Shapiro test		**Result**
Statistics	0.897	Fail to reject H0
p	0.052	Data looks Gaussian
Anderson test		
Statistics	0.703	
p @15%	0.503	Reject H0 Data does not look normal
p @10%	0.573	Reject H0 Data does not look normal
p @5%	0.687	Reject H0 Data does not look normal
p @2.5%	0.802	Fail to reject H0 Data looks normal
p @1%	0.954	Fail to reject H0 Data looks normal
Kolmogorov-Smirnov test		
Statistics	0.192	Fail to reject H0
p	0.465	Data looks Gaussian

Table D.10: The results of the statistical test of *Vessel 1* from *Company 3* while active.

Shapiro test		**Result**
Statistics	0.952	Fail to reject H0
p	0.406	Data looks Gaussian
Anderson test		
Statistics	0.333	
p @15%	0.506	Fail to reject H0 Data looks normal
p @10%	0.577	Fail to reject H0 Data looks normal
p @5%	0.692	Fail to reject H0 Data looks normal
p @2.5%	0.807	Fail to reject H0 Data looks normal
p @1%	0.960	Fail to reject H0 Data looks normal
Kolmogorov-Smirnov test		
Statistics	0.126	Fail to reject H0
p	0.871	Data looks Gaussian

Table D.11: The results of the statistical test of *Vessel 1* from *Company 3* while in transit.

Shapiro test		**Result**
Statistics	0.983	Fail to reject H0
p	0.963	Data looks Gaussian
Anderson test		
Statistics	0.204	
p @15%	0.508	Fail to reject H0 Data looks normal
p @10%	0.579	Fail to reject H0 Data looks normal
p @5%	0.694	Fail to reject H0 Data looks normal
p @2.5%	0.810	Fail to reject H0 Data looks normal
p @1%	0.963	Fail to reject H0 Data looks normal
Kolmogorov-Smirnov test		
Statistics	0.122	Fail to reject H0
p	0.879	Data looks Gaussian

Table D.12: The results of the statistical test of *Vessel 1* from *Company 3* while waiting.

Shapiro test		**Result**
Statistics	0.927	Fail to reject H0
p	0.172	Data looks Gaussian
Anderson test		
Statistics	0.426	
p @15%	0.503	Fail to reject H0 Data looks normal
p @10%	0.573	Fail to reject H0 Data looks normal
p @5%	0.687	Fail to reject H0 Data looks normal
p @2.5%	0.802	Fail to reject H0 Data looks normal
p @1%	0.954	Fail to reject H0 Data looks normal
Kolmogorov-Smirnov test		
Statistics	0.156	Fail to reject H0
p	0.720	Data looks Gaussian

D.1.4. Second Analysis *Vessel 2* Over 20 Weeks

Table D.13: The results of the statistical test of *Vessel 2* from *Company 3* while Idle.

Shapiro test		**Result**
Statistics	0.902	Fail to reject H0
p	0.052	Data looks Gaussian
Anderson test		
Statistics	0.641	
p @15%	0.505	Reject H0 Data does not look normal
p @10%	0.575	Reject H0 Data does not look normal
p @5%	0.690	Fail to reject H0 Data looks normal
p @2.5%	0.804	Fail to reject H0 Data looks normal
p @1%	0.957	Fail to reject H0 Data looks normal
Kolmogorov-Smirnov test		
Statistics	0.182	Fail to reject H0
p	0.498	Data looks Gaussian

Table D.14: The results of the statistical test of *Vessel 2* from *Company 3* while active.

Shapiro test		**Result**
Statistics	0.958	Fail to reject H0
p	0.536	Data looks Gaussian

Anderson test		
Statistics	0.326	
p @15%	0.505	Fail to reject H0 Data looks normal
p @10%	0.575	Fail to reject H0 Data looks normal
p @5%	0.690	Fail to reject H0 Data looks normal
p @2.5%	0.804	Fail to reject H0 Data looks normal
p @1%	0.957	Fail to reject H0 Data looks normal

Kolmogorov-Smirnov test		
Statistics	0.157	Fail to reject H0
p	0.681	Data looks Gaussian

Table D.15: The results of the statistical test of *Vessel 2* from *Company 3* while in transit.

Shapiro test		**Result**
Statistics	0.926	Fail to reject H0
p	0.128	Data looks Gaussian

Anderson test		
Statistics	0.557	
p @15%	0.506	Reject H0 Data does not look normal
p @10%	0.577	Fail to reject H0 Data looks normal
p @5%	0.692	Fail to reject H0 Data looks normal
p @2.5%	0.807	Fail to reject H0 Data looks normal
p @1%	0.960	Fail to reject H0 Data looks normal

Kolmogorov-Smirnov test		
Statistics	0.151	Fail to reject H0
p	0.698	Data looks Gaussian

Table D.16: The results of the statistical test of *Vessel 2* from *Company 3* while waiting.

Shapiro test		**Result**
Statistics	0.939	Fail to reject H0
p	0.248	Data looks Gaussian

Anderson test		
Statistics	0.457	
p @15%	0.505	Fail to reject H0 Data looks normal
p @10%	0.575	Fail to reject H0 Data looks normal
p @5%	0.690	Fail to reject H0 Data looks normal
p @2.5%	0.804	Fail to reject H0 Data looks normal
p @1%	0.957	Reject H0 Data looks normal

Kolmogorov-Smirnov test		
Statistics	0.145	Fail to reject H0
p	0.768	Data looks Gaussian