Energy Efficiency - The Data-driven Decision Support System Perspective

A Case Study About Long Distance Towage for Boskalis

Casper S. van Nie

Master of Science Thesis: SDPO.19.008.m.

TU Delft

Energy Efficiency - The Data-driven Decision Support System Perspective

A Case Study About Long Distance Towage for Boskalis

by

Casper S. van Nie

to obtain the degree of Master of Science
at the Delft University of Technology,
to be defended publicly on Tuesday April 30th, 2019 at 10:00 AM.

Student number:	4204476	
Project duration:	May 1, 2018 – April 30, 2019	
Thesis committee:	Prof. ir. J.J Hopman,	TU Delft, chairman
	Ir. J. W. Frouws,	TU Delft, supervisor
	Dr. ing. S. Schreier	TU Delft
	G. A. H. Steentjes (BSc),	Boskalis

This thesis is confidential and cannot be made public until May 1, 2024.

Preface

This thesis is the result of my graduation project for the completion of the Master Marine Technology at Delft University of Technology. The project was initiated by the head office of Boskalis Westminster N.V at which I have been a graduate intern at the Offshore Energy Fleet Management department. I was engaged in the initiatives to improve energy efficiency of the fleet and wrote this thesis from May 2018 to April 2019. The readers of this thesis are expected to have foreknowledge about Marine Engineering, Statistics and preferable about Information System Development. This document lays a foundation for an information system to monitor and improve energy efficiency of work vessels at Boskalis Offshore Energy, which will be implemented for the entire Boskalis fleet after my graduation.

I am proud of the result and very satisfied about the process towards this. The type of work I did for my research was very well aligned with my interests and goals I had for a graduation project, which has kept me motivated and enthusiastic during the past months. The support I got from my daily supervisors - Gaby Steentjes and Koos Frouws - has contributed enormously to the result. Gaby, I would like to thank you for your extensive involvement, inspiration from practise experience, valuable feedback and unlimited enthusiasm. Your trust and the freedom gave me to carrying out my research, to develop my own perspective and do meaningful work for Boskalis. Koos, I would like to thanks you for sharing your scientific experience, honest opinion about my writings and drawing the link between theory and practise.

Finishing this project is a personal milestone marking the end of six amazing years of studying in Delft and rewards the decision for going back to pre-university after one year of college. My deepest gratitude goes to my mother who has always supported me during this time. Your continuous support helped me making the right decisions and taking the opportunities which has made my study time the amazing time it was. Besides I am grateful to me girlfriend, who supported me during the most socially isolated winter months. Thank you for everything.

Casper S. van Nie
Rotterdam, February 2019

Glossary

Abbreviations	
AI	Artificial Intelligence
BID	Business Intelligence Design
BPMN	Business Process Modelling Notation
PMS	Performance Monitoring System
CPP	Controllable Pitch Propeller
CSR	Corporate Social Responsibility
DP	Dynamic Positioning
DSS	Decision Support System
EDA	Exploratory Data Analysis
EEDI	Energy Efficiency Design Index
EEOI	Energy Efficiency Operational Index
ERD	Entity Relationship Diagram
GHG	Green House Gas
GloMEEP	Global Maritime Energy Efficiency Partnerships
HFO	Heavy Fuel Oil
IRR	Internal Rate of Return
IMO	International Maritime Organisation
KPI	Key Performance Indicator
LTD	Long Distance Towage
MCR	Maximal Continuous Rating
MEPC	Marine Environment Protection Committee
ML	Machine Learning
MGO	Marine Gas Oil
NPV	Net Present Value
OED	Offshore Energy Division
ORC	Organic Rankin Cycle
PI	Performance Indicator
QFD	Quality Function Deployment
RPM	Revolutions Per Minute
SEEMP	Ship Energy Efficiency Management Plan
SFOC	Specific Fuel Oil Consumption
SPI	Shipping Performance Indicator
SNA	Social Network Analysis
WHR	Waste Heat Recovery

List of Figures

List of Tables

Summary

The global Offshore Energy recession since 2015 and the increased threat from Asian competitors made the Boskalis Offshore Energy Division have to "tighten their belt". Moreover, to prevent human induced irreversible disastrous climate change, the IMO introduced their Green House Gas reduction strategy. This requires Boskalis to reduce fleet carbon emissions with 40% and 50% in respectively 2030 and 2050 compared to 2008. Currently, the Boskalis Offshore Energy Division is unable to quantify and improve the energy efficiency of their fleet, since the required operational information is not available for data-driven decision making. Nevertheless, the digital revolution gives the opportunity to collect, transfer and analyse large amounts of data onshore for energy efficiency control and cost-effective improvements.

The objective is to develop a data-driven decision support system for cost-effective improvement of the fleet's energy efficiency, to (i) create competitive advantage for Boskalis, (ii) reduce operational energy costs and inherently (iii) comply with future law and legislation about energy efficiency and carbon emissions.

To fulfil this objective, a method is composed from Information System Development Theory and Data Science. With this method a conceptual Business Intelligence Design for the Offshore Energy Division is developed and applied to the Long Distance Towage case study for development of the detailed prototype.
This conceptual Business Intelligence Design enables Boskalis to communicate the insights from operational data to all management levels for data-driven Decision Support. The Business Intelligence Design phase identified eight different vessel categories and introduces the data-driven organisation and decision hierarchy model. The performance control model for work vessels is developed, which is a composition of concepts about the marine drive chain, sensor technology and operational profile description. These two developed models required specified data input, which is used for the ideal database development and within the case study for data collection.
The built prototype for Long Distance Towage quantifies the operational vessel profile, enables performance monitoring and supports optimisation decisions. One dimensionless Shipping Performance Indicator is formulated to quantify the overall energy efficiency of the Long Distance Towage, which can internally be used for strategic control and possibly for legislation. The Key Performance Indicator of the quantified operational modes are related to benchmarks and targets for fuel efficiency control at tactical organisation level. To control energy efficiency, the Performance Indicators were integrated within the Business Process Modelling Notation. The developed prototype gives performance insights to make decisions about engines, hotel and auxiliary performance optimisation. For example, the insights quantified the rapid decrease of engine efficiency over time after an overhaul. Based on these insights different measures were considered for optimisation. These measures to improve energy efficiency were classified by their payback periods and "data readiness". This way, the quick and more long term wins for energy efficiency improvement were identified.

The data-driven decision support system gives a competitive advantage by the cost-effective improvement of the fleet's energy efficiency and by the controlled compliance with the IMO Greenhouse Gas Reduction Strategy. The conceptual Business Intelligence Design provides the foundation for data-driven decision support about energy efficiency for the entire Offshore Energy fleet. Boskalis Long Distance Towage department can cost-effectively improve their energy efficiency by 40% toward 2030 with respect to 2008 and thereby fully comply with the outlines of the IMO Greenhouse Gas Reduction Strategy.
Boskalis offshore energy is recommanded to implement a Data-driven Decision Support System to manage the cost-effective energy efficiency improvement and the reduction of carbon emission. The organisational awareness and willingness to improve is a prerequisition for successful implementation.

Contents

Chapter 1

Introduction

The topic of this master thesis is about how the concept of a data-driven decisions support system can help to improve the energy efficiency of shipping at Boskalis in a cost-effective manner. The situation and complication of Boskalis are explained in the background below (see section 1.1). In the objective is stated how the complications within the current situation can be solved (see section 1.2). The scope is explained, about what will be done for achieving the stated objective (see section 1.3). The thesis outline includes the reading manual of this master thesis (see section 1.4).

1.1 Background

Boskalis owns 900 floating assets, that together emits 600 and 800 thousand tons of CO_2 every year. The international authorities will increasingly hold Boskalis responsible for these emissions. The concerns about the global warming made the United Nations (UN) formulate their global Greenhouse Gas (GHG) reduction strategy. As a consequence, the International Maritime Organisation (IMO), which is the specialised organisation of the UN for shipping, is challenged to reduce the approximately global emission share by shipping of 2% to 3%, equivalent to an annual emission of 800 million tons of CO_2 (IMO, 2014). In April 2018 the IMO adopted their GHG reduction ambition of 40% and 50% in respectively 2030 and 2050, compared to 2008 (Øyvind Endresen, 2018). By IMO rules, shipowners are responsible for aligning of their performance with these IMO-ambitions. To accelerate the energy transition, shipowner already received the MARPOL guidelines about energy efficiency and the corresponding emissions. Additionally, the IMO will publish their more specified GHG reduction strategy in 2023, which is about five years from the start of this research. The five year docking interval of a vessel is the best opportunity to cost-effectively improve the energy efficiency of the design and the technical installations. The UN climate scientists agreed that irreversible disastrous climate change is not likely to be prevented by these slow developments (Carrington, 2018). According to these scientists, Boskalis should actively improve their energy efficiency and not wait to be forced by the IMO.
The second IMO GHG study stated that 75% GHG reduction is feasible by operational excellence and existing technologies, of which many are also cost-effective and thus offer financial benefits too (H. Lindstad, 2009). The cost-effective improvement of energy efficiency creates additional leverage when Boskalis starts using higher priced renewable energy sources or low sulphur fuel from 2020. The shipowners who do not anticipate for an alignment with the IMO GHG strategy, which is already outlined, take a risk for non-compliance and additional costs in the future due to e.g. fines.

The improved connectivity by satellites above the sea enables Boskalis to develop an information system to support decisions onboard and onshore about fuel efficiency and related GHG emissions of each of their vessels. The connectivity at sea improved over the last decades from the situation of receiving a global location twice per day in 1992 to an affordable 24/7 VSAT connection for video calls in 2020. Moreover, the costs of broadband internet over the stable satellite connections are expected to drop over the next decades. The internet is one of the most revolutionary digital concept of the last decades and the concept of the Internet of Things (IoT) is expected to be the next (Jonathan Holdowsky, 2015). IoT is about the connection of machines to humans, machines to machines and to establish automated interactions, which can be translated to concepts of automation, remote controlled and autonomous shipping. These two concepts are highly promising (C. Kooij and Visser, 2018) for the reduction of scarcely available crew and improvements of ship design. Their research field is focused on the avoidance and mitigation of technical and operational failures of systems and less on the possible effects on energy efficiency, which makes this research interesting for exploration. Third-parties offer data services to control and improve energy efficiency of vessels, like Damen Shipyard, We4sea, Rolls Royce, Aviso instruments, TecnosVeritas and Enginei. The sustainability and technology leaders of shipping like Maersk, Stena Line and Wallenius already developed information systems for decision support to achieve operational and technical energy efficiency excellence and consequently this gave them competitive advantage in their markets.

The Offshore Energy Division of Boskalis has no information system to support decisions about fuel efficiency and GHG emissions, and their knowledge on the accompanied threats and opportunities is limited. Boskalis Westminster N.V. is a Dutch global operating all round maritime service contractor, employs 10.700 people and owns 900 floating assets over 75 countries in six continents. HAL Investments B.V is with a 40,3% shares the most influential shareholder and has the reputation to have 'deep pockets'. The other shareholders own less than 5% each and are widely spread internationally. In 1910 Boskalis started as a dredging company and expanded in 1980 their activities to the Offshore Energy and later to the Towage & Salvage markets. Together these activities form the three division of the Boskalis organisation (see fig. 1.1).

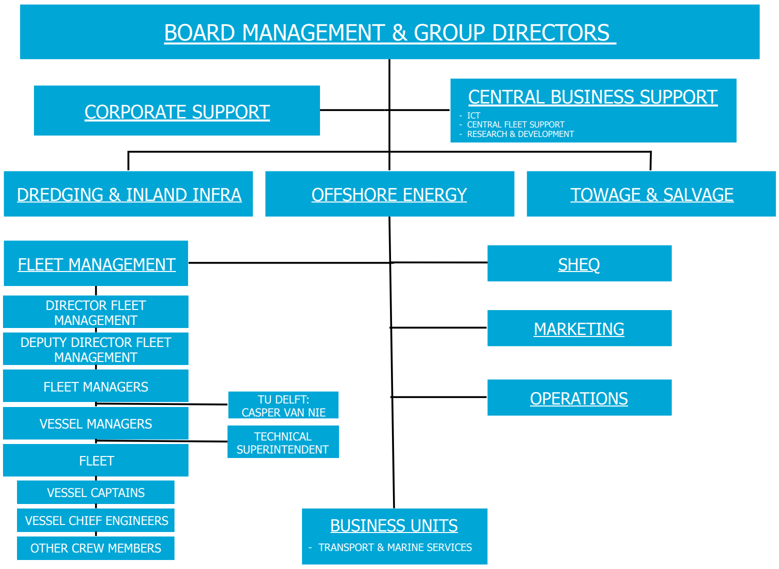


Figure 1.1: Organisation structure of Boskalis (own composition)

The Offshore Energy Division owns an extremely diverse work vessel fleet in terms of design and operational profile. This is more challenging for cost-effective improvement of fuel efficiency, compared to shipping companies with a focus for one type of vessel and with a more constant operational profile. The seven business units of the Offshore Energy Division operate in different segments of the Offshore Energy market with all rather volatile characteristics. The OED is top-down organised and hierarchical, with many management layers, for the controlled unification of acquired companies such as SMIT international (2010), Dockwise & Fairstar (2013 & 2016), Fairmount (2014), STRABAG, VBMS and Gardline (2018). The fleet management department is responsible for the asset management of the acquired second-hand fleet. A significant part of the technical management is responsible for the subcontractor Anglo-Eastern from Hong Kong. They deliver crew, Technical Superintendents and they coordinate the daily operational support. Anglo-Eastern provides a cost reduction of the technical management for Boskalis and owns more advanced technical data management systems than the Boskalis Offshore Energy Division. The role of Boskalis Offshore Energy is increasingly that of a marine contractor or broker and less of a shipowner, considering the outsourcing the technical fleet management. Nevertheless the responsibility to reduce GHG emissions remains by law at Boskalis, so they have to take suitable decisions about their energy efficiency. These complex and important decisions are preferred to be data-driven instead of intuitive.

The use of an information system to provide insights for data-driven decisions about the cost-effective improvements of energy efficiency. This is interesting for Boskalis Offshore Energy to create competitive advantage and to realize the required GHG emission reduction. This is the first scientific research about the combination of the energy efficiency challenges and the opportunities of new digital information technologies at Boskalis Offshore Energy fleet management. There were and are many different initiatives within the Boskalis organisation related to this subjects, but nothing was organised at a corporate or division level, at the start of this project. The GHG emission reduction task force group, that was founded during this research, agreed about the urgency and showed interest in the research results. The taskforce and others struggle with the lack of information and expertise to advice executives or to initiate and realize improvement bottom-up.

The case study of the Long Distance Towage (LTD) vessels developed a prototype to support decisions about investments and maintenance for the 'quick wins' of energy efficiency. Boskalis owns five identical designed vessels that were previously owned by Fairmount Marine Service. The available data of daily reports and the newly installed sensor data logging systems are used to build the prototype for data-driven decision support onboard and onshore.

1.2 Objective

Develop a data-driven decision support system for cost-effective improvement of the fleet's energy efficiency, to (i) create competitive advantage for Boskalis, (ii) reduce operational energy costs and inherently (iii) comply with future law and legislation about energy efficiency and carbon emissions.

1.3 Scope

This data-driven decision support systems development for shipping of the Offshore Energy Division is enabled by the information and communication technology developments of the last decade and is part of a more long term development towards autonomous and smart shipping. The scope with respect to this development from intuitive to autonomous shipping is graphically explained by fig. 1.2. This development research is from the data-driven perspective for decision support and is focused on the operational data and not on physics based modelling simulations or redesign. This research about both the technical and the operational energy efficiency improvements is focused on intelligence for asset management and not on the vessel (weather) routing.

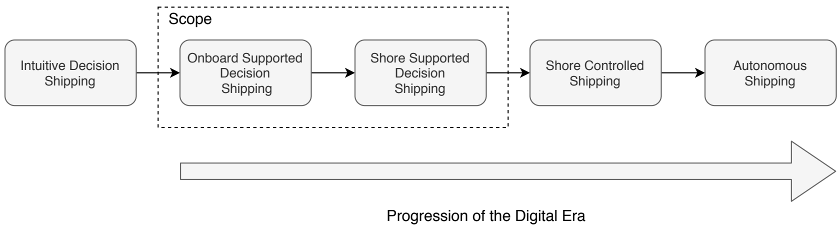


Figure 1.2: Scope with respect to development of autonomous shipping (own composition)

A methodology will be developed for both a conceptual business intelligence model for the Offshore Energy Division and the prototype system for LTD. This methodology will be a composition from different scientific disciplines found by literature study. The data input of the model and prototype are the daily reports and additional logged sensor data received onshore. The study about this development method will specify the type of information system that suits the offshore energy division best. A methodology for financial analysis of design or operational improvements of energy efficiency will be part of this research, to argument decisions how to improve the energy efficiency cost-effective or not. The financial analysis is focuses on the 'low hanging fruits' with short payback times, which makes additional sensitivity analysis overburden. The costs for full implementation of the system will not be considered, nor whether to realize the system internally or with a third-party.

The system development drivers will be investigated and specified for a wide scope about the application opportunities at Boskalis, which is the shipowner perspective. The main focus will be the cost-effectiveness of energy efficiency improvement and how to gain competitive advance consequently. The recent law and legislation development from the IMO will be considered to identify the urgency and current state of Boskalis' adaption. Carbon taxing will be noticed but is not considered for future financial scenarios. The Energy Efficiency Operational Index (EEOI) and Energy Efficiency Design Index (EEDI) are both not affecting the existing Boskalis fleet at the moment and are beyond scope for this reason. The LTD market will be studied to understand how the clients, competition and contracting are related to energy efficiency.

The conceptual business intelligence design will consider how operational time-series data from vessels can be processed by algorithms for different levels of the organisation and their decisions about energy efficiency. The focus will be the operational and tactical level of the Offshore Energy organisation and their corresponding decisions. The main focus about the fleet management department and their responsibilities about maintenance and design improvements. The improvement ideas for the operations and sales departments will be mentioned and possibly quantified, but are not within the main focus of this research. Voyage optimisation and weather routing will not be quantified by the information system.

The different energy consuming systems on board of vessel will be identified by their efficiencies and related operational profile. The Social Network Analysis is an essential part of a business intelligence design and will be done with the Business Process Modelling Notation (BPMN). This is the notation for visualisation of business processes and their relations with information technology. A BPMN will be applied for the current and an improved process of LTD with integration of the prototype. The business intelligence model will provide what data and data quality are required for a well functioning system in the future.

Two out of the five equally designed Fairmount sister vessels of LTD are within scope for the prototype. The Glacier and Sherpa are used to represent the whole LTD fleet and for the initial benchmarking of fuel efficiency. The case study prototype will have a focus on the engines, turbocharger, hotel and auxiliary systems, since the daily reports extensively considered these together with the logged engine sensors.

1.4 Thesis Outline

The main structure of this thesis is defined by the composed development approach (see chapter 2), which resulted in the graphical overview (see fig. 2.11).
The drivers (see chapter 3) for the system development are explained and reports the context of this research and the divergent process toward the more convergent conceptual design for the Offshore Energy Division (see chapter 4). This conceptual design is applied for the case study of LDT (see chapter 5).
The conclusion (see chapter 6), and recommendation (see chapter 7) summarise and evaluate the research results together.

Chapter 2

Decision Support System Development Methodology

This chapter connects the previous introduction chapter about the objective and the scope with the decision support system developed in the flowing chapters, documented by this thesis. First the fundamentals of DSSs are explained in section 2.1 for defining the term data-driven decision support. The fundamentals of Data Science are explained in section 2.2 for understanding what data science is and how the model is used to develop the DSS prototypes. The energy efficiency improvement approach of section 2.3 shows how the operational, maintenance and design measurement are found, correlated and financially analysed. The development methodology is composed from studied literature and graphically represented in section 2.4. After reading this chapter the reader understands the terminology and the model of DSS, Data Science, energy efficiency improvement and the financial terms used in this thesis.

2.1 Fundamentals of Decision Support Systems Development

The goal of this section is to introduce readers with the theory of DSS development and to explain how the developed system design is defined. First the DSS category is specified and related to other Information in section 2.1.1. Second the DSS categories are considered and the developed system defined as Data-driven in section 2.1.2. The system development methodology is specified and related to existing systems at Boskalis in section 2.1.3. Finally a model about sense making of data is introduced to distinguish different progression states form data to a decision in section 2.1.4.

The conclusions are that DSS is per definition an indispensable element at the core of the IS field between Management Information Systems and Organisational Computing. The evolution DSSs during the 20th century resulted in many categories of DSS and the system design is Data-driven, which is a Intelligent DSS based on time series data. The evolutionary prototype approach with Python is selected, because this suits raped development of DSS. The DSS needs to progress from raw data to decisions in six independent steps to make sense.

2.1.1 Information System Categories

A DSS is an information system (IS) devoted to supporting and improving human decision-making. Within the field of IS science, the DSS is located at the core between Management Information Systems (MIS) and Organisational Computing (OC), as shown in fig. 2.1.
The concept of a MIS provides structured information in pre-specified reports for structured problems and frequently made decisions, typically at the operational level of organisation. The DSSs are distinguished by the capability to serve ad-hoc decisions, derivation or discovery of new insights, direct accessibility by their decision-making users, user specific customisation of functionality and interfaces, and/or learning from prior made decisions (F. Burstein, 2008).

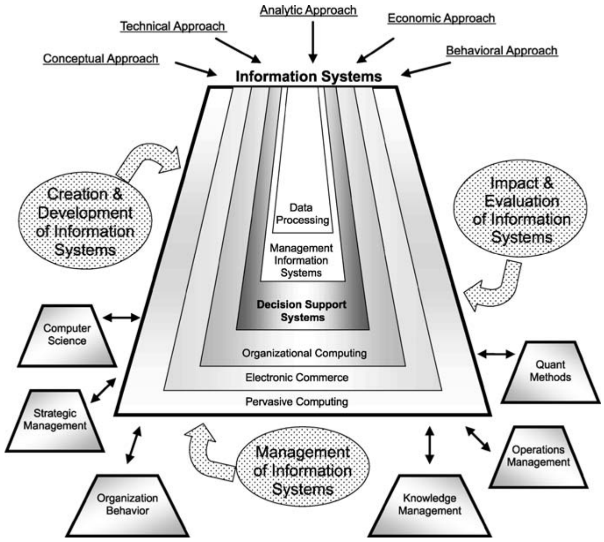


Figure 2.1: DSS indispensable element at the core of the IS research field (F. Burstein, 2008)

The OC systems are computer-based systems that enable or facilitate multi-participant activities. These multi-participant organisation range from dyads to complex enterprises. The OC systems serve activities include entertainment, education, commerce, design, research, and multi-participant decision making. Typical topics of OC systems are computer-mediated communication, computer-supported cooperative work, coordination systems, groupware, enterprise systems, and inter-organisational systems. The development the multi-participant activities enriched to DSS developments of Group Support Systems (C.W. Holsapple, 1996).

The system design for cost-effective reduction of bunker costs is a DSS, which is an IS category, that theoretically lays in between the MIS and OC categories. The system contains elements of both system categories, since development of DSS is influenced by both other system developments in history. The development of DSSs on-itself is captured by the next subsection about DSS categories. The multi-approach of the system design is conceptual, technical, analytical and financial. The discipline fleet management has the focus, within the broad discipline of shipping management.

2.1.2 Decision Support System Categories

The category of DSS as IS contains many different categories to be distinguished. The development of DSS evolved significantly over the last decades, as the graphical overview of fig. 2.2 suggests.
The first personal DSS was developed during the 1970s by fundamentals originating from Computer-based Information Systems, Operation Research and Behavioural Decision Theory. These first systems evolved under the influence of other scientific developments during 1980s and this resulted into three different subcategories: Intelligent Decision Support Systems, Executive Information Systems and Group Support Systems. The evolution proceeds during the 1990s and resulted in concepts of: Knowledge Management Bases DSS, Data Warehousing and Negotiation support systems.

The developments after the 2000s are not included in fig. 2.2, but the evolution did not stop. The concept of the Data Lake was developed during 2010s, which is an evolution of Data Warehousing and Machine Learning that originates from Artificial Intelligence. A Data Lake contains a temporary large storage of semi-structured high quality data to train ML algorithms for DSS. The virtual overflow of the Data Lack determines the history presence within the Data Lack. A Data lake is present at the Dredging Division of Boskalis and this concept is not introduced at the OED.

The system design is an Intelligent Decision Support Systems considering the literature study. The system design called data-driven because this is the taxonomy for DSSs based on time series from internal and some-

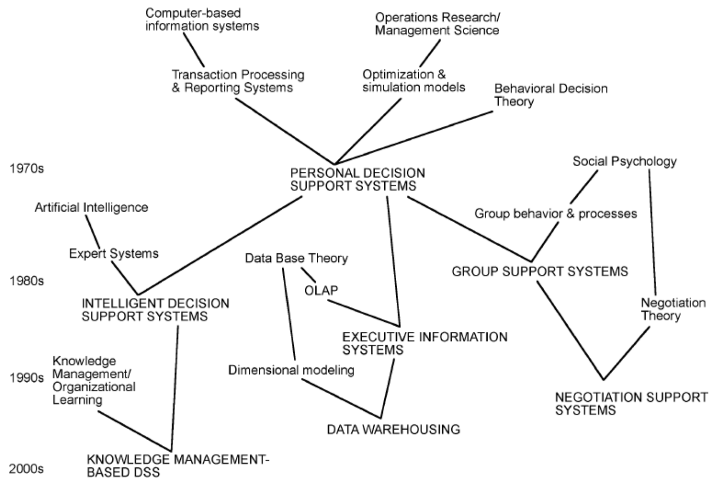


Figure 2.2: Evolution of DSS field (Arnott and Pervan, 2005)

times external data. Found opportunities for Boskalis considering other categories will be stated within the recommendations.

2.1.3 System Development Methodology

The different DSS categories or DSS typology can be developed with different methodologies. A review study created an graphical overview about the relations between different DSS typology and development methodology in fig. 2.3. The study provided insight about what methodologies are suitable or not to develop the data-driven DSS system in mind. The data-driven DSS is not explicitly mentioned in fig. 2.3, but is most related to the individual DSS. When Looking beyond scope of the research, the typology of Group Decision Support Systems and Hybrid DSS are interesting to fulfil the objective of this research, which is more explicitly explained within the chapter 7.

Methodology, methods or technique / DSS Typology	SDLC	ROMC	Functional Category Analysis	General Process for DSS Development	RAD and XP	Prototyping	Unified Process	UML
Individual DSS	√	√	√	√	√	√	√	√
EIS (Executive Information Systems)	√			√	√	√	√	√
GDSS (Group Decision Support Systems)	√	√		√	√	√	√	√
ES (Expert Systems)	√		√	√	√	√		√
IA (Intelligent Agents)	√		√		√	√		√
GW (groupware)	√	√		√	√	√	√	√
DW (Data Warehouse)			√	√	√	√		√
OLAP		√	√	√	√	√	√	√
DM (Data Mining)			√		√	√		√
HDSS (Hybrid DSS)	√		√		√	√	√	√

Figure 2.3: Methodologies, methods and techniques for development different DSS types (Brandas, 2011)

The Prototyping methodology is chosen, because this seemed applicable for all different types of DDS typology and enables non implemented evaluations of DSS(Brandas, 2011). The Data Science approach in Python can produce the prototype visualisations to be improved over time, without implementation required. There are two types of prototyping mentioned within the literature: throwaway and evolutionary prototyping. The throwaway prototype built is not meant to be implemented, in contrast to the evolutionary prototype. The evolutionary prototype is typically implemented and evolves over time by adding new functionalities and improve existing content. The back-end development of the realized DSS prototype in Python is evolutionary and the front-end development (visualisations) are throwaway prototypes. This prototyping approach provides relatively fast development of the back-end design.

Python is often used for back-end development of platforms, like for example Netflix, Google, Facebook, Spotify and We4Sea. Front-end development is commonly not done with Python at these platforms, but for example with the Dash package, an open-source library for building advanced interactive dashboards which is provided under licence of MIT. Programmes like MS Power BI and Tableau are more user friendly to develop front-end of applications. The director of the IT department of Boskalis, Karel Parre, stated that Boskalis is an Microsoft based company and the focus is on further development of Data Warehousing (MS Azure) and Power BI applications at Boskalis. The back-end development within python can be implemented as function of the total corporate intelligence platform, called Boskalis World, that is programmed in C# and python according founder Kees Pruis. The front-end examples are remade within MS power BI to illustrate possibilities of a interactive dashboard. The development of the database with Python is evolutionary and the developed Power BI dashboard are build upon this database, which makes the development evolutionary. The real application of the developed system is beyond scope of the research.

2.1.4 Progression of Knowledge

This subsection is not explicitly about the development of the system design or methodology, but about a more fundamental theory about how data provides decision support. The fig. 2.4 originates from knowledge management literature and show the progression form data to decisions, corresponding steps defined (van Lohuizen, 1986). The model is used for understanding the different states for sense making of the data-driven DSS prototype.

Three phases are distinguished in the model: Intelligence, Design and choice. All three phases, with corresponding steps need to be surpassed for support of a data-driven DSS. The Intelligence phases is about gathering information with data, the Design phase about the databases, algorithms, visualisation and presentation of information, while the choice phase is about how decisions maker have to judge information and evaluate to make decisions.

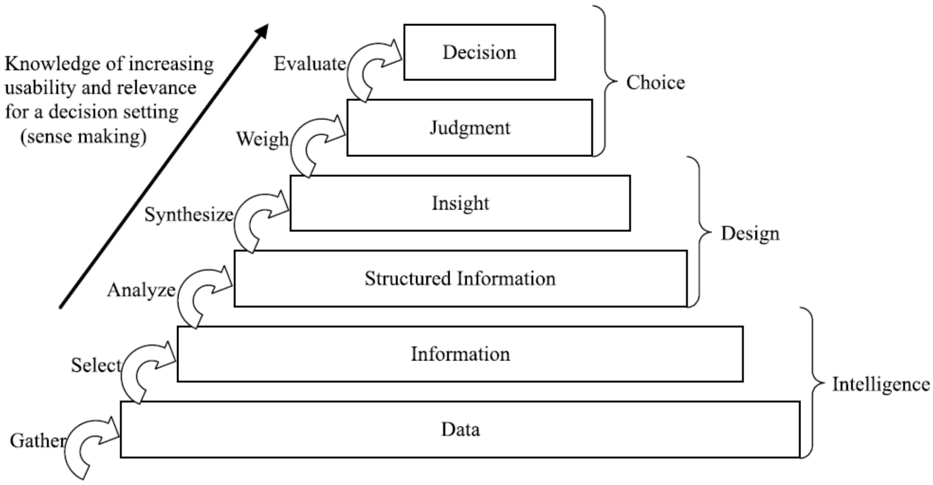


Figure 2.4: Knowledge as progression of states (van Lohuizen, 1986)

The lowest layer called data is gathered during operations. Only a selection of this data cleaned, represents information about reality. This information can be analysed to created structured information by for example filtering and labelling a data table within a database. Synthesised structured information can create insight with filtering, statistics, predictions and visualisation of history. With created insight, decision makers weights the importance of the insight for a judgement. Evaluation of this judgement leads to a decision. The effect of made decisions changes reality that is captured by the data and creates new insight and judgement for future decisions making.

2.2 Fundamentals of Data Science

Reader who are not familiar with domain of Data Science are recommanded to read this section. The term Data Science is defined by explanation of the development in section 2.2.1 and the process model in section 2.2.2.

The conclusion is that Computer Science and Math & Statistic together developed Machine learning, which is a subset of AI. Together with expertise of shipping management and navel architecture Data Science can be performant. Data Science is typically practised by multi-disciplinary teams, which indicates a fully working product is unlikely to be developed during this project.

2.2.1 Development of Data Science

Real-time Data from vessels can be sent to shore and enables opportunities to monitor, control and support vessels by office and development new business models. These opportunities are typically explored by Data Science. Large company do frequently ask for Data Scientists, since The Harvard Business Review of 2012 called Data Scientist "The sexiest Job of the 21st Century", which caused an explosion of data scientist jobs on the market. Data Scientists commonly use open source programming languages as R and the most fast growing programming language Python. Innovative maritime start-ups like We4Sea and Xiomnia (Shipping Technology) are both Data Science oriented companies, who realise 'Digital Twins' and autonomous vessels. The Data Science perspective is already demonstrated to be effectively for predicting the balanced optimisation of cargo vessels (Andrea Coraddu and Anguita, 2018).

Data Science can be considered as a 'Buzz word', resulting from a lack of definition, respect from conservative science communities and a high noise-to-signal ratio in daily conversation (Rachek Schutt, 2014). Data Science is related to Information Science, Computer Science, Statistics, Predictive Modelling, Algorithms, Machine Learning, Business Analytics and (Business) Intelligence. James Nicholas Gray, imagined Data Science as a 'fourth paradigm of science' next to empirical, theoretical and computational science. Data-driven science as the 'fourth paradigm of science', enabled by the data deluge (explosion of available data).

Data science is practised by multidisciplinary Data Science teams (Rachek Schutt, 2014), which typically consists of a Data Scientist (Math & Statistics), Data Engineer (Computer Science) and a domain expert (Substantive Expertise). The illustration of fig. 2.5 graphically explains the overlap of these three domains. The term 'Hacking Skill' can be translated to the more formal term of Computer Science, but is explicitly called 'Hacking skill' for a reason. The term 'Hacking skill' refers to life hacking, which is about unconventional use of ICT to process overburden of information available.

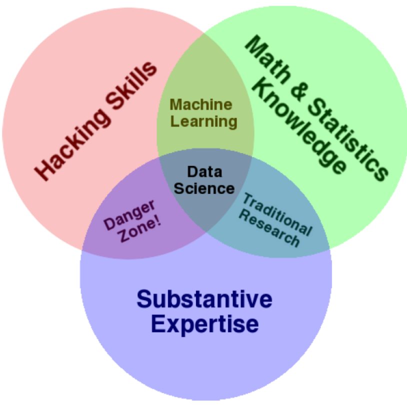


Figure 2.5: Drew Conway's Venn diagram of data science (Rachek Schutt, 2014)

Data science is typically practised by a multidisciplinary team, creating the Data Science team together, as shown in fig. 2.5. Substantive experts (Domain and Business knowledge) about shipping within this project were found at the TU Delft, Boskalis and within the curriculum of the writer. Knowledge about mathematics and statics were present in curriculum of Marine Engineering and much is learned during this project. Hacking skills for processing big data sets were lacking at the start, but were developed during this project to do the Data Science, instead of traditional research without hacking skills. Some literature states that Data Science within the Venn diagram should be replaced by Unicorn. Data science can captured by a circle around this whole Venn diagram as well, since nobody can do 'real' data science alone. The field of machine learning, as part of AI became understandable, but building tool requires real expertise.

2.2.2 Data Science Process Model

The fig. 2.6 gives graphical representation of the data science process. The reality of shipping is captured by raw data. When the process starts, raw data have to be collected from organisations, departments, databases and employees. When all required data is collected, the data can be processed for development of structured database, which is ought suitable for Exploratory Data Analysis (EDA). The cleaning or cleansing of data is mostly required for EDA, which is about restoring or deleting corrupted data.

The cleaning and EDA provide insight about the Data Quality. When all data is processed and (big) data sets are developed, a Data Quality Assessment (DQA) is done. The DQA explicitly states the data quality of the available data and the feasibility of significant outcomes of models and algorithms. A common saying of modellers is: "Rubbish in is rubbish out", which means that if there the data quality is to low, the model will not produce significant outcomes. DQ need to be predefined for development and design of systems(Fu. Qian, 2017)). Two frameworks to determine data quality are explained within section 2.2.4.

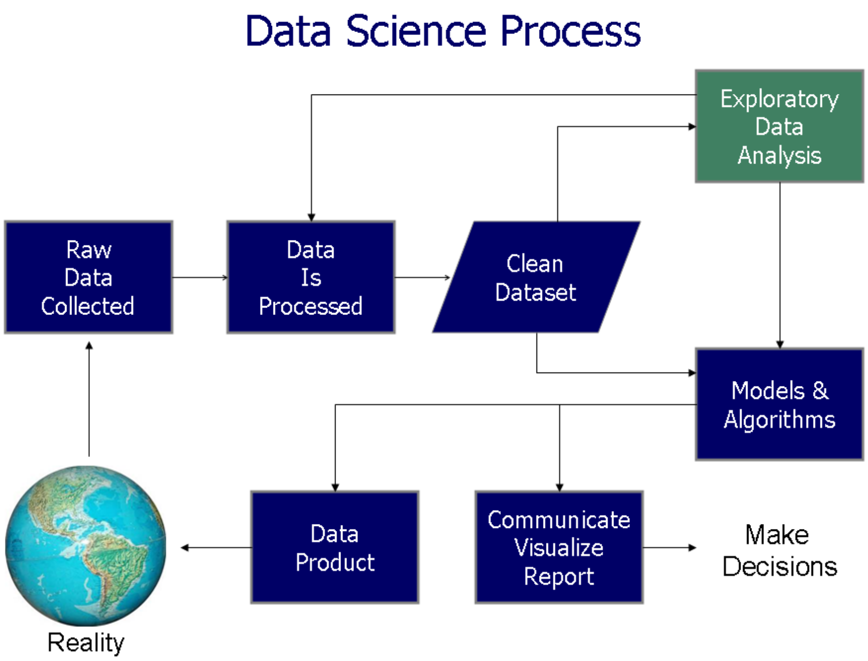


Figure 2.6: Data science process (Rachek Schutt, 2014)

The EDA results in additional processing of data for analysis and useful models and algorithms. The additional processing can done when time and DQ are sufficient or are recommanded for future development. The results Models and Algorithms are communicated by this thesis for Decision making.

The Models and Algorithms can implemented in the data product which is a Data-driven DSS. A positive feedback loop can occur due implementation of the data product. User and data collectors of the data product become aware of the importance of data quality. Implementation of the Data product is beyond scope of this thesis.

2.2.3 Machine Learning

Machine learning is the scientific study of algorithms and statistical models that computer systems use to effectively perform a specific task, without using explicit instructions, relying on patterns and inference instead (Bishop, 2006).

There are basically three branches of Machine Learning: Supervised learning, unsupervised learning and Reinforcement learning. Supervised learning is used when a pattern is expected, typically classification and regression methods. Unsupervised learning is about finding unknown patterns and correlations for predictions, like clustering of data to label and classify. Reinforcement is about how a software agent ought to take actions in an environment so as to maximise some notion of cumulative reward. A Graphical overview in fig. 2.7 visualized a flowchart to find the suitable estimator for a certain problem.

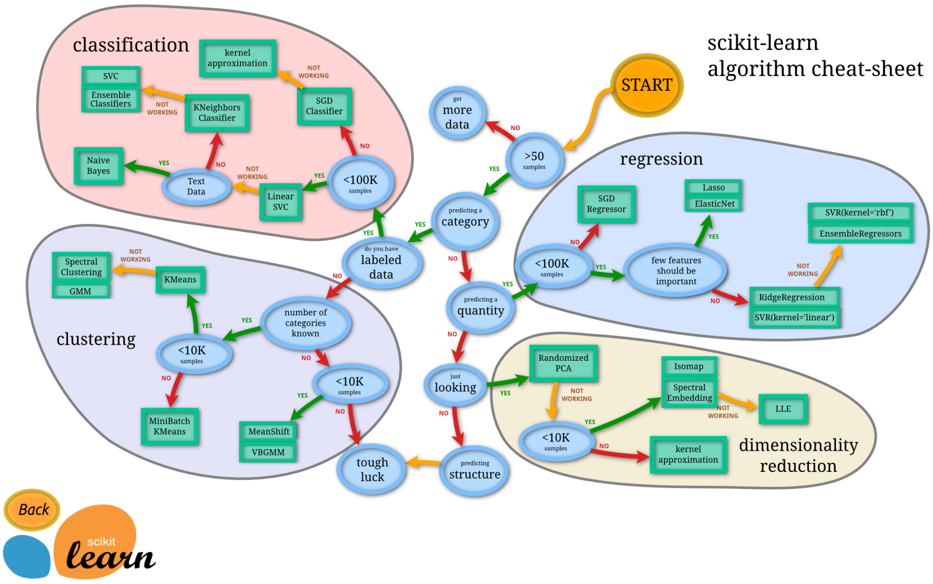


Figure 2.7: Flowchart for choosing the right estimator (Scikit-learn, 2018)

Mention that the Artificial neural network is not mentioned in chapter 2. Artificial neural networks or connectionist systems are computing systems, vaguely inspired by the biological neural networks, that constitute neurons of the brain (van Gerven and Bohte, 2017). The neural network itself is not an algorithm, but rather a framework for many different machine learning algorithms to work together and process complex data inputs.

Regression (Lucy Aldous, 2013) and Artificial Neural Networks (E. Bal Beşikçi, 2015) models have both proven to be accurate for prediction fuel consumption of vessels. Wallenius and Stena line, who are shipping company from Scandinavia, stated the use Artificial Neural Networks to control their fleet, at the lighthouse conference of 13-06-2018.

Deep Learning is a branch of Machine Learning and can be divided Image Recognition and Computer Vision. Image and Video data are both not consider for the DSS.

2.2.4 Data Quality Frameworks

The input data for data-driven DSS needs a required data quality for a sufficient representation of reality. The term data quality suffers a lack of consensus among managers, so the frameworks are introduced to create a consensus about and to understand the definitions and relations (see fig. 2.8 & fig. 2.9).
The required data quality depends on the goal to be achieved, this concept is called: "fitness of purpose". The required data quality is preferably predefined before collecting data for analysis or data acquisition systems development. A not clearly defined purposes and 'blind' maximisation of the data quality requires unnecessary FTEs, data transfers and storage. In the worst case, the information infrastructure fails due overload or clock synchronisation per second (ships are not electrical grounded).

The next two paragraphs are about the two data quality framework from scientific literature: 'The Data Quality Hierarchy' and 'The Primary Data Quality Dimensions'. These two frameworks are consistent but differ in the perspective of data quality. The both framework explicitly contain accuracy, completeness and timeliness.
The hierarchical framework (R. Y. Wang and Kon, 1995) is from organisational perspective and specifies the quality parameter of Attainability. This data quality framework is most applicable for considering the organisational and business process data quality
The six primary quality dimensions framework (management association, 2013) centralises the accuracy dimension and is with a more technical perspective. This framework is useful for data quality assessments (see section 5.1.2) data acquisition and database design (see section 4.3.2).

Data Quality Hierarchy

The hierarchy framework illustrates the data quality terminology in relation to use of corporate information systems (see fig. 2.8). On top of this hierarchy is the term data quality explicitly located and split below in Attainability, Accuracy and Credibility. These three parameter are explained by the paragraphs below.

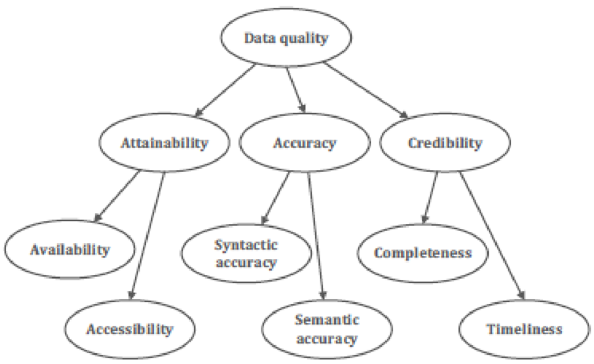


Figure 2.8: Hierarchical structure of data quality (R. Y. Wang and Kon, 1995)

The Attainability can be split in availability and accessibility, which says something about how much data is present, known or usable by employees. Data leadership is related to attainability, which can be split in data dictatorship and democracy. If data dictatorship is the reality for an organisation, only one person has access to the data or only knows about existence and possibilities. Within the a data democracy all related employees are do use and improve the for continues improvement of the data-driven decision making organisation.

The accuracy is split into Syntactic (form) and Semantic (content). The syntax is about the 'grammar' of the data, while semantic is about related to the meaning of the data.

The Credibility of the data can be split in Completeness and Timeliness, which are both about 'intrinsic values' of data. The completeness is about the present data observations and attributes are complete enough to sufficiently represent the reality. The timeliness is about whether the timing of data is consistent and allows observations to be compared.

Six Primary Data Quality Dimensions

This framework is applicable specific content of data tables or databases (see fig. 2.9). Next to these six core dimension are the secondary dimensions, such as usability, flexibility, confidentiality and the value for business (management association, 2013). Besides always question if the data are understandable, simple, relevant and compatible. Only the six primary dimensions are further explained by this paragraph.

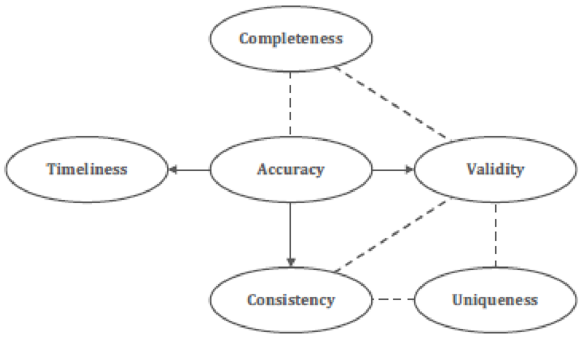


Figure 2.9: Six primary data quality dimensions (management association, 2013)

The definition of accuracy is the degree to which data correctly describes the "real world" object or event being described. Accuracy is the centralised core dimension of this model with stronger relations to Validity, Timeliness and Consistency. A less strong relation to Completeness is stated in this model, since this is about the amount of observations.

The definition of Completeness is the proportion of stored data against the potential of 100% complete. The business rules which define what is this 100% and what is critical data or significant amount of data. The completeness of time series data is mostly required to be 100%, because this enables to summarize data over longer periods. For example, the engine fuel consumption over one year have to be known and a few weeks of data are missing, this causes a low completeness and consequently an inaccurate estimation.

The consistency of different data is 100% for perfect accurate data. A 100% consistency results in absence of difference, when comparing two or more representations of a thing with the same definition. For example, the fuel consumption summation of four quarter periods of 2018, should be 100% consistent with the annual value of 2018. Another example, within the case study the engine power according controller and backward calculation by shaft and alternator powers were inconsistent (see fig. C.4b).

Uniqueness of 100% states that all objects are indentified by one unique identity number. Labels, IDs or data attributes should be stored uniquely by an organisation and not multiple times within the individual or different systems. A percentage can be calculated by dividing these number of thing in real world by number of records describing these things.

The definition of Timeliness is degree to which data represent reality from the required point in time, referred to the time of the real world event. A PMS logs engine power every second of the day and these values summarized to average over the day, which gives a high data accuracy onboard. If this data is real-time update onshore, the timeliness onshore is also high.

2.3 Energy Efficiency Improvement Approach

The data-driven DSS design is for cost-effective reduction of bunker fuel consumption. The previous sections of this chapter were about the DSS as an instrument and this section is about the energy efficiency improvement approach. This improvement approach explains how measurements are found, related and financially analysed for decision making, supported by the insights from the DSS. This section is an introduction to methodology used for making judgements about energy efficiency of a vessel, based on insights from the DSS.

The conclusions are that improvement of energy efficiency is systematically approachable, but the quality of results depend on the data availability and accuracy. Literature about how to improve energy efficiency of vessels is widely available but is mostly focussed on cargo vessels and not non-transport vessels, a problem that can be solved by insights from the Data-driven DSS design.

2.3.1 Generation of Measures

Measures for improvement of operations and design are actively studied by the scientific communities. Literature study (Armstrong, 2013),(et al., 2018),(IMO, 2018a),(Andrea Coraddu and Anguita, 2018), Exploratory Data Analysis and Marine Engineering expertise are required for judgement about the applicability of measures, but can be supported by a DSS. Recent study proved that tools can be build for cargo vessel to predict the best measurements to improve energy efficiency over longer periods by Markov chains (van den Berg, 2018). A long list of all found measures is available in appendix D.1.

Results of a review study about 150 GHG reduction measures cases are presented in fig. 2.10. Most measures do affect energy efficiency one-to-one, while others do only reduce GHG emissions. The scientist who made this boxplot charts recommend to focus at the third quartile and exclude outliers, for a more realistic impression of measure potential in general. Mention that the work vessel are considered as outliers, since they are no cargo vessels, that are considered to be the norm. All data points in the boxplots originates from 150 case studies, with different vessel designs and markets and a large spread of reduction potentials as result. Most effective potentials for carbon emission reduction are the vessel size, biofuels, speed optimisation and capacity utilisation. Speed optimisation seems most interesting for work vessels and is within scope. These results of scientific research are used as starting point for finding energy efficiency improving measures. Another long list is abstracted, with related indications about initial investment costs and energy efficiency improvement potential as presented in appendix D.1.

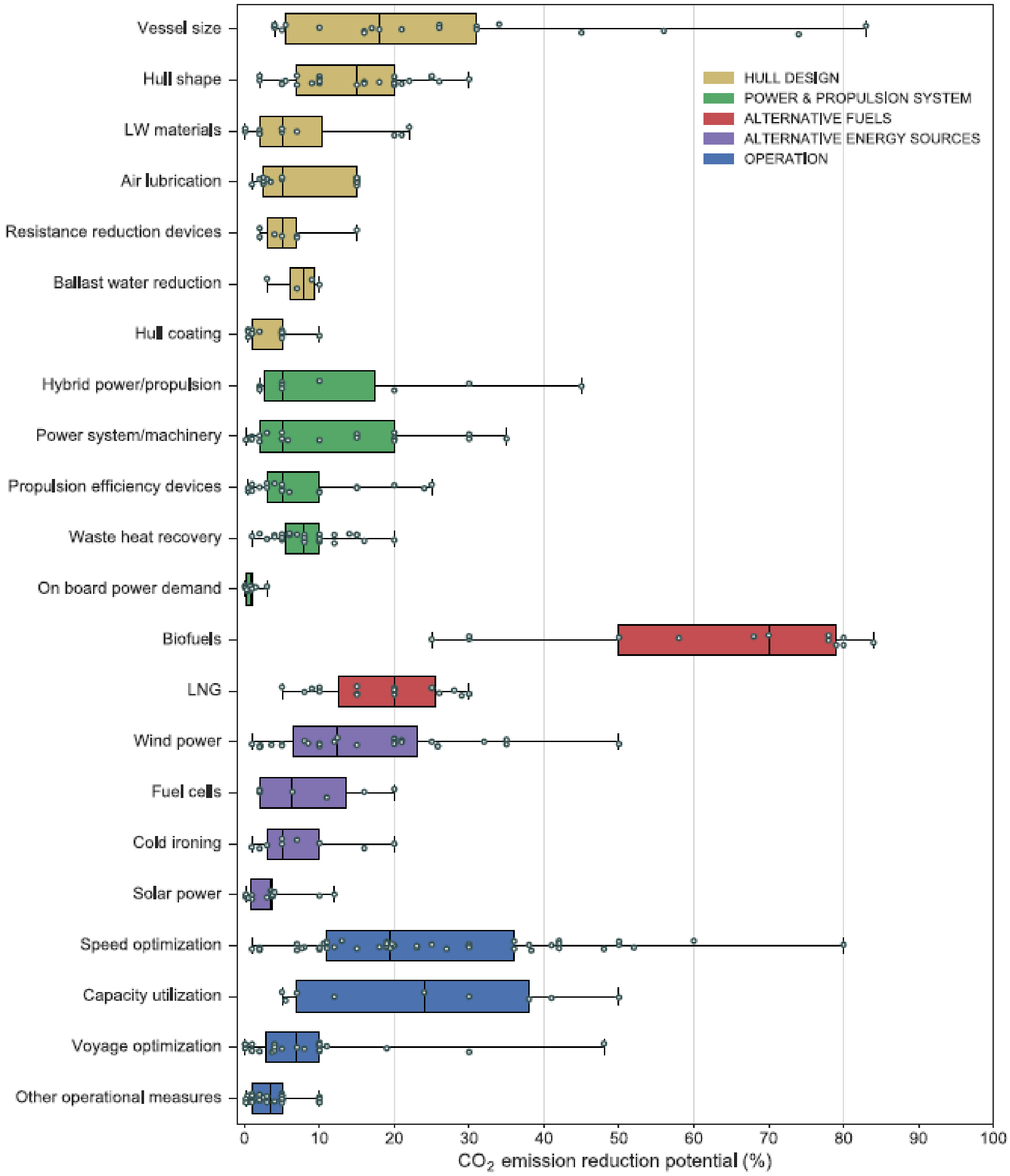


Figure 2.10: CO2 emission reduction potential from individual measures, classified in 5 main categories of measures (et al., 2018)

A Marine Engineer with knowledge about ship design and energy efficiency is capable of finding the best applicable ideas from these literatures and proved cases, to develop a short list of interesting measurement for the case. The found improvements are not necessarily stand alone measures and can be related to each other for finding the best package, with required effect and synergy.

2.3.2 Correlation Analyses

Applicable measurements are incompatible, create synergy or do not affect each other. These relations between measurements need to be known for optimisation of energy efficiency. Incompatibility between measurement means that they can not be combined technically or economically. When both measures are cost-effective, a decision which one to be chosen need to be made. The relations to other cost-effective measures need to be considered before making the decision between two incompatible measurements. Synergies of measurements can be both positive or negative. This can be identified by graphical representation of a technical correlation matrix.

The idea of a technical correlation matrix originates from Quality Function Deployment (QFD). Dr.A.A. Kana thought and provided lecture slides about QFD, during a SDPO master course called Design of Complex specials. The QFD is useful for new build and conversions designs decisions. A QFD analysis quantifies relation between a Voice of Customer and what is most effective considering a service or design to satisfy, by possibly including weight to different stakeholders(Warkwick, 2007). QFD technique is not a form of hard science and can be used in many different ways, as it suits the case.

When the voice of customer gives importance to sustainability, energy efficiency or fuel efficiency and carbon emissions, this results in more energy efficiency products, operations and vessels of Boskalis. Development of a QFD is useful to specify how important energy efficiency is related to other parameters for customers, new buildings, conversions or projects. Other parameters could have been safety, duration of project (downtime) and cash flow for example.

The scope of only energy efficiency is to narrow for a full QFD analysis to make sense, but is still to recommend for new build and conversion to identify importance of energy efficiency. The 'roof of the QFD house', the technical correlation matrix, seemed to be useful for finding possible combinations of energy efficiency improvement measures, both technical and operational. The case study result of the relation analysis is shown in fig. 5.31.

The relation matrix is an useful method to specify relations of energy efficiency improvement measurements in the conceptual design stage of both operations and design.

2.3.3 Financial Analysis

The financial analysis about cost-effectiveness for decisions supported by data is expressed in Net Present Value (NPV), Payback Time and Internal Rate of Return (IRR). The Total Cost of Ownershipeq. (2.1) difference by energy efficiency improvement is ideally used over the economical life time of a vessel. The investments create a positive cash flow by reduced fuel costs over multiple years, compared with "doing nothing". Maintenance measurements are not considered as investment over multiple years, but only for one year without discounting. The periods of years is equal to expected economical life of the vessel and the period of five years is considered to identify quick wins. The expected second hand market or scrap prices are considered within the C_{total}, to quantify the leverage of energy efficiency for the asset.

$$C_{total} = \underbrace{C_{investment}}_{\text{fixed}} + \underbrace{C_{maintenance} + C_{fuel} + C_{operation} + C_{carbon}}_{\text{variable}} \tag{2.1}$$

This simplified representation includes the costs of carbon, which is considered to be zero by Boskalis at the moment. Although Boskalis can include the cost of carbon internally to stimulate reduction of their carbon emission, there is a risk of carbon pricing by the governmental organisations, for example the IMO, in the future. The cost of carbon are politically controversial and are mainly based on scientific estimations about the human impact on the global warming and discounting on the future generations of human populations. The climate costs of carbon are assumed to be between €40 and €390, depending on observation period and impact assumptions, according Dr.S.T.H. Storm's lectures about sustainable energy economics.

The objective function of NPV of C_{total} is used to analyse investment for improvements of energy efficiency eq. (2.2). The number of year within the NPV of an investment is zero, is called the DPT. The Discount Rate is assumed to be 10% for proven concepts and 15% for early adopter measurements. The discounting is applied to compensate the future value of money because of interests, inflation, risks and alternative investments. The Discount Rate can be considered as the minimal IRR required for investment.

$$NPV(C_{total}) = C_0 + \sum_{t=1}^{T} \frac{C_t}{(1+r)^t} \tag{2.2}$$

Where:

C_0	= Initial Investment Costs	€
C_t	= Total costs in year t	€
r	= Discount rate	%
t	= Number of year	year
T	= Period number of years	years

The IRR is a percentage of what the discounting (or WACC when excluding the risk free rate) can be for still have a profitable investment over a certain period of timeeq. (2.3). When the IRR is negative, this means a negative discounting is required and the investment is expect no to cost-effective.

$$IIR = NPV(C_{total}) = \sum_{t=1}^{T} \frac{C_t}{(1+r)^t} - C_0 = 0 \tag{2.3}$$

This model lacks the perspective of revenue from improved market position and only considers reduced C_{total}. Budget and cash flow constraints, which are typically important for financial decisions within business, are not considered by this financial model. These are all important to consider for making the real decision. This models is able to quantify cost-effective improvement of energy efficiency and is applied within case study to demonstrate the financial benefits of energy efficiency.
A sensitivity analysis can be made for bunker fuel prices, vessel utilization and operation profile variations. This research is focused on the by problem owner requested quick wins with a DPT below two years. The Sensitivity analysis is less interesting for investment decision over relative short periods of time and beyond scope of this research.

2.4 Developed Method Composition

The evolutionary prototyping approach of the Data-driven DSS is graphically presented by the own developed composition in fig. 2.11. The composition contains a feedback mechanism, which originates form traditional IS development based on systems development life cycle that is considered to be the founder of all other development methodologies(Brandas, 2011). This life cycle development methodology refers to evolutionary prototyping approach, also known under the name iterative design(E. Turban, 2010). Evolutionary prototyping is common for rapid and integrated development approach. DSS development is focused on a specific, dynamic and complex activities which requests series of updates and testing. Mention that chapter and section indications are represented, which makes the model useful as reader manual for this thesis.

There are five phases of development that can be distinguished and the first three are within scope of this thesis, as suggested by the arrow in fig. 2.11. First the objective and scope are stated, which are formulated by analysis of the drivers for the system development. The Business Intelligence Design (BID) process starts afterwards and results in a conceptual model design of the system for the whole OED fleet of Boskalis. The conceptual BID design is applied for the case study and practised by the DS process. The two following phases are beyond scope and about implementation of the system, which is considered and roughly outlined to complete the entire development cycle of information systems.
All the phases contain specified task to be proceed for procession of the development phase and system. Colours that are specified in the legend represent the expertise required for the tasks for the system development. No colours are included within tasks of the first two phases, because these are related to multiple fields of expertise.

The graphical overview of fig. 2.11 graphically represent the overview of how the DSS was developed in this thesis and can be used as manual. Moreover, this structured approach can be translated to other studies for development of Data-driven systems and refined to a project guide for further professional development and implementation of the system.

2.4.1 Drivers for Decision Support Development

The three main drivers for the system development are all ready spoiled within fig. 2.11. The driver are the motives for why to develop a certain IS. The objected and scope are abstracted from the analysis of drivers, this avoids changing objective and scope for the system design during development of the BID. The added value of the data-driven DSS for cost-effective reduction bunker costs is specified, together with secondary and tertiary objectives. The driver analysis succeed when it support development of a long term vision for IS development.

2.4.2 Business Intelligence Design

The BID starts when the primary and preferably the secondary and tertiary objectives and scope are ought not to change during the development project. The BID starts with the task of Business process modelling or social network analysis to find participants and their decisions within the processes to support. A new data supported business process can be developed and is specified by the task of performance control design about models and algorithms to use for support. Finally requested data is specified to be collected within the development of the preliminary design.

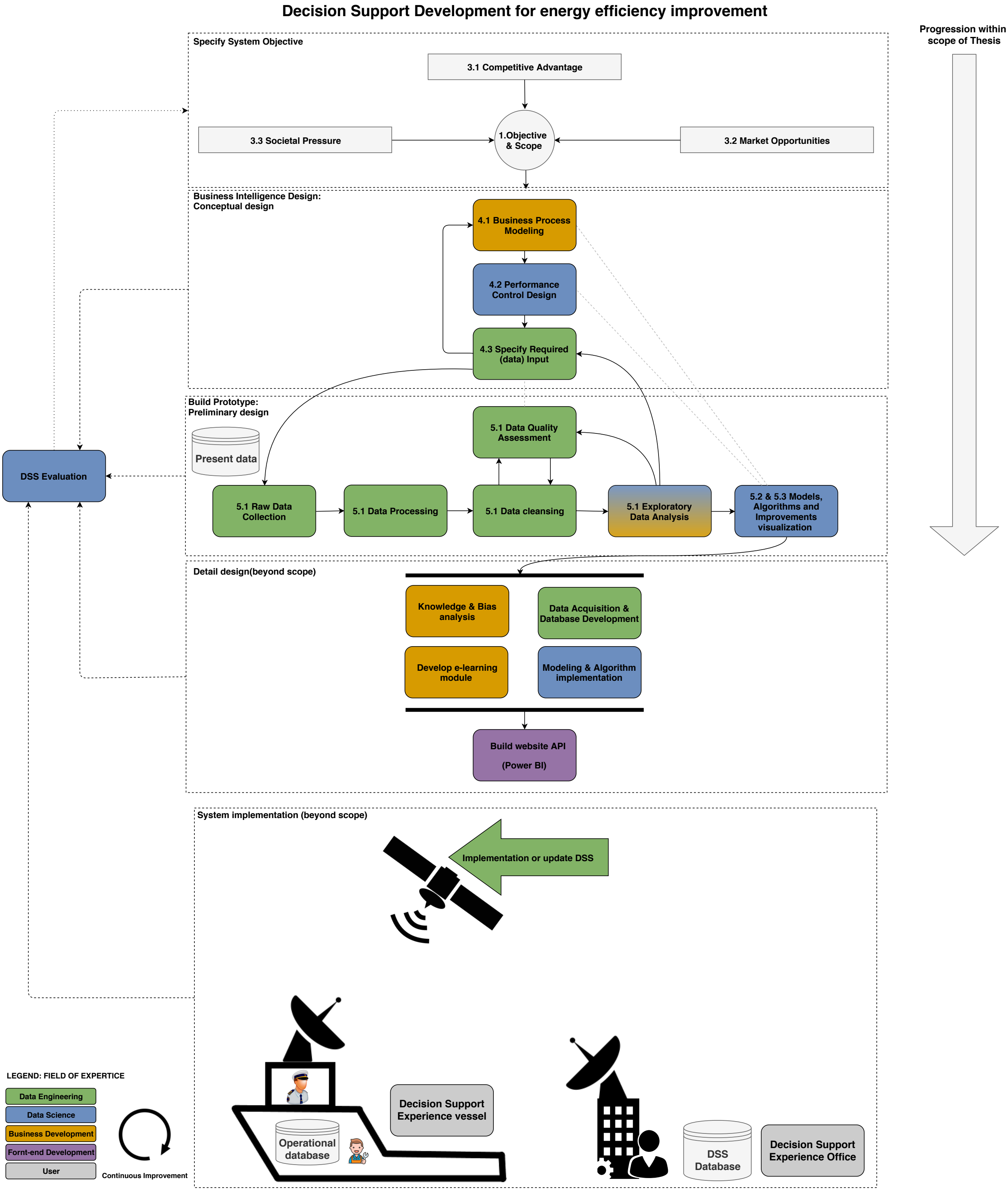


Figure 2.11: Decision support system development cycle approach (own composition)

2.4.3 Preliminary design: Case study

The preliminary design is made by using python for back-end development of the system for the case study. The DS process model is specified and applied for the case. This preliminary design learns the current state of data quality and opportunities for algorithms and models. Mention that in practise their is an interaction between lessons learned and further development of the BID.

2.4.4 Detailed design

Detailed design can start for creating the decision support content for user experience. This Detail design is done sufficiently when data is enabled for judgement and decision. The user experience affects operational decision making and operational data. Evaluation of the data proves energy efficiency improvements or not and will be the input for possible new development ideas and objectives.

A DSS should always stimulate creativity of the users and not substitutes logical thinking. When vessel crew, who collects operational data is involved in the system, they are expect to improve data quality and become aware of energy efficiency of the vessel.

2.4.5 Hardware and software application: Implementation phase

The system implementation is beyond scope, but considered since this is an important part of system development in shipping. The costs and bandwidth of VSAT data transfer from Marlink are summarized in appendix D.4. The whole fleet of Boskalis is currently connected to the Marlink satellite system. The NMEA and VDR at vessel are first systems to logged and transfer the data from.

Chapter 3

Drivers for System Development

The problem of energy efficiency at Boskalis is driven by three different drivers that are inherently connected. The Design of the Data-driven DSS is aligned with these three drivers. The first driver, that is aligned with the primary objective, is about competitive advantage for Boskalis by cost-effectively improved energy efficiency and is explain in section 3.1. The market driver of LTD is explicitly considered for understanding this niche market and the competitive advantage by cost-effectively improvement of energy efficiency in section 3.2. Finally the societal pressure for improvement of EE is considered in section 3.3.

The conclusion is that the Data-driven DSS provides competitive advantage due more cost-effective operations and being in control of the changing and increasingly stricter policy environment of energy efficiency and corresponding emissions. Boskalis can make to most cosy-effective decision toward suitable fleet development, supported bu insights of operations and design. The market of LTD is price competitive and there are market opportunities for fuel efficient towing, especially outside the oil and gas market.

3.1 Competitive Advantage for Boskalis

One of the fundamental ideas of markets mechanism is that competition stimulates companies to innovate their business. The market strategy and market positioning of Boskalis are briefly explained and related to the competitive environment in section 3.1.1. The financial benefits of energy efficiency are explained by **??**. When Boskalis gains control about their bunker fuels and energy efficiency, this creates an additional advantage as described by section 3.1.3.

3.1.1 Competitive Environment

The strategy of Boskalis is to be an all round global maritime service provider. Boskalis participates for this reason at the markets of Dredging, Coastal Engineering, Infrastructure, Offshore Energy, Salvage, Wreck Removal and Harbour Tug Assistance. The general idea is that customers ask Boskalis to design and build their ports or other projects and to deliver services to operate them. Boskalis wants to move forward as one strong brand and all vessels will be painted grey with Boskalis logo and called for example BOKA Sherpa and BOKA Vanguard.

Boskalis competes with smaller and larger companies spread over several markets. Especially the Chinese companies are winning ground and water (LLC, 2018), with their fast response and large ambitions for the Offshore and the Shipping Markets, as part of their 'Belt and road project', to restore 'the old silk road'. The Closed-stern Heavy Lifting Transport vessels are sold for scrap during the second half of 2018, because of competition (Wallis, 2018). They CEO Peter Berdowski stated during interview with Fairplay: "This (lower-end) segment is rapidly becoming a commodity transport market, often not oil- and gas-related, that is structurally confronted with Asian overcapacity." This statement indicates that Boskalis was not capable of competing with the Asian market at sides of the offshore energy market. This development is projected at the LTD market that is considered in section 3.2

The developments of technology create competitive advantage for the companies who adapt. The concepts of digital transformation, as Big Data, IoT, AI and Blockchain are often considered as threat and opportunity for business. Boskalis needs to adapt to this technological transformation or is likely to loose competition on the long term. The R&D of Boskalis is already actively applying these concepts to improve the core business of Boskalis. The fleet is considered as equipment and not to be the core business at the OED, resulting in less priority for innovation of shipbuilding and shipping management. New ship building projects only happened at the Dredging Division, but never at the OED. Shipping competitors outside the Offshore Energy like Maersk, Wallenius and Stena line are more adapted to digital information technologies for controlling and improving and their fleet, systems and bunker consumption. The company We4Sea offers their data solution to smaller shipping companies, who are not capable of own development, to control and improve their fuel efficiency. The subcontractor of Boskalis for fleet management, Anglo-eastern, showed more advanced information infrastructure for technical control of the fleet, compared to the system of Boskalis. Boskalis as shipowner did increasingly outsource their fleet management to reduce costs and has a low level of applied information technology at the OED.

3.1.2 Financial Benefits

The costs and revenues of shipping need to be distinguished first and for that reason a graphical overview is presented in fig. 3.1. The model shows that costs of bunker fuels are not included, which makes this model outdated considering increasingly importance consumption and related emissions (Victor N. Armstrong, 2015).

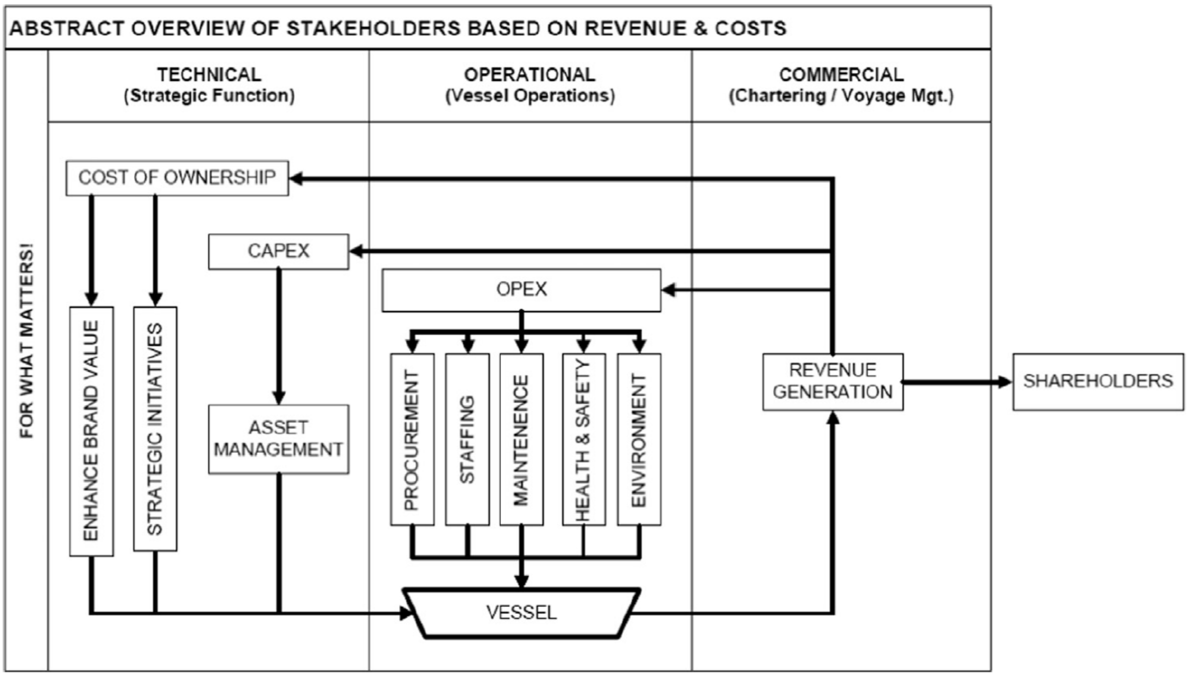


Figure 3.1: Abstracted Revenue & costs related to stakeholders within shipping company (Victor N. Armstrong, 2015)

.

Boskalis OED considers costs of fuel as an out-of-pocket expenditure, that is paid by the client. Sometimes fuel is supplied by the client during a time chartering, but in the most cases supplied by Boskalis. The clients contracts typically lumpsum the charter fee and the fuel costs for the predicted project duration, with an risk coverage clause about bunker price fluctuations. The commercial stakeholder, as mentioned in fig. 3.1, realized financial benefits if the 'real day rate' is minimised to gain higher margins or offer sharper prices. Cost-effective improvement of energy efficiency contributes to the minimisation function of eq. (3.1). Commercial added value depends strongly on the client interests. The improvement of fuel efficiency can require initial investments and additionally risks for the shipowner, assumable to increasing the charter fee and decrease fuel costs for the client. Together the day rate of the vessel should be minimised by leverage of improved energy efficiency. Moreover, A data-driven DSS provides insight about actual fuel performance of a vessel for more accurate prediction of fuel consumption, which decreases financial risks of contracting.

$$MIN(Dayrate) = Charterfee + bunkercosts \tag{3.1}$$

The technical added value of energy efficiency can be gained by enhance of the brand value. A green brand image can appeal clients who prefer responsible organisations, with possibly willingness to extra fee for additional green initiatives, like bio-fuel. A vessel with a strong brand can have higher value on the second hand market, in case of disinvestment. More attention is paid to EEDI and EEOI, which can become increasingly important, together with the operational cost in case of market recession. A data-driven DSS system identifies the operational profile of vessels, which provides insight about how to improve the technical system design for matching with operations.

The operational added value can be gained when maintenance cost are decreased, next to fuel costs. Real-time data of a data-driven DSS provides insight about system health and required maintenance for fuel efficiency, which means improved control and predictions of maintenance intervals. The future scenario of carbon pricing can influence operational costs of value. Energy efficient vessels can prevent costs of carbon emissions in the future.

3.1.3 Control of Business

The main objective is to cost-effectively reduce bunker costs. The competitive advantage can be gained with a first-mover advantage, when Boskalis takes more effective and earlier decisions about fuel efficiency, ceteris paribus. Insight from the data-driven DSS system is required for those decisions. Boskalis need to know how much fuel they consumed for what and the corresponding efficiencies according section 4.2.

Although cooperate strategy of Boskalis is beyond scope of this thesis, there are opportunities at tactical and operational level to become a more lean and agile organisation for reaching goals by top-down formulated strategy. Achieving goals more efficiently (lean) and improve responsibility to environmental or organisational changes (agile), can improve competitiveness of Boskalis. The challenge is to cut bunker costs most effectively, without affecting production and to monitor and control the results. Control of Business provide insight how to improve operations, maintenance and design of their vessel. They can determine optimise speeds, best engine configurations, retrofits and provide information about expected design requirements for new vessels. The DSS system provides information to make sound business cases about new suitable technologies like hydrogen fuel cells, hybrid conversion and waste heat recovery.

The IMO request an increasingly amount of data for compliance with law and regulations. The data-driven system can automatically compile reporting for compliance with the DCS of IMO. When the strategy of the IMO changes or increases pressure, the data-driven system provides information about how to adapt.

3.2 Market Opportunities of Long Distance Towage

Shipping management is about how technology as product of shipbuilding serves economic prosperity at a certain market. The market of LTD is analysed to understand how improvement of energy efficiency by a Data-driven DSS creates added value for Boskalis' sales and operational departments. First the market outline in section 3.2.1 explains the context of the nice market of LTD. The competition at the market is considered in section 3.2.2. The contracting of LTD is explained section 3.2.3 to identity how fuel performance are related to client satisfaction.

3.2.1 Market Outline

The LTD market participates at the larger market of the Offshore Energy market that is briefly explained first. The offshore energy market can be considered as late cyclical, that means the market reacts delayed to the global economics and oil prices. The delay is typically about two years, since this is the duration of projects and contracts. A recession of the offshore energy market is a driver for cost reductions and focus on continuation of cash flow. The lower oil prices due recession of the offshore energy contradict the incentive to cost-effectively reduce bunker costs, but the lower bunker prices do not compensate the slink of the margins and the order book. The International Energy Agency(IEA), which is considered as 'the authority' about global energy market, predicts difficult times for the energy market, according their World Energy Outlook 2018 (Luttikhuis, 2018). The lower oil prices are expected to remain after 2018 and to create a scarcity consequently by lack of investments by oil and gas companies (IEA, 2018). The renewable energy market is expending, but this cannot avoid scarcity till 2023 due the increase of global energy demand and the lack of investments of the oil and gas industry. The IEA warns this scenario threatens development of renewable energy market and suitableness growth of the energy market. Boskalis is a contractor who serves these markets and have to deal with this scenario. The LTD market experienced strong fluctuations of the markets the last five years, which resulted in extreme situations form lay-up of vessels to sailing fast-as-possible.

The OED business unit of Marine transport & Services divided their transport activities in vertical (Lifting) and horizontal (Transport) transportation. The transport market is divided in wet transport by Tugs and dry transport by Semi-submersibles. The LTD fleet exclusively serves the niche market of the wet transport over long distances. The LTD vessel additionally serve the salvage market since the vessels have fire fighting equipment and are highly manoeuvrable. The LTD vessel are not participation at the market of Anchor handling, due slow winch response and no present Dynamic Position system. The LTD vessel do perform contract for only LTD, but also participate in larger contracts of the Boskalis Corporate. The participation of Boskalis at LTD market is not clearly profitable or a cross-subsidisation.

The spot market or tramp trade of LTD is changing over time, according the sales manager Laurens Corporal who serves the LTD for more than five years. The portfolio of LTD is shifting towards the lower-end markets of scrap and oversized not oil- and gas-related cargo over the last few years, comparable to the sold closed-stern fleet (Wallis, 2018). There are opportunities at the lower-end markets (often called offshore commodity markets) by these require a lower day rate, partly possible by cost-effective improvement of fuel efficiency with fuel as 60% to 70% of the total operational costs. The high-end or capability markets will become more price-driven by the global sulphur capture of 2020, since MGO tugs will become more price competitive with former HFO tugs.

3.2.2 Market Competition

The introduction of the Semi-submersible heavy lift vessels since 2000 was a significant threat for the LTD market(van Dokkum, 2011). The clients of Boskalis have to decide to transport their asset wet or dry. The economical optimum depends mostly on price and time of the transport. The trade-off between dry and wet is basically determined by the thrusters of the asset, the time pressure for first oil production, the structural integrity, the free board and the weather restrictions.

The Long distance towage is an oligopoly niche market with three significant participants: Boskalis, Alp Marine Service and POSH Terasea. Boskalis is market leader with a market share of approximately 42% of the market, according Laurens Korporaal. Boskalis showed interest in acquisition of both competitors This is questionable to be accepted by market authorities for preventing monopoly. Boskalis is well known for their relatively high cash reserves and acquisition of many offshore energy competitors.

The competitor Alp Marine Services from Rotterdam is founded by former Fairmount employees and is acquired by the Teekay Offshore Partners in 2014. Alp Marine Services has a fleet of 10 comparable and more advanced vessels. They can be indicated as a capability competitor for Boskalis. Their vessels are more advanced by higher bollard pull performance, anchor handling capabilities (DP class 2) and Ulstein X-bow design hull structure for improved work-ability range. Their new Alp striker, Defender, Sweeper and Keeper are called the Ultra Long Distance Anchor Handling Tugs, which can sail full power for 45 days, sufficient for non-stop Trans-Atlantic/Indian, Pacific Ocean towing operations without fuel calls. Niigata shipbuilding built these vessel with 300 ton bollard pull, Ice class (1B) Ulstein design hull, FiFi-2 and DP-2 in 2016. The LTD vessel of Boskalis were built at the same shipyard during 2006-2008 (see section 1.4).

POSH Terasea is considered as a price fighter from Singapore with 9 newer vessels compared to Boskalis, causing relatively high price competition level at Asian region. Their newest vessels have DP-1 and anchor handling capabilities. Posh Terasea develops their fleet with less sister vessels compared to the others.

Boskalis works with their brokers and face approximately between 1200 and 1800 tenders for LTD annually. Laurens Korporaal stated that 70% of not won tenders is result of price competition. Operational expenditures of towing full power are approximately 13.000 euro per day and 20.000 euro for bunkers. Lower bunker costs can improve both competitiveness of LTD. A DSS system provides insight and control of the energy performance and supports decisions for cost-effective reduction bunker consumption, which forms an important part of the competitiveness.

3.2.3 Contracting

The LTD department of Boskalis uses standardized BIMCO contracts for time chartering (see appendix B.2). The idea behind this contract is that all agreements are signed for the project by this one single contract. The required bunker costs are roughly estimated by the operation department by a 'rule of thumb' and looking at SPOC. This estimation is contracted lump-sum, with an additional bunker escalation clause to cover the risk bunker price fluctuations for both parties. The crew and other operational management are provided by Boskalis.

These contracts avoid separate contradicting or overlapping contracts, claims and payments. Therefore the most contracts contain two days of 'spare time' before and after transport, two days for mobilisation (to replace crew, store bunkers and consumables) and two days for unforeseen delays of transport due speed reduction. Additional charter fee and bunkers have to be paid by the client if the demurrage exceeds the delay and 'spare time' of the contract. Some client contract additional bonuses for arriving earlier.

The 'Split incentive' between Boskalis and charterers can be considered as a serious barrier to improvement of fuel efficiency(Delft). The charter fee will increase as consequence of investments in energy efficiency, while fuel efficiency benefits are clear for the clients. This can have a negative consequence for commercial activities, although the total day rate can lower. The split incentive can be avoided by communication of the decreased day rate by cost-effective fuel savings. Whether a shipowner can recoup a share of fuel efficiency wins, depends on two factors. First, the equilibrium of the market, found be micro-economic analysis, shows benefits are shared, depending on price elasticity of demand and supply. Second, the fuel saving measures can create risk of underperformance and unsatisfied charterers, while over performance risk should be covered by charter rates to avoid only benefits for the charterer.

The standardized contract do explicitly contract the predicted fuel consumption. The actual daily consumption is shared with the clients during the transport. The clients use the consumption as a performance indicator and start complaining when the predicted amount of fuel is not burned. The daily consumption is shared by e-mails containing unprotected excel sheets, with sensitive information about the performance of LTD. New contract forms that exclude explicit numbers of fuel consumption and contain wire tensions and towing speeds can be developed. A data-driven DSS system can provide accurate predictions and real-time monitoring of these performance.

3.3 Societal Drivers

The public opinion and political developments around GHG can not by ignored by Boskalis and the data-driven DSS is useful for acting in the future. First the reduction strategy of the IMO is explained in section 3.3.1 and the SEEMP that already affects Boskalis in section 3.3.2. The increased importance of CSR at Boskalis is explained section 3.3.3.

3.3.1 Greenhouse Gas Reduction Strategy of the International Maritime Organisation

The IMO is developing a GHG reduction strategy that makes shipowner responsible for their emitted GHG. The decarbonization mega-trend is expected over the next decades, according the IMO GHG reduction strategy (Øyvind Endresen, 2018). At April 2018 the IMO adopted their GHG reduction ambition of 40% and 50% at 2030 and 2050 with respect to 2008. The strategy and targets will be specified by policy that is expected in 2023. This GHG reduction policy will be based on collected data and the fourth GHG study, which will be completed in 2019. The Maritime Environment Protection Committee (MEPC), works actively on this GHG dossier, to achieve agreements between UN policy and Maritime industry.
The IMO aligns their policies with the Kyoto - DOHA amendment and UN for GHG reduction. The first GHG study of the IMO was to monitor and forecast the GHG-emission of the maritime sector. The second study was for effective reduction of GHG-emission of the maritime sector. The second study stated that 75% is feasible by operational excellence and existing technologies, about many are cost-effective and offer financial benefits. The third study combined both new collected data and knowledge for a GHG reduction policy, with the SEEMP as result. The Marine Environment Protection Committee is currently developing stricter policy for the GHG ambitions.

The future outlook of bunker fuel related is shown in fig. 3.2. The global sulphur cap of 2020 is expect to disturb the residual fuel market prices, that will affect the energy intensive shipping more than energy efficient shipping. The most effective for improvement of energy efficiency will be the carbon taxing, but is not explicitly mentioned in fig. 3.2. The EEOI and EEDI are both mentioned in the overview and will have impact on all the new building vessels. The EEOI is not obligatory and the EEDI is for new build vessels and both not explicitly formulated for LTD vessels. The laws and regulations were mainly focused on NOx, Sulphur and less on GHG. A fundamental difference between NOx, Sulphur, PMs with respect to GHGs is that they rain down and GHGs do accumulate in the atmosphere, with human induced global warming as result. The GHG have to be captured for restoring concentration to pre-industrial time concentrations.

The GHG policies aim to avoid reaching the so called tipping point between 1.5 and 2.0 degrees Celsius increase, with respect to pre-industrial times. At this tipping point further global warming is expect to enforce itself and to be irreversible. Heat reflecting ice (with allot of methane captured) change in heat absorbing black deep waters, as example reason. Mention that future warming of oceans increase CO2 absorbents, lower PH value, consequently solve calcium and magnesium based stones and Coral, emitting CO2 again and damage restore ability of the global ecosystem.

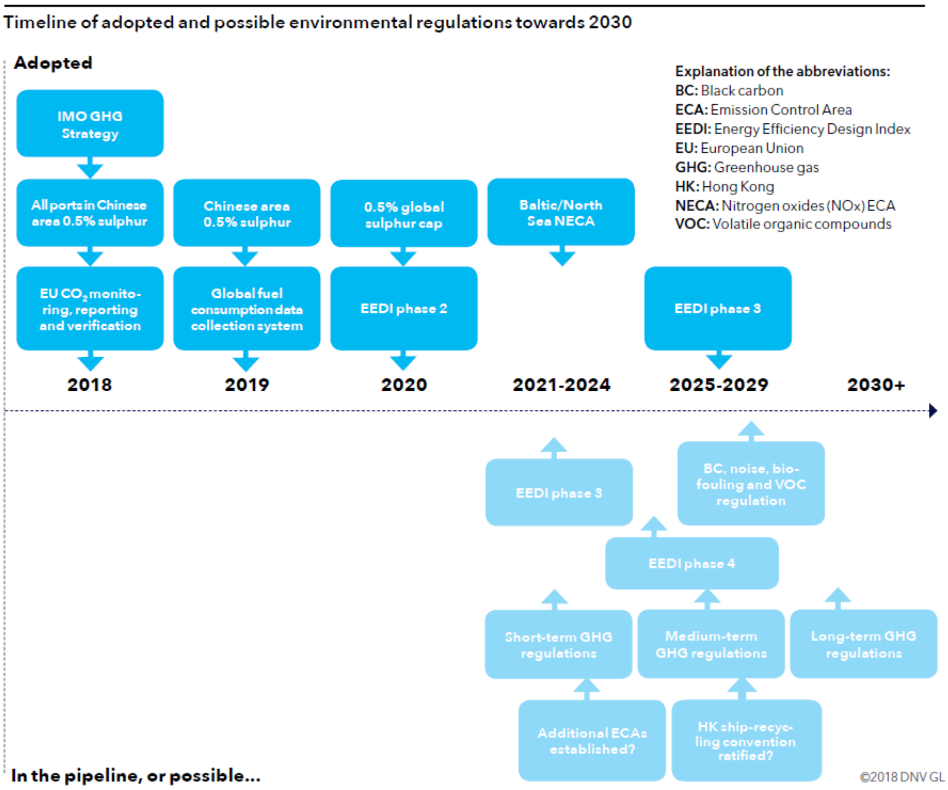


Figure 3.2: Future outlook to emission policies (Øyvind Endresen, 2018)

3.3.2 Ship Energy Efficiency Management Plan

The resolution MEPC.203(62) was adopted on 15 July 2011 and includes regulation for energy efficiency for ships in the MARPOL Annex VI. This was the first legally binding climate change treaty to be adopted since the Kyoto Protocol by the IMO. A new International Energy Efficiency Certificate (IEEC) is required by 1 January 2013, which shall be issued for both new and existing ships above 400 gross tonnage to which the chapter 4 of MARPOL Annex VI applies.

The International Association of Classification Societies (IACS) introduced the Ship Energy Efficiency Management Plan (SEEMP) for compliance with IEEC. The Ship Energy Efficiency Management Plan (SEEMP) is an operational measure that establishes a mechanism to improve the energy efficiency of a ship in a cost-effective manner. The SEEMP also provides an approach for shipping companies, to manage ship and fleet efficiency performance over time using, for example the Energy Efficiency Operational Indicator (EEOI) as a voluntary monitoring tool (IMO, 2018b). This EEOI is not applicable for work Vessels at Boskalis.

The SEEMP is considered as a 'living document' and is part of the annual survey, which only requires presence of SEEMP document on board. When no SEEMP is present on board, this is communicated with flag state, who provided the IEEC. Non-compliance of the SEEMP does not affect International Air Pollution Prevention Certificate (IAPP) of the vessel. The SEEMP is renewed like all other certificates after five years, which is at 1 January 2019 for all vessels at Boskalis Offshore Energy built before 2013.

The IMO Data Collection System (DCS) requires mandatory reporting about Fuel oil consumption for all vessels about 5000 gross tonnage, as first step to collect data for the GHG-reduction strategy as presented by the IMO in 2023 (Øyvind Endresen, 2018). The reporting methodology is described in the SEEMP, part II, as integrated part of the current SEEMP and need to be submitted at 31 December 2018. Details to be reported: Period of calendar year, distance travelled, amount of each type of fuel consumed in total, hours underway under own propulsion and DWT to be used as cargo proxy.

The LTD vessels have to comply with the SEEMP, which is renewed and approved by 1 January 2019. The

SEEMP-II requests data, which has no approval requirement for these vessels below 5000 gross tonnage. Boskalis is not obliged to deliver data of the LTD vessels to the IMO.

Data Collection System development

The Glomeep published a white paper about what data should be collected for validation of performance of energy efficiency technologies, again focused on cargo vessel (to Support Low Carbon Shipping, 2018). This white paper is related to the DCS of IMO and possibly represents minimal required data that should be collected by industry. Shipowners who prefer the minimal data-driven development can use the presented table in section 3.3.2 and DCS of SEEMP-II as bare minimum data requirement.

	Basic Noon Report	Noon reporting system with GPS	Performance monitoring system
Automated or manual process	Manually entered only	Manually entered with GPS related parameters generated automatically	Automated but can be supplemented by manually entered data
Data frequency	1 data point per day	1 data point per day	Data points collected in seconds / minutes intervals
Ship speed over ground		x	x
Ship speed through water	x	x	x
Distance and course over ground (COG)	x	x	x
Power from propeller shaft torque meter		x	x
Water depth		x	x
Additional sensors such as for cargo and controllable pitch		-	x
Draft aft and fore		x	x
Cargo aboard and/or draught	x	x	x
Fuel used (by tank soundings or flow meters)	x	x	x
Position (GPS) and time (in order to obtain wind speed, wind direction and current from weather service provider)		X All data is limited to the time when the noon report is transmitted	x

Figure 3.3: Data sources that can be obtained from using different data monitoring systems (to Support Low Carbon Shipping, 2018)

3.3.3 Corporate Social Responsibility Policy

Boskalis considers Corporate Social Responsibility (CSR) required for survival. The maritime environment of Boskalis does ask for a strategy to be sustainable in the future. The Strategy at corporate level is ought to be interpret by all people within the organisation for being effective. Corporate Social Responsibility (CSR) is increasingly important for Boskalis' Stakeholders, clients, employees, partners and 'the war on talent'. The Chairman Peter Berdowski stated more funds and resources will be available for decision support tools to achieve CSR goals, at the CSR event at 29-10-2018 in Rotterdam.

Boskalis decided to start CSR activities and publicised the first annual CSR report in 2009. The CSR report of 2017 (Boskalis, 2017) used a materiality matrix fig. 3.4 to explain the twenty most important topics for Boskalis. Both emission and energy transition are highly ranked to the top twenty at Boskalis. Moreover, the emissions are expected to have the largest business impact for Boskalis after health and safety.

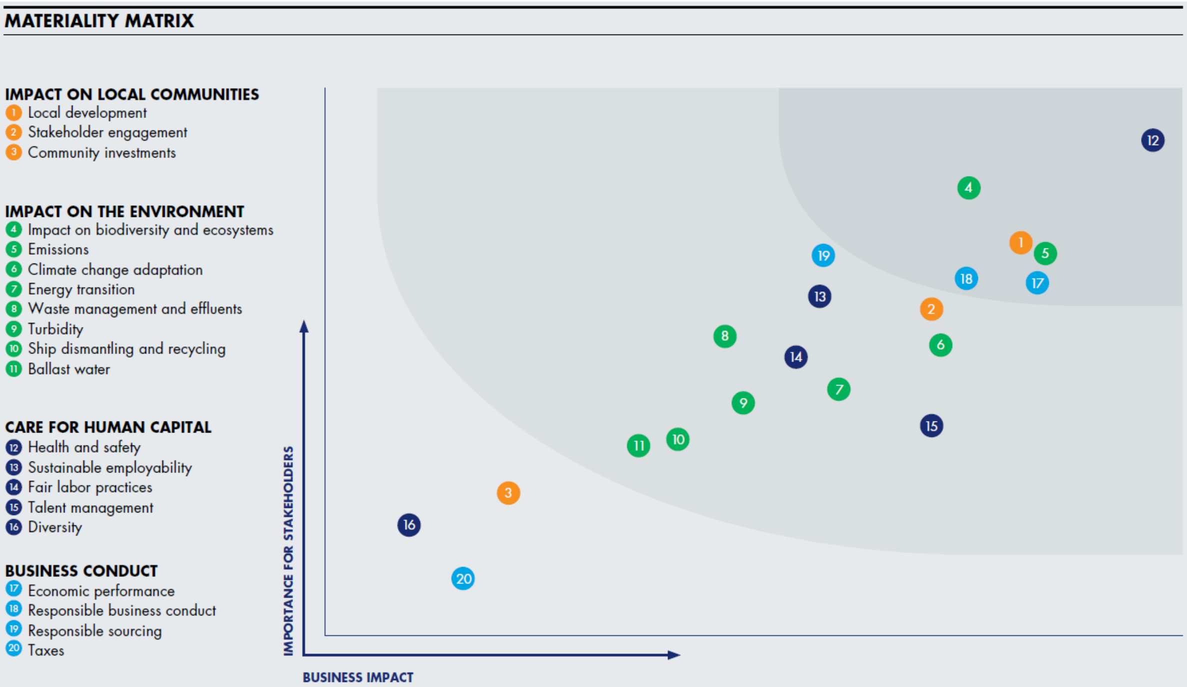


Figure 3.4: Materiality matrix of Boskalis (Boskalis, 2017)

The CSR initiative provided the CSR data about fuel consumptions and the publication of 2017. The CSR data was useful as starting point for prototyping the data-driven DSS. Boskalis had a total emission 1.223 MT C02, for which the fleet was accountable for 99.7% and 0.3% by offices. The OED used 134.000 MT HFO and 78.000 MT MGO. Consequently OED produced 669.000 MT CO_2, which is 55% of Boskalis. Boskalis uses a conversion factor of 3.026 MT CO_2 and 3.114 MT CO_2 per MT of fuel, but internal CSR reports are all in cubic meters. The LTD department reports in MT and CSR converts this in Cubic meters and carbon emissions, which is inaccurate for about ±10% (see section 4.2.3). There were no other noteworthy development within the offshore energy fleet about fuel consumption and associated emissions, regarding the lower total amount with respect to 2016 (790.000 MT CO2), except the nearly flat utilisation rate of Heavy Transport fleet (accountable for 56% of Offshore Energy emissions in general). No data is available to specify activities or performance of Boskalis. The CSR reporting only provides indicator instead of performance related indicators, like proposed in section 4.2.

The Data-driven DSS design improves the currently available data about both fuel consumption and carbon emissions. The system enables Boskalis to understand the fluctuations and trends of their carbon emissions.

Chapter 4

Business Intelligence Design

Quote: "if everything that lives is defined by information structures within corresponding DNA? What is an organisation without structured information?" (Inspired by Robbert Dijkgraaf)

This Design of business intelligence enables the OED to quantify and control their energy efficiency with the data-driven DSS. Business Intelligence enables organisations to process their raw data into insights and make data-driven decisions. The developed conceptual models, algorithms and required data are specified in this Business intelligence design and are applied in the case study.

The Business Intelligence Development process is illustrated in the geographical overview of fig. 4.1, which is part of the entire developed DSS methodology shown in section 2.4. The drivers are previously explained and clarified about why Boskalis is interested in data-driven DSS for energy efficiency. The BID is part of the whole evolutionary prototyping methodology and the chronology of iteration steps indicate a logical sequence for progress of BID, but is not necessarily required.
First the concept of a Data-driven shipping organisation is explained together with Business Process Modelling Notation to specify the process of energy consumption in section 4.1. Performance control for energy efficiency is developed for work vessels to gain insight and judgement about vessels of the categories of OED in section 4.2. The Required data input for the DSS is specified and contains all found data attributes as input for an advanced system in section 4.3 and is the starting point for raw data collection of case studies.

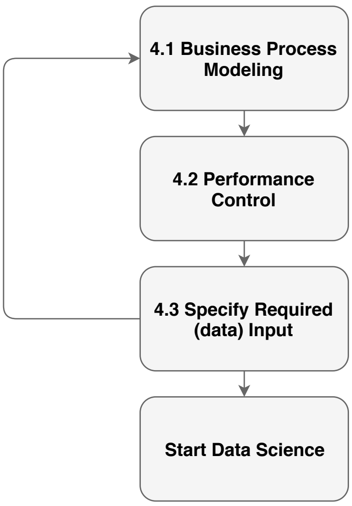


Figure 4.1: Geographical overview of BID, as structure of this chapter (own composition)

4.1 Business Process Modelling

The organisation, business processes and their corresponding decisions structures and characteristics are explained, which all need to be understood for building a suitable DSS or prototype. The concept of the data-driven shipping organisation is explained in section 4.1.1, to understand how the organisational goal, hierarchy, decision characteristics and operational data are related. Operational decisions need to be known explicitly to identify both decision makers and the required insights from data. The Business Process Modelling Notation (BPMN) is used and the method is explained in section 4.1.2. This method is located in this section and not in chapter 2, since BPMN is a method for a Social Network Analysis within the development of DSSs.

4.1.1 The Data-driven Organisation

The pyramid of section 4.1.1 graphically represents the relations of the hierarchical organisation, decision making and operational data. This model provides overview and understanding of the fundamentally different requirement for DSS design and prototyping.

At the top is 'the goal of organisation' is present and is the main reason for all activities. Three layers are distinguished: the strategic, the tactical and the operation levels of the organisation. The corresponding decision characteristics (left) and indicators (right) for controlling business are specified. The operational data (right below) is processed toward the goal of organisation and consequently decisions are made for the top-down control of the operations. The departments and executives corresponding to different layers of organisation are discussed in following paragraphs of this subsection.

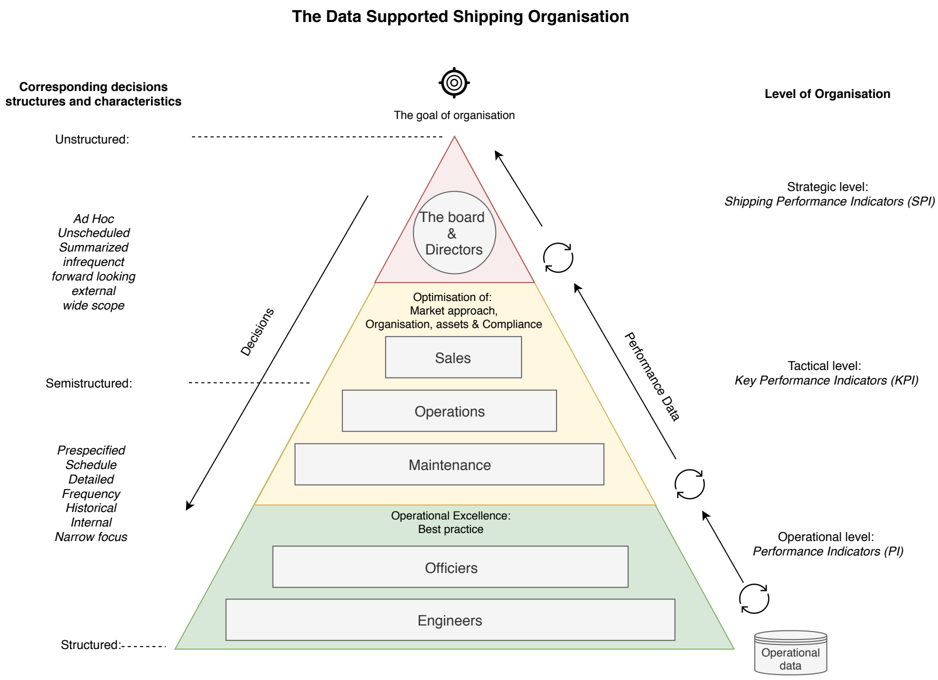


Figure 4.2: Data-driven performance decision hierarchy model (own composition)

At the top, the board members and executives, state the goal of organisation for which a strategy is formulated, by considering the business environment and core values of organisation. The decisions made at this level do effect the long term energy performance of the Offshore Energy fleet. The typical decisions are to build a completely new fleet, which is very fuel efficient, or to buying 30 year old, not fuel efficient vessels and possibly modify them. There are many parameters besides the energy efficiency of vessel for the decision making at this level of organisation. The indicators at this level are called Shipping Performance Indicators (SPI), which are highly summarized numbers that represent the performance of the whole company, divisions, business units and departments. The number of accidents is a well known example of a SPI at Boskalis and SPI for energy performance is developed by this project.

At the tactical level the strategy is interpreted, by Business Unit managers and self-directed teams. The medium term (one to three months typically) decisions are made for alignment with strategy and for optimised organisation of operations. These decisions should typically be the main concern of sales, operations, engineering and fleet management departments of shipping organisations. Typical decision examples are speed optimisation of voyages, weather routing, maintenance interval planning and awareness training. Targets and benchmarks can be set and be monitored by KPIs. These KPIs typically are a number between 0 (no improvement) to 100 (target fully accomplished), but can also surpass 100 (overachieved target). The KPIs can be formulated differently for departments that work vessel or project oriented, but need to be consistent and related. This 'unification of data' prevents conflicting truths and sub optimisation of departments.

The operational level of organisation realises the projects offshore. The operating managers and Self-directing teams, make decisions typically on daily or weekly based. When the intentions and targets of tactical level are not clearly communicated, people on board will not notice the urgency of energy efficiency or do not how to improve it. Procedures, training or a dashboard to monitor their performance can stimulate better energy performance. Performance Indicators (PI) shows crew how they performance on a daily bases. Management can indicate minimums or challenge crew by competition between crews and vessels about energy efficiency. Gamification and awareness training are both proven to be effective for improvement of energy efficiency Delft.

The model of section 4.1.1 is the starting point of the BID, since it allows to specify required insights and translate these to required operation data and algorithms to process. The section 4.1.2 explains to method for more specific process analysis of the organisation and the next sections of this chapter are about the algorithms and required data for the OED.

4.1.2 Fundamentals of Business Process Modelling Notation

The DSS development theory states that a BID proper design should contain a Social Network Analysis (SNA) and the orchestration analysis. The BPMN is more specific about stakeholders, decision makers activity sequence and supporting information, compared to previous explained model of section 4.1.1. The current process and the improved automated process illustrates the potential to increase process quality and reduce costs, related to labour, material and capital. The decision for BPM is motivated to document requirements for IT projects in general. This graphical notation gives the ability to communicate process and procedures to gain understanding of performances, collaboration and business transactions between the organisations. This section is mainly inspired by the master lectures of Prof.dr.ir. M.F.W.H.A. (Marijn) Janssen, with expertise about IT & Governance, who responsible for the Business process modelling and Technology. This paragraph briefly explains BPMN which is ought to be a simplistic technique to be interpretable for both business and IT people.

Readers who are not familiar with BPMN can see appendix B.1 and read this explanation. BPMN contains pools, which represent stakeholders of the business processes.

BPMN applied for the current situation create insight about how DSS can be improve (within) the current IT-architecture and process. This research is about how operational data can be integrated within business process to support decisions. The integration of DSS is done by adding the DSS as virtual stakeholder for the process. Mention that there are many types of DSS systems as stated in fig. 2.2. Within the case study BPMN is applied for understanding the relative complex process of LTD shipping and decisions that affect energy consumption en efficiency.

The BPMN for the improved process results in information requirement as stated in both section 4.2 and section 4.3. These sections describe how to control FC and EE more into detail and what data is required to provide information to improve the process.

4.2 Performance control

The insufficient insight from operational data about energy performance disables data-driven decision making at the OED. This is considered as a serious barrier for several shipowners(Delft) to improve their energy performance. This performance control design enables full control about energy efficiency business and generates support for decision making.

Theoretical implementation of SPIs, KPIs and PIs for different levels of organisation were already stated in section 4.1.1. The section explains these into more detail for energy performance of work boats. These indicators are explained by section 4.2.1, section 4.2.2 and section 4.2.3, which were explicitly requested by Boskalis.

4.2.1 Shipping Performance Indicator

The SPI are used at strategy level of a shipping organisation for decisions that affect for example energy efficiency for over one year. They are used to communicate overall performance to the stakeholders of the company. Typically SPI are used for financial, health & safety, human capital, technical, environment performance. SPIs are aggregated expressions and can be calculated by a weighted average of KPIs (research council of Norway, 2013).

Boskalis already reports fuel consumption and corresponding carbon emission in their annual and CSR reports. Only the indicative numbers are collected per vessel. These numbers are based on bunker delivery notes about bunker transfer volumes. These volumes are multiplied with factors to determine mass and carbon emission, which is inaccuracy. Boskalis can improve this indicator by relating them to activities and defining targets for creating a SPI. The measured mass of the fuel instead of the volumes to calculate carbon emissions, since this is more accurate. The days hired per vessel is an attribute in the CSR data, which has an average correlation between 0,6 and 0,8 with fuel consumption, according analysis of LTD. These correlations are to low and unspecified for performance control. Additional to the total amount of fuel and carbon, an energy efficiency SPI is developed to communicate performance independently and stronger correlated to production activities.

When quantities and performance are sufficiently known about energy consumption and efficiency, they can be used for decision making. Typical decisions are about 'code of conduct' for business or the scrap, retrofit, modification or new build vessels. Benchmark can be enables to see how EE can be improved most effectively, when improvement potentials and cost of amendment are clear per vessel, fleet or type of project. There is a risk (Øyvind Endresen, 2018) of non-compliance with IMO GHG reduction strategy fig. 3.2, this is represented by C_{carbon}.

The energy performance is one of the many aspects of shipping performance, but typically between 20% and 60% of total costs of work vessels. The Cost-effective improvement of EE can have significant impact on total cost reduction. The share of total cost depends on the vessel category and utilization.

The bunker expenses are currently considered as out-of-pocket expense and are payed by the client, who are mostly oil related companies, which causes the split incentive (Delft) as barriers for improvement. Boskalis and other shipowners do not consider bunker fuels as part of Total Cost of Ownership (TCO), which can be considered as not taking accounting responsibility for carbon emissions. Nevertheless, Boskalis can start collecting data for finding opportunities of cost-effective reduction and prepare future carbon pricing and compliance.

Price on the second hand vessel market is related to bunker consumption as part of OPEX. If energy efficiency of a vessel is undoubtedly better, total costs of shipping with the vessel will be lower, ceteris paribus. Added value with smart improvement of energy efficiency, possibly results in a higher market price with leverage. The risk and consequences of carbon pricing and non compliance can enforce this speculative phenomena, since OPEX increases for energy inefficient ships.

The conclusion is that a SPIs for fuel performance are 'very straight forward' for cargo shipping and less for the offshore work boats, since their operations are more diverse and complex. An SPI for fuel performance is important for decision making since 20% to 60% ot Total is fuel consumption. A SPI for fuel performance can simply be translated to one about CO2 emissions for CSR reporting and control alignment for future law and legislation, because these have an one-to-one relation. The SPI of fuel performance gives insight about fuel performance and is aggregated from other numbers that can explain the SPI in more detail, which are not necessarily interesting for decision at board level of organisation.

SPI for work vessels

Boskalis faces an additional challenge to quantify energy efficiency, together with policy makers of for example MEPC. Container, bulk and RORO transportation is relatively easy to quantify compared to work vessel, cause of their less constant operational profile. The production is transport of a certain unit of cargo over a certain distance. When this is related to a certain quantity of fuel mass or energy consumed, an equation like eq. (4.1) can be formulated.

$$SPI_{EE,cargo} = \frac{Units_{cargo} * Distance_{travelled}}{Energy_{consumed}} \tag{4.1}$$

The fleet of Boskalis OED is very diverse and is distinguished in eight different categories of vessels, shown in the table below. Each category is different in purpose, design, operational profile and corresponding fuel performance. Decision makers who use the SPI should be careful when comparing different categories with the SPI. The Heavy lift and LTD can be compared since they both transport a mass over a distance. The Geophysical Research vessels, Cable layers and fall-pipe vessels are comparable in the way they all three have a tasks related to work at the sea bottom over long distances at reduced speed. The floating sheer legs and Dive Support Vessel are comparable because of operations at their required DP-II systems.
The found vessel categories of Boskalis OED are summed below:

1. Heavy-lift Transport Vessels
2. Long distance Towage
3. Geophysical Research Vessels
4. Cable layers
5. Fall-pipe vessels
6. Anchor Handling Tugs
7. Crane Vessels & Floating Sheerlegs
8. Dive Support Vessels

The proposed eq. (4.2) enables to benchmark and compare vessels and to improve the project organisation. Today, Boskalis can not compare Heavy Lifting or LTD transport for tenders with low GHG requirements and bonuses, while they both transport a mass over a distance. The described formula enables Boskalis to gain competitive advantage by offering clients the most carbon lean contract. The production is the towing force or added resistance by additional displacement over a distance and the total energy is the equivalent mass of bunkers or carbon emissions. The predicted total amount of fuel is still interesting to compare, because the two type of transport have fundamental different parameters. Mention that fuel required for 'free-running' to pick-up the project must be included for 'fair' comparison.

$$SPI_{EE,work} = \frac{Production_{total}}{E_{total}} \tag{4.2}$$

The E_{total} is a summation of all energy from different fuel consumptions for a certain production, which is shown in eq. (4.3). The 'SPI' can be split and calculated by including or excluding modes, fuels, projects or periods, so all energy consumption data is labelled by these attributes. This way of data storage enable Boskalis to quantify and analysis their energy efficiency by operational data. For example Boskalis can see the quantity of bio-fuel used for a certain project or period for meeting their GHG reduction targets. Energy efficiency of certain vessels and periods can be compared to control progress and operational costs of energy.

$$E_{total} = \sum_{i,j,k,l} E_{i,j,k,l} \tag{4.3}$$

Where:

i	: Mode of operation	[-]
j	: Type of fuel consumed	[-]
k	: Project ID	[-]
l	: Period of time	[hours, days, weeks, quarters, years]

To understand the SPI and the E_{total}, more detailed information is required. eq. (4.3) shows how energy consumption can be captured and modelled by data in a numerical way. The operational data about consumption should be labelled per mode of operation, type of fuel, period and project. This way Boskalis gains insight of their consumptions.

4.2.2 Key Performance Indicators

The concept of Key Performance Indicators (KPIs) enables management to communicate benchmarks and targets and to monitor actual performance. KPIs are widely used in business for setting targets and monitoring progress. KPIs can be applied at vessel, fleet, project, Business Unit, division or corporate level over a certain time. Targets in KPIs form can be divided in sub-KPIs for understanding and communication to organisation levels below.

The KPIs are typically used by the middle management at tactical level for targets with a time span between one to three months. These KPIs can be used to create awareness and to stimulate creativity of the organisation to meet their energy efficiency targets, which is one of the most effective and accepted way within shippingDelft. Additional bonuses for achievement of targets enforces the effect of implemented KPIs.
KPIs result in a value typically between 0-100, but can exceed 100 in case of overachievement. The input values of target value and minimal value (benchmark) are required for the KPI formulation, as shown in eq. (4.4).

$$KPI = \frac{KPI_{value} - KPI_{MinReq}}{KPI_{Target} - KPI_{MinReq}} \tag{4.4}$$

The Visualisation and communication of KPIs is done by dashboards. Examples of an Econometer and Bullet charts are given in fig. 4.3, which both are suitable for KPI representation. Years and months can be selected to represent KPIs over certain preferred periods. A real-time data stream will provide up-to-date KPIs in the dashboard.

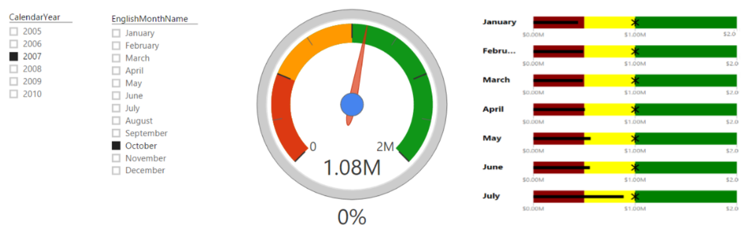


Figure 4.3: KPI visualisation examples in Microsoft Power BI

Example of KPI for work vessels

One KPI is developed for the overall performance for every operational mode over a certain period of time, as described in eq. (4.5). A target and minimal required vessel efficiency is defined for cost-effective improvement every three months. When targets are met, energy efficiency of the vessel is cost-effectively be improved.

Previously a data analysis quantifies the current energy performance per operational mode to determine the required minimal value of the KPI. A realistic target can be set for three months, which corresponds with the improvement plans of the organisation. A weighted average of efficiencies can be used to determine the $KPI_{EE,vessel}$, that is explained by eq. (4.5).

$$KPI_{EE,vessel} = \sum_{i,j} \frac{KPI_{value} - KPI_{MinReq}}{KPI_{Target} - KPI_{MinReq}} * \tau_{i,j} \tag{4.5}$$

Where the $\tau_{i,j}$ represent a fraction, between 0 and 1 and cumulative equals 1, of consumption by a certain operational mode (i) and fuel type (j).

The KPI example of eq. (4.5) can be considered in a more abstracted manner. The concept of KPI can be applied for categories of the fleet and varying time period. The KPI provide clear communication of benchmarks and targets of energy efficiency within visualisation that is understandable for everyone with limited explanation provided about algorithms.

4.2.3 Performance Indicators

The PI provide insight about energy efficiency both onboard and onshore. These insights are synthesized (see fig. 2.4) from an structured data both onboard and onshore. Research concluded that fuel efficiency of LNG tanker can be predicted by regression algorithms, containing less than nine attributes, results in R^2 of 0.88 for noon reports and 0.95 for PMS(Lucy Aldous, 2013). Research of the IMO concluded that PMS data is preferred over noon report for quantification of new sustainable technologies(to Support Low Carbon Shipping, 2018). The energy efficiency quantification of Non-transport vessel is complex compared to transport vessels and requires more detailed analysis about vessel operations and systems(Henrique M. Gasper, 2009). For this reason the energy efficiency control model for work vessels is developed during this research (see fig. 4.4). This whole subsection is dedicated to explanation of this model.

The model of fig. 4.4 is a composition of marine drive chain theory, operational profiles and related sensor application. The model can distinguishes the missions or projects, operational modes of profile, events and related efficiencies of work vessels. The level of detail about operations depends on the available data quality and triggers for observation. No only the whole vessel can be considered, but the different systems efficiencies (PIs) are captured by this model. The full statistical control of energy efficiency provides Boskalis to monitor efficiencies and quantify financial results of improvement.

The model of fig. 4.4 divides the total vessel performance, 'the black box', in smaller parts of performance for operational mode function of the vessel. Each block of the model can be quantified, if values of the circle symbols are attributes of the data. When attributes are missing, blocks can be analysed together but insights of performance are less. When the input and output of every block is known, a PI is calculated within the related distributions for insight of the performance. When benchmarking shows a block performs significantly low ('weakest link'), corresponding measure examples are given below in the figure.

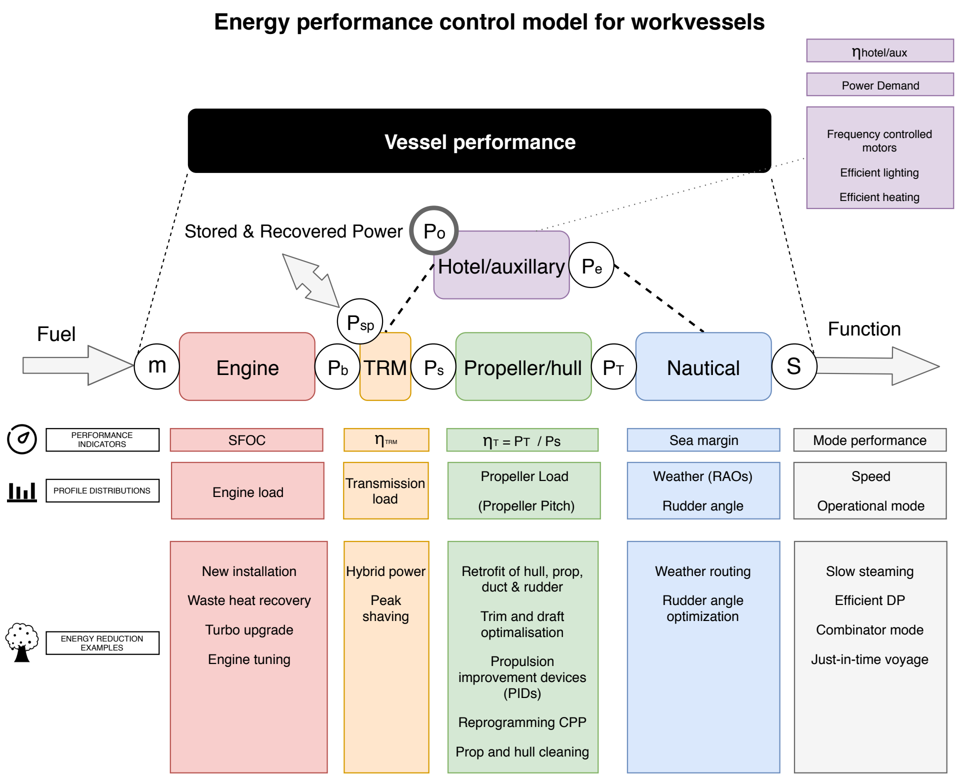


Figure 4.4: Energy efficiency model for work vessels (own composition)

An Artificial Neural Network can combine the different Machine Learning algorithms and data sources for advanced application of illustrated model in fig. 4.4. For example, the real-time series data of the machinery control room, bridge controls, nautical weather data and bunker supplies can be used as input for this model. Stena line already implemented an Artificial Neural Network for energy efficiency improvements and a graphical overview is shared in fig. 4.5. The current data quality onshore at the Offshore Energy is not sufficient to develop an Artificial Neural Networks for energy efficiency. The current situation requires an expert team to develop data quality and an acquisition system.

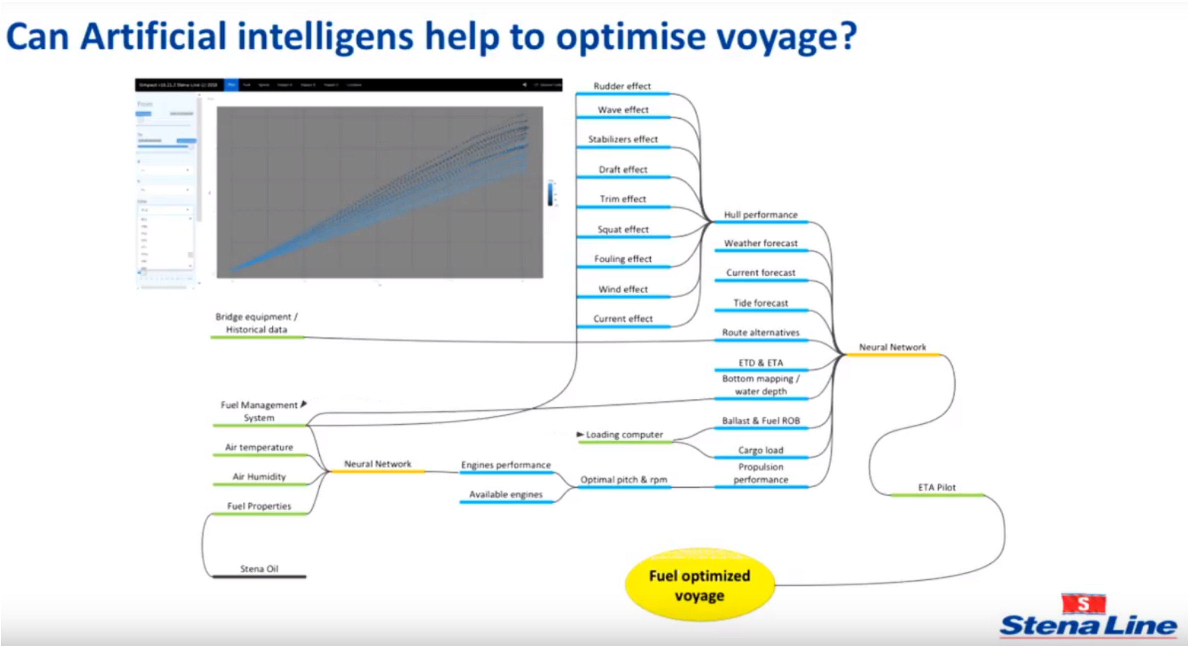
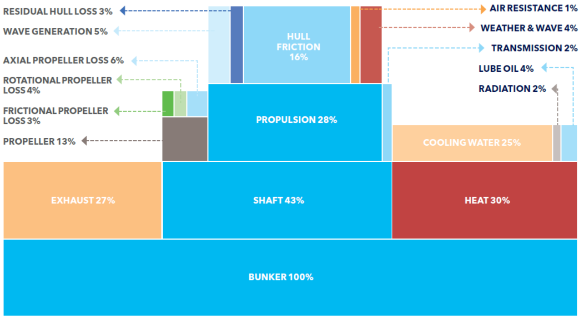


Figure 4.5: The Artificial Neural Network slide of Stena line at the Lighthouse conference about energy efficiency in 2018

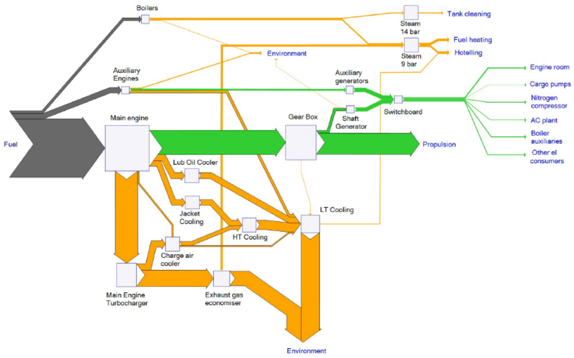
A digital twin is an offline vessel simulation model, which is build by ship design and operational profile information and can be built by data of the model in fig. 4.4. The operational profile and design of the digital twin can be changed and the effects can be predicted by the simulations. Implemented changes of design and operation can be validated and be used to improve the digital twin algorithms. The company We4Sea from Delft uses digital twin concepts for fuel efficiency control and improvement consults for cargo vessels. The company NAPA from Helsinki uses digital twin concepts to improve their ship design and operational solution software. No digital twin applications for change of ship design of operations were found at Boskalis. The Artificial Neural Networks, found during the research, typically emphasises more on operational decisions, compared the digital twin solution. Since Boskalis is an operator the application of an Artificial Neural Network for energy efficiency seem to be more supportive for the core business of an operator.

Energy consumption diagrams

The energy consumption diagram do visualize energy flows of system and can be applied for vessels as illustrated in fig. 4.6. These diagrams are typically made for the steady and frequently occurring conditions and operations of a vessel for with the most energy is consumed. Vessel and 'flows' can compared to find and quantify the improvement potential.



(a) Quantified Propulsion energy diagram of a well-maintained cargo ship, head sea of Beaufort 6.(H. Lindstad, 2009)



(b) Non-quantified Detailed Shankey diagram example(Baldi, 2013)

Figure 4.6: Examples of energy consumption diagrams

The summarized overview of energy consumptions and efficiencies (PIs) provides quantitative insight about the actual performance at different moments and can be used to communicate changes of design or operation. The impact by these changes can by visualized for overall energy system. These diagrams are often used in literature to explain that diesel engines produce more heat than propulsion energy and the improvement effects due waste heat recovery.

These models can by used at Boskalis energy to communicate energy efficiency related matter to people who not familiar with the topic, because these are easy interpretable. High quality data is required about the engines, the systems onboard and the vessel environment for a detailed diagram like in the examples of fig fig. 4.6.

Vessel Performance Indicator

The overall vessel KPIs for work vessels are the weighted average of KPIs from all operational modes. The eq. (4.6) shows how all operational mode KPIs can be compromised by one number per vessel. The Vessel KPI provide insight how performance are related to benchmarks and targets of Boskalis.

$$KPI_{vessel} = \sum KPI_i * \tau_i \tag{4.6}$$

Where:

KPI_i: Dimensionless KPI number of operational mode

τ_i: Mode fraction of total fuel consumption

The different PIs of operational modes are not normalised values like the KPIs, but provide one number for the actual performance. Different examples are shown for free-running (see eq. (4.7), production (see eq. (4.8)), Dynamic Positioning (see eq. (4.9)) and Idle (see eq. (4.10)). Mention that fuel mass can be converted to energy units, GHG emission or vice versa. The efficiencies together with total consumption can explain what performance are, with respect to a certain distribution, for example kg/NM per sailing speed.

$$PI_{vessel,free-running} = \frac{m_{fuel}}{D_{covered}} [kg/NM] \tag{4.7}$$

$$PI_{vessel,production} = \frac{U_{production}}{m_{fuel}} [unit/kg] \tag{4.8}$$

$$PI_{vessel,DP} = \frac{m_{fuel}}{S_{corrected}} [kg/NM] \quad or \quad \frac{m_{fuel}}{T} [kg/t] \tag{4.9}$$

$$PI_{vessel,Idle} = \frac{m_{fuel}}{T} [kg/t] \tag{4.10}$$

These PIs give insight about the actual performance of a vessel. Behind these numbers of the whole vessel are the performance of systems that provide the performance, like illustrated in the control model of fig. 4.4. The following paragraphs show how to quantify these other PIs.

Onboard Energy Measurements

The most important attribute of energy performance data is the quantity of energy input at the vessel. An uncertainty of ten percent, results in the same uncertainty for both the overall vessel performance and the engine performances. For this reason, this paragraph is dedicated to fuel measurement on board and start with the best method and end by the less accurate method.

The most accurate way to measure energy consumption on board is to measure and log the chemical energy value input of the engines every second. Chemical energy quantities can not directly be measured onboard, but the mass can be measure by a Coriolis meter and the Net calorific value of fuel, without water contamination, can be determined by drip sample tests in the lab. Without lab test, Lower Heat Values (LHV) ranges between 40 and 43 MJ/kg(Hans Klein Woud, 2002). The calculation according eq. (4.11) provides an uncertainty about < ±1%.

$$E_{Coriolis} = m_{fuel} * LHV_{fuel} \tag{4.11}$$

m_{fuel}	= Mass of fuel measure by Coriolis meter	[kg]
LHV_{fuel}	= Net Calorific Value of fuel by lab	[MJ/kg]

The second most accurate way of measurement is by a volumetric flow meter, as shown in eq. (4.12). This meter measures the volume of fuel that passed the meter. The lab tests of the drip samples provide both the density and the heat value to calculate the energy. The density range of marine bunkers is between 840 kg/m3 to 1010 kg/m3 at 15 °C(Hans Klein Woud, 2002), which is the ISO 12185 condition. The temperature of fuel though the volumetric flow meter have to be logged, since the expansion coefficient $(1 * 10^{-}3)$ results approximately in 1% density uncertainty per 10°C temperature uncertainty. The temperature differences of 50°C are common at flow meters. MGO is typically about 25°C and HFO between 95 and 130 °C. When temperatures are measures at the flow meter, the uncertainty of the measurement is expect to be < ±2%. The volumetric flow meter requires proper maintenance to maintain this accuracy.

$$E_{volumetric} = V_{fuel} * \rho_{fuel,T} * LHV_{fuel} \tag{4.12}$$

V_{fuel}	= Volume of fuel	$[m^3]$
$\rho_{fuel,T}$	= Density of fuel at certain temperature	$[kg/m^3]$

The worst case scenario is no flow meter is installed onboard. Tank soundings need to be done and energy values to be calculated according eq. (4.12). A manual tank sounding is typically of lower quality compared to sounding by PMS, since the low measure frequency of the manual method. Flow meters and automated sounding systems can log data at relative high frequency. The Tank soundings measure the dept of tank filled with fuel. Agreement between the two tank readings themselves is only within ±2.5%, without additional disturbance of ship motions or air mixture(14 authors, 2008). The motions of the vessel can increase inaccuracy of soundings significantly depending on tank location and weather conditions. A trim table of corresponding tank indicates how to determine the volume of fuel within the tank by sounding, with an additional uncertainty. When fuel temperatures are measured, the uncertainty within calm waters of these measurements are < ±5% and useless for analysis at heavy seas.

$$E_{sounding} = L_{sounding} * C_{volume,trim} * \rho_{fuel,T} * LHV_{fuel} \tag{4.13}$$

$L_{Sounding}$	= Fuel level of tank	$[m]$
$C_{volume,trim}$	= volume of tank at certain trim	$[m^3/m]$

Both the bunker transfers and the bunker consumption measurements are important to consider and compare. The validity of energy consumption data can be improved over longer period by comparing these two measurements of a certain vessel. These two measures can be compared over a period (T) as stated in eq. (4.14). The lost energy indicates uncertainty of data over time and when there are relative high losses within system, there are example cases of back wash of purifiers in sludge tank, leakage of piping or theft.

$$E_{lost} = \sum_{T} E_{transfers} - \sum_{T} E_{consumed} \tag{4.14}$$

The Bunker transfers data is typically of very low resolution, since bunker transfers happen a few times a year. Fuel-pilferage, 'Cappuccino effect', water added and air in piping are additional parameters causing uncertainties. Coriolis meter for marine fuel bunker transfer application measures a single phase flow with an accuracy of 0.1% and two phase generally within 0.2% to 3%(14 authors, 2008).

Engine performance

The engine performance is in the context of this thesis mainly about fuel efficiency. The engines onboard convert chemical energy first into heat energy and second to mechanical energy, which is called Brake power. The engine efficiency performance are expressed in a engine efficiency percentage or the Specific Fuel Oil Consumption (SFOC), that is expressed in grams of fuel per kWh output. The efficiency percentage of marine medium speed diesel engines is typically between the 35% and 50% and a corresponding SFOC between 250 and 180 g/kWh. When the fuel consumption and brake power are known, the engine efficiency can be calculated by integration over time (see eq. (4.15)).

$$PI_{engine} = SFOC = \int_t \frac{P_b}{\dot{m}_{fuel}} dt \tag{4.15}$$

Where:

$SFOC$	= Specific Fuel Oil Consumption	$[g/kWh]$
P_b	= Engine Brake Power	$[kW]$
$\dot{m}_{fuel}$	= flow through meter	$[g/s]$

The SFOC of marine engines is related to the operational use with respect to speed and load (W. Shi and Stapersma, 2010). The marine engine efficiency in relation to the operational envelop are graphically indicated (see fig. 4.7). The best efficiencies are typically found within the region of 85 to 95% engine speed and 65 and 90% engine load. A DSS should suggest to operate within these envelopes, for which the total power plant system provides the highest efficiency.

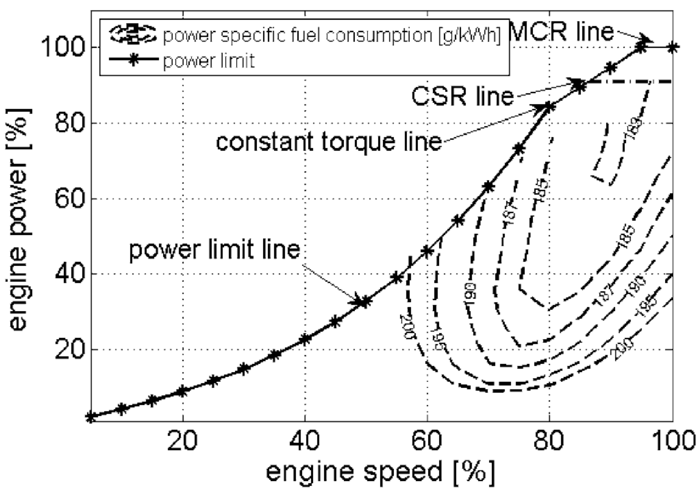


Figure 4.7: Operational envelop of a typical diesel engine(W. Shi and Stapersma, 2010)

The engine load can be measured in three different ways, by controller, shaft power output or mean effective pressure and rpm of cylinder(Listewnik, 1999). The controller data is very unreliable, since these controllers are manually calibrated and are not based on the actual engine output. When the running hours from the overhaul increase, differences between the controller output and the actual brake output increase, sometimes up to 20% as appeared in the case study.
The measurement of mean effective pressure per cylinder is strongly recommended by literature and measured typically every month during engine test in practice. The individual cylinder 'health' can be measured. The sensitive equipment that is required for testing of mean effective pressure can not continuously been installed during common operations, which is the disadvantage of this method. This method might be used to calibrate the controller data every month, if an electrical engineer is onboard.
The shaft power meters can directly measure the brake power output at the engine shaft or when installed at the propellers shaft for backward brake power calculation. These shaft power sensors are a few percent

accurate and not to decay over time when frequently calibrated.

The ISO 15550:2016 standard refers to the SFOC correction calculation (ISO 3046-1) for the ambient condition to enable comparison with the SFOC specifications of the engine manufacturer. The formulas for ISO correction (see eq. (4.16), eq. (4.17) and eq. (4.18)) are explained and considered for the case study.
The K-value (eq. (4.16)) corrects for the engine inlet air temperature and pressure, together with the charge air coolant temperature. The engine inlet air temperature refers often to the machinery room temperature and can be above 40 degrees Celsius instead of the 25 °C reference value. The inlet temperatures, expressed in Kelvin, has the highest power factor of 1,2 for the K-value. The charge air coolant temperature, expressed in Kelvin, can be above the 40 °C instead of the 25 °C reference value. The operational coolant temperature before and after the intercooler have to be known for this correction. The natural barometric pressure is typically between 990 and 1040 hPa, but can be higher within the machinery room. The reference value is 1000 hPa for calculation of the K-value. The humidity of the inlet air can additionally be related to the engine and intercooler performance (condensation), but this is not included within the ISO correction.

$$K = \left(\frac{P_x}{P_{ref}}\right)^{0.7} * \left(\frac{T_{ref,air}}{T_{x,air}}\right)^{1.2} * \left(\frac{T_{ref,coolant}}{T_{x,coolant}}\right)^{1} \tag{4.16}$$

Where:

K	= Ratio of indicated power	[-]
P_x	= barometric pressure during test	[hPa]
P_{ref}	= standard reference barometric pressure	[1000 hPa]
$T_{ref,air}$	= reference air temperature	[298 K]
$T_{x,air}$	= air temperature during test	[K]
$T_{ref,coolant}$	= reference charge air coolant temperature	[298 K]
$T_{ref,coolant}$	= charge air coolant temperature during test	[K]

The α-value is related to the K-value and the mechanical efficiency of the engine (η_{Mech}). This mechanical efficiency is typically between 0,8 and 0,9 for marine diesel engines and is assumed to be 0,8 for the ISO correction by Wartsila in 2006.

$$\alpha = K - 0.7 * (1 - K) * \left(\frac{1}{\eta_{Mech}} - 1\right) \tag{4.17}$$

Where:

η_{Mech}	= mechanical efficiency (0.8-0.9)	[-]

The next step for the ISO correction is about the LHV of the fuel and the engine driven pumps (EDP). The low quality fuel with a lower LHV requires relative large corrections, since the direct multiplication with the factor of LHV (see eq. (4.18)).

$$SFOC_{ISO} = \frac{\alpha}{K} * \frac{LHV_x}{LHV_{ref}} * SFOC_x - EDP \tag{4.18}$$

Where:

$SFOC_{ISO}$	= Specified fuel oil corrected	[g/kWh]
$SFOC_x$	= Specified fuel oil of sample	[g/kWh]
LHV_{ref}	= Low Heat Value reference	[42.7 MJ/kg]
LHV_x	= Low Heat Value of sample	[MJ/kg]
EDP	= Engine Driven Pump correction	[5 g/kWh]

The difference between a corrected and uncorrected SFOC can be above 20 g/kWh for 'unfavourable' conditions, which is equal to 5% of the engine efficiency. An unfavourable condition example is the case of a LHV equals 40 MJ/kg, inlet air temperatures above 40 degrees Celsius, 1040 hPa air inlet pressure, intercooler coolant temperatures above 40 degrees Celsius and EDP.

When all the operational conditions and the reference values are equal, the ISO correction has no effect on the SFOC value. The ISO-correction is useful for comparison of the operational SFOC with ISO corrected SFOC data delivered by the engine manufacturer.

The maintenance of the diesel engines and Turbochargers influences the SFOC. A lack of maintenance gradually decreases the SFOC and can eventually result in total engine failure. The rule of thumb from midrange diesel engines is to overhaul every 24.000 running hours on MGO and 12.000 on HFO at Boskalis. Wartsila publicised their conclusions (see fig. 4.8) about specified maintenance jobs, recommanded running hours intervals for maintenance and the relation with fuel efficiency. The SFOC before overhaul is typically cumulative increased by more than 5% (±20 g/kWh), compared to after overhaul. The conclusions of Wartsila are indicative for their maintenance intervals in between the overhaul interval. The numbers provided by Wartsila are more detailed and are consistent with conclusions of IMO about manual engine performance optimisation (IMO, 2018a).
The fouling of turbochargers can be responsible for more than 2% increase of the SFOC. Turbo washing is recommanded with a typical interval about 500 running hours when sailing at HFO according Gaby Steentjes. The cleaning or replacement of the nozzle ring should be done every 4.000 running hour interval, especially when sailing on HFO. The turbochargers need to be fully cleaned and reconditioned during the overhaul. The fouling of the air intake filters and air coolers can increase SFOC together with 1,5% and both be cleaned every 4.000 running hours. The injection pump wear can increase SFOC by more than 1% and should be replaced every overhaul.
The combustion quality is correlated to the mean effective pressure within the cylinders and the engine performance. The engine charge pressures and temperatures, together with exhaust gass temperatures can give frequently insight about the combustion quality. An engine performance test with cylinder pressure sensors additionally installed can give more detailed insights about 'health' per cylinder and the total engine. The incorrect valve and injection timing per cylinder can be found by installing these cylinder pressure meters during tests.

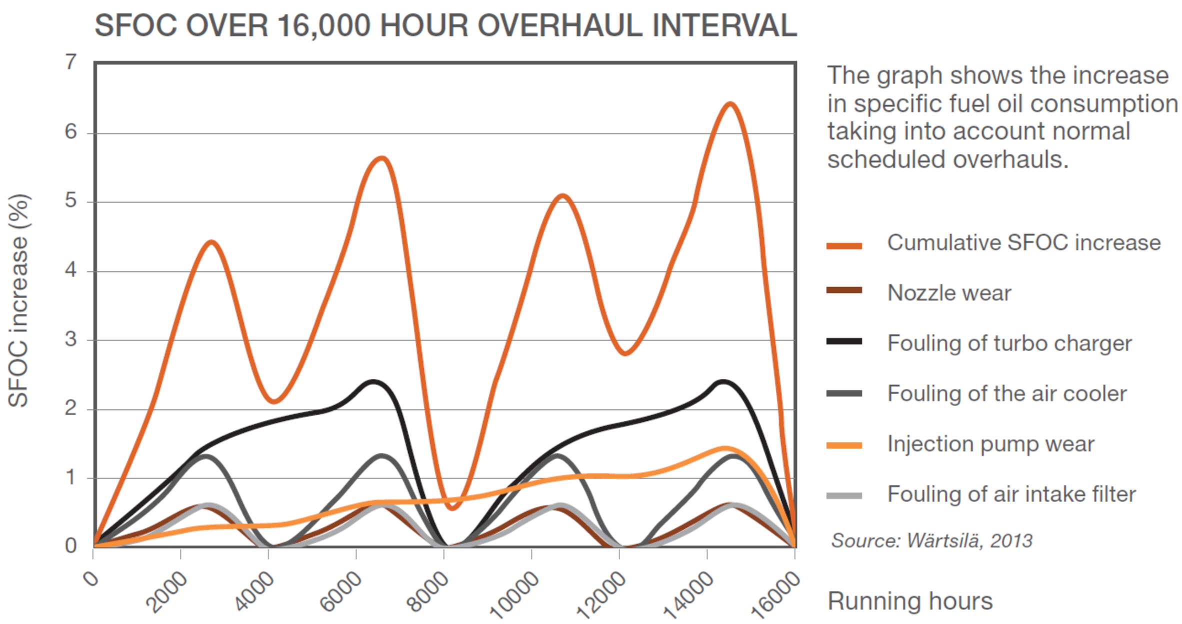


Figure 4.8: The impact of maintenance on fuel efficiency between overhaul

The Turbochargers connected to marine engines deliver increased pressure for better internal combustion within the cylinders and higher engine efficiencies. The Turbo speeds, pressures and temperatures are parameters to monitor to control performance of engines. The intercoolers after the turbo chargers decrease the temperature of the compressed scavenge air for the cylinder. These intercooler have to be monitored for their pressure difference before and after and temperature output.

The engineers of AVK provided their performance monitoring sheet for engine performance tests after overhaul (see)fig. 4.9). They relate the relevant operational parameter to their engine specifications after overhaul. This model inspired for development of the prototype but is not implemented, because the graphical design is relatively hard to interpreted for crew onboard and to complex for a prototype. Moreover, this model of AVK works with kg/h instead of SFOC.

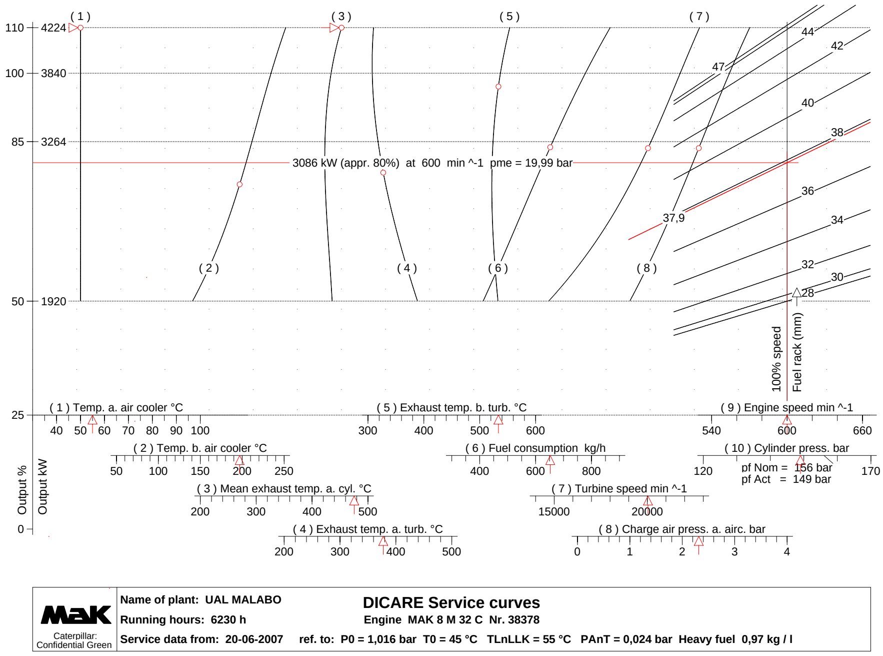


Figure 4.9: AVK engine performance monitoring example sheet

A DSS prototype for manual engine performance optimization is provided by the case study of this thesis (see section 5.3.4). The actual available uncorrected performance values of this PI are related to the engine specifications.
The SFOC increase can be plotted over time to identify the relation between overhaul, performance decrease over time and the relation to maintenance procedures.

Transmission Performance

The transmission PI is about the transmission equipment and control management system to transform energy flows within the technical systems of a vessel. A hybrid vessel uses stored electrical power for propulsion instead of running an engines at inefficient loads and speed. The energy flows are fundamentally about chemical, mechanical, hydraulic, electrical and thermal. The typical transform equipment components examples in shipping are gearboxes, shaft alternators, electrical converters and heat exchangers. Management of energy flows can enable storage within batteries, boilers, thermal oil tanks and hydraulic pressure tanks. Systems that improve energy efficiency by smart management of energy flow and storage are often called hybrids in literature. The direct driven propulsion systems do have a typically transmission efficiency about 97 to 98%, depending on load of the system. These efficiencies are important to consider, for the operational performance of the transmission systems and the quantification of the improvement potential.

The formula in eq. (4.19) explains how to quantify Transmission performance as defined in fig. 4.4. This formula does not directly indicate the advantage of smart transmission management, but indicates how a system is transforming energy w.r.t the engine output and the stored power. Power inputs of the transmission are the engine brake power and the stored power that entries the transmission system (by WHR-orcan modules or batteries for example). The outputs are propeller shaft power, electrical power on switchboard that is transmitted to storage.

$$PI_{TRM} = \int_t \frac{P_{shaft} + P_e + P_{sp,out}}{P_b + P_{sp,in}} dt \tag{4.19}$$

$PI_(TRM)$	: Performance Indicator of Transmission	[-]
P_{shaft}	: Propeller Shaft Power	$[kW]$
P_e	: Electric Power	$[kW]$
$P_{sp,out}$	: Stored Power out to Storage	$[kW]$
$P_{sp,in}$	: Stored Power in from Storage	$[kW]$
P_b	: Brake Power from engines	$[kW]$

The stored power within exhaust gas, cooling waters can be used by waste heat recovery. Thermal energy can directly be used for preheating of bunkers, lube oils, condensation within fresh water makers or for heating of water and Air conditioning. When waste heat quantities are sufficient, heat can be used to generate power via steam turbines or Organic Rankine cycle. This all will decrease both brake power and electrical consumption, but efficiency of transmission is expected to increase as whole because less conversion losses will be the case.

Battery technologies developed over the last decades and enabled already full electric ferries in Norway. The energy density and charge speed are not sufficient for crossing oceans today. Though, hybrid applications and intelligent transmission management can improve EE. Examples of applications are Peak Shaving during DP or electric powered drive train for manoeuvring or sailing low speeds. Stored power in Batteries can be used as spinning reserves for DP-II systems.

Thrust performance

The thrust power is required for most operational modes, like free-running, towing or DP for example. The thrust efficiency gives an efficiency about how the shaft power is converted to the thrust power over time, as stated in eq. (4.20). The thrust is the force that is produced by propeller(s) of a vessel. The axial compression of a propeller shaft is measured by strain gauge and the produced thrust can be calculated. The difference between the power on shaft and thrust produced by a propeller over time can be considered as lost energy. The operational propeller efficiency is between 10% and 70% for marine application.

$$PI_{Trust} = \int_t \frac{P_T}{P_{shaft}} dt \tag{4.20}$$

The efficiency calculations of a propeller are complex, but can be simplified for operational practice. The propeller performance is best, accordingly simplified disk theory, when the propeller diameter and dept are maximised, revolution speed is minimised and there is uniform axial water flow though the propeller. The wave system of the hull has preferably a high pressure at the propeller position. A trim and draft optimisation can improve the propeller efficiency.

The two fundamentally different types of propellers are the Fixed Pitch Propeller (FPP) and the Controllable Pitch Propeller (CPP). The FPP has a smaller hub and theoretically higher efficiency, when operating at design load point. The CPP has a theoretically lower efficiency at design load point, but a relative larger operating range with high efficiency, compared to FPP.
The section 4.2.3 illustrates the effect of operating with variable RPM (combinator mode) related the constant RPM. The FPP design is 10% more efficiency at lower RPM, than a CPP at constant higher RPM. The CPP is interesting for vessels with a varying operational profile, like most work vessels. The concept of adaptive pitch control of CPPs can result in 5 to 15% fuel efficiency improvement and 30% improvement of acceleration(R.D. Geertsma, 2018).

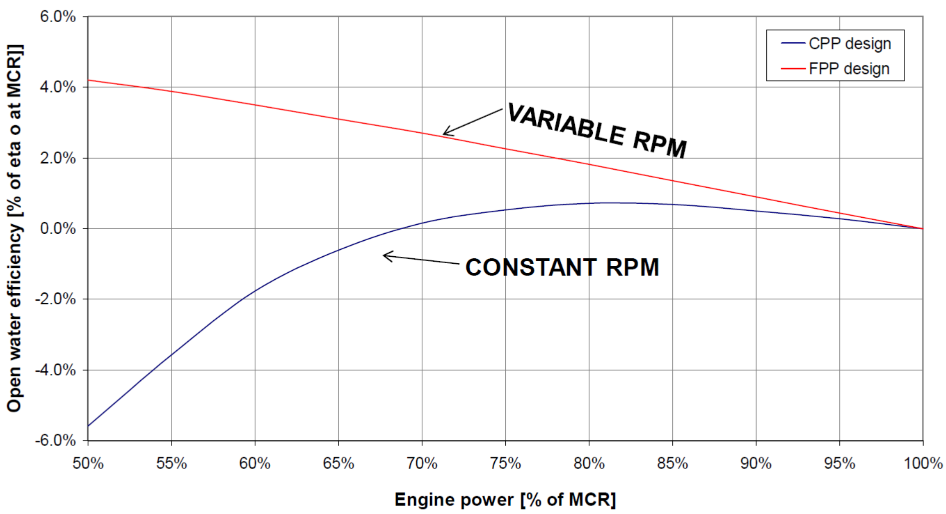


Figure 4.10: Open water propeller efficiency differences of fixed and variable frequency (J. Grevink, 2018)

The thrust power is hard to measure accurately in practise. The strain gauges can be placed at the propeller shaft to measure the axial deformation of the propeller shaft by generated thrust. The solid shafts are more difficult compared to the think-walled tubes, because the axial deformation of solids will hardly pass the noise levels. Moreover, the strain gauges need to be place with an accuracy of less than one degree with respect to the axial hard line of the shaft, otherwise the torsion of the shaft will corrupt the measurement significantly.

Nautical Performance

When the hull is clean, anti fouling paint and water most smooth, the reference speed related to a reference resistance and thrust can be determined. This best practise reference operational sailing of a certain vessel will decrease over time. The fouling of the hull and the Sea Margins will occur after finding this optimum. When eq. (4.21) can be assembled by operational data attributes, decrease of hull performance can be quantified and the system performance corrected by weather data.
The reference resistance can be validated with calculated resistance with for example Holtrop & Mennen. Large differences between references resistance and calculated resistance can be reason to investigate the hull structure or the operational data for errors.

$$PI_{Nautical} = \int_t \frac{(R_{ref} + R_{added} + R_{SM}) * V_{ship}}{P_T} dt \tag{4.21}$$

R_{ref}	: Reference Resistance from best practise measurement	$[kN]$
R_{added}	: Added Resistance by fouling	$[kN]$
R_{SM}	: Resistance additional due Sea Margin	$[kN]$
V_{ship}	: Corresponding ship speed	$[m/s]$
P_T	: Thrust power	$[kN]$

Data accuracy is required for success implementation of this PI. Deviations of all parameters over time are preferably collected within the data system, to judge for example noon data point on their accuracy. The 'gold standard data' is with minimal deviations of all parameters over the measured hours or days.
Over time the hull roughness increases and can be monitored by this PI. An example visualisation is given in section 4.2.3. The performance of different applied coating can be determined, hull and propeller cleaning intervals optimised and weather routing effects be predicted. Weather routing is not considered, but can additionally considered by adding high quality from VDR or ECDIS data about heading, speed and location.

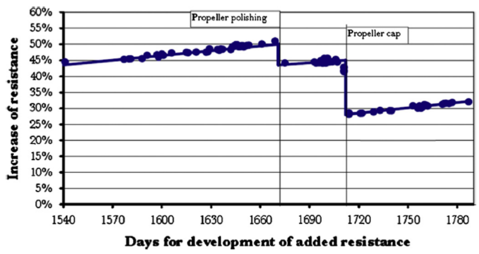


Figure 4.11: Added Resistance (Armstrong, 2013)

The Sea Margins can be measured by crew at bridge or by a PMS. A graphical representation in section 4.2.3 shows how external vectors can by identified as attributes for high quality data. The Sea Margins can be determined by simplified models with as input only length between perpendiculars and Beaufort number (Fransen en de Jong, 1976) or more advanced empirical models (Kwom, 2008).

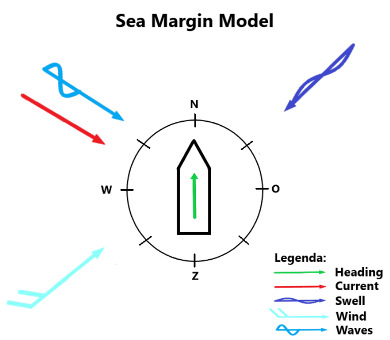


Figure 4.12: Sea Margin vector model (own composition)

The nautical performance can be captured by a DSS design, but many data attributes of high quality are required for convincing optimisation strategies. The Work vessel are smaller and do sail less in general compared to cargo vessels, which makes this PI of lower development priority for the Offshore Energy Division.

Hotel & Auxiliary Performance

Many systems onboard prove auxiliary and hotel functions, depending on the vessel design and the operational profile. The hotel systems are related to human presents onboard, like heating of water, cooling of food, lighting and air conditioning. The auxiliary systems are related preheating of engines and bunker, but also to the navigational equipment and the pumps for cooling and the lube oils. The P_o in eq. (4.22) represents specific equipment for operations like cranes, equipment for divers or towing equipment. The fuel is typically consumed by boilers or auxiliary engines.

$$PI_{H\&A} = \int_t \frac{(P_e + P_h + P_o)}{\dot{m_{fuel}}} dt \tag{4.22}$$

P_e	: Electrical Power of base load	$[kW]$
P_h	: Heat Power of base load	$[kW]$
P_o	: Additional Power required for work operation	$[kW]$

The load balance provides information about what systems are installed and their expected operational profile of power demand. The actual power demands over time are Preferable captured by the data, which can be logged at engines, shaft alternators and the switchboard. The single line diagram and machinery room layout are interesting information sources when considering improvement of energy efficiency onboard. The crew numbers, moment of the day and temperatures of environment are interesting to create additional information from the data.

The most effective way to improve hotel and auxiliary performance is due reduction of required fuel by the baseload of the vessel. The base load is the minimal power demand over time of a certain operational mode, required by continuously demand of equipment. Recovered waste heat can deliver heat power to freshwater makers, heaters for bunkers, accommodation (AC) and hot water boilers. The electrical baseload demand can be reduced by efficient emergency lighting (with demand 100% of time), variable frequency controlled motor of seawater cooling pumps and sensors and timers to switch-off lights, heaters and computers.

4.3 Required Data Input

"Rubbish in is rubbish out, independent of the model used"

The required data for the data-driven DSS for energy efficiency is specified by this section, which is the last step of this BID. The required data is specified by the required data accuracy according the DAMA framework (see section 2.2.4) and the required data availability for development and prototyping.
The concept of data quality is previously explained (see section 2.2.4), a data quality assessment is written in the next chapter (see section 5.1.2) and many data quality related matters are considered within the previous paragraphs of this chapter.
Nevertheless, the required data quality is shortly specified in the next paragraph (see section 4.3.1).
The next paragraph about the required available data gives an generic overview of all data attributes the were found useful for quantifications about energy efficiency, within an Entity Relationship Diagram (ERD) format that can directly been translated to a data acquisition and database design. (see section 4.3.2)

4.3.1 Required Data Quality

The data quality frameworks are previously explained (see section 2.2.4), the data quality assessment of the LTD case study is written in the next chapter (see section 5.1.2) and many data quality related matters are considered within the previous paragraphs of this chapter.

The time series data for the data-driven DSS requires high quality data for being effective for decision making and further development or prototyping, compared to financial data for annual corporate reporting.

The six primary dimensions are briefly specified now. The completeness for daily summarized data needs to be 100% for 100% consistent quantification of energy performance in history over longer periods. The timeliness is preferred to be high, with a least a daily data update. Moreover, the timeliness need to be consistent for the different datasets for being consistent. The uniqueness of the vessels and equipment need to be guaranteed by validity rules. These validity rules need to enable a 'happy flow' of data from ship to the shore databases, without being corrupted or missed.

4.3.2 Required Data Available

The Required data is determined for quantification of energy efficiency. This subsection give examples of entities (tables) and their proposed cardinality (relations). A database programmer or 'Big data engineer' is able to formulate this Entity relationship Diagram (ERD) after reading this phase of intelligence development, who can directly translate this ERD to a database format, in SQL or Hadoop for example. When the data is acquired and transferred from a vessel, this can automatically be processed into the database. This database is used to train model, develop model and output's visualisation, which can be presented in a dashboards to monitor, control and predict the energy efficiency. This subsection does not answer the question about how to relate this system to existing data structures within the company.

The entity examples below do contain attributes at the left entity column and the data type on the right column. All these example entities aim to capture all required data found during this development research.
Every Entity is interconnected according below defined cardinality (see fig. 4.13). The unique IDs of for example a certain vessel or engine connects the data according these cardinalities. The attributes do each represent a column of the at row indexed time series data. The data type explains how to formulate the attribute within the database and is a 'float' if the unit is specified.

The examples entities below are derived from this entire development study. These are found within the case study or are recommanded to be collected in the future for further system development research. The high level (see table 4.1) entity can be interpreted as a data table, by readers who are not familiar with database programming. This high level table contains different IDs with cardinalities to the other data tables. For example, the call of a Glacier ID can deliver all Glacier related data captured by the following fuel, maintenance and engine entities.

Table 4.1: High level data entity

Corporate Meta data:	
Attributes	Data type
Class IDs	'Strings'
Fleet IDs	'Strings'
Vessel IDs	'Strings'
Project IDs	'Strings'
CSR ID	'Strings'
Engine Manufacturer ID	'Strings'

The cardinality presents the relations between entities in the database. the Examples of cardinality notation are presented in fig. 4.13. The cardinality follow logically from reality considering the examples below. One fleet contains many vessel, one ship contains many engines and one vessel many project and vice versa.

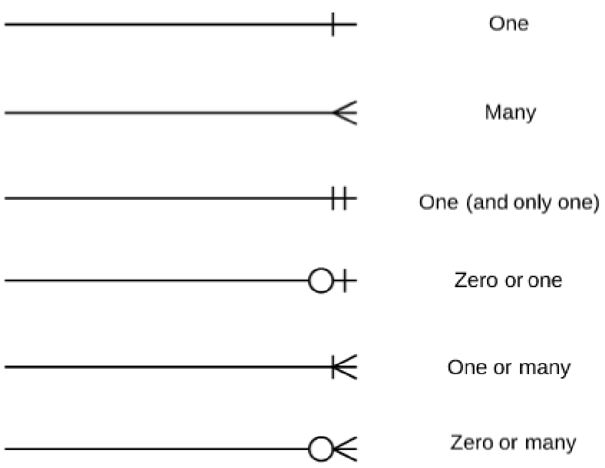


Figure 4.13: Cardinality notation examples

A table like below can be related one-to-many, considering the meta data to vessel level. A table can be generated to compare all vessel performance, but a specific vessel can be considered into more detail as well. Attributes like fuel consumption and efficiency can be abstracted by using formulas and data tables related to the vessel.

Basic vessel data:	
Attributes	Data type
Vessel ID	'string'
Fleet ID	'string'
Last Update moment	YYYY/MM/DD ; hh:mm:ss
Project ID	'string'
Captain ID	'string'
Chief engineer ID	'string'
Operational mode	'string'
Fuel consumption	MT
Fuel efficiency score	n
Carbon emission	MT of CO2

Sample data:	
Attributes	Data type
Vessel ID	'string'
Time of observation (UTC)	YYYY/MM/DD ; hh:mm:ss
Time of observation (local)	YYYY/MM/DD ; hh:mm:ss
Duration of sample	hh:mm:ss
Time of sample received	YYYY/MM/DD ; hh:mm:ss
Sample Trigger	Clock or Technical trigger

Maintenance data:	
Attributes	Data type
Vessel ID	'string'
Dry docking dates	YYYY/MM/DD - YYYY/MM/DD
Engine overhaul dates	YYYY/MM/DD - YYYY/MM/DD
Hull cleaning dates	YYYY/MM/DD
Propeller polish dates	YYYY/MM/DD
Turbo washing dates	YYYY/MM/DD
Calculated financial optimum for intervals	days %

Fuel Data:	
Attributes	Data type
Fuel ID	HFO, MGO, BIO
Vessel ID	'string'
Mass Quantity in tanks	$MT \vee MWh$
Mass Quantity used	$MT \vee MWh$
Mass Quantity remained	$MT \vee MWh$
Heat value of different masses	$MJ \vee MWh$
Carbon content	%
Bunker Supplier ID	'string'

Engine Data	
Attributes	Data type
Vessel ID	'string'
Engine IDs	'string'
Engine Manufacturer ID	'string'
Engine Maintainer ID	'string'
Number of engines running	n
Running hours since last overhaul	hh
Load input of controller	$\% \vee mm$
Engine speed	RPM
Engine output	$kW\&kWh$
HT temperatures and flow rates	$Celsius\&kg/s \vee m3/s$
LT temperatures and flow rates	$Celsius\&kg/s \vee m3/s$
Exhaust gass temperatures and flow rates	$Celcius\&kg/s \vee m3/s$
Lub oil consumption	kg/kWh
Calculated Costs of maintenance	€/hrs or €/kWh

Turbo Charger data:	
Attributes	**Data type**
Vessel ID	'string'
Engine ID(s)	'string'
Turbo ID	'string'
Number of engines coupled	n
Inlet temperature, pressure and humidity	$C, bar, \%$
Pressures and temperatures over compressor wheel	C, bar
Pressures and temperatures over intercooler	$C, millibar$
Speed of compressor wheel	RPM
Temperatures before and after turbo wheel	°C

Transmission data:	
Attributes	**Data type**
Input of WHR	kWh
Output of WHR	kWh
Input battery	kWh
Output battery	kWh
Storage and capacity	% MWH
Efficiency of alternators (load and powerfactor)	%, factor 0-1
losses over Gearbox	%

Propulsion data:	
Attributes	**Data type**
Shaft powers	kW
Propeller trust power	kW
Propeller speed	RPM
Propeller pitch	$\% \vee p/d$

Nautical data	
Attributes	**Data type**
Geographic Coordinates	LAT: degrees:mm:ss LONG: degrees:mm:ss
Heading	$-\pi to + \pi$
Trim and drafts(for,mid,aft)	$\% and m$
Dept of water	m
Speed over ground	knots, m/s, km/h
Distance covered over ground	NM, km
Speed through water	knots
Distance covered through water	NM, km
Current speed and direction	$knots, -\pi to + \pi$
Dominant Wave speed, height and direction	$knots, m, -\pi to + \pi$
Dominant wind speed and direction	$knots, m, -\pi to + \pi$
Swell speed, height and direction	$knots, m, -\pi to + \pi$
Air and sea water temperature	°C
Vision	m

Chapter 5

Case Study of Long Distance Towage

The prototype and other results of the case study about LTD are written in this chapter. First the BPMN models about the current and new situation are visualised, to learn the overall process of fuel consumption, allocate decision, stakeholders and how related operational data is used (see section 5.2). The Data Quality Assessment is explicitly reported, since DQ seemed a significant constraint for data analysis and improvements of the prototype (see section 5.1.2). The about data quality judged data is used to quantify the actual energy performance (see section 5.3). An financial analysis for cost-effective reduction of bunker fuel consumption is made, which is supported by the developed performance control (see section 5.4).

5.1 Case Study Outline

This chapter describes the outline of the LTD case study for understanding the vessel design, operations and the prototype model input (section 5.1.1). First a brief history about the vessels and organisation of the current LTD department. The five equally designed LTD vessels or previously called 'Fairmount vessels' are all built by Niigata Shipbuilding in Japan between 2006 and 2008. The Fairmount organisation was initially a shipbroker from Rotterdam, the technical management was done by Hanzevast and the shipowner was an external investment fund. The vessels are low cost of-the-shell designs with low level sea trials documentation. The Hanzevast organisation did the technical management for a few year and Fairmount took-over later, before Boskalis acquired Fairmount. Boskalis initially did the technical management in-house, but outsourced the technical management to Anglo-eastern since 2018-2019.

Vessel Design

Limited technical information about the vessel was available from navel architecture perspective. Only the minimal required documentation for the technical management survived all the organisational migrations over the years. The design drawings are not owned by Boskalis, but paper copies of required documents for asset management are available, like the general arrangement, shell plating and some construction drawings in pdf-format. The most relevant data sheets are shared in appendix A.1 and summarised in section 5.1. The MARIN had no available data about the vessel design or researches of the past. The original operational settings and fuel performance of hull, propellers and other equipment are unknown at Boskalis.

Table 5.1: Design specification of BOKA Glacier and Sherpa

Main particular of the five LTD sister vessels			
Builder	Niigata Shipbuilding, Japan	Storage Capacity (HFO / MGO)	1.994-2.201 / 539-746 [m3]
Building year	2006	Main engines	4 x Wartsila 6L32
Vessel type	Long Distance Towage	Installed engine power	12.000 [kW]
GT / NT	3239 / 971 [ton]	Installed shaft alternator power	2 x 1.200 [kw] (50Hz)
Displacement	5320 [MT]	Installed Thermal oil boilers	2 x 800 [kW]
Length overall	75 [m]	Installed generator power	2 x 370[kw]
Beam	18 [m]	Installed CPPS	2 x D3.85-4x0.625
Depth	8 [m]	Speed (cruise/max)	9 / 15 knots
Design Draft	4-6 [m]	Certified bollard pull power	200 [MT]

The mono hull displacement vessel with a C_b of 0.72 and has no bulb. The power system outline drawing is present in appendix A.1. Four medium-speed Wartsila 6L32 are installed with 3 MW power at 100% MCR each, parallel in sets of two. Each set has a PTO with a shaft alternators with a maximum electrical power output of 1.2 MW. The vessels have keel skegged twin-screw ducted CPPs 4-0.645 from Wartsila, with A-brackets and oil lubricated shafting. The both nozzles are fixed and the propeller cap is simple, with no boss cap fins. The spade rudders are installed after both propellers. The two manoeuvring thrusters are installed at the bow one of 825 kW and at the stern one of 736 kW.
The initial ship design theories of Holltrop & Mennen, marine power plants and propellers can be used to predicts the theoretical required propulsion energy and efficiency of the LTD vessels. The theoretical daily fuel consumption can be specified for certain speed and sea margins for regression analysis.

Two towing drums of with wires of 1500 m x Ø 76 mm and a working drum with 300 m x Ø 76 mm work wire is present after wheel house. The towing wire pay-out is typically about 1000 m in length and the up to Ø 100 mm. The vessels both have a characteristic low, flat afterdeck with no obstructions, allowing to change angles with respect to towed object. A gob robe around the towing wire prevents the angle becoming unsafe during operations. The stern roller(Ø 2,500 mm x 5,400 mm) has a 300 MT save working load, to prevents blockage and damage when setting objects overboard. The two pedestal mounted 360 slewing deck crane of 8t safe working load at 7 m outreach are present at the after deck.

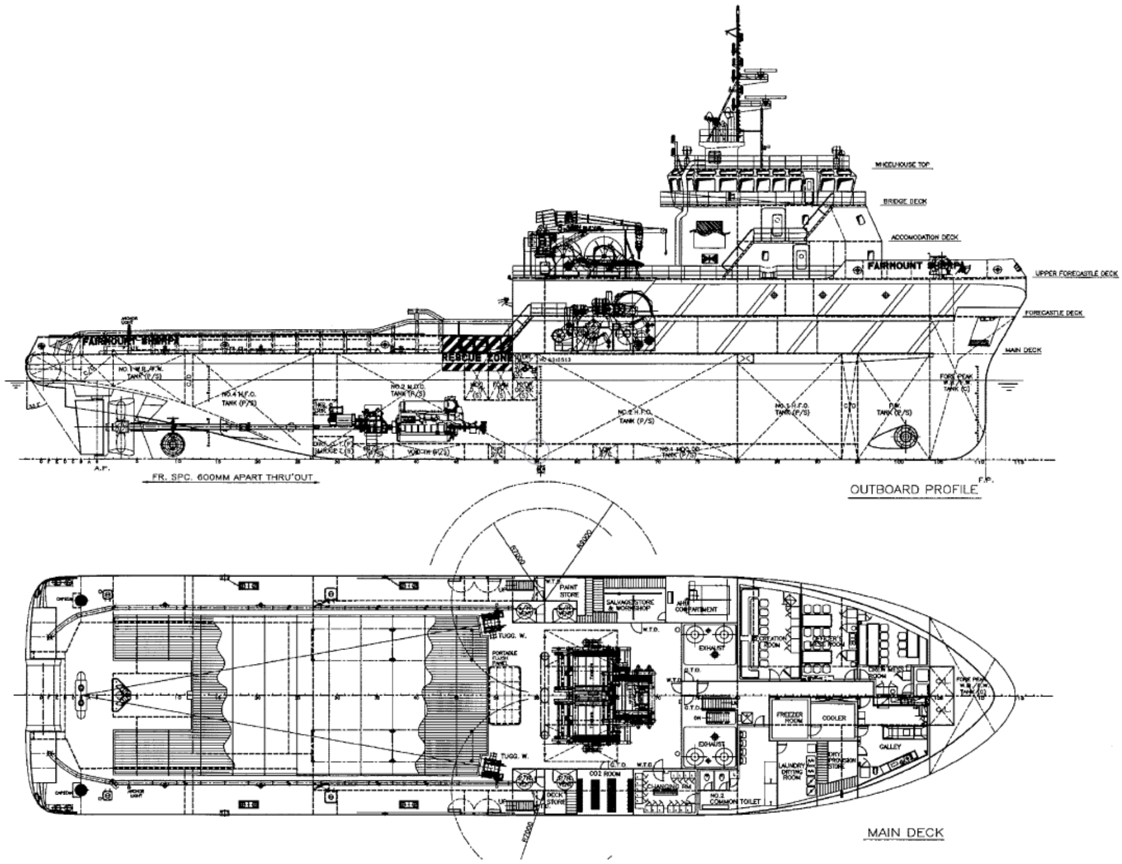


Figure 5.1: Outboard Profile and main deck drawings

The tugs are highly manoeuvrable and have fifi-1 classification, which enables the vessels to do jobs related to salvage, steering assistance and environmental services to avert an imminent environmental disaster. The two 813kW fire fighting pumps are installed and direct-driven by separate gearboxes at engine 1 and 4 (see appendix A.1). The vessels are no Anchor Handling Tugs (AHT), although they have a stern roller which is typical for a AHT. They are not AHT, because the towing drums do have slow reaction times and the vessel has no DP system.

Vessel Operations

The vessel are ought to deliver a continuous bollard pull of 200 MT for five minutes during the bollard pull tests every 10 years, which is certified by class society. When the vessels induce a towing speed, the hull resistance will reduce the effective bollard pull to approximately max 180 MT. The structural integrity of the towed object need to be sufficient for such extreme loads. Both the wire length and the towing speed are limited within areas with shallow water and high traffic density. The towing wires bends by its own weight and can easily hit the bottom in shallow waters, which require reduced wire-pay-out and consequently reduced towing speed by the wake.

The project examples are shown in fig. 5.2. The offshore installation is the most profitable market that the LTD serves followed by scrap and other exceptional transports, which are more explicitly described in section 3.2.

Figure 5.2: Photo impression of LTD operations

The projects can be done by a single vessel operation or up to three vessels. The number of vessels required is determined by the project engineering department, who uses by class prescribed bollard pull requirements for save transport of the towed object. The highest bollard pull certificate is preferred from compliance perspective. Operations are executed with an angle with respect to the direction of the towed object, which currently is the result of using the two rudders constantly causing additional resistance.

5.1.1 Prototype Model Input

The available data and required processing (see section 5.1.1) to obtain useful time-series data as prototype model input are both explained by this subsection. The Data Quality Assessment explains 'the usefulness' of the model input and the current state of data development of the LDT shipping at Boskalis.

Data Processing description

The Data Science process before data analysis, modelling and visualisation is sequentially illustrated by section 5.1.1. The next paragraphs describe these three process blocks and evaluate the ouput of the collected, processed and cleaned case study data.
The origin and fundamentals of Data Science are previously explained by section 1.1 and section 2.2. This subsection describes how this DS process is executed before EDA and modelling the data.

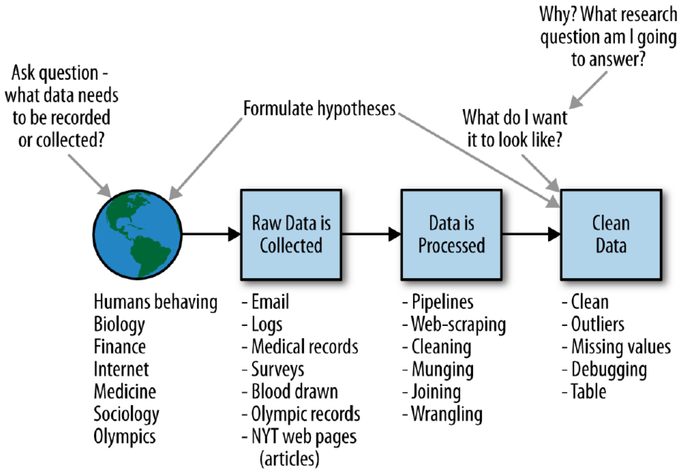


Figure 5.3: Data Science work before EDA and modelling(Rachek Schutt, 2014)

Raw Data Collection

The table 5.2 shows an overview of the collected data. These data are found at the Boskalis Sharepoint and the PMS database was shared by NPS-Diesel within separate CSV-files. The table gives an overview about the number of files, their format and included observations and attributes. The cells that contain a – do not represent the parameter.
No automated data collection or infrastructure available for LTD, so all data was manually collected and added over time. Real-time prototyping was not possible due the not available IT-infrastructure.

Table 5.2: Table of collected data

Name of data file	number of files	format of files	Observations	Attributes
Daily Progress Reports (DPR)	1824	Excel	± 800	39
Daily Technical Reports (DTR)	1824	Excel	± 800	26
Performance Monitoring Systems (PMS)	2	csv	+50.000	56
Sea Trial Reports of shipyard	4	pdf	-	-
Sea Trial Reports of Wartsila	1	pdf	-	-
Bunker report Summary	1	Excel	± 10	-
Corporate Social Responsibility	2	pdf	20 (x5)	3

The two daily noon report, called Daily Progress Report (DPR) and Daily Technical Report (DTR) from 2016, 2017 and partly 2018 were collected. The two unprotected excel files (see appendix C.1 and appendix C.1) were sent to shore by outlook e-mail. This historical manual data was collected at the Boskalis sharepoint with months of delay. Software was written to process these DPR and DTR to a time-series database, which will explicitly explained by the following paragraph. The both report have many overlapping attributes, which means that the actual attribution per day were less. The DPR data is manually copied by the invoice management and shared with CSR.

The PMS has an extremely high number of observations compare to the noon reports, because of high sample frequency. The PMS data was processed and stored in a single table per vessel of the case study. The time-series data was frequently triggered and no averages were calculated within the intervals. The database was located at the third party NPS-diesel and no direct excess was provided. The data was sent to shore by e-mail over the 4G internet in coastal waters, typically days delayed.
The NPS applied many useless post processing scripts and were not willing or able to share these algorithms or provide significant accuracy indications of the logged sensors data. The sensor loggers were installed at the engine controllers, fuel flow meter, shaft alternators, NMEA and shaft power meters. The useful attributes were: GPS position and time, flow meter reading without temperatures, both shaft powers, both electrical alternator outputs and clock values (see table 5.3).

Table 5.3: Overview of significant PMS data

Data attribute	Sensor & source	unit of entry	accuracy indication
Time GPS	NMEA	seconds	
GPS speed	NMEA	$10^{-}1$	2%
GPS distance	NMEA	$10^{-}1$	2%
Fuel flow	Volumetric flow meter	litres	1%(Seafish, 2009)
Engine load	Engine controller	percentage	23%
Fuel rackpos	Engine controller	mm	-
Shaft power	Torque sensor	kW	1%
PTO power	Three phase power transducer	kWe	1%

The densities and LHV's were found within the bunker report data (see table 5.4). No information about the fuel used during the operations was available, so the min, maximum and accuracy of these two attributes were both considered for HFO and MGO. Together the inaccuracy of density and LHV is below 2%.

Table 5.4: Overview of bunker report data

2017-2018	density [kg/m3] HFO @ 15 °C				Lower Heat Value HFO [MJ/kg]				Total
	min	max	accuracy		min	max	accuracy		inaccuracy
Glacier	988	991	3	0,3%	39,80	40,30	1	1,2%	1,5%
Sherpa	988	992	4	0,4%	33,90	40,30	6	15,9%	16,3%
2017-2018	density [kg/m3] MGO @ 15 °C				Lower Heat Value MGO [MJ/kg]				Total
	min	max	accuracy		min	max	accuracy		inaccuracy
Glacier	856	859	3	0,4%	42,63	42,67	0	0,1%	0,4%
Sherpa	856	856	0	0,0%	42,66	42,66	0	0,0%	0,0%

Data processing

All files had to be processed and assembled in one big datatable or database to enable EDA. This process is called data wrangling, data munging or data crunching. After the data processing, the data cleaning was executed.

The data processing in general is about conversion of the raw data in the desired and usable format. The main concern was the processing of the non-protected and unstructured data to the structured time-series database. The DPR, DTR and PMS data is outer joined per day, with additional classification labels and calculated values by use of available data.

The major challenge was to programme the automated process to convert all separate noon reports per day to one big time-series datatable over years. All the report files were collected at Sharepoint and downloaded with a certain directory format, which was structured by year, month and vessel name. At every directory location were one DTR and DPR file for every day of the month. The excel file were format as unprotected tables at one sheet. The object names, sheet names and table formats were randomly changed over time by office and crew, which cause an additional challenge for both processing and cleaning.
A python script was built with Operating System, Pandas and Datatime packages. The script was able to create an structured Database with all reports processes in one single run. For loops were built for a variable working directory by years, months and vessel names for both DPR and DTR files. When the 'for loop' determined a certain directory, all DPR and DTR sheets of that specific month were opened and placed within one table, with original format. Another 'for loop' was used to select entries per day and place them at one single row together.
The result was the software function for automated data processing in Python. The function input were period of time and vessel name of the LTD fleet. This script generated one big database of time-series data with all DPR and DTR data per day on one row and columns of the operational data attributes. Since only the LTD vessels share the same noon report format, only LTD report can be processed by the script. Additionally the PMS was joined to validate data of both data acquisition systems.

Data Cleansing

Data cleaning or cleansing, which both mean the same, is about upgrading data quality for EDA. The corrupted data is cleaned by correcting syntax, removing outliers, interpolate missing values or deleting not repairable observations. The process of cleansing has a reputation and is time consuming, several websites stated that Data Science is about cleansing data for 80% of the time. The automation of cleansing and together with smart data management avoids unnecessary time spent on cleaning. This paragraph aims to explain how the data cleansing is done effectively.

Manually redo of cleansing should be avoided by automation. This can be done by integration of cleansing functions within the data processing script. When processing is done for other data entries, vessel or period of time, the cleansing will automatically be done. Working with one cleaned, labelled and joined Data table is recommended, because this avoids in consistency between Data tables with same raw data origin and extra cleaning required. There is always a trade-off between deleting data or repair. Deleting data has negative effect on the completeness of the data and analysis reliability. Manual cleansing can sometime be frustrating and time consuming.
The best way to avoid cleansing is a well designed acquisition system. Preferably wrong or lacking entries are bounced and unauthorised people are not allowed to change validity rules and formats.
The results of this research about cleansing were 'power coding' for automated cleaning and knowledge to support the design of the new data acquisition system at OED. Martijn Rijnsoever and Youri Buskens, both intern students from Industrial engineering and management of Rotterdam school of applied science, were challenged to redesign data acquisition temples of OED within 6 months. They worked from August to January and were supported by the DAMA Data Quality frameworks (see fig. 2.9) and found and solved the many corruptions during cleansing of the noon reports of this research.

The accepted data had a certain quality requirement to be allowed. The separate noon reports had not to be totally corrupted and the processing algorithm had to be able to process them to the database. The daily fuel consumption DPR and DTR had to be consistent for every day. All the invalid entries were automatically or manually cleaned for the zero error data attributes. The strange outliers were manually corrected for remaining the day of reporting or were excluded for the analysis.

Results for Model Input

The noon data (see table 5.5), PMS data (see table 5.3), bunker analysis (see table 5.4), CSR data (see appendix C.1) and other mentioned in table 5.2.
The completeness of 72% and 33% which is low, but sufficient for prototyping.

Table 5.5: Noon data input after cleansing

	Idle		Free-running		Towing		Completeness	
Vessel	Number	Perc	Number	Perc	Number	Perc	Number	Perc
Glacier	122	13	56	6	479	52	657	72
Sherpa	145	16	88	10	62	7	295	33

5.1.2 Data Quality Assessment

The case study data quality is considered to be 'very low'. What the required data quality should be is already stated within section 4.3 and different framework about data quality and progression of data were presented within this thesis (see chapter 3).

The progression of data to knowledge is introduced in fig. 2.4 and enables the explanation of the current state and what is achieved with the prototype. No significant structured information was available about the fuel performance at the start of the case study. The information that was selected from the gathered noon data was sampled over 24 hours and of low accuracy. The PMS provided infrequently sampled observations about seconds till hours within unrelated and inconsistent datasets for the engines and the winches. The PMS provided semi-structured information and a dashboard, which did not give useful insights for decision makers at the LTD.

The noon data is judged by the six primary dimensions (see fig. 2.9) and the hierarchical structure (see fig. 2.8). No database of noon reports is available for the LTD business unit. The Noon reports are stuck at the Sharepoint and do contains information, which are uploaded with a delay of months. The data acquisition of noon data was done by unprotected excel files, which are changed frequently over time, with no entry validity rules. The excel templates were changed mostly accidentally by crew and kept unnoticed at shore, causing inconsistency of the data structures, which is challenging for automated database development. The database as input for modelling (see table 5.5) had completeness 72% for the Glacier and 33% for the Sherpa, which is very low for operational profiling. More than 20% of all entries had to be cleaned for analysis. The accuracies of the data attributes were low, fuel volumes were reported without temperatures, towing forces only over 10 minutes at noon, no outputs of shaft power or alternator meters were reported, no ambient conditions or running hours at the machinery room and no average speed through water. The low data quality of the LTD noon reports is concerning, if LTD want to other important data analysis in the future. A new data acquisition design should be build with more relevant attributes of required quality (see section 4.3).

The PMS system provided semi-structured time-series data of low quality. The semi-structure does not allow to related the dataset about engines, winches and noon reports in an accurate way, since they were inconsistent. The PMS needs a clock-trigger every hours to enable integration over 24 hours and comparison with the noon data. The system-based triggers of the engines and winches need to be synchronised to be consistent. when this data is consistent, the more accurate measurements can distinguishes the fuel performance per operational mode. The mean values and deviations over the observation period may be calculated and logged by the system to enable filtering of the most accurate observations.
The third party NPS Diesel provided many post-scripted attributes within the datasets and was unclear about the meaning and accuracy of these values. The analysis found that these post-scripted attributes are so low in accuracy, that they can be considered useless. The average temperatures at the flow meter were not measured, so fuel measures were still inaccurate about 10% and the engine controller data was badly calibrated and was very inconsistent with shaft powers and alternator powers (see fig. C.4b). The winch data did not measure the highest peak bollard pull, but measured a sample of 20 MT less during the bollard pulls tests.

The low data quality at the LTD business unit seems the result of no data leadership. All the effort to improve the data acquisition failed during this research. There seemed a lack of IT expertise and the willingness or the urgency to improve the data quality at LTD. The first introduction with the LTD data included a statement that nothing about the data acquisition could be changed, which was the reality during this research. The people at LTD who tried to improve data quality in the past, were pessimistic about the future of the data developments. The Anglo-Eastern's structured information of noon reports, was not shared after several requests.

There were no IT employees available within LTD or budgets for any support from outside. These examples are given to illustrate that people are the biggest constrained for progression of knowledge at LTD and not the affordable technology. There is no data dictatorship or democracy, but data anarchy at LTD, within scope of this research.

5.2 Business Process Modelling

The conceptual BID (see chapter 4) is applied for the LTD case study to monitor and control the fuel performance. First the business process model is explained by one overview and the specified indicators (see section 5.2.1). The current LTD BPMN explains the process of fuel consumptions and the relation to IT architecture (see section 5.2.2). A new BPMN design is made to explain the improvements by a Data-driven DSS implementation (see section 5.2.3).

5.2.1 Business Process Model

The model overview for LTD is at the next page (see fig. 5.4) and is a composition of the previously explained models (see section 4.1 & section 4.2)). The SPI, KPI's and PI's are specified by the right column on the next page. Not all the data was available to calculate the values, but these number can control performance if present within the Boskalis organisation.

The Shipping Performance Indicator

One dimensionless number quantifies the energy performance of the LTD (see eq. (5.1)) to monitor, control and target the energy efficiency and the carbon emissions at the strategic level of organisation. The core business of towing over a (long) distance is quantified and related to consumed energy types, by this single number. The SPI enables benchmarking and comparison with different LTD vessels or even with Heavy Lift Transport (HLT) vessels, if an corresponding dimensionless number is realized for HLT.

The data behind the SPI should contain the information about the fuels used (i), the speeds sailed (v) and the corresponding periods of time (t) for the explanation of the SPI, which is the summation of these all. The SPI can be calculated individually for the vessels, for the whole fleet over one or multiple years.

$$SPI_{LTD} = \sum_{i\in I}\sum_{v\in V}\sum_{t\in T}\frac{\overline{F_{vt}} * D_{vt}}{E_{it}} \geq SPI_{Target} \tag{5.1}$$

where:

SPI_{LTD}	= Performance Indicator of towing	[-]
v	= Vessel speeds	[-]
t	= periods of time	[-]
i	= Fuel types	[-]
$\overline{F_{vt}}$	= Average wire tension over time	[kN]
D_{vt}	= Covered distance over ground and period	[km]
E_{it}	= Total energy of certain type over period	[MWh]

The actual SPI of the Glacier and Sherpa over 2018 can not be determined with the currently available data, since no average wire tensions are known (see section 5.1.2). The theoretically approximation of 50% engine efficiency and 50% efficiency for the other equipment and systems, suggests that the number will be positive and below 0,25.

The SPI can be used for the control of the carbon emissions. For example, Boskalis wants to reduce their carbon emission with 50%. The SPI, which represents the overall fossil fuel efficiency of 2018, is assumed to be 0,10. The SPI target will be 0,20 and can be achieved by improvement of technical and operational energy efficiency and use of biofuels. The improved energy efficiency requires less energy consumption for the same work and the biofuels have partly to be included for the fossil fuel consumption.

The IMO wants that shipowners reduce their carbon emissions with 40% in 2030 with respect to 2008 (Øyvind Endresen, 2018). The used fuels and energy efficiency did not change since the LTD vessel were build during 2006-2008. The economical life time expectancy of ocean going vessels is between the 20 and 30 years, depending on the shipping and scrap market conditions. This means the LTD vessels are expected to be operational towards 2030.
First Boskalis needs to quantify their SPI of LTD and afterwards formulate a strategy to align with the IMO

GHG strategy, to avoid unnecessary non-compliance costs and irreversible environmental damage. The SPI might be used by the IMO to regulate the energy efficiency of LTD.

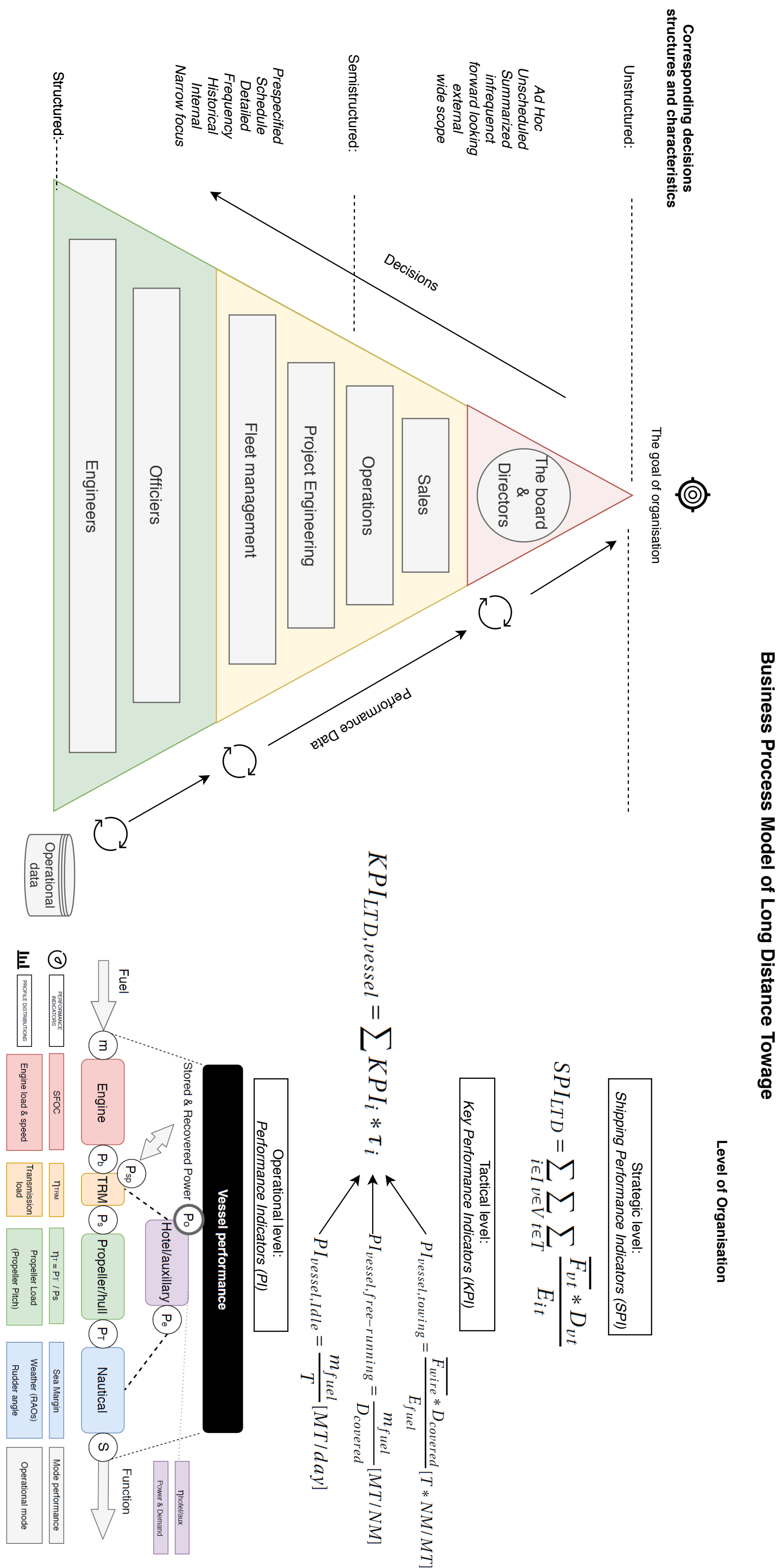


Figure 5.4: Business process model for LTD (own composition)

Key Performance Indicators

The KPI's capture the fuel performance reality for control at tactical level of the organisation (see section 4.2.2) for decisions about typically months. These KPI values are dimensionless in relation to a benchmark and target value.

The three PI's (see eq. (5.4), eq. (5.3) & eq. (5.5)) are translated to KPI format and can form together one KPI number, which is a fuel consumed weighted average per operational mode (see eq. (5.2)).

$$KPI_{LTD,vessel} = \sum KPI_i * \tau_i \tag{5.2}$$

Where:

KPI_i	= Dimensionless KPI number of operational mode	[-]
τ_i	= Mode fraction of total fuel consumption	[-]

The towing activities do consume the most fuel per day (see fig. 5.11) and is related to the towing wire force, distance covered and speed. The increased towing speed non-linearly increases the resistance of both the vessel(s) and the towed object, ceteris paribus. The resistance and installed propulsion power of the towed object is dominant, compared to the vessel's hull resistance. The dimensions and displacement of the towed object are interesting to consider for predictions of fuel consumption.

$$PI_{vessel,towing} = \frac{\overline{F_{wire}} * D_{covered}}{E_{fuel}} [T * NM/MT] \tag{5.3}$$

The free-running LTD vessels consume tons of fuels per nautical mile for a certain speed (see fig. 5.12). The nautical performance are included for analysis of the operational performance and can be excluded for analysis of the technical performance. A thrust meter data or sea-margin correction are required to subtract the environmental effects, which both were not available for the case study. The nautical performance are included for analysis of the operational performance and are excluded for the analysis of the technical performance. A thrust meter data or sea-margin correction are required to subtract the environmental effects, which both were not available for the case study.

$$PI_{vessel,free-running} = \frac{m_{fuel}}{D_{covered}} [MT/NM] \tag{5.4}$$

The Idle condition is quantified by ton of fuel consumed per day. The use of onboard auxiliary, shore power or a generator on deck need to be specified and quantified per day.

$$PI_{vessel,Idle} = \frac{m_{fuel}}{T} [MT/day] \tag{5.5}$$

The LTD vessel do have other operational modes, like for salvage and manoeuvring, but these modes are excluded because they have a negligible share of total fuel consumption.

5.2.2 Current Business Process Modelling Notation

The current situation of LTD is shown in fig. 5.5. The model contains the six operational process stakeholders, that are related to the fuel performance of LTD.

The larger amount of stakeholders within the process constraint the flexibility and the innovation. The BPMN shows that six stakeholder are involved in relation to the fuel performance. All these stakeholders need to communicate and argue their interests and priorities within this process, which can be contradicting. For example, Operations does not want to do turbo washing since the transport will slow down and fleet management give instructing to wash every day, this results in that turbo washing moments are skipped or done with too high temperatures, causing damages of components and lower efficiency of both turbo and engines. No structured information about the actual performance is available for group decision making and for example turbo wash optimisation.

The Operation department is the most influential decision maker of the whole process and works with rough estimates about fuel performance. The operational manager is supported by his own 'rule of thumb', SPOS for weather forecasting and difference project collected in the Final Voyage Records (see fig. 5.5). The fuel predictions are not done by the use of statistics, but by 'intuitive' guesstimates. These are used for tendering and for control of operational fuel performance.

The standardized BIMCO provides a lump-sum agreement about the total fuel required for the project, with a coverage of bunker price fluctuation risks for both parties. These contracts do not challenge LTD to improve their fuel efficiency, because "the customer pays the fuel anyway attitude. The sales department stated that reduced OPEX will have positive results for the competitiveness of LTD. The improved contracting contain less explicit fuel consumption statements, but only an accurate predicted fee for the project.

There are no numbers about fuel efficiency available, no structured overviews for benchmarking and targeting improvements of fuel performance and there is no feed-back mechanism to do fuel predictions when fuel efficiency is improved. There is no database present within the business process, but only separate Word, Excel and PDF files. The LTD is not able to develop dashboards or do optimisation calculations with actual performance data, because all noon data is 'stuck' within separate unprotected excel files. Moreover, LTD is the only fleet without a database of noon data. The TSI of LTD has to search through separate excel files day-by-day and has low trust in the data. His requested attributes like Shaft alternator powers and shaft powers were never answered by the business unit.

The daily fuel consumption data is shared unprotected with the clients, who consider the amount of fuel burned as an actual performance. The clients have no idea about what the efficiencies are or how the fuel consumptions are related to towing forces and speeds. Besides, this information is sensitive of Boskalis and enables cooperate espionage by competitors about the variable but approximately 60% fuel share of the total OPEX. The LTD may consider to protect their data or not share fuel consumption on daily bases, but only share the towing forces, speed and E.T.A.

Sub-optimisation of the stakeholders negatively influence the fuel performance of LTD. This is not captured by the model, but explained by this paragraph. All the departments of LTD have their own financial performance. The operational department is responsible for operational cost when the vessels are sailing, but Boskalis Corporate when the vessel lays idle. This stimulates the operational department to do higher speed free running transits, than is optimal for the entire business unit. This mechanism is preventing slow steaming, which is very effective for energy efficiencyet al. (2018).

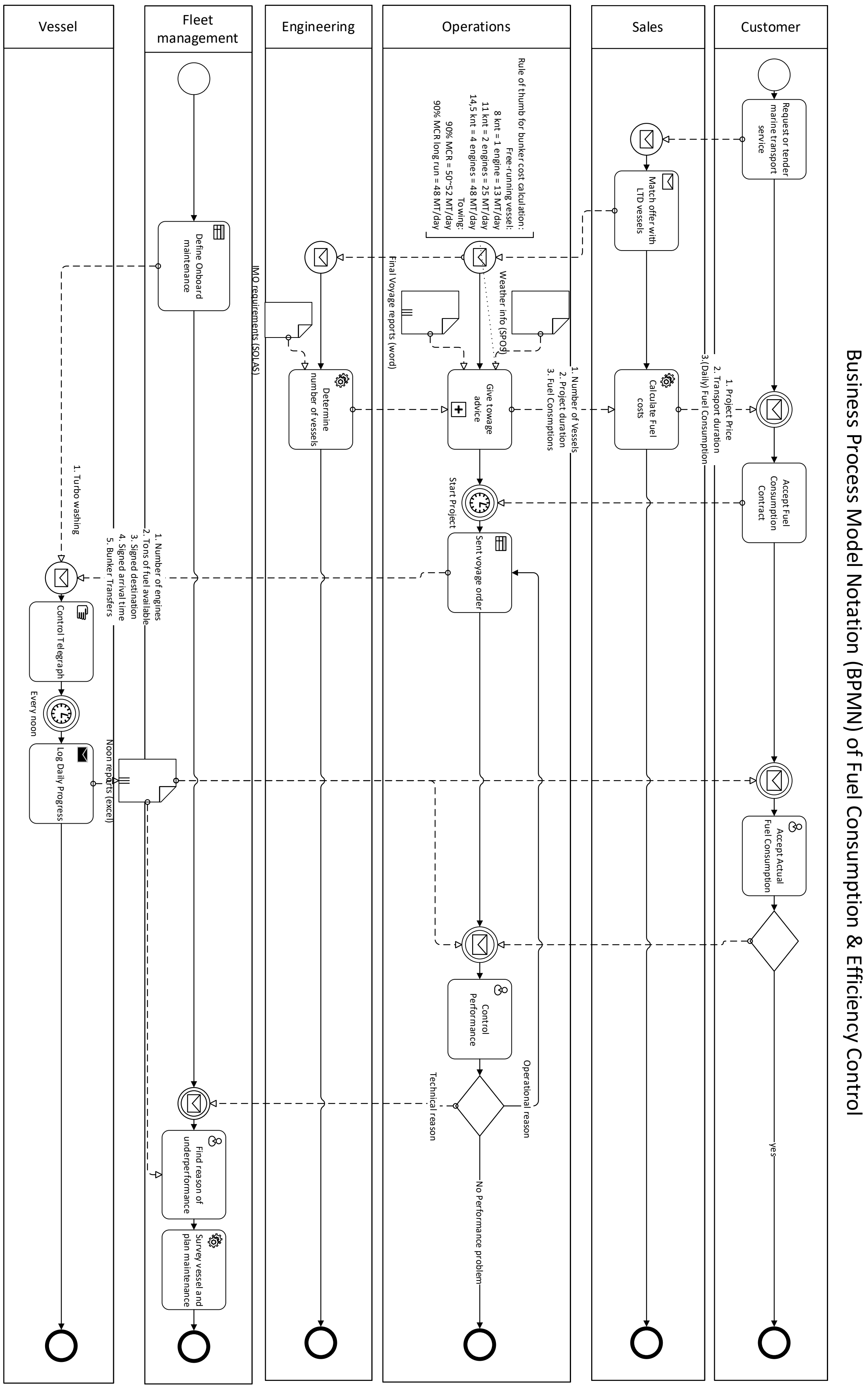


Figure 5.5: BPMN of current situation (own composition)

5.2.3 Data-driven Business Process Modelling Notation

The data-driven decision support system is integrated within the business process in fig. 5.6. The system provides a back-end system that stores all reports and PMS data onshore in a database or cloud. The required minimum and targets about fuel performance can be combined and by a processing scripts translated into PIs, KPIs consistently for both the fleet management, the operations and the vessel crew. The actual performance and corresponding visualisations support decisions of vessel operations. The 'big data' stored by this system will be used for prediction at operational, tactical and strategic level of the organisation.

A front-end design, called dashboard, will provide protected insights about the transport operation. The client does not receive any explicit daily information about bunkers, but only the delivered towing force, the speed and E.T.A. The dashboard can provide daily and project overviews and predictions with uncertainties in the future.

The feedback loop of information is realised, which provides insight about performance, improvements and predictions for tendering by Sales and Operations. The Fleet management is enabled to control the relation between maintenance en fuel consumption by Decision support.

Mention that a DSS system for LTD can and maybe should be used for more than only fuel performance. If the implementation of the proposed system is done, other relevant data and algorithms can be included at this IT-architecture. Examples are a Negotiation Support System for sales, shipping planning optimisation as groupware for whole LTD and Condition Based Maintenance.

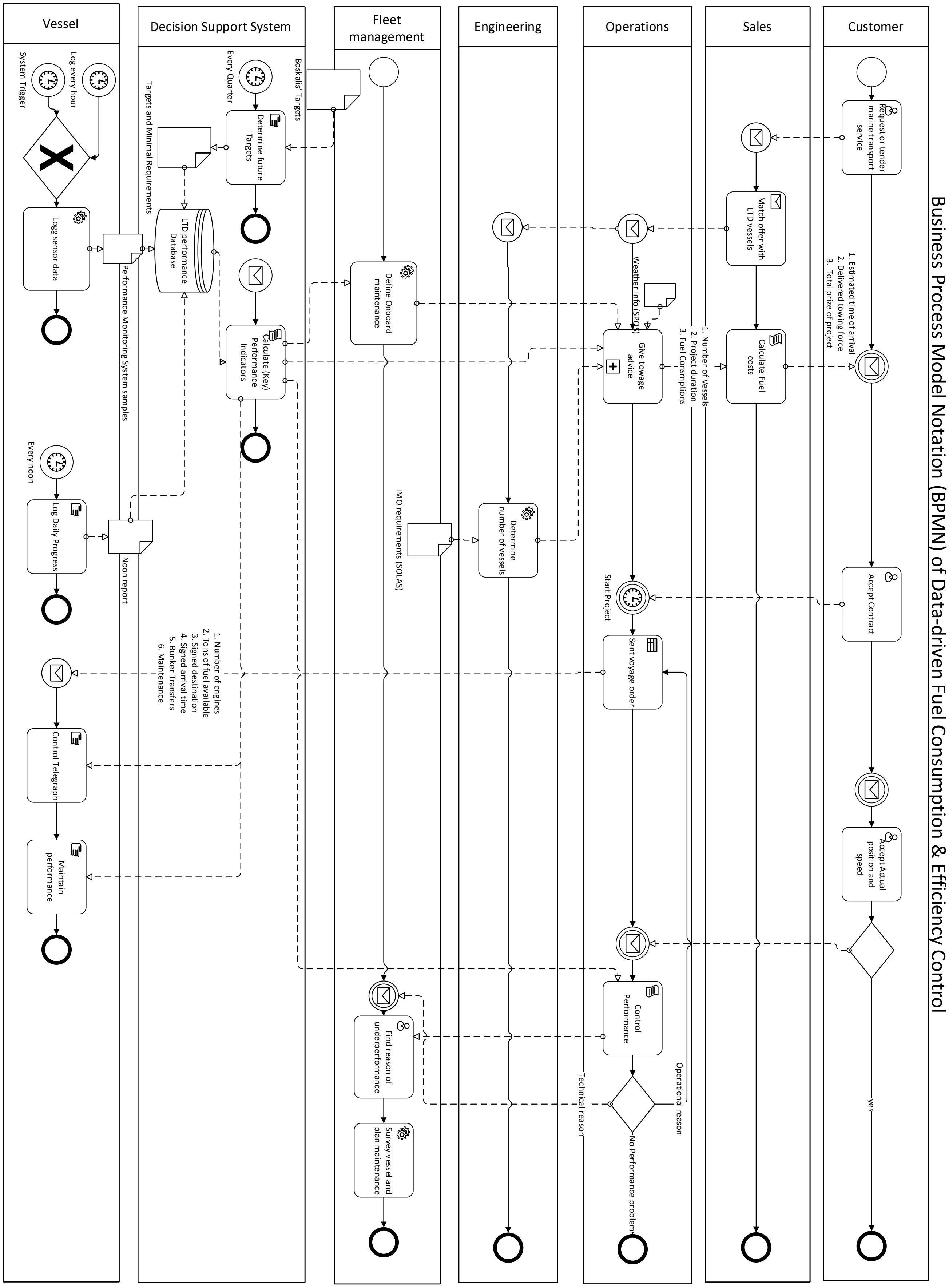


Figure 5.6: BPMN of Data-driven Decision Design (own composition)

5.3 Prototype for Performance Control and Optimisation

Quote: "All models are wrong, but some are useful"

The Data-driven DSS prototype shows examples about how operational information can by visualised for fuel efficiency insights and decision making. The vessel performance paragraph (see section 5.2.1) provides an overview of the annual fuel consumption and typical shares per operational mode. The daily vessel performance are quantified per operational mode (see section 5.3.2). The engine performance (see section 5.3.4) and turbo performance (see section 5.3.5) are analysed and a more detailed DSS prototyped is presented for onboard and TSI onshore. The hotel and auxiliary performance are analysed and quantified for both vessels (see section 5.3.3). All the quantified performances are used to support energy efficiency improvement measures for the remained economical life time of the LTD vessels (see section 5.4.2).

Many variables are assumed to be constant, to reduce the complexity of the prototype (see table 5.6). The values are averages and for the calculations within this section and the next section.

Table 5.6: Variables assumed to be constant

Used constants		
$\rho_{HFO,15°C}$	0,990	$MT/m3$
$\rho_{MGO,15°C}$	0,857	$MT/m3$
$T_{HFO,meter}$	85	°C
$T_{MGO,meter}$	30	°C
$C_{Thermalexpension,fuel}$	$1*10^{-1}$	$m^3/\Delta T$
H_{HFO}	40,4	MJ/ kg
H_{MGO}	42,6	MJ / kg
$MJtokWh$	0,2778	kWh/MJ
$Price_{HFO}$	450	USD/MT
$Price_{MGO}$	660	USD/MT
$EuroforUSDrate$	0,87	EURO/USD
$Emission_{HFO}$	3114	CO2/MT
$Emissions_{MGO}$	3206	CO2/MT
$\eta_{gearbox}$	0,97	-
$\eta_{generator}(AVK)$	0,95	-

5.3.1 Annual and Quarter performance

The annual fuel consumption data indicates a range of 0,5 and 10,5 thousand MT and the 6,4 thousand MT mean(see fig. 5.7). The first and third quartile interval are between 5 and 8 thousand MT, which can be used for scenario analysis. The consumption spread over periods is relatively large compared to merchant vessel, which are assumed to sail more constantly. Fuel predictions per quarter or year for these work vessel is more complex, compared to vessels that sail standardized routes and speeds.
All the five vessel are included for their individual fuel consumption per quarter and year from 2014 till 2017. The fuel required to serve the LTD market is statistically stronger, compared to only considering the Glacier and Sherpa. Both the HFO and the MGO masses are included and calculated by multiplication of volumes and assumed densities of table 5.6. Some quarter of the fig. 5.7 show zero consumption, caused by docking or lay-up.

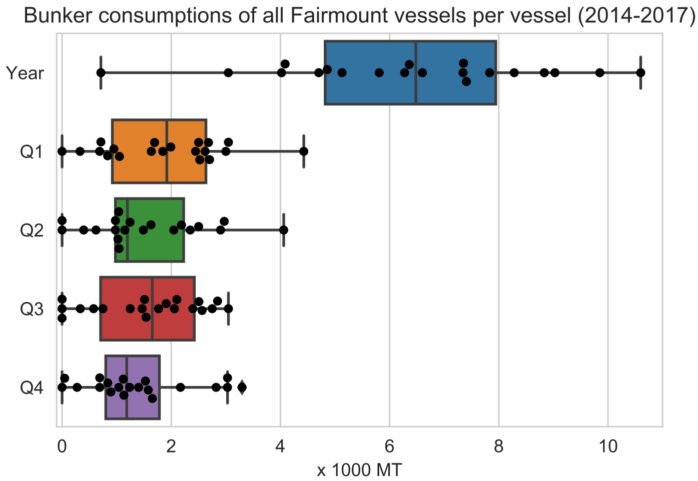


Figure 5.7: LTD fleet consumption according CSR data (own composition)

The fuel measurement procedures of LTD and corresponding calculations (see section 4.2.3) have the inaccuracy of the CSR data, which is $< \pm 15\%$. When the fuel temperatures are included within data for the measured volumes and the calculation procedures are done correctly, the inaccuracy can be improved to at least $< \pm 2\%$. The CSR data stated volumetric consumption of bunker fuels per quarter. The LTD business unit reports volumes every month to CSR of Boskalis. The invoice managers, like Karolien Boeynaems, manually sums all at noon reported fuel mass for every month. These calculated masses are translated to volumes again for CSR reporting, without corresponding temperatures of the volumes. The density used by CSR is not standardised and is uncertain. The incompleteness of the noon reports in the developed database for prototyping did not enable significant comparisons of CSR and daily reporting.

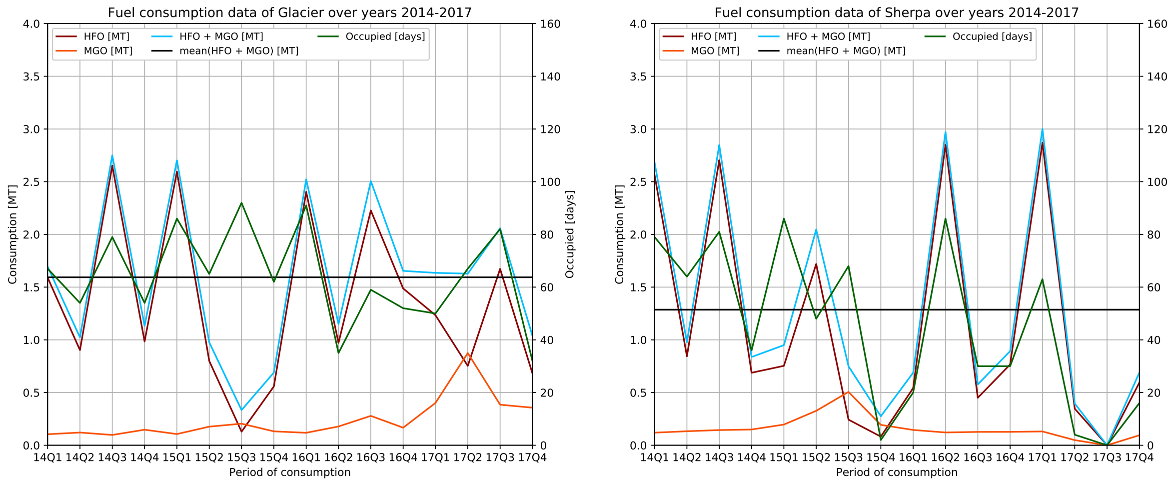
The full table of statistical results is present in the appendix (see appendix D.5) and the year results are summarised below (see table 5.7). The conclusions for every vessel are that the mean values per year equals 212 days hired, 6.400 MT of bunker fuels, € 2.3 million costs, 72 thousand MWh and 20 millions MT of CO2 emitted. The statistic overview provide the low quality benchmark with the currently available data.

Table 5.7: Summarised statistics of LTD consumption

Statistics of LTD CSR consumption								
	count	mean	std	min	25%	50%	75%	max
year Occupied days	20	212	76	20	181	237	258	305
year HFO m3	20	5.695	2.397	387	4.287	5.937	7.048	10.022
year MGO m3	20	897	536	321	630	699	933	2.354
YEAR HFO MT	20	5.638	2.373	383	4.244	5.877	6.977	9.922
YEAR MGO MT	20	768	460	275	540	599	800	2.018
YEAR BOTH MT	20	6.406	2.435	711	4.819	6.480	7.944	10.600
YEAR HFO USD	20	2.207.220	929.163	150.019	1.661.653	2.300.937	2.731.580	3.884.377
BOTH USD YEAR	20	2.648.486	976.007	338.222	1.991.869	2.764.263	3.295.918	4.273.620
YEAR HFO EUR	20	1.920.282	808.372	130.516	1.445.638	2.001.815	2.376.475	3.379.408
YEAR MGO EUR	20	383.901	229.625	137.281	269.534	299.169	399.434	1.007.973
BOTH EUR YEAR	20	2.304.183	849.126	294.253	1.732.926	2.404.909	2.867.449	3.718.049
YEAR Energy MWH	20	72.363	27.396	8.179	54.436	73.481	89.776	119.366
YEAR GHG MT	20	20.020.354	7.593.583	2.244.068	15.060.561	20.293.107	24.832.611	33.069.729

The occupation is captured within the CSR data indicates the days of being contracted clients. The correlation analysis showed that the correlation between occupation and consumption is between 0,6 and 0,8. This correlation concluded to be low and not usable for statistical analysis.

The time-series visualisation of LTD consumption (left axes) and occupation (right axes) are shown below in fig. 5.8. The weak correlation is visual, together with fluctuations of HFO and MGO consumption over time. The HFO consumed for 80% of total, but when operation in Emission Control Areas the MGO consumption is higher compare to the HFO consumption. The average fleet consumption (1,6 thousand MT) is almost equal for the Glacier and lower for the Sherpa (black line). At 15Q3 of Glacier, occupation and consumption show no correlation, this is because of laying idle for long time under contract.



(a) CSR data of Glacier

(b) CSR data of Sherpa

Figure 5.8: Time-series virtualisation of CSR data

The conclusion is that a LTD vessel mean consumption and standard deviation is 6.406 ± 2.435 MT of fuel, which indicated high uncertainty for predictions of future consumption. This consumption is divided over different operational modes: free-running, towing and Idle. Again the FC over a period of a certain operational mode is uncertain, because this differs per period. The QD of noon data did not allow accurate statistical analysis per mode, but a educated guess by filtering data per period in the Power BI showed FC share of towing and free-running differs approximately around 20% per period.

Operational mode consumption shares

The PMS and noon data were not able to distinguish different operational modes consumptions and durations, because the data was incomplete (see section 5.1.2). The shares of fuel consumption per operational do differ over time, which was not quantifiable by available, but a guestimate by use of Power BI tools showed variation over 20% per quarter.
The winch data and the other vessel data samples have different triggers and sample timings, resulting in two unrelated data sets. When this data quality problem is fixed, a more accurate estimation can be done.
The noon data is used to assemble a typical operational profile (see fig. 5.9) for one operational year. The fuel consumption share per operational mode varies over the periods of time. The found consumption per day of mode and summation per quarter are used to determine an typical share per operational mode. The estimation is visualised in the figure below (see fig. 5.9). This approximation can be improved data quality, which is not available at the moment.

The absolute and share values about averages and spreads of fuel consumption and time have to be known for full control. This information will enable Boskalis to quantify operational and technical improvements of their vessel. Possibly the new build project and maintenance procedures can be matched with such quantified operational profile.

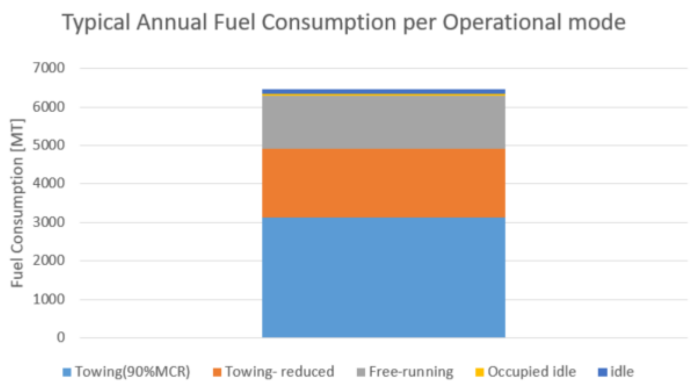
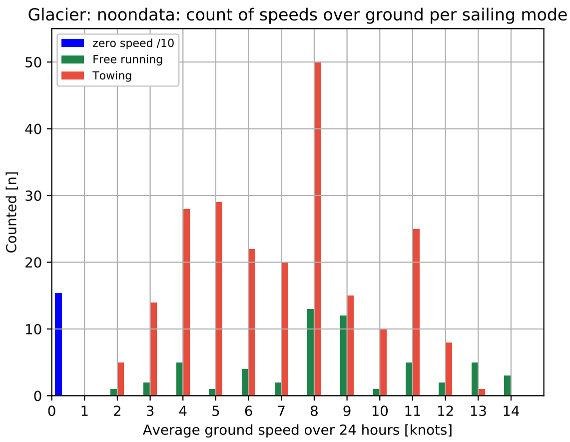


Figure 5.9: estimated typical year of fuel consumption and shares of operational modes

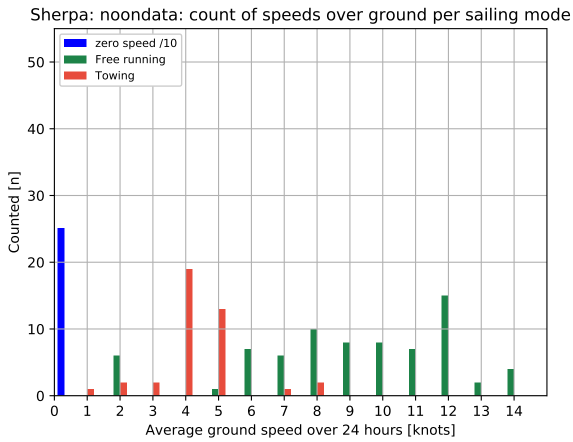
The operational condition of towing is the most fuel consuming mode and can theoretically be split with intervals of example 50 MT constant wire tensions. The Fire Fighting and Salvage operations can be distinguished, which was undoable with the available data. This model can also be used for history project overviews to substitute the Final Voyage Report that are used now.

5.3.2 Speed Profile

The cleaned noon data is used to show the operational profile distribution over 2016, 2017 and first half of 2018 as illustrated for both Glacier and Sherpa in fig. 5.10. The distributions do give a representation of how operational modes and SOG were present in the data. More data is available for the Glacier compared to Sherpa, which is partly explained by the fact the Sherpa was docked for three months and had lower utilisation. the Free running mode of the Sherpa drives faster compared to Glacier, while the towing speeds of Glacier were higher. These figures illustrate how modes and SOG with corresponding consumption and efficiency can differ over time, while the design of hull and propulsion systems are identical.



(a) Operational profile distribution of Glacier



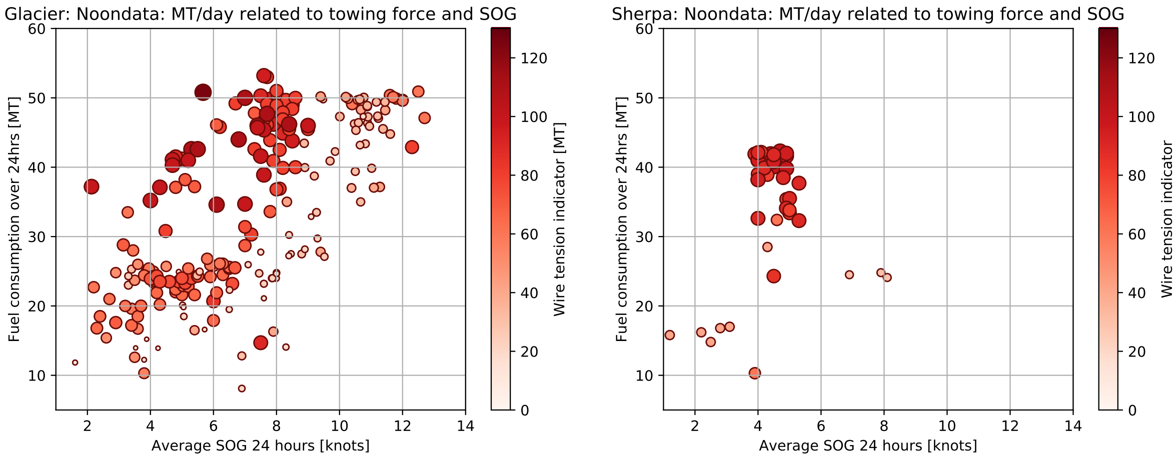
(b) Operational profile distribution of Sherpa

Figure 5.10: Operational profile distribution of cleaned data

Ships between 0-10 knots have increased fouling problems, especially in warm waters, because the anti-fouling does not release the grown fouling. The fouling of hull and propeller can reduce speed by 10-15%, increased required engine power by 23-38% and increase fuel consumption with 25-40%. This added resistance can occur in case of cleaning twice per five year (van Dokkum, 2011). The speed profiles show that both LTD vessel mostly operate below 10 knots SOG or laying idle, which both are indications of increased hull fouling growth. Cleaning more often than twice per five year is interesting for the LTD vessel.

Towing performance

The towing mode is the most frequently measured with the highest consumption per day, with a fundamental correlation to the towing force and the speed. In fig. 5.11, the consumption per day is related to average SOG and wire tension indication over the latest 10 minutes at noon. The clusters that appear within these visualisations represent 'steady runs' of different projects. This data already enables LTD to fine tune there 'rule of thumb' about fuel consumption. The used assumption of 50-52 MT fuel per day for full power towing is true according the figures. These figures show the increase of hull resistance with speed, since scatter points over the line of 50-52 MT are non-linear divided by lower speed with higher towing force and higher speed with lower responding forces.



(a) Towing consumption of Glacier

(b) Towing consumption of Sherpa

Figure 5.11: Towing consumption related to SOG and Towing force

The towed structure resistance is measured by these data point and can validate the prediction models of the engineering department. Cleaning of the towed structure underwater surface can increase the transport speed up to 10-15% and reduce the resistance and required fuel up to 25-40%.

The scatters of fig. 5.11 do have wide ranged clusters, which is the reason of other operational variables. The weather conditions can induce a Sea Margin of typically 20-30% for both the vessel(s) and the towed structure. The vessel and weather interaction can accurately be predicted by analysis of required nautical data (see section 4.3). The towed structures resistance is initially determined with Holtrop & Mennen and the Sea Margins with the additional operational data analysis.

The PI for towing mode (see eq. (5.6)) will enable Boskalis to develop a KPI with by formulation of a benchmark and target, but more variables than currently available should be included. This PI will provide an initial benchmark of performance and can future developed. The mass of fuel can be converted to energy (MWh) to realize a dimensionless PI or the η_{tow}. The towed structures and vessel can be distinguished in the equation for more detailed analysis of performance. If the observations of data are labelled per speed (v), period (t), project and environmental condition class, this PI can be used for control of improvement over time, project evaluation and quantification weather routing effects.

$$PI_{tow} = \eta_{tow} = \sum_{v \in V} \sum_{t \in T} \frac{\overline{F_{wire}} * D_{covered}}{E_{fuel}} * (1 - C_{environment}) \tag{5.6}$$

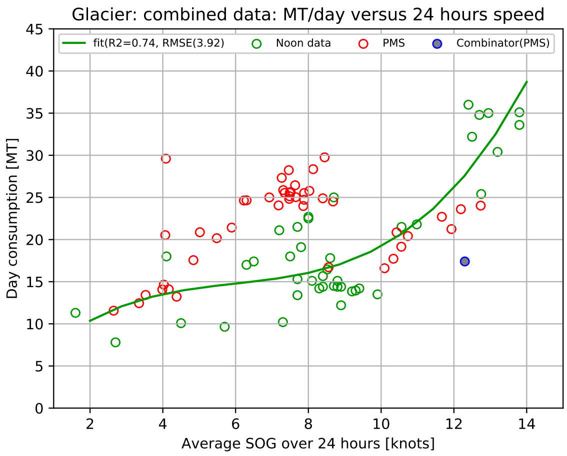
where:

PI_{tow}	= Performance Indicator of towing	[-]
η_{tow}	= Tow efficiency	[-]
$\overline{F_{wire}}$	= Average wire tension over time	[kN]
$D_{covered}$	= Covered distance over time	[km]
E_{fuel}	= Energy of consumed over time	[MWh]
$C_{environment}$	= Environment correction factor	[-]

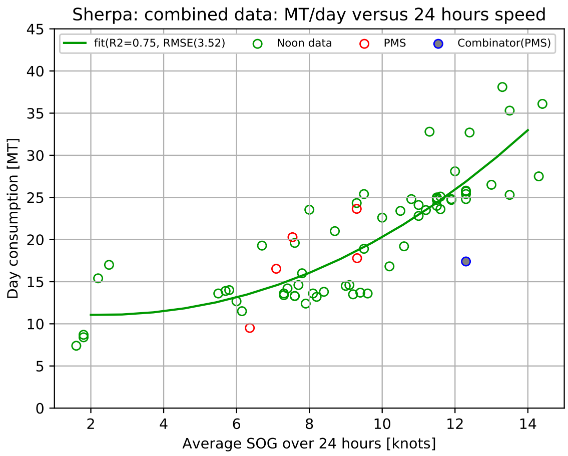
The concept of towing efficiency can be used for validation of physics-based modelling and simulation for naval architecture of LDT.

Free-running Performance Optimisation

The free-running condition is analysed in relation to SOG in fig. 5.12 and a fit for noon data by a third order polynomial. Both the PMS (red) and noon (green) data are plotted and are consistent, except the 'towing cluster' of the Glacier(see fig. 5.12a).
The 'steady state' data is filtered for the 24 hours average ground speed almost equals distance covered over 24 hours (see fig. C.4a) and for the speed deviation of less than 1 knot over 24 hours. The data is not corrected for environmental condition, but will provide the fit with R^2 of 0.75 till 0.95 (Lucy Aldous, 2013). The regression of that accuracy is sufficient for predictions and control of the free-running fuel performance.
No significant differences were found between sailing HFO or MGO. The boiler consumptions are included within these daily performances.
The initial ship design theories of Holltrop & Mennen, marine power plants and propellers are used to predicts the theoretical required propulsion energy of 0,04 MT/NM for 9 knots, which seem feasible and is below the operational performance. These theories found and assumed a 136 Kn hull resistance, 60% propeller efficiency, 97% transmission efficiency and 40% engine efficiency. This theoretical daily fuel consumption seems reasonable and can be specified for all service speeds and sea margins for a regression analysis.



(a) Free-running consumption of Glacier

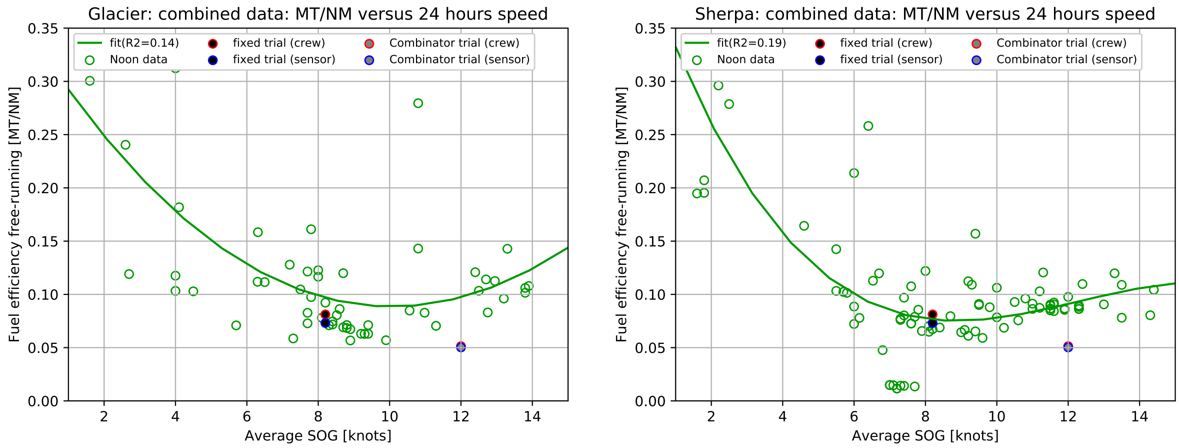


(b) free-running consumption of Sherpa

Figure 5.12: free-running consumption

A PI for free-running (see section 4.2.3) is MT per NM covered for different speeds, which is visualised within fig. 5.13. The outliers were hard to be removed by additional constraints and are still in both figures to illustrate control of fuel performance at the LTD.
A sea trial was organised to test the combinator mode of the Glacier. Both the crew manually reported results and the PMS data was used to compare the fuel efficiency. There seems a significant potential of the combinator mode to increase fuel efficiency of the free-running mode about 15 to 30% (see fig. 5.12 & fig. 5.13). The three hours during sea trial results are extrapolated to daily consumption 14.9 MT and corrected for boiler, hotel and auxiliary consumptions of 2,5 MT. The consumption for fixed frequency operation is 27 MT for both vessel according the fit. The combinator mode consumes 65% of the required fuel for the fixed frequency mode at the speed about 12 knots.

The Glacier did the trial during sunny weather and very little wave and currents around 1-2 knots, with variable directions. The Glacier sailed one way fixed frequency and back at the combinator mode, instead of the instructed two directions over one line per mode, to correct for the environmental effects. More trials or experience with the combinator mode at different speeds and weather conditions provide an additional fit and support the decision about to sail combinator mode or not.

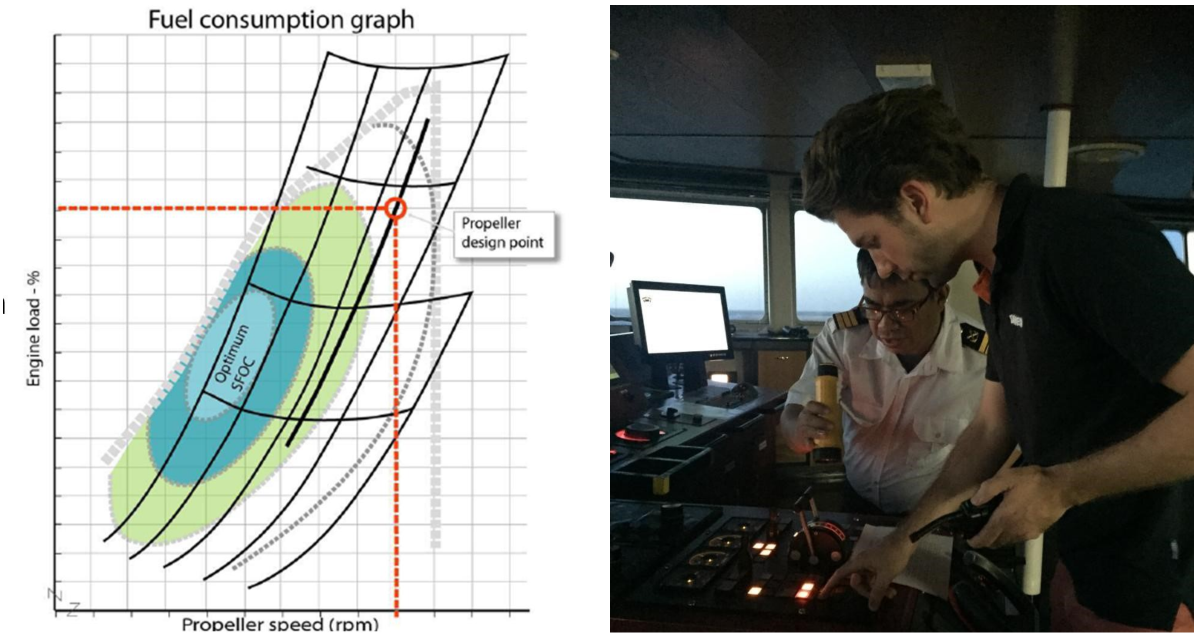


(a) Free running FE of Glacier

(b) Free running FE of Sherpa

Figure 5.13: Free running FE of both vessels

This significant fuel saving by combinator mode is theoretically explainable. The difference of SFOC between combinator mode and fixed frequency is typically about 2 g/kWh(Grevink, 2018). The openwater efficiency of a FPP is up to 10% higher compared a CPP at constant RPM (see section 4.2.3). Sailing combinator mode can be 15% to 30% more efficient by optimisation of both the RPM and the propeller pitch. The main principle of combinator mode is visualised and the combinator mode button at the bridge of Sherpa is designated in fig. 5.14.
The Shipyard included the combinator mode within the vessel design and installed the controls. Not using the combinator mode is a off-design vessel operation.



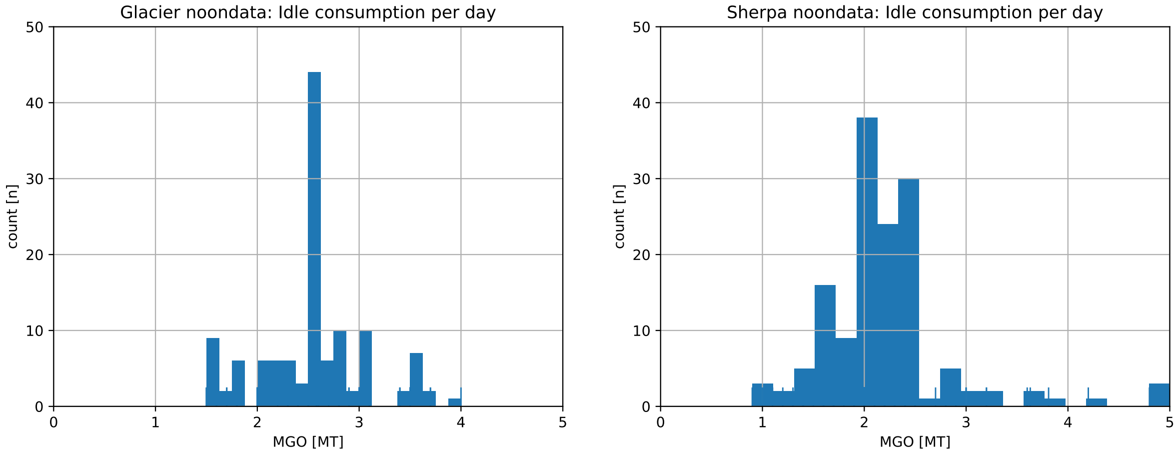
(a) The generic combinator curve from Wartsila

(b) Chief officer and the author pushing the combinator button at the Sherpa

Figure 5.14: Free running FE of both vessels

Idle performance

The idle performance distributions are shown in fig. 5.15 for both vessels and range between 1 and 5 MT of MGO per day. The data originates from manual filled noon reports, both the boilers and the auxiliary engines run only on MGO. The data does not contain information about by shore supplied electricity or generators from the ports at deck. No flow meters installed for MGO and the measurements are done by reading the gauge glass of the MGO daytank. The consumption of the boilers and the auxiliary engine can not be distinguished at the LTD fleet.



(a) Idle consumption of Glacier

(b) Idle consumption of Sherpa

Figure 5.15: Idle consumption

The most frequently measured values are between 2 and 2,5 MT per day, with between 1,25 and 1,5 consumption of boilers, the electricity demand seem to require between 0,5 and 1,25 MT of MGO. These number are important for decisions about implementation of for example solar panels, cold ironing or heat storage onboard.
The consumption of the Glacier seems higher compared to the Sherpa, but no conclusions about efficiencies can be drawn from these differences, which can be the result of seasonal conditions or activities onboard.

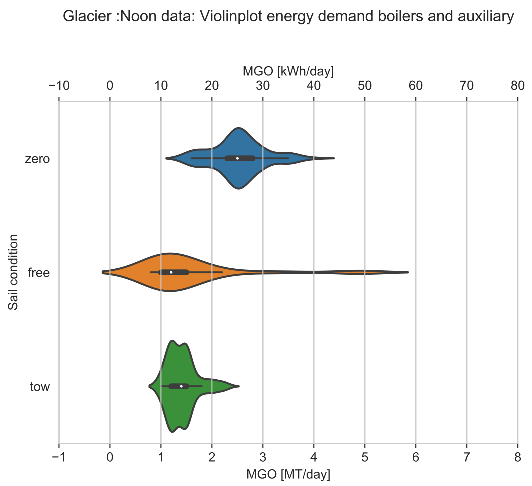
5.3.3 Hotel and Auxiliary Performance Optimisation

The hotel and auxiliary equipment have an energy demand about roughly 5-15% of the total and are considered separately for the different operational modes. The switchboards and boilers can be monitored separably to determine operational electricity and heat demand. The demand always consists about both the power and the energy for matching, depending on operational modes and weather conditions.

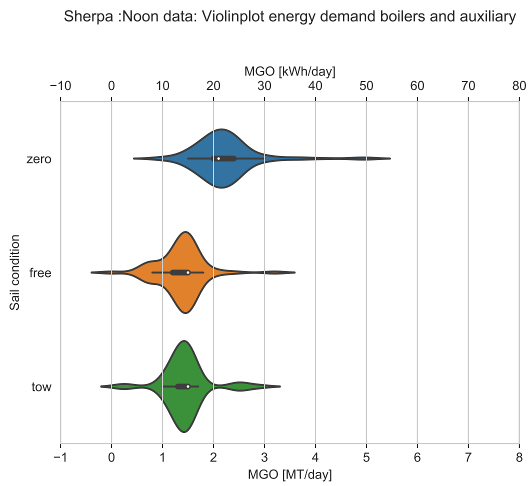
Heat Performance Optimisation

The heat demand onboard is delivered by two 800 kW thermal oil boilers (see fig. 5.16) and ±450 kWe by different electrical heaters. The heat baseload is defined as the average heat power demand over a whole day and equals ±740 kW by boilers and approximately ±100 kW by other electrical heaters. The daily heat consumption of both the boilers and the electrical heaters, which requires about 1,5 MT of MGO and ±600 kWhe.

The daily boiler consumptions for free-running and towing are between 1,25 and 1,5 and are graphically represented (see fig. 5.16). These boilers heat the thermal oil system for HFO bunker heating and lube oil heating to 50° Celsius. The noon report MGO data was filtered for remaining only the boiler consumption for sailing, which was measured by gauge glasses onboard. The differences between the two vessels are not significant, because these are below 0,5 MT and the measurement are ±10% inaccurate. The kWh's at the upper horizontal axis are rough indications and need to be multiplied by 1000.
The total idle or zero speed consumption of 2-3 MT of MGO of fig. 5.16 are not correct and are correctly shown in the previous paragraph (see fig. 5.15).



(a) Boiler and Auxiliary consumption per 24 hours



(b) Shaft alternator power distribution

Figure 5.16: Boiler Consumption

The heat baseload at the electricity grid onboard is assumed to be 100 kWe while sailing, which is equal to 2400 kWh and 0,5 MT MGO per day. The 'electrical' heat baseload and consumption are not measured onboard, but assumptions are made by use of the available load balance (see table 5.8). The HFO trace heater (25 kW) is specified to be working 100% of the time and is specified as 'c' in the most right column of the table. The other electrical heater units are specified as variable over time and specified by 'v'. The AIRCO unit is assumed to run at least with one electrical heater of 40 kW and the other consumers demand the other 45 kW baseload. If Boskalis is interested in operational data, they can install sensors and loggers at the switchboard.

Table 5.8: Load balance summary of heaters

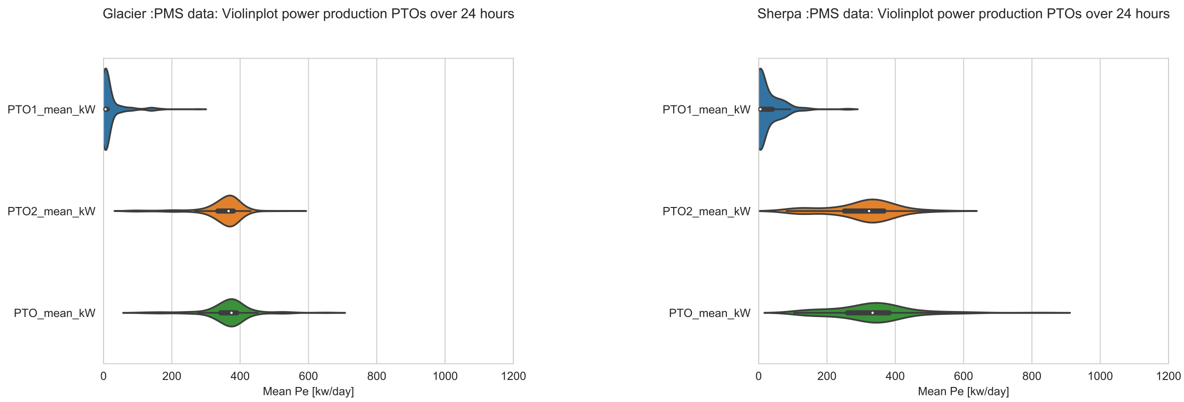
Heaters	number	Output [kW]	total input[kW]	sailing mode
Main engine preheat	1	72	72	v
Fuel oil heater	2	48	96	v
Lube oil Heater	2	45	90	v
Eletrical heaters AIRCO	3	40	120	v
HFO trace heater	1	25	25	c
Heater(accommodation)	23,5	2	47	v
Hot water boiler	2	3	6	v
Total			456	

The boilers can be switched of or set lower in power, while laying in port or at warmer locations. Moreover, one heat exchangers for a 950 kW engines can deliver 670 kW heat power by exhaust gas recovery (see appendix D.3), which is sufficient to switch off the boilers and save €860 of MGO per day. The installation of one exchanger cost about €6000 (see appendix D.1). The pay-back period of one exchanger is 7 operational days by only substitution of the MGO boilers. The financial effect over longer period, together with replacement of electrical heaters are analysed in section 5.4.

Electrical Performance Optimisation

The both vessel have an electric baseload of 350±50 kW for the sailing conditions (see fig. 5.17), which is responsible for 1,0 and 2,0 MT of fuel per day. The previous paragraph argued a 100 kW baseload is reasonable for the share of electrical heaters. The installed pumps and ventilators have a baseload power demand of ±140 kW according the load balance (see table 5.9). Another 110 kW electrical power demand is left for the lighting and other smaller and infrequent demanding consumers onboard.
The electrical power demand onboard can theoretically ranges from 0 to 3270 kW, when including all installed engine and alternator powers. The operational data showed the power demand almost never require more than 400kW, except when using the manoeuvring thrusters or deck crane. The alternators efficiencies are about 93-95 %, depending on the load and the powerfactor. The both alternators are always grid synchronized and can deliver a constant maximum power of 1.200 kWe each.

The mean sailing baseload for Glacier is about 385 kW and the Sherpa 350 kW. These numbers are interesting for matching with power suppliers onboard, since one auxiliary engine onboard can deliver a constant output of 350 kW at 100% MCR. The use of the combinator mode requires the power supply from the auxiliary engine(s). Operating with one auxiliary engine will save fuel and maintenance, compared to operating two auxiliary engines at lower loads and SFOC. Moreover, the classification companies require one standby generator to cover the electrical baseload, which may not be the emergency engine of 100 kW. The reduction of the electrical baseload with about 100 kW is required to enable combinator mode and to avoid auxiliary engine overloads while sailing long distances.



(a) Electrical performance of Glacier

(b) Electrical performance of Sherpa

Figure 5.17: Electrical performance of LTD

The electrical performance optimisation can by achieved by installation of LED sensor lighting, frequency controlled electric motors and thermal oil heaters. The main engine seawater pumps and machinery room ventilation are the most interesting for frequency controlled electric motors application, since they both run at constant 100% power while sailing (see table 5.9).
The application of a battery system is recommended to "peak shave" short and small electricity demands both the power of one auxiliary engine.

Table 5.9: Load balance summary of electrical consumers, excluding electrical heaters

Pumps:	number	Output [kW]	total input[kW]	sailing mode
Main eng SW cool pump	2	25	50	c
Air con Units SW cool pump	1	25	22	c
LO purifiers pump	2	8,6	15	v
Compressor AHU	3	75	243	v
Vent. Fan for engine room	4	15	65	c
Sailing constant			137	c
Total			395	

The use of the combinator mode and inherently the auxiliary engines do cover the additional maintenance and fuel costs. The overhaul of one auxiliary engine is required after about 16.000 running hours (see fig. 4.8), which costs €100.000 per overhaul. The engines can run for 667 days with additional maintenance cost about €150 per day.
The high-speed 4-stroke auxiliary line-engines can only use MGO, which is more expensive compared to the use of HFO. The engine efficiency differences between main and auxiliary sets or cost of maintenance per hr of kWh are not known at LTD. The use of 2 MT MGO instead of the 2 HFO by the alternators, costs €420 per day for assumed constant fuel prices. The combinator mode saves about 7,5 MT per day, which equals €3750 per day for the assumed fuel mixture.

The use of electrical rectifiers after the shaft alternators and Organic Rankin Cycle (ORC) Technology are interesting for avoiding the additional maintenance and fuel costs by the auxiliary engines, but are both not considered to be 'quick wins' for Boskalis since they require investment over the €100.000 and not all required data is available at the moment. The both design improvement are considered by a 'back-in-the-envelope' calculation below and are technically considered over the vessel life time in section 5.4.
The electrical rectifier can save the additional maintenance costs and possibly price difference, which is €570 per day. The initial investment will be about €100.000, with a minimal pay-back period of 175 days sailing. The pay-back period will be longer in reality due the assumption of €420 saving per day on fuel prices is optimistic, but a pay-back investment within 2-4 year seems not unlikely.
The ORC technology can save maximum €1320 of fuel (2MT MGO) and €150 maintenance per day. The initial investment is assumed to cover the electrical baseload and assumed be 4 time €175 thousand, equal to €700.000 (see appendix D.1). Divide this investment by the daily maximum saving of €1470 and conclude the pay-back period over 476 days, when all four engines are running. The pay-back period is higher in reality since, the savings are lower and the ORC installations require maintenance. Moreover, this optimisation solution is not 'data ready', since the running hours and related HT-cooling water properties are not known. The main principles of ORC are explained by appendix D.3.

5.3.4 Engine Performance Optimisation

The operational performance of the four Wartisla 6L32 engines of both vessels are expressed and related to the operational engine load distribution, the temperatures of exhaust gas, HT-cooling water and turbocharger performance (see section 5.3.5). The relations between engine and turbocharger are graphically explained by fig. 5.18. The data of point 1 and 3 were not available and this subsection considers the available data of the other points.

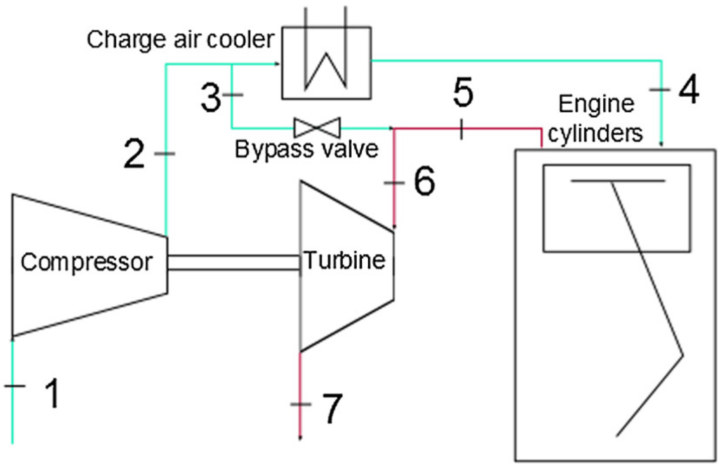
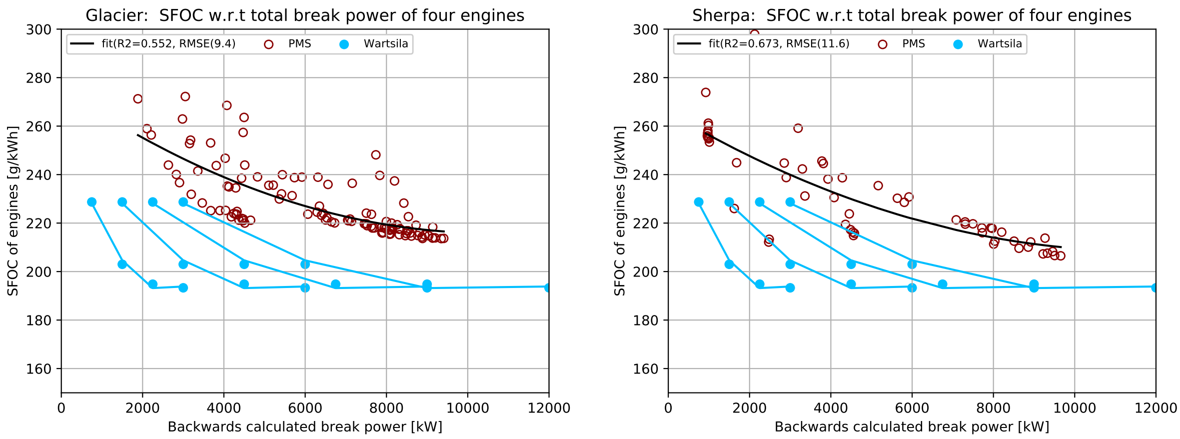


Figure 5.18: Data and interaction of the engine and turbocharger (Baldi, 2016)

The engine PI can be expressed in both engine efficiency percentage or SFOC. Boskalis explicitly required SFOC expressed in gram of fuel used per kWh of output. An advantage of SFOC compared to an efficiency percentage is less inaccuracy by assumptions for calculations. The most heat energy of the fuel is wasted and transported via engine and intercoolers coolants and exhaust gasses, which are both interesting for decisions about WHR.
No information was available to distinguish MGO or HFO engine runs, but should be distinguished if fuel temperature data at the flow meter is available. The engines do operated fixed at 750 RPM, variable engine speeds will require inclusion of this parameter as third dimension. This dimension can be visualised by the use of a third axis or contour lines of SFOC regions.

Specific Fuel Oil Consumption

The uncorrected vessel SFOC regression is visualized, together with corresponding SFOC according the Wartsila 6L32 specification data of 2006 (see fig. 5.19).
The four blue Wartsila curve-fits represent from left to right the allocation of one, two, three and four engines running at the power plant.
The PMS data about the one flow meter, duration, shaft alternator powers and two shaft power meters are used to assemble the operational SFOC. The flow meter reading over 24 hours was used to determine the consumed volume. The grams of HFO fuel are calculated according eq. (4.12) and an expansion by 70°C ΔT was corrected. The backwards calculated brake power originates from the sum shaft power and alternator power meters with constant gearbox correction.
The day duration is used and is filtered for values between 22 and 24.5 hour, the corresponding duration weighted average kWh values were used for the SFOC calculations. The average speed is above 4 knots and the standard deviation below 2 knot for filtering the 'steady runs'.
No ISO correction is applied since there was no ambient data available of the LTD vessels.



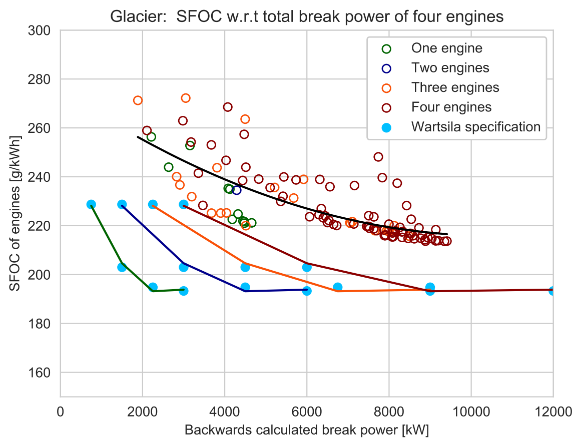
(a) SFOC of Glacier

(b) SFOC of Sherpa

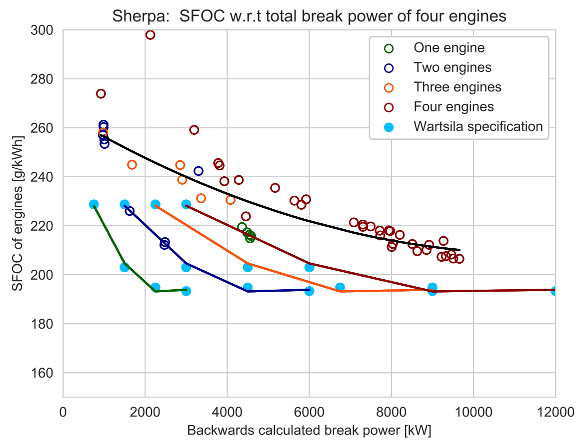
Figure 5.19: SFOC over 24 hours integration from PMS data of both vessels

The regression analysis (see fig. 5.19) shows increased SFOC for many days at both vessel compared to Wartsila specifications. The Sherpa (see fig. 5.20b) performed according the Wartsila specs for 6-8 days in April 2018 after the engine overhaul, which indicates that regression analysis makes sense. The operations with two and four engines can be distinguished and the increased SFOC of LTD is a fact.
The Glacier has a more increased SFOC compared to the Sherpa, which can be explained by the last overhaul of the Glacier in 2017. The Glacier is running four engines at loads between 20% and 40% MCR, which is closed to the Wartsila specifications.

The next iteration of SFOC visualization can distinguish the number of engines running, related to the specified SFOC of Wartsila (see fig. 5.20). The number engines are counted by average RPM above zero at the certain day. Four engines are allocated while two would be sufficient considering required brake power and this increase the SFOC by about 20 g/kWh.
Some green scatters passed the 3000 kW brake power, which is unrealistic. The engine counting algorithm works, but the PMS loosed contact with engine controller data. Later these problems were fixed by NPS.



(a) SFOC and engine count of Glacier



(b) SFOC and engine count of Sherpa

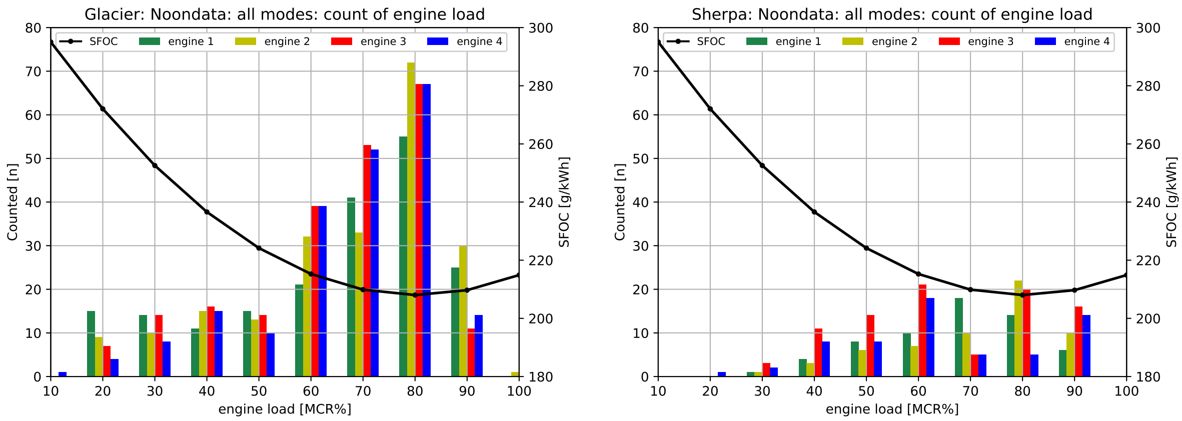
Figure 5.20: SFOC and engine count in relation to total brake power

The engine performance optimisation can be controlled by this prototype and saves 1-4% of the annual fuel consumption (IMO, 2018a), but this is conservative for the LTD case since both vessel regressions showed an increase over ±20 g/kWh (equal to ±5% engine efficiency). The implementation of this control system for engine performance optimisation cost about €10.000 and 1% of annual fuel consumption is €23.000 per vessel, which makes this a strong business case. The performance optimisation with 5% improvement seems to save €115.000 and 5% CO_2 emissions and €575.000 for all five LTD vessels per year.

The SFOC only shows the decreased engine performance, which can be the reason of avoidable low engine loads, decreased combustion quality, wrong or not provided maintenance procedures for engines and turbochargers or unfavourable ambient conditions. The ambient conditions and maintenance procedures and data were not available, but the other reasons are considered within the next paragraphs.

Operational Engine Load Distribution

The previously shown SFOC regression (see fig. 5.19) showed the suggestion of low engine loads and this is confirmed by the operation engine load distribution (see fig. 5.21).
The Wartsila 6L32 run for many days at load below 70% MCR and constant speed, which is fuel inefficient, this is illustrated by fig. 5.21. The engine load indicators over 24 hours are shown in the distribution of fig. 5.21 over the 2016, 2017 and first half 2018. The SFOC of the Wartsila 6L32 is lowest between loads of 70% and 90% MCR, like the black SFOC line indicates.
The load indication can be 20% inaccurate above the 50% MCR load according the DQA. The fit of SFOC-curve originates from individual engine performance of PMS data and is projected at this graph, to illustrate typical SFOC relation of the diesel engines.



(a) Distribution of SFOC Glacier

(b) Distribution of SFOC Sherpa

Figure 5.21: Operational engine load distribution of both LTD vessels

The both LTD vessels can improve their SFOC by avoiding the engine loads below the 60% MCR. The situation running four engines at loads below the 50% occurred frequently, for spinning reserves and 'redundancy' which are not required by Classification company. The LTD vessel might decide to run the minimal number of engines required, to improve the fuel efficiencies with typically 20 to 40 g/kWh, which is equivalent to 5 to 10% engine efficiency.

Exhaust Gas Temperatures

The low combustion quality or insufficient engine cooling result in higher exhaust gas temperatures, which is the case for the both LTD vessels (see fig. 5.22).
The exhaust gas temperature noon data is visualised for all engines, together with the Wartsila specifications. The lowest and highest temperatures of the 6 cylinders are logged and visualised for HFO and MGO.

The regression (see fig. 5.22) shows that the temperatures are increased about 50°C and 100°C compared to the Wartsila specification. If engine loads increase, the temperatures are relatively more increased, which can be result of more frequent low quality combustion.
The corresponding scavenge or often called charger temperatures are decreased by 5° degrees according regression (see fig. 5.29). These charge and exhaust temperature have a typical 1:10 relation, according the 'rule of thumb' used by engineers onboard. One degree increased charge temperature results in ten degrees exhaust gas temperatures, which means that exhaust temperatures are increased by 150° without tuning of the intercoolers.
The engineers onboard tune the intercool to avoid the alarm value of 500°C per cylinder, which is known by the TSI onshore. The crew onboard tunes the high temperatures back to 475°C to avoid alarm value and this is obvious for engine three at the Glacier. If tuning of the intercooler is not enough for avoiding the alarm values, engineers onboard do change the fuel pump offset on the fuel rack. The changed fuel pump offset results in lower outputs for the same engine controller loads, which are on the horizontal axis. The scatters have to be translated to the left over the load on this horizontal axis.
No significant differences are found between MGO and HFO within the data, but temperatures for MGO seem slightly lower.

The increased temperatures of all eight engines are indications of low 'engine health'. The result is a relative high thermal loads of both the engines and the turbochargers, causing increased wear and tear and decreased engine performance (see fig. 4.8). The technical reasons are unbalanced ignition or valve timing, polluted injector nozzles by hard carbon or compression losses of turbocharger and cylinders. The engines running hours are positively correlated to the increase of temperatures over time, with relations to the maintenance activities, especially by use of HFO. The engine overhauls are done every 12.000 hours for HFO and 24.000 for MGO according procedures, but these intervals are extended in cases of project opportunities.

The data about exhaust gasses area PI's that can be used onboard and by TSI. The engine health can be monitored and result in maintenance decisions and interval optimisation. The engineers onboard can for example decide to clean injection nozzles and do technical check if temperatures are increased by 30° Celsius or switch to another engine by 100° increase. TSI can judge the urgency of an overhaul according the increased temperatures and SFOC and benchmark before and after the engine overhaul.

The curve fit of the bowman heat exchanger specification data (see appendix D.3) has the equation: $y = 0,7055x + 1.8788$. This means between 70-90% MCR, the recoverable heat power is 1500-1900 kW per engine. This is sufficient for ORC recovery about 120-260 kWe for one engine and 180-400 kWe for two engine, according (appendix D.3).

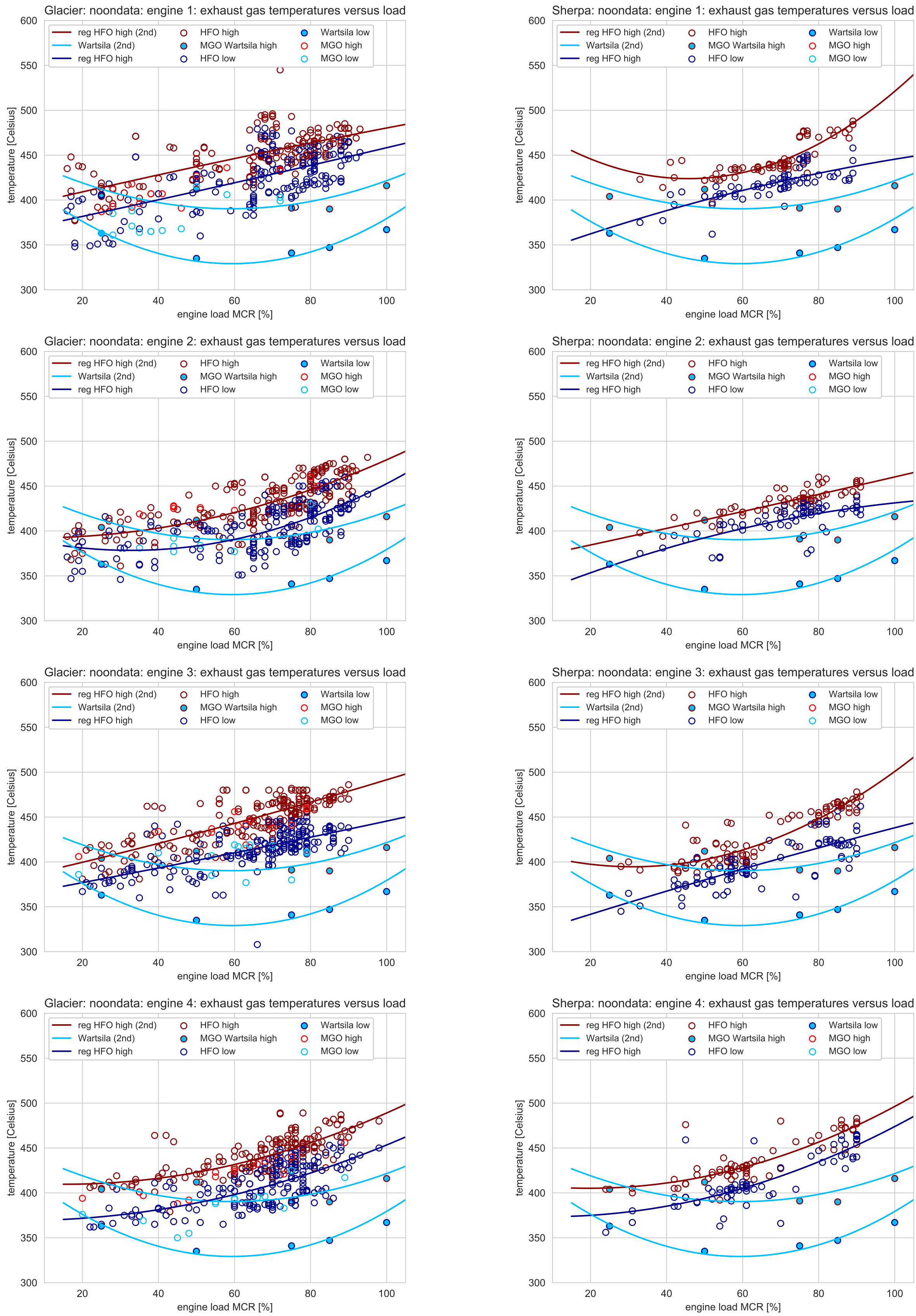


Figure 5.22: The exhaust gas temperature PI

High Temperature Cooling System

The HT-temperatures, pressures and flow rates of the cooling water system are interesting for decision making, since the system transports typically about ±30% of the total heat energy produced. The cooling waters or coolant do cool down the engines and the Turbocharger intercoolers.

No data was logged onboard about the cooling temperatures, but the Wartsila specification stated what temperature differences before and after engines should be, as shown in table 5.10. A constant specific heat of 4180 kJ/cbm*K is assumed for the cooling water to calculate the HT heat power per engine. Every engine delivers a constant heat power between 280 and 650 kW (see table 5.10). The HFO seems to provide more heat power compared to MDF, but this is not confirmed by operational data. The operational data represents the reality better and is recommended to be collected in the future.

The decisions about maintenance, the frequency controlled electric cooling motors, the thermal energy storage or the waste heat recovery are supported by the HT heat power. The power and efficiency of for example an ORC modules by the determined typical operational heat power profile over the year. The interesting information about cooling systems are specified in table 5.10 and section 4.3.
The curve fit of the bowman specification data (see appendix D.3) has the equation: $y = 0,2956x + 0.7396$. This means between 70-90% MCR, the recoverable heat power is 620-800 kW_{th} per engine. This is sufficient for replacement of the one boiler required for sailing. Thermal oil storage can be considered, since the vessel mostly operate with two or four engines.

Table 5.10: HT data from Wartsila for 6L32

load	25	50	75	85	100	110	25	50	75	100
fuel	HFO	HFO	HFO	HFO	HFO	HFO	MDF	MDF	MDF	MDF
HT before	93	92	83	87	85	80	92	92	88	83
HT after	96	95	90	90	90	87	93	94	92	88
HT delta	3	3	7	3	5	7	1	2	4	5
Flowrate [m3/hr]	80	80	80	80	80	80	80	80	80	80
HT_wh_kW	279	279	650	279	464	650	93	186	372	464

5.3.5 Turbocharger Performance Optimisation

The 6L32 engine's SFOC is related to his corresponding the Napier 297 turbocharger performance. The charge pressure and temperature do influence combustion quality within the cylinder (see fig. 5.18). The turbochargers are running of design and this is quantified by regression analysis of turbine temperatures, compressor speeds, charge pressure and temperatures in the next paragraphs of this subsection.
All the turbocharger PI's called in the previous sentence support decisions about turbocharger replacement, upgrades and maintenance.

The general turbocharger work principle and components are shown by fig. 5.23 and **??**. The turbocharger has the turbine section with exhaust gas inlet and the compressor section with machinery room air inlet. The compressed air passes the intercooler before being charged within the cylinders.
The inlet and outlet temperatures of turbine section, speed of compressor wheel, pressure and temperature after intercooler are reported and used for regression. The operational engine protocols of Wartsila were used for benchmarking these operational parameters.

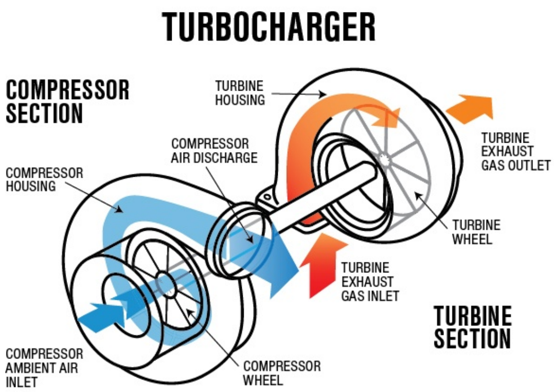


Figure 5.23: Turbo Charger operation diagramRich (2019)

The turbocharger of LTD have a bad reputation at the fleet management department, due many occurred failures and relative high maintenance costs and downtime, compared to other turbochargers of the OED fleet. The LTD project can require running with maximum engine power for many days at HFO, which results in relative high thermal loads and pollution (see fig. 5.24). The pollutions found are indications for decreased turbocharger and engine performance.
The visits and interviews onboard of the Sherpa and Glacier explained no or minimal maintenance procedures were available. This paragraph explains how to support and control maintenance decisions and procedures onboard.

(a) Constipated inlet filter of Compressor section

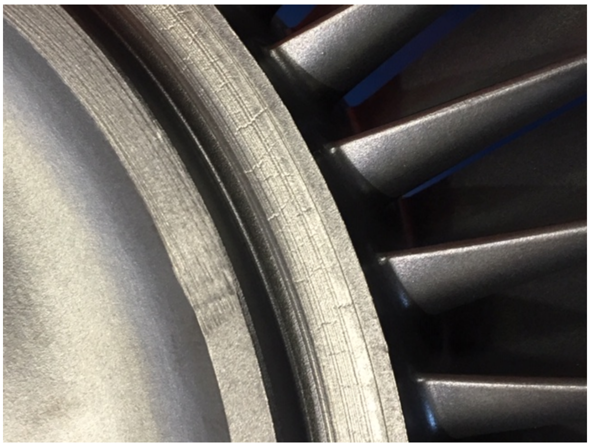
(b) Constipated nozzle-ring of Turbine section

Figure 5.24: Examples that indicate low TC performance of LTD

Turbine Section Temperatures

The increased temperatures before and after the turbine causes increased thermal loads and inherent maintenance, while the temperature differences are slightly increased or according Wartsila specification for the most engines.
The temperatures before the Turbine section are related to the exhaust gas temperature of the corresponding engine and operate both within the range between 300° and 600° Celsius, as shown in fig. 5.22 and fig. 5.26.
At the engine loads above 60% MCR the temperatures increased and below the 60% MCR decreased. The increased temperatures with 100°C are not uncommon and cause increased thermal load of the turbine sections, with additional maintenance costs. More than 30° Celsius is considered undesirable and above 50° Celsius alarming according TSI's. The LTD turbochargers turbine wheels showed initial cracking, possibly due increased temperatures and turbo washing at high temperatures (see fig. 5.25b). The turbine nozzle rings were buckled and penetrated (fig. 5.25a), this is called blown away, reducing the turbo speeds and charge pressure. The low temperatures indicate to reduces available energy within the exhaust gases for the turbochargers, this can consequently result in reduced turbo speeds and pressures. The temperature difference over the turbine is a better PI to consider in relation with speed and charge pressures.

(a) Buckled and Penetrated nozzle ring of turbine section



(b) Turbine wheel with initial cracking

Figure 5.25: Examples that indicate low TC performance of LTD

The energy or entropy absorption from exhaust gasses is presented by the temperature differences over the turbine section. The increased energy absorbance is the case for most engines of the Glacier, which is related to the increased compressor speeds. These both result in increased wear and tear, with reduced life-time of

components.
The temperature differences of the Sherpa are considered within acceptable range.

The DQA showed that data point above 70% often can be translated 10 to 20& MCR lower, which means less alignment with Wartsila temperature differences specifications.

The increased temperatures and energy absorption result in reduced life time of the turbine section. The engineers and TSI should avoid increase temperatures and energy absorption over the turbine sections. This data should always be considered in relation to compressor speeds, charge pressures and other temperatures.

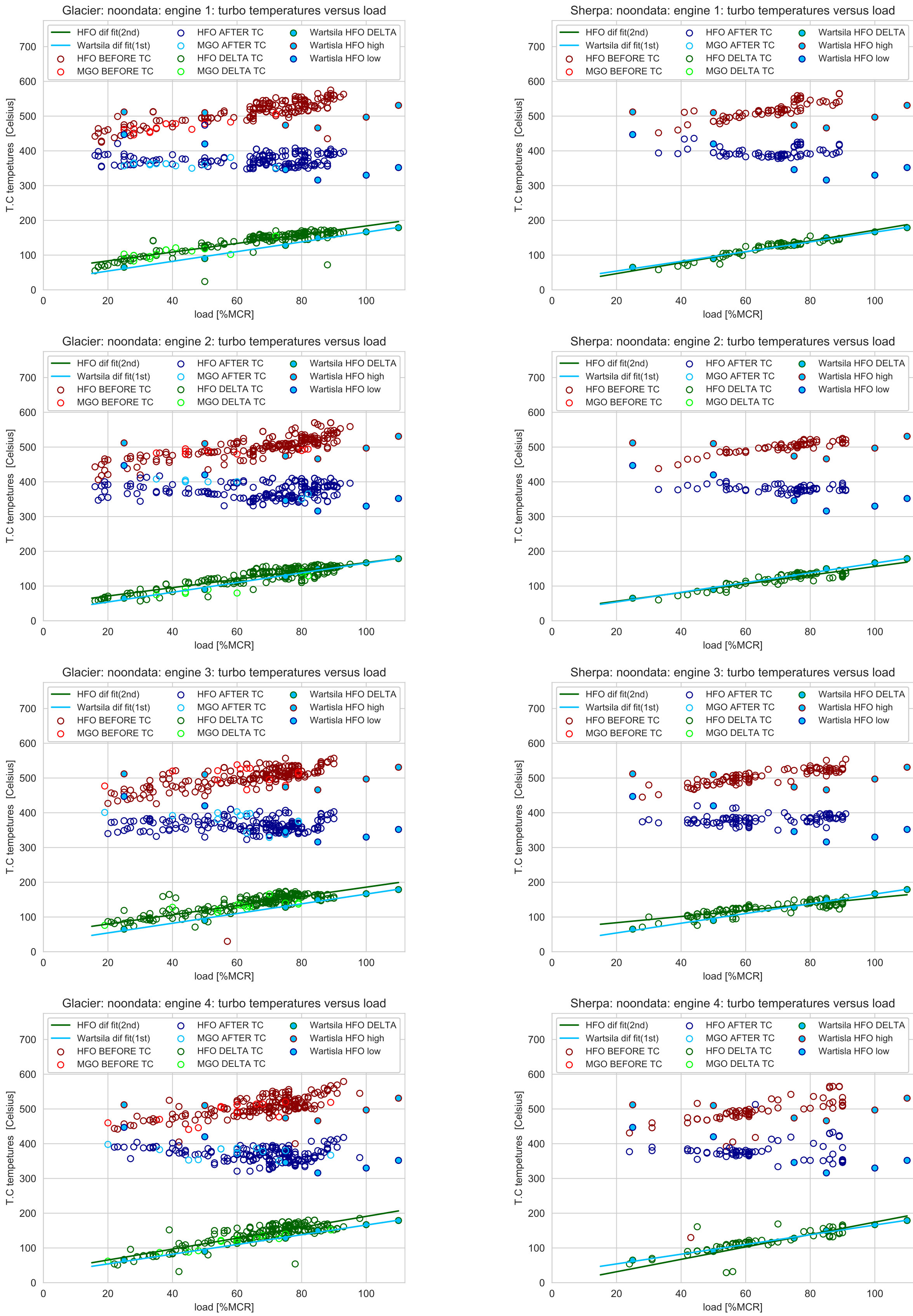


Figure 5.26: PI of turbine temperatures

Compressor Speed

The absorbed exhaust gas energy by the turbine wheels induce the compressor wheels. These compressor wheels ’suck’ air through an inlet filter from the machinery room and compresses an airflow through the intercooler and the inlet of the engine cylinders. The speed of the compressor wheel is related to the engine load and required pressure for combustion.

The increase speeds, compared to the reference speed from specs, are found at the Glacier (see fig. 5.27). this results in reduced life time off components, compared to an at design working turbo unit. The increased speeds are an indications of low inlet pressure of the compressor section, which can be caused by low machinery room pressure or constipated of the inlet filters as shown in fig. 5.24a. Mention this is the case for all four engines at the Glacier.

The reduced speeds, compared to reference speed from spec, are found at the Sherpa see (fig. 5.27). This logically results in decreased charger pressures and lower SFOC, which is the case at four engines of the Sherpa. The reasons for these decreased performances are damaged or constipated turbine sections or a constipated intercooler units. The pressures over the intercoolers are measures onboard by not communicated to shore. When the high pressure drop over the intercooler can be confirmed, this confirms this explaines the decreased performances.

This PI represents the performance of the compressor section to create the improved charger pressure. This realtime PI can create awareness about the off-design compressor wheel speeds and support decisions for maintenance actions. The inlet filter, intercoolers and nozzle rings might be checks and cleaning.

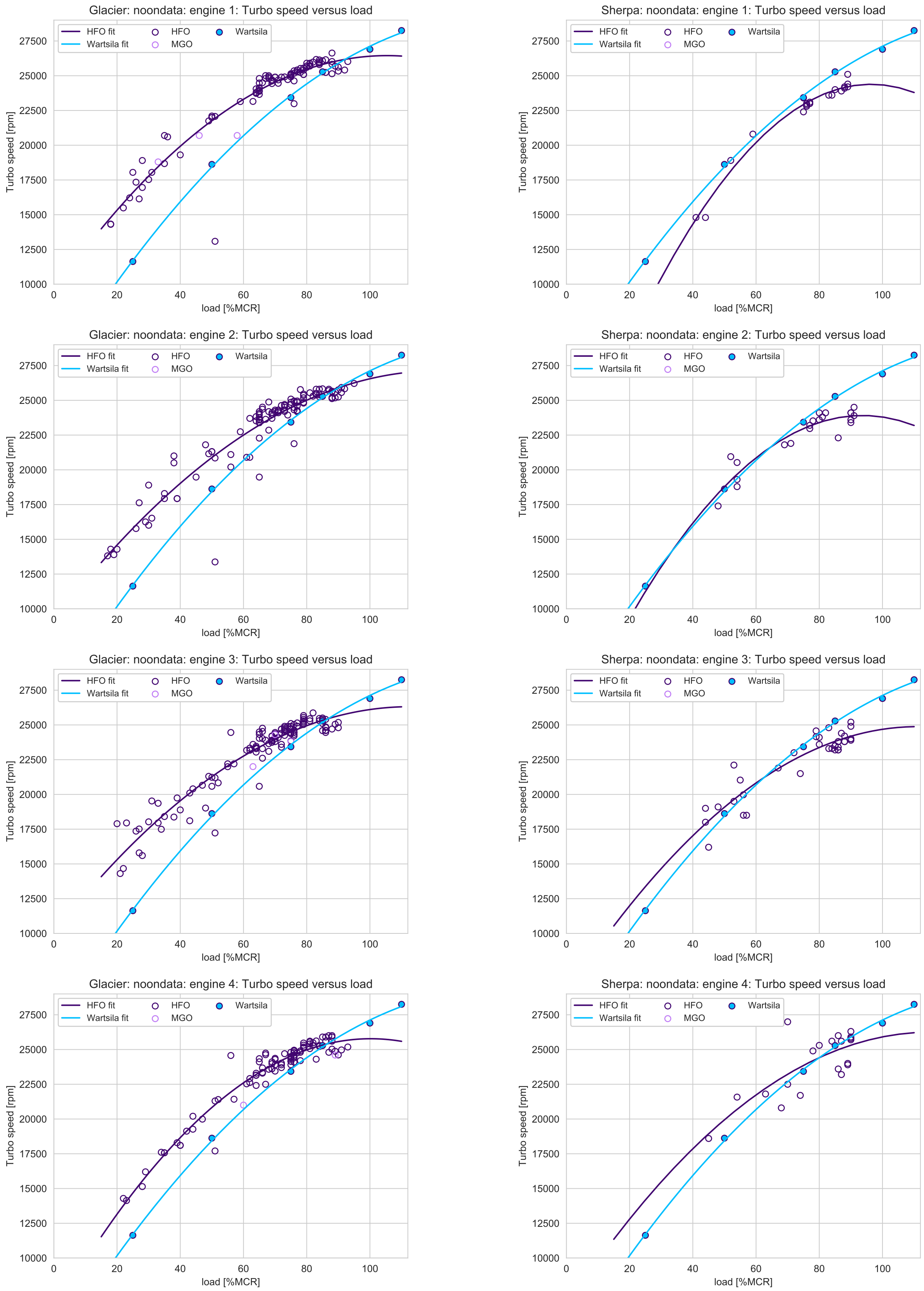


Figure 5.27: The PI of compressor speed

Charge Pressure

The engine cylinders are filled with air for combustion with a charge pressure, these Napier turbos have a compression ratio of 3 for 100% MCR (see fig. 5.28).

The decreased charger pressures after the intercoolers at the Glacier and Sherpa (see fig. 5.28) indicate the less charged oxygen within the cylinders, which means lower combustion quality. The combustions of decreased quality will have lower mean effective pressures within cylinders and higher exhaust gas temperatures, which means lower SFOC and reduced life time of turbo components. The decreased charger pressures, compared to specs, can be the reason of damaged gaskets or polluted turbine (see compressor speed), damaged or polluted compressor wheel or constipated intercoolers and constipated inlet filter.

The increased charge pressures at the lower engine load regions of the Glacier are overcharging the cylinders. The increased pressures on the valves can have a negative effect on the combustion timing and engine balance.
The increased charge pressures are in line with the increased compressor speeds and the situation. The engine 3 of Glacier is most increased of all engines and the same is truth for the increase temperature difference and compressor speeds. These thee show a relation, but the technical reason is not known. The SFOC is expect to be higher, compared the an at design running engine and turbo, but this cannot be quantified by available data.

Charge Temperatures

The charge temperatures are manually tuned at the intercooler onboard to avoid alarm values of the exhaust gas temperatures. The linear regression analysis shows reduces charge temperatures compared to the Wartsila specifications (see fig. 5.29).
Scavenge temperatures after intercooler is a PI of the intercoolers, which is visualised in fig. 5.29 and is related to engine and exhaust temperatures.

When the charge temperatures are increased with respect to specification, this results in decreased combustion quality, higher SFOC and higher thermal loads of engine and turbo chargers. The most charge temperature data is on or below specification.

The decreased charger pressure for a certain load or wrong settings of the intercooler. The crew possibly set the intercooler to lower to avoid alarm values for increase exhaust gas temperatures, which is form of symptom fighting and no solution of the actual problem of low engine health. The decreased temperatures can be the result of both under performing inter-coolers and relative low charger pressures, which are both unlikely. The decreased charge temperatures can result more oxygen for better combustion, but also higher thermal engine load due larger temperature difference within the cylinders by injected air.

The PI of charge temperatures does support the decisions about solving the real problem of high engine temperatures. The scavenge temperatures need to be known to see if the problem is compensated by relatively low temperatures settings of the intercoolers.
The pressure and coolant differences over intercoolers should be known to quantified the performance of the intercooler.

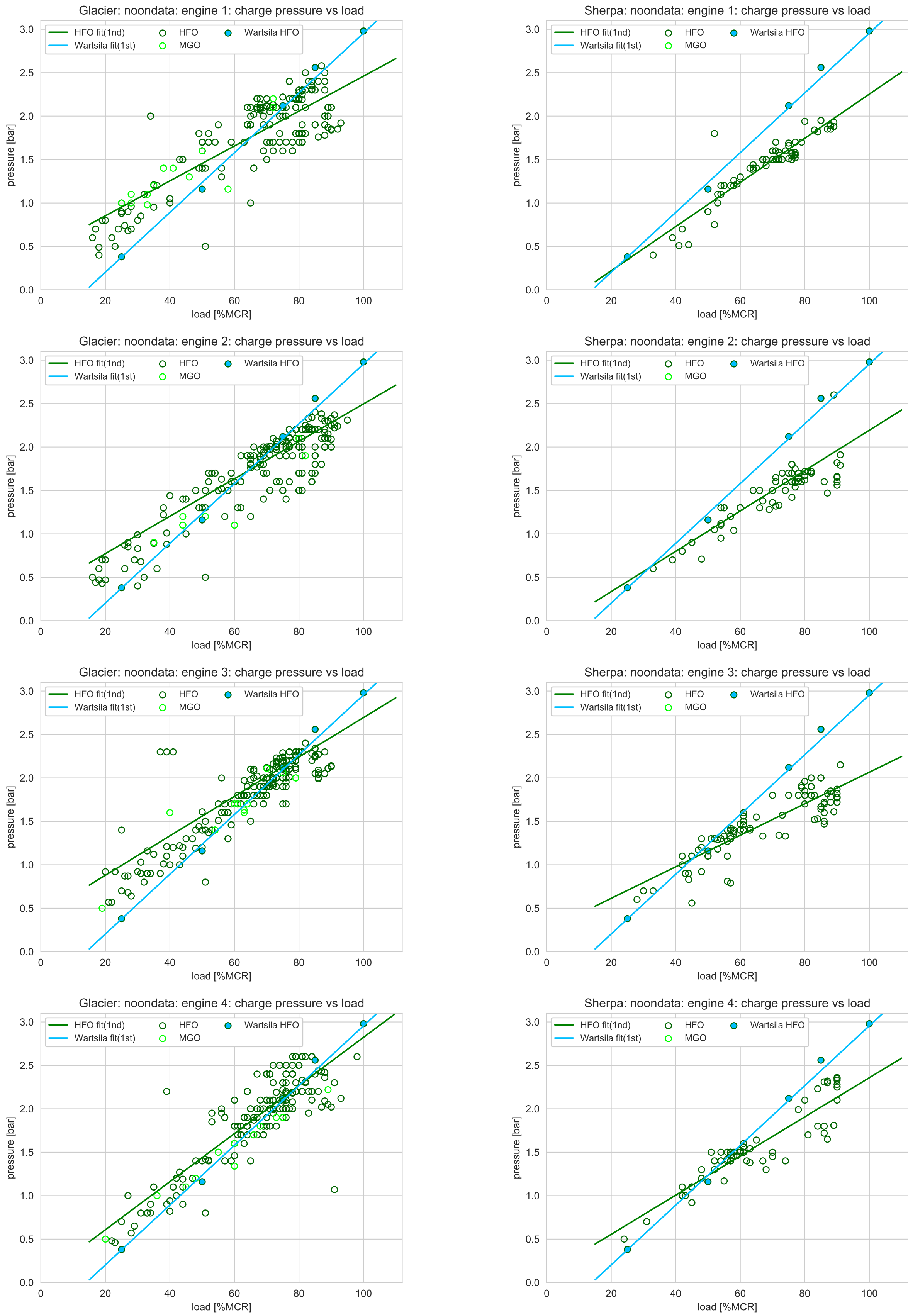


Figure 5.28: Examples of PI TC pressure

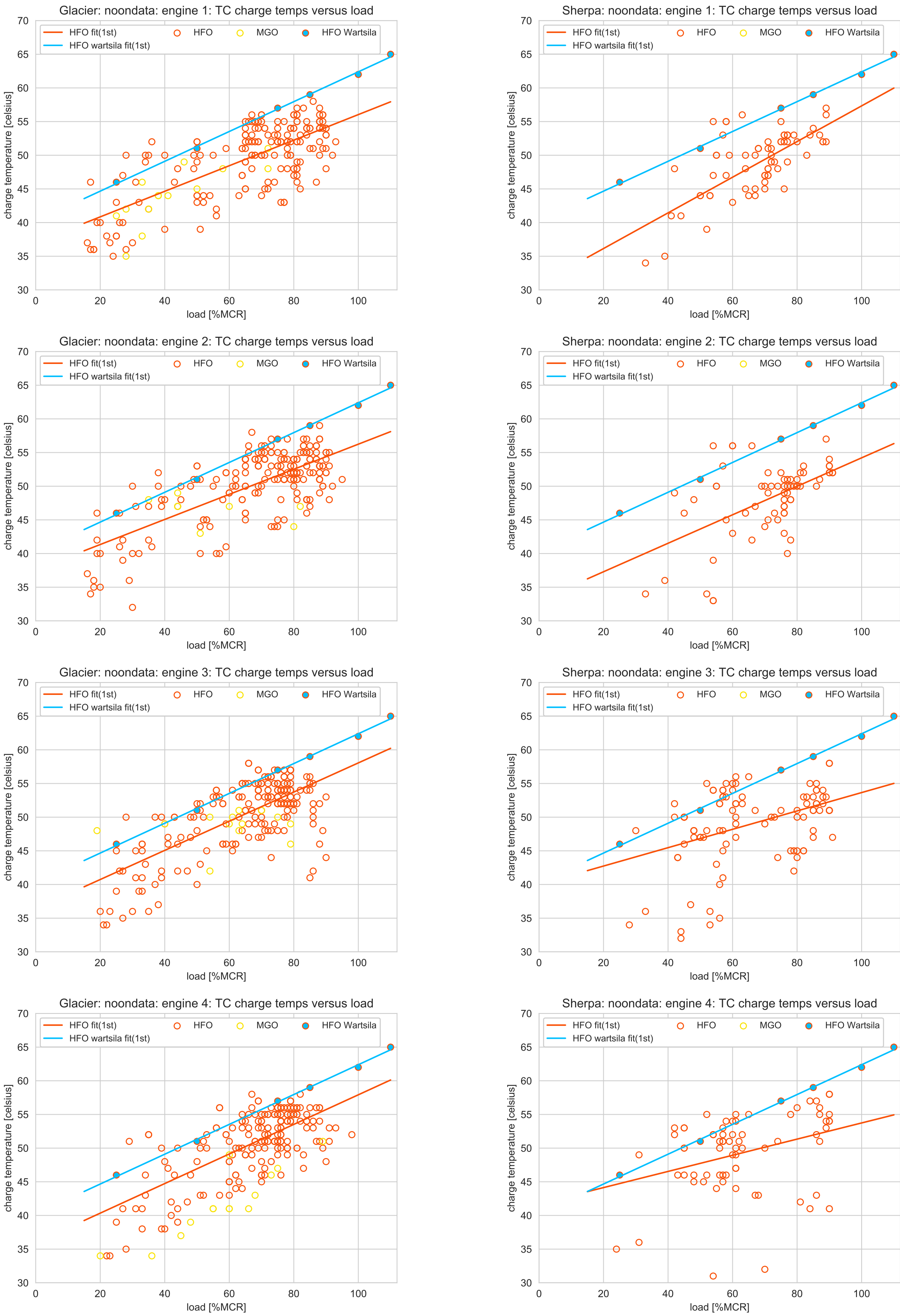


Figure 5.29: PI of charge temperatures

5.4 Data-driven Measures Classification

The previous sections of this chapter had the focus on management and decisions support for energy efficiency, while this section is about the decisions to improve both the technical and operation energy efficiency. Both are interrelated, since the support by the DSS enables quantification of the initial and long term measure effects over the time.

The relation of the performance control model with measure correlation analyse triggered the own development of the classification matrix, which is graphically explained on the next page (see fig. 5.30).
First the operational data and the performance control model are used to quantify the operational performance profile (see section 5.4.1). This performance profile is used for measure selection and financial calculations in the measure analysis (see section 5.4.2). The classification matrix graphically summarises the results of this section (see section 5.4.3)

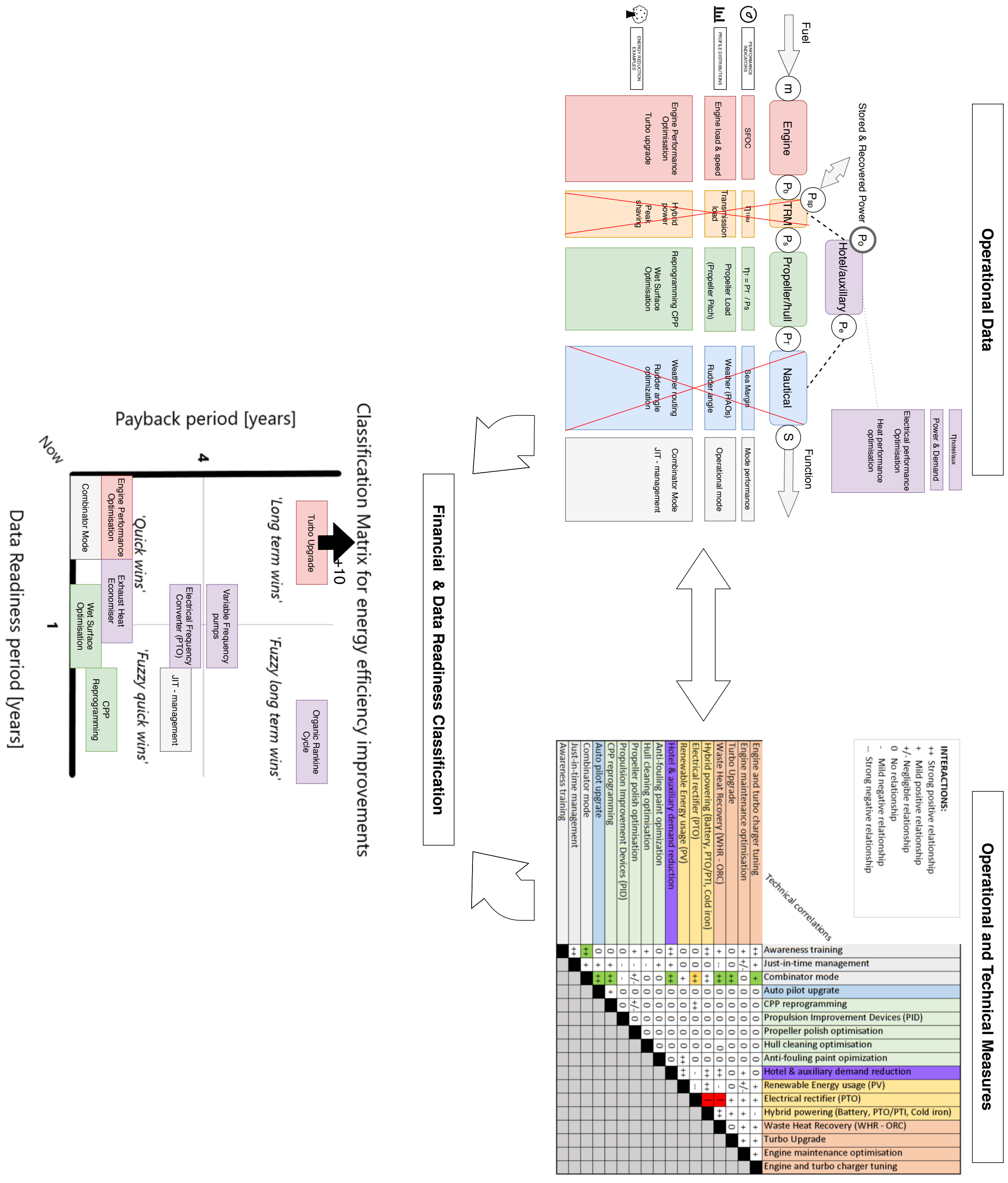


Figure 5.30: Overview of how operational data and improvement measures are used and result in the Classification matrix

5.4.1 Operational Performance Profile

The case study data "went thought" the the performance control model algorithms (see section 4.2) and resulted in the below described summary for financial calculations.

The operational annual profile (see section 5.4.1) specifies the annual consumption per operational mode and the vessel utilization. The total annual fuel costs and shares per operational mode are previously determined (see section 5.3.1). These assumed costs per operational mode numbers are estimates from the noon report analysis.
The vessel utilization was subtracted from the CSR data and additional by onboard meter readings. The onboard reading divided by the operational years gave 0,57, which is close the utilization 0,58 according the hired day from CSR data. These values should not be equal since the some hired days are idle, but this analysis indicates the number are not contradicting and can be used for the financial analysis.

Table 5.11: Operational annual profile for financial analysis

Operational profile used for financial analysis					
Operational Fuel costs			Vessel utilization		
	[x€1000]	[-]		[days/year]	[-]
Total cuel costs (CSR)	2.300	1	Days hired(CSR)	212	0,58
Towing	1.610	0,7		[hours/year]	[-]
Free-running	460	0,2	Engine running	3571	0,41
Idle	230	0,1	Vessel(gearbox)	5000	0,57

The performance control model is quantified for the sailing modes (see table 5.12). The original performance are given by the shipyard, the actual are measured by operational data and optimal are the theoretical optimal performance.
Only the engine performance are fully quantified, because of the available data from Wartsila, the PMS system and DTR data. The actual engine performances are significantly lower, compared to original specification and the theoretical optimum. Moreover, according the operational data the four engines never deliver loads above 80% MCR.
The propeller efficiencies were not measured, but the combinator trail showed about 30% improved propulsion efficiency. The theoretical propeller efficiency optimum is between 60 and 70%. The educated guess by use of the available number argues an operational propeller efficiency between 20% and 30% for free-running and reduced speed towing. The actual propeller efficiency might be higher for full power towing, but recent bollard pull tests (see fig. A.5) showed decreased propeller performance (180 MT bollard pull) compared to the original (200 MT bollard pull). The reason might be increased tip clearance with the fixed propeller ducts or less likely a wrong calibrated the pitch control.
The original hull resistance is unknown and the actual was not determined. The optimal can be determined due new efficient hull design, which was beyond scope of this research.
Both the actual daily heat and electrical performance demand are between 1 and 2 MT of MGO every day, but the electrical demand is mostly delivered by on HFO running shaft alternators. The heat demand of boilers can be fully reduced by a retrofit to sail fully on MGO. The original consumption are not specified by the shipyard, but the electrical baseload (350-400 kW) is high, compared to other vessels.

Table 5.12: Generic performance quantification of LTD

Vessel System Performance Overview						
	Engine performance		Propeller/Hull Performance		Hotel & Auxiliary Performance	
	Engine [g/kWh]	Load [% MCR]	Propeller efficiency [%]	Hull[kN]	Heat [MT/day]	Electical[MT/day]
Original	190 - 230	?	?	?	?	?
Actual	210 - 270	20 -80	20 - 30	?	1 - 2	1 - 2
Optimal	180 -200	70 - 100	60 - 70	?	0	0

The CSR data analysed showed the HFO and MGO mixture about 80:20 represents the average annual fuel mixture. The €/kWh is calculated (see table 5.13) by considering the different SFOCs, the mixture and the constants about fuel properties (see table 5.6). The numbers of this table can be used to calculate the fuel efficiency effects or switching fully to MGO by 2020. The SFOC is translated to the engine efficiency percentage and 20 g/kWh is about equal to 5% engine efficiency.

Table 5.13: Fuel costs and efficiency overview

Fuel efficiency, costst and mix						
SFOC [g/kWh]	m3/kWh	MJ/kWh	efficiency [%]	HFO euro/kWh	MGO euro/kWh	Mix(80:20) euro/kWh
180	196	7,2	0,50	0,070	0,103	0,077
200	217	8,1	0,45	0,078	0,115	0,086
220	239	9,9	0,41	0,086	0,126	0,094

5.4.2 Measure Analysis

This analysis explains the relations between measures for finding "synergy" for energy efficiency improvement. Afterwards, the financial analysis is done to show how fuel efficiency can be improved cost-effectively.

Measure relations

The correlations matrix is previously explained (see section 2.3.2) and is used to specify technical relations between energy efficiency improving measures (see fig. 5.31).

The measures are located at both the axis and the colours are according their corresponding part of the performance control model (see fig. 4.4). The relations of measures are indicated from strong positive '++' to strong negative '–' and incompatible '!'. The correlation matrix supports decisions about which measures to combine for fuel efficiency improvement en development towards low carbon shipping.

INTERACTIONS:
++ Strong positive relationship
\+ Mild positive relationship
+/- Negligible relationship
0 No relationship
\- Mild negative relationship
-- Strong negative relationship

Technical correlations	Awareness training	Just-in-time management	Combinator mode	Auto pilot upgrate for yaw control	Upgrade CPP controls	Propulsion Improvement Devices (PID)	Propeller polish optimisation	Hull cleaning optimisation	Anti-fouling paint opimization	Hotel & auxiliary demand reduction	Renewable Energy usage (PV)	Electrical Frequency Converter (PTO)	Hybrid powering (Battery, PTO/PTI, Cold iron)	Waste Heat Recovery (WHR - ORC)	Turbo Upgrade	Engine maintenance optimisation	Engine and turbo charger tuning
Engine and turbo charger tuning	++	+	+	0	0	0	0	0	0	0	+	+	-	+	+	+	
Engine maintenance optimisation	+	+/-	+	0	0	0	0	0	0	+	+/-	+	+	+	+		
Turbo Upgrade	0	0	+	0	0	0	0	0	0	0	0	+	+	0			
Waste Heat Recovery (WHR - ORC)	+	--	++	0	0	0	0	0	0	++	-	!	++				
Hybrid powering (Battery, PTO/PTI, Cold iron)	++	0	++	0	0	0	0	0	0	++	++	!					
Electrical Frequency Converter (PTO)	0	0	++	0	++	0	0	0	0	-	--						
Renewable Energy usage (PV)	0	0	+	0	0	0	0	0	++	++							
Hotel & auxiliary demand reduction	++	+	++	0	0	0	0	0	0								
Anti-fouling paint opimization	0	+	0	0	0	0	0	0									
Hull cleaning optimisation	+	-	0	0	0	0	0										
Propeller polish optimisation	+	-	+/-	0	+/-	0											
Propulsion Improvement Devices (PID)	0	-	-	0	0												
Upgrade CPP controls	0	+	++	+													
Auto pilot upgrate for yaw control	0	+	++														
Combinator mode	++	+															
Just-in-time management	++																
Awareness training																	

Figure 5.31: Correlation matrix of measures (own composition)

The use of the currently installed combinator mode is beneficial and does not require significant investments. Due the combinator mode the engine speeds will decrease and exhaust gas temperatures possibly increase. These side effects can be managed with the previously by this research developed engine optimisation tool (engine en turbo tuning plus engine maintenance optimisation in matrix).
The combinator mode requires to switch-off the shaft alternators and switch-on one or two auxiliary engines. The hotel and auxiliary demand reduction, to reduce the required baseload while sailing, can avoid the need of two auxiliary engines and has therefore a strongly positive correlation with the combinator mode.
The hotel and auxiliary baseload demand reduction has a strongly positive relation to the WHR-ORC, because this technology required relatively large investment for the installed power. The baseload demand reduction can be effective for reduction of this required investment. Mention that this WHR-ORC technology works for

both fixed frequency and combinator mode and auxiliary engines can be switched-off.

The electrical frequency converter after shaft alternators will enable to switch-off all auxiliary engines during combinator mode activation, but this system is incompatibly with the WHR-ORC since they both share this same purpose. The electrical frequency converter can be interesting for reduction of maintenance costs and to save the additional costs of MGO with respect to HFO. The LTD vessels will fully switch to MGO by 2020, so the second argument is not valid any more.

Other interesting measures in combination with combinator mode are updates of the CPPs control for improved propeller efficiency and possibly with an autopilot for yaw control while towing, to eliminate rudder angles with additional drag. These two measures were not quantifiable by available data and DSS.
A turbo upgrade is strongly positive with the combinator mode, since the upgraded turbos will have faster response times and can generate relative high speeds and pressures for improved SFOCs, while running at variable frequency.

The positive correlated measures to combinator mode are considered within the next financial analysis, together with some other measures.

Financial Analysis

The previously specified and related measures are considered by this financial analysis. The measure's NPVs and payback periods are quantified to support decision about energy efficiency improvement. The suggested improvement measure package (see section 5.4.2) contains the combinator mode, the engine performance optimisation, the heat optimisation, the Frequency Controlled Electric (FCE) motors and the annual cleaning of propellers and hull. Together these measures will cost-effectively improve the energy efficiency and reduce carbon emissions between 20-30%. The actual improvement depends on the execution of improvement, but seem to improve energy efficiency by at least 20%. The most measures have a payback period below one year and all are all cost-effective.

The economical life-span for LTD activities is assumed to be maximal 10 years and NPS calculations are considered for this period. Boskalis explicitly requested to find the investments with a payback period below 4 year, called "quick wins". No sensitive analysis is done, because of the relative short payback periods.
The cumulative cash flow over the expected remained economical life-span of 10 year is added for people who do not understand the principles of discounting.

The financial analysis results are summarised by one table (see section 5.4.2) and are explained by next paragraphs of this subsection. The full overview of the NPV calculations are shown within the appendix. The analysis shows that Boskalis LTD can cost-effectively improve their by at least 20%, compared to the current situation that is assumed to be unchanged since 2008. This 20% is a conservative estimation and be proved to be 30% by the developed DSS in the future. Other possible cost-effective improvements, like for example the ORC, can future improve energy efficiency toward 40% by 2030 to comply with the IMO GHG reduction strategy.

Table 5.14: Financial overview of selected measures for LTD

Financial results							
Measures X €1000	C_0	Fuel saving [%]	$\Delta C_{fuel,n}$	$\Delta C_{maint,n}$	$Payback$	NPV_{10}	$\sum_{n=0}^{10} C_n$
Combinator mode	€1	4,5	€105	€0*	<1	€580	€1.600
Engine optimisation	€10	3,0	€70	€0*	<1	€380	€1.600
Heat optimisation	€24	7,8	€180	€0	<1	€980	€1.770
FCE motors	€8	0,5	€10	€3	<5	€45	€80
Annual propeller Polishing	0	2,5	€50	€4	<1	-	€480
Annual hull cleaning	0	2,0	€40	€10	<1	-	€315
Total	€45	20	€460	€15	<1	€2.410	€4.350

This financial analysis is not an investment proposal, since the scope is limited to quick wins only, but is made to illustrate the benefits of onshore data for decision support. The TCO should be considered over the by Boskalis expected life-time of their vessels. The scenarios of expected fuel and carbon prices can be included for comparison of the 'quick wins ideas', including additional 'long term wins' ideas, second hand options and the new building options. The maintenance costs should be considered more extensively together with more detailed engineering of measures for a investment proposal. For example, the additional maintenance cost for engine performance optimisations is no or hardly quantifiable in advance.

Combinator mode

The combinator mode tries to optimise both the CPP pitch and RPM, to improve the daily fuel efficiency by 30%(see section 4.2.3 & section 5.3.2), equivalent to 7,5 MT, for the free-running consumption share of 20% (see section 5.2.1 & fig. 5.13), which is equivalent to 6% annual fuel saving. The combinator mode is currently installed and operational at all vessels, but not used except during the organised sea trial, so €1000 is assumed for the initial investment to train and instruct the crew.

The lowest annual fuel save of 4,5 (22,5% more efficient per nautical mile) is assumed for a "careful" calculations, since more experience with the combinator mode is required, but still the choice for combinator mode is obvious. A discount rate of 10% is used for this a low risk investment. The NPV_5 is €360 thousand and the NPV_{10} is €580 thousand. If the combinator mode effectively will save 15% instead of measured 30% of the daily free-running fuel consumption, the NPV_5 is €273 thousand and the NPV_{10} €443 thousand. For both cases of 15% or 30% the payback period is less than one year.

The combinator mode seems interesting for reduced towing modes at two engines, but the LTD department did not test this during this research. The effect and improvement potential can be quantified by the developed data-driven DSS.
The programming logic controller for combinator mode can be updated for 1-3% additional fuel saving (Armstrong, 2013). A combinator mode was installed by the shipyard and has a relatively simple PLC that only considers the RPM and Pitch of the engines. The PLC seems to linear interpolate between 8 defined point, which is a simple control

The results are not validated for different engine loads and speeds, but a combinator curve next to fixed frequency can be produced for MT/NM by the data-driven prototype for operational decision support onboard.

Engine Performance Optimisation

A data-driven decision support tool for engine performance optimisation was developed (see section 5.3.4 & section 5.3.5) and showed SFOC improvements about 10 to 30 g/kWh to a 200 g/kWh average (see section 5.3.4)), equivalent to 2,5% and 7,5% engine efficiency improvement.
The 3% of section 5.4.2 conservative and might by 60 g/kWh, since the current awareness of SFOC and related daily maintenance and tuning is low onboard and the not available data. Engine performance optimisation in general as the potential the save 1 to 4% of annual fuel consumption (IMO, 2018a) and the shipping company Stena Line claimed they achieved a 8% fuel saving during their lighthouse conference presentation about energy efficiency.

A discount rate of 10% is used, considering this measure as low risk investment. The initial investment to implement the system onboard is maximal 10.000 euro (IMO, 2018a) and no significant maintenance costs are required. The estimated annual fuel saving is 3% and the NPV_{10} of €380 thousand. The payback time less than one year.

Heat optimisation

The heat optimisation is mainly about the two MGO boiler, that consume 1,5 MGO per day all year, which is about 7% of total annual fuel consumption. The LTD vessel can stop using HFO or install exhaust gas economisers to heat HFO by thermal oil instead.

One exhaust gas economiser is assumed to cost €6.000,- and is installed at all four engines, resulting in a investment of €24.000,-. The two boilers burn together 1,5 MT of MGO equals €860 per day. The vessels are sailing 57% of the year and produce enough heat 208 days, that saves €180.000 per year. $Noadditionalmaintenancecostarea$

The financial results are a NPV_{10} of €980 thousand and a payback period of less than one year.

The kWh output of one exchanger is more than required to substitute both boilers (see appendix D.3). The overcapacity can be stored and used instead of electrical heaters. A control system will be required to prevent overheating over thermal oil and storage of heat. Future research can be done to investigate implementation of two exchangers instead of four. These heat exchanger can be used for application of ORC (see appendix D.3).

Frequency Controlled Electric Motors

The seawater cooling runs a full power while sailing, without a sense for the required power. The electrical baseload can be reduced for improvement matching of auxiliary engines or ORC. The energy saving is 0,5 of the total annual energy consumption (IMO, 2018a). A frequency controlled motor can save 20-30% of energy consumption compared to fixed frequency controlled motor. The investment, additional maintenance costs and gains are respectively small, but the payback period about 2-4 years for the two seawater pumps of 25kW each.
The required initial investment is different according different website, but the prices are expected to drop fast during the coming decade due expected increased demand. Per 100 kW installed pump power 150 USD initial investment is assumed and €2.600 additional maintenance (IMO, 2018a).

Electrical Frequency Converter

The EFC can be installed after shaft generators to produce a synchronised AC power for the grid, when the main engines are running at variable frequency during combinator mode. No additional auxiliary engines are required that consume higher prices MGO instead of HFO, but this situation will not occur, since all LTD vessel will switch to MGO before 2020.

The EFC is not expected to cover instantaneous power demands of for example bow thrusters, but this is not a problem since the EFC will only be used during combinator mode. Possibly the EFC cannot handle other relatively small power demands onboard, which can be solved with a battery and 'peak shaving' control system.

Organic Rankin Cycle

The working principle and calculation sheets (see appendix D.3 and appendix D.3) give insight about how to quantify the measure. The operational data was not sufficient to match the ORC system with the vessels, because relevant flow rates, temperatures and running hour were not available in the data. Nevertheless, an educated guess is made.
The ORC systems are only operation for 'steady state' situations of the power plant, which is during freerunning and towing. For the current situation, the average baseload is assumed to be 350 kW for 5000 running hours per year, for 0,115 €/kWh (MGO price at 200 g/kWh). The WHR-OCR can theoretically deliver the electrical baseload and save €200.000 every year. The initial investment of €450.000-€750.000 and annual maintenance costs are €1.700. Together the estimated payback period will be between 2 to 4 years, according the simplified assumptions.
Operational data have to show the hours that the ORC system actual can deliver the required baseload, which is unknown for sailing at two allocated engines. The actual operational data of LTD is not convincing and the payback period can also by 6 years or even longer. Future research can find more accurate numbers for decision support.

Turbocharger upgrades

The upgrade of turbochargers costs €175.000 per turbocharger and assumed to save 1-3% of annual fuel consumption. The NPV calculation showed a required payback period of about 20 year per upgrade.

Propeller Polish and Hull cleaning

The annual hull cleaning can save between 1-5% and propellers polish 3-4% of the annual fuel consumption (IMO, 2018a). The estimates of 2% and 2,5% respectively are conservative, but are still cost-effective. These maintenance procedures are currently done every 2,5 to 5 year.

The prototype system did not quantify added resistance by fouling, but the BID did explain how this can be done and what data is required.

5.4.3 Classification

The primary objective of this research is to develop a DSS to improve energy efficiency cost-effectively. The data-driven DSS perspective can theoretically include all measures, (i) which can financially be quantified or not. If the DSS is capable to quantify, (ii) the measure may have a short or long pay-back period. These two parameters together form the four classes of energy efficiency measures catagorisch (see fig. 5.32). This classification matrix gives a generic overview about the seriously considered measures by this research, their payback periods and 'Data Readiness'. This matrix does not represent a static environment and parameters can significantly change overtime, due fuel price fluctuations, technology prices and for example future carbon prices.
The term 'Data Readiness' is introduced to softly quantify if the DSS is capable of quantification of the payback periods. The Data Readiness is expressed in required years for the data collection and DSS development to support these decisions about investment. The Data Readiness of one year is chosen because of the equal case study duration, to divide the 'quick wins' and 'long term wins'. The Data Readiness is related to the measure complexity and the available data (quality) onshore.
The payback period is the financial parameter of the classification matrix and divides the quick and long term wins by the duration of four year. This duration can be doubted, but is assumed for this case study to illustrate the overview.

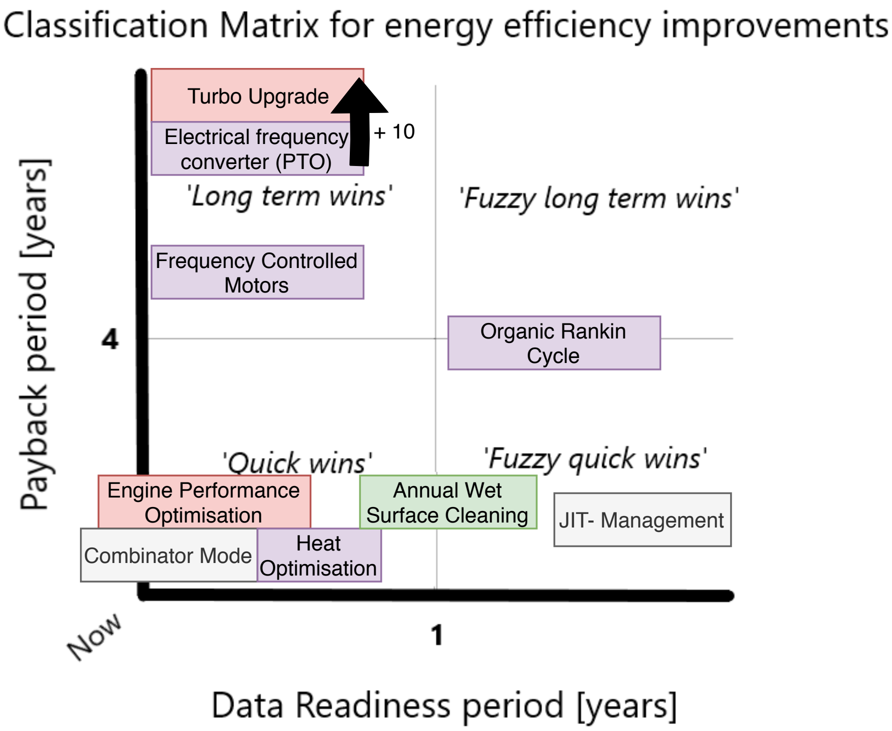


Figure 5.32: Measure Classification matrix (own composition)

The Classification matrix concept is applied for the case study in a simplistic manner, but classification is a branch of machine leaning. If Boskalis collects the relevant data of all vessels, all the measures can be classified for all vessels. The measures can be dots, seized by their NPV-value, so a roadmap the further cost-effective improvement of energy efficiency.

This same calcification matrix is used for SEEMP workshops at Boskalis. Most 'quick wins' were related to human behaviour and awareness. The implementation of a DSS in combination with awareness trainings (Delft) is not explicitly mention in fig. 5.32, but the most effective measure.

5.5 Conclusions of Case Study

This case study for development of a data-driven DSS was the first initiative development for data-driven decision making about energy efficiency at Long Distance Towage business unit. No previous related studies or ICT systems were internally available from previous work. The prototype system is built from 'scratch' with historical low quality data. The LTD organisation has no awareness about fuel efficiency or data quality and did not improve during this case study research.

The LTD organisation can cost-effectively increase their competitiveness on the wet transport markets by improvement of their fuel efficiency, which is about 60-70% of the total OPEX. The older vessel designs cannot compete the capabilities of the newer LTD vessel designs of ALP, but can be more price competitive then they are now. This price competitiveness is especially interesting for the offshore commodity market which has a 30% share of the total projects and is expect to increase to 45% by 2021. The capability market competition of the oil and gas installations will become more prices driven by 2020 due the sulphur capture, since more MGO vessels are expected to enter this LTD market.
The proposed dimensionless shipping performance indicator for energy efficiency can be used to quantify, monitor and control by Boskalis and authorities. The key performance indicators do enable the middle management to monitor their benchmarks and target of operational fuel efficiency.
The business process modelling notation showed the complexity of the fuel consuming business process, with many decision makers involved and no available database with relevant data. The developed prototype is implemented within the new process design and illustrated the applicability for the data-driven decision making.

The LTD organisation did not previously quantify their fuel consumption and efficiencies in relation to their systems or activities. The developed prototype proved that onshore control of fuel efficiencies is possible, to enable data-driven decision making for optimisation.
The combinator mode was tested and quantified for the free-running mode optimisation decisions. The prototype can define the combinator curve to support the decision of sail combinator mode.
The engine performance optimisation tool found the days after overhaul on the Wartsila specifications and is capable of real-time engine performance monitoring, if real-time data becomes available. The engine controller data is unreliable, since data was missing and inaccurate. Both improved the engine allocation and maintenance procedures can be monitored by this engine performance optimisation prototype in practise. The turbocharger underperformance are specified and monitored by the prototype, but the data quality did not allow to find the quantitative relation with the SFOC.
The hotel and auxiliary performance optimisation quantified the heat and electrical performance and supported optimisation opportunities.

The use of the combinator mode, the engine performance optimisation, heat optimisation, frequency controlled electric motors and annual hull and propeller cleaning save at least 20% of the annual fuel consumption and carbon emissions. The NPV of this package over 10 years is €2,4 million. The 20% is conservative, but theoretical complies the LTD vessel with IMO GHG strategy till 2025. The fuel mixture of 80% HFO and 20% MGO is likely change to 100% MGO or higher priced low sulphur HFO from 2020, which will increase the NPV and this measure package. The LTD organisation is recommended to take action and prepare for the future before 2020.
The Organic Rankin Cycle based wast heat recovery systems can be cost-effective, but convincing operational data is not available. This technology is not a proven concept yet, but the investment can be a payback period of 2 to 6 years.

5.6 Future work

This Data-driven DSS prototype development case study was limited by time and can be further developed in the future. This section highlight some possibly interesting future work. The following suggestions are purely related the DSS system and not to improvement of operations or design.
The time series indexes of both the PMS and the noon report can be matched in the future, to related and integrated these data source to each other. Moreover, the winch data and engine related data cannot by joined without large quality losses, again this is result of unmatchable time series indexes. If these data are integrated, different parameters can be connected within, for example a Artificial Neural Network that related turbocharger and weather to the engine performance.

The both data acquisition systems can be improved for higher data quality and more rapid evolution of the prototype. The noon reports require a protected format with all relevant information, which can automatically be processed within the onshore database. The PMS system can sent daily or real-time data to the onshore database, instead of days delayed. The improved timeliness will enable 'real time' decision support at the fleet management department.

The degreased performance over time can be visualized by a corrected value of decrease to determine optimal maintenance intervals. For example, the increased hull resistance corrected for weather effect or increases SFOC corrected for environment and power output.

The relation of propulsion efficiency, rudders and propeller speed, pitch and the advanced water inlet speed can be quantified for free-running and towing modes. The combinator mode and rudder angle optimisation seem interesting to improve fuel efficiency beyond already quantified optimisations.

The statistics and operation data can be used in combination with physics based simulation modelling, which is called 'a digital twin'. The theoretical optimums can be determined and large design conversion be quantified. The digital twin supports decisions for new build projects, conversion or retrofits.

Chapter 6

Conclusions

The data-driven decision support system, developed during this research, gives a competitive advantage by the cost-effective improvement of the fleet's energy efficiency and by the controlled compliance with the IMO green house gas reduction strategy. The conceptual Business Intelligence Design provides the foundation for data-driven decision support about energy efficiency for the entire Offshore Energy fleet.

Boskalis Long Distance Towage can cost-effectively improve their energy efficiency by 40% toward 2030 with respect to 2008 and thereby fully comply with the IMO green house gas reduction strategy. The suggested measures can improve the energy efficiency between 20% and 30%, the actual improvement have to be measured by the developed data-driven decision support system. Additional measures can cost-effectively improve the remained required energy efficiency improvements in the future. The formulated Shipping Performance Indicator can monitor the energy efficiency improvements over time by one dimensionless number. The conclusions of this whole development study are summarized and thereafter each point is explained in a separate paragraph.

- The developed system provides a competitive advantage by cost-effective reduction of fuel consumption;
- The system gives insight and organisational control of fuel performance by quantitative benchmarks and targets about energy efficiency, which supports compliance with future law and regulations about energy efficiency and green house gas emissions;
- The developed work vessel energy performance control model is required to derive insights from the vessel data;
- The low data quality and the not available information infrastructure are the major constraints for development and prototyping of the data-driven decision support systems at the Boskalis Offshore Energy Division;
- The Long Distance Towage prototype gives useful insights for energy performance optimisation of engines, turbochargers, hotel and auxiliary systems, free-running and towing;
- The Long Distance Towage case study showed a realistic cost-effective reduction of annual fuel consumption by at least 20%.

The cost-effective improved energy efficiency has the financial benefits of lower costs and less fuel stock or less bunker transfers required. The improved energy efficiency creates additional advantage, when Boskalis will switch to higher priced low sulphur fuels or renewable energy sources like bio-fuels. Being more cost-effective enables Boskalis to offer sharper prices to clients or create additional profit. The competitive advantage by fuel efficiency is larger at the more elastic price-driven offshore commodity markets, compared to the inelastic availability offshore markets.

The Corporate Social Responsibility department collects the best available fuel consumption and carbon emission data with a ±10% inaccuracy per quarter of a year. Moreover, this data has no significant relations to operational activities or technical systems and therefore provides no performance insights. The developed Business Intelligence Design and prototype both do give insights and organisational control about energy efficiency by Shipping Performance Indicators, Key Performance Indicators and Performance Indicators, which are mathematically related. This organisation control supports compliance with future law and legislation with the IMO greenhouse gas reduction strategy.
The developed energy performance control model for work vessel give a graphical overview of what operational data to collected and how to relate this data for insights. The currently available unstructured operational vessel consumption data gives no insights for decision making. The structured data related to the operational modes, operation and design profiles and the equipment do give insights.

The currently available data quality is insufficient for advanced energy efficiency analysis and algorithms. The data is inaccurate, because the data is incomplete and inconsistent, contains non-unique identities, lacks validity rules and has both an inconsistent and delay timeliness. The information infrastructure can not provide real-time or a daily data flows, which is a constraint for decision support prototyping at operational, tactical and strategic level of the organisation.

The prototype system of the case study is a preliminary design made after the conceptual Business Intelligence Design. The engine performance optimisation tool had the focus and gives insight and performance control about Specific Fuel Oil Consumption. The energy performance decrease is quantifiable after overhaul and the energy efficiency of different engine allocations. The related turbochargers performance were off-design and have a negative effects on combustion quality. Engine performance optimisation can at least save 3-6% of annual fuel consumption.
The developed hotel and auxiliary system optimisation tool gives insight to improve energy efficiency by better matching of auxiliary engines with the baseload. These insight are useful for optimal use of the combinator mode, which was quantified by the system for free-running.

The suggested optimisation package for Boskalis Long Distance Towage can cost-effectively save at least 20% of the annual fuel consumption, with an investment payback period below one year and a combined 10 year Net Present Value of €2.5 million. This package focused for sailing long distances at combinator mode, with a onboard tool for engine and auxiliary system optimisation, together with annual cleaning of hull and polishing of propellers. The 20% saving is an absolute saving for equal productivity and is a conservative prediction. The actual savings in the future can be monitored by the developed data-driven decision support system.
The waste heat recovery with the Organic Rankin Cycle was not convincingly quantifiable with the currently available data, but has an expected payback period between 2 to 6 years and the potential of 6-9% cost-effective improvement of fuel efficiency. The financial benefits of this measure will increase by fully switching to MGO from 2020.

Chapter 7

Recommendations

The research conclusions are translated to recommanded actions for Boskalis Offshore Energy. The interrelated bullet points below are related to their previously stated conclusion bullet points. The bullet point below are explained per paragraph of this section.

- Implement a data-driven decision support system for cost-effective reduction of fuel consumption, competitive advantage and compliance with the IMO greenhouse gas reduction strategy;
- Define and communicate actual energy efficiency performances, benchmarks and targets for the organisation and their corresponding fleet catagorisch to support compliance with the IMO greenhouse gas reduction strategy;
- Use and improve the developed work vessel and organisational energy performance model for all present vessel catagorisch of Boskalis Offshore Energy to create insights about energy efficiency;
- Implement an improved data acquisition system and a real-time information flow for required data quality;
- Implement and further improve the developed monitoring system for all the vessel of Boskalis Offshore Energy;
- Create awareness about energy efficiency within the Boskalis Offshore Energy organisation.

The implemented system for energy efficiency will create a competitive advantage for Boskalis Offshore Energy. Find the most cost-effective improvements of every vessel. The system can be realized as extension of Boskalis.world or by third-parties like We4Sea. Consider to build an API for Anglo-eastern and Boskalis.world. Other large shipping companies, like Maersk, Wallenius and Stena line already made this decision and preferred the in-house development.

Define the energy performance understandable for the project oriented organisation to improve productivity, cooperation and creativity of both individuals and departments. Mitigate the risk of no performance monitoring and control if the IMO regulation demands it.

Develop and monitor Shipping Performance Indicators and Key Performance Indicators for all the eight vessel catagorisch of Boskalis energy to monitor overall improvement. Use and further develop the energy performance control models for more business intelligence. Enrich the noon report data and the performance monitoring systems data with the required data, according to the Business Intelligence Design within this thesis. Find opportunities of physics-based simulation models or Artificial Neural Networks that can be built or validated with this data.

The data quality have to be improved for required insights of the energy efficiency. The time series data have to be 100% complete, 100% consistent, contain 100% unique identities and only valid entries. The timeliness of performance monitoring systems and reports need to be consistent for integration of these data sources and to create additional additional added-value. This level of data quality requires a new data acquisition system at Boskalis Offshore Energy. This system is recommended to be structured by standardized general modules and fleet category specific modules. Establish an information flow from vessels to the onshore databases and dashboards with at least a daily update.

The developed monitoring system can be further improved by more focus for effects over time and the maintenance interval optimisations. The engine performance optimisation tool has the potential to improve energy efficiency and can be implemented at every vessel with diesel engines.
Boskalis Long Distance Towage is recommended to use the data-driven system to quantify effects of combinator mode for reduced towing and reprogramming of the Controllable Pitch Propeller controls and rudder angles elimination for long distance towing.

Start to create and train energy efficiency awareness onboard and onshore. This research found many way to cost-effectively improve energy efficiency and the incentive of the IMO strategy about Greenhouse gas reductions. Most employees within the operational and tactical management layers were not aware or convinced by the benefits of energy efficiency or the societal responsibility of Boskalis.
The developed Data-driven Decision Support System is an useful tool, but the wiliness of the organisation to improve energy efficiency and cut carbon emissions is a prerequisite for being effective.

Bibliography

M.Duta form university of Oxford 14 authors, including: M.P Henry. Two-phase flow metering using a large coriolis mass flow meter applied to ship fuel bunkering. *Measurement and Control -London- Institute of Measurement and Control- · September 2008*, page 20, 2008.

Francesco Baldi Andrea Coraddu, Luca Oneto and Davide Anguita. Vessels fuel consumption: A data analytics perspective to sustainability. *Studies in Fuzziness and Soft Computing*, 2018.

Victor N. Armstrong. Vessels optimisation for low carbon shipping. *Ocean engineering*, pages 195–207, 2013.

D. Arnott and G. Pervan. A critical analysis of decision support systems research. *J Inf Technol*, 20:67–67, 2005.

Francesco Baldi. Improving ship energy efficiency through a systems perspective. *CHALMERS UNIVERSITY OF TECHNOLOGY*, 2013.

Francesco Baldi. Optimal load allocation of complex ship power plants. *Energy Conversion management*, 2016.

Christopher Bishop. *Pattern Recognition and Machine Learning*. Springer, ISBN 978-0-387-31073-2, 2006.

Boskalis. Corporate social responsibility report. 2017.

Claudiu Brandas. Decision support systems development: a methodological approach. *Journal of Applied Business Information Systems*, 2(4), 2011.

R.G Hekkenberg C. Kooij, M. Loonstijn and K. Visser. Towards autonomous shipping: Operational challenges of unmanned short sea cargo vessels. 2018.

Damian Carrington. Hitting toughest climate target will save world 30tn in damages, analysis shows, 2018. URL `https://www.theguardian.com/environment/2018/may/23/hitting-toughest-climate-target-will-save-world-30tn-in-damages-analysis-shows`.

A.B. Whinston C.W. Holsapple. Decision support systems: A knowledge-based approach. *St Paul*, 1996.

CE Delft. The fuel efficiency of maritime transport - potential for improvement and analysis of barriers.

O.Turan A.I.Ölçer E. Bal Beşikçi, O. Arslan. An artificial neural network based decision support system for energy efficient ship operations. *computers and operational research*, 66(9):393–401, 2015.

D. Delen D. King E. Turban, R. Sharda. Business intelligence. 2nd Edition, 2010.

E.A. Bouman et al. State-of-the-art technology, measures and potential for reducing ghg emissions from shipping: A review of 150 studies. 2018.

C.W. Holsapple (editors) F. Burstein. *handbook on decision support systems 1*. Springer, USA, 2008.

Easton. John Fu. Qian. Understanding data quality: Ensuring data quality by design in the rail industry. *Cambridge University*, pages 3792–3799, 2017.

Jasper Grevink. Lecture of mt44005 marine propulsion systems, 2018.

J.J. Corbett Ø. Endresen V. Eyring J. Faber S. Hanayama D.S. Lee D. Lee A.Z. Markowska A. Mjelde D. Nelissen J. Nilsen C. Pålsson J.J. Winebrake W. Wu K. Yoshida H. Lindstad, Ø. Buhaug. Second imo ghg study 2009. 2009.

Douwe Stapersma Hans Klein Woud. *Design of propulsion and electric power generation systems.* IMarEST, 80 Coleman street, London, 2002.

Stein Ove Erikstad Henrique M. Gasper. Extending the energy efficiency design index to handle non-transport vessels. 2009.

IEA. *World Energy Outlook 2018.* International Energy Agency, Paris, 2018.

IMO. Energy efficiency technologies information portal, 2018a. URL `https://glomeep.imo.org/resources/energy-efficiency-techologies-information-portal/`.

IMO. *MARPOL.* 2018b.

The IMO. Third imo greenhouse gas study. 2014.

Michael E. Raynor Mark Cotteleer Jonathan Holdowsky, Monika Mahto. *Inside the Internet of Things.* Deliotte University press, UK, 2015.

Jerzy Listewnik. Possibilities of reliable and safe main engine load evaluation on board ship. *Institute of Ship Propulsion Operation*, 1999.

MultiMedia LLC. Onze waterbouwers vissen achter het net in afrika: Chinees totaalpakket is onweerstaanbaar, 2018. URL `http://www.maritiemnederland.com/achtergrond/nederlandse-waterbouwers-vissen-achter-het-net-in-afrika/item3025`.

Richard Bucknallc Lucy Aldous, Tristan Smithb. Noon report data uncertainty. *Low Carbon Shipping Conference*, 2013.

Paul Luttikhuis. Oliemarkt krijgt grote problemenFatih Birol, hoofd IEA Energieagentschap IEA is somber over klimaat én energiesector. „Een energiecrisis leidt niet tot minder uitstoot van broeikasgassen, 2018. URL `https://www.nrc.nl/nieuws/2018/11/16/oliemarkt-krijgt-grote-problemen`.

Data management association. The six primary dimensions for data quality assessment - defining data quality dimensions. 2013.

M. P. Reddy R. Y. Wang and H. B. Kon. Toward quality data: an attribute-based approach," decision support systems - special issue on information technologies and systems. *MIT*, 13:349–372, 1995.

Cathe Oneil Rachek Schutt. *Doing Data Science: straight talk from the frontline.* O Reilly Media Inc, 1005 Gravenstein Highway North Sebastopol CA, 2014.

R.R. Negenborn R.D. Geertsma, K. Visser. Adaptive pitch control for ships with diesel mechanical and hybrid-propulsion. *Aplied elsevier*, 2018.

The research council of Norway. *The Shipping KPI System V2.2.* 2013.

Eagle Rich, 2019. URL `https://www.eagleridgegm.com/what-is-a-turbocharger-and-how-does-it-work/`.

Scikit-learn. Choosing the right estimator, 2018. URL `https://scikit-learn.org/stable/tutorial/machine_learning_map/index.html`.

the authority on seafood Seafish. Fact sheet: Fuel flow meters – individual and turnkey. *Research & Development*, 2009.

IMO-GloMEEP GIA Global Industry Alliance to Support Low Carbon Shipping. White paper on the "validation of the performance of energy efficiency technologies for ships". 2018.

Seb van den Berg. A decision support tool for implementation of co2 reducing measures. master thesis, TU Delft, 2018.

Klaas van Dokkum. *Ship knwowledge*. DOKMAR, Maritiem publisher, Enkhuizen, The Netherlands, 2011.

Marcel van Gerven and Sander Bohte. Artificial neural networks as model of neural infromation processing. 2017.

C.W.W. van Lohuizen. Knowledge management and policymaking. *Knowledge: Creation, Diffusion, Utilization*, 8(1), 1986.

Charlotte Banks Victor N. Armstrong. Integrated approach to vessel energy efficiency. *Ocean engineering*, 2015.

H.T. Grimmelius W. Shi and D. Stapersma. Analysis of ship propulsion system behaviour and the impact of fuel consumption. *International Shipbuilding Progress 57 (2010) 35–64*, 2010.

Keith Wallis. Boskalis makes eur397 million special charge as it exits low-end heavy transport market, 2018. URL https://fairplay.ihs.com/dredging/article/4305446/boskalis-makes-eur397-million-special-charge-as-it-exits-low-end-heavy-transport.

Warkwick. *Product Excellence using Six SigmaSection 6 Quality Function Deployment*. 2007.

Tore Longva Øyvind Endresen, Magnus S. Eide. Maritime forecast to 2050: Energy transition outlook 2018. 2018.

Appendix A

Design Information of Long Distance Towage Fleet

A.1 Main Particulars

Main Particulars

PRINCIPAL DIMENSION		
TYPE OF SHIP	TOWING / SALVAGE TUG	
MATERIAL OF SHIP	STEEL	
LENGTH (oa)	75.05	m
LENGTH (pp)	66.60	m
BREADTH (mld)	18.00	m
DEPTH (mld)	8.00	m
DESIGNED LOAD DRAFT(mld)	6.00	m
GROSS TONNAGE	3239	ton
SHAPE OF STERN	CRUISER	
DEPTH OF KEEL	0.016	m
SPEED TRIAL MAX.	16.65	kt

MAIN ENGINE	
TYPE × NUMBER	4-CYCLE DIESEL ENGINE × 4
MODEL (ENGINE NUMBER)	6L32 No1:PAAE025698
	No2:PAAE025699
	No3:PAAE025697
	No4:PAAE025696
MAX. CONT. OUTPUT.	3,000 kW × 750/155 min^{-1}
NO. OF CYL. × DIA. × STROKE	6 × ϕ320mm × S400mm
MAKER	WARTSILA

REDUCTION GEAR	
MODEL × NUMBER	TCH250-S53 × 2
REDUCTION RATIO	1 : 4.84
MAKER	WARTSILA

PROPELLER	
TYPE × NO. OF PROPELLER	CONTROLLABLE PITCH TYPE × 1
DIAMETER	3850 mm
E.A.R. × NO. OF BLADE	0.625 × 4
RAKE OF BLADE	-
DIRECTION OF ROTATION	Outward
MATERIAL	NiAl bronze
MAKER	WARTSILA

GRADE OF OIL

[Fuel oil]

Fuel oil : HFO 158 Cst @ 50°C

Density : 0.9684 @ (15°C) g/cm^3

Net Heating Value : 40650 J/g

[Lubricating oil]

TEXACO TARO 40XL40

TRIAL CONDITION		
KIND OF TRIAL	OFFICIAL SEA TRIAL	
DATE	July 13, 14 2006	
DAYS AFTER LEAVING DOCK	106 days	
PLACE	Off Niigata	Off Sado Island
DEPTH OF SEA	50~100m	60~120m
WEATHER	CLOUDY	CLOUDY
WIND DIREDTION	NW	W
WIND VELOCITY	ab. 6m/s	ab. 5m/s
SEA CONDITION	CALM	Smooth
	July 13	July 14

DRAFT FORE	2.35	m
DRAFT AFT.	5.67	m
DRAFT MEAN	4.01	m
DRAFT TRIM	3.32	m
DISPLACEMENT	3602.2	t
Cb	0.720	
Cp	0.724	
Cw	0.890	
Cm	0.994	
WETTED SURFACE (incl.APP.)	1444.9	m^2
UNDERWATER LATERAL AREA	251.4	m^2
IMMERSION OF PROPELLER TIP	1.19	m
IMMERSION OF RUDDER TOP	1.15	m
K G	6.27	m
G_0M	3.09	m
G M	3.22	m

DETAILS OF DEADWEIGHT

[Fuel oil]	
No.3 H.F.O.T. (P&S)	99.8 t
No.5 H.F.O.T. (P&S)	253.8 t
No.6 H.F.O.T. (P&S)	67.1 t
H.F.O. DAY TK (P&S)	23.9 t
No.1 M.D.O.T. (P&S)	93.8 t
No.2 M.D.O.T. (P&S)	9.7 t
M.D.O. DAY T. (P&S)	11.0 t
TOTAL	559.1 t
[Fresh water]	
F.W.T. (P)	39.6 t
No.2 W.B.T. (P&S)	69.2 t
TOTAL	108.8 t
[Lub. Oil etc.]	
L.O.S.T. (No.1 ~ No.4)	20.5 t

Figure A.1: Main particulars from Shipyard: Niigita

CONSTRUCTION/CLASSIFICATION	
Flag/Port of Registry	The Netherlands / Rotterdam
Builder	Niigata Shipbuilding, Japan
Building year	2005 - 2007
Classification	LRS +100 A1 Tug, FiFi-1 with Water spray, SCM + LMC

MAIN DATA	
Length overall	75.05 m
Length B.P.	66.60 m
Breadth overall	18.00 m
Depth (moulded)	8.00 m
Min/Max. draught	4.08 / 6.8 m
GT/NT	3,239 t/ 971 t
Max. speed	15 knots

FIFI I & OIL-POLLUTION CONTROL

- 2 dual foam/water monitors, capacity each 1200 m³/hour, remote controlled
- Oil dispersant system

MAIN COMMUNICATION/NAVIGATION EQUIPMENT

- INMARSAT C
- INMARSAT F
- GMDSS area 3, MF/HF Radio
- NPT

MAIN ENGINES	
Make/type	4 x Wärtsilä / 6L32
BHP/KW	4 x 4,080 Bhp / 3,000 KW @ 750 RPM
Propeller	2 x CPP, dia. 3,85 m in nozzles
Bollard pull	approx. cont. 200 t, max. 205 t
Bow thruster	12.5 t / 825 kW
Stern thruster	10.5 t / 736 kW

CAPACITIES	
HFO 180 cst	2,201 m³/2113 t *SECA areas:* 1,994 m³/1,914 t
MGO	539 m³/469 t *SECA areas:* 746 m³/649 t
Potable water	216 m³
Foam tank	11 m³
Dispersant tank	11 m³
Deck area	384 m²

ACCOMMODATION	
Total Bunks	36
Officers and ratings	12 (6x1 + 3x2)
Project crew	24 (6x4)

Figure A.2: Main particulars from sales department

A.2 Deck Arrangement

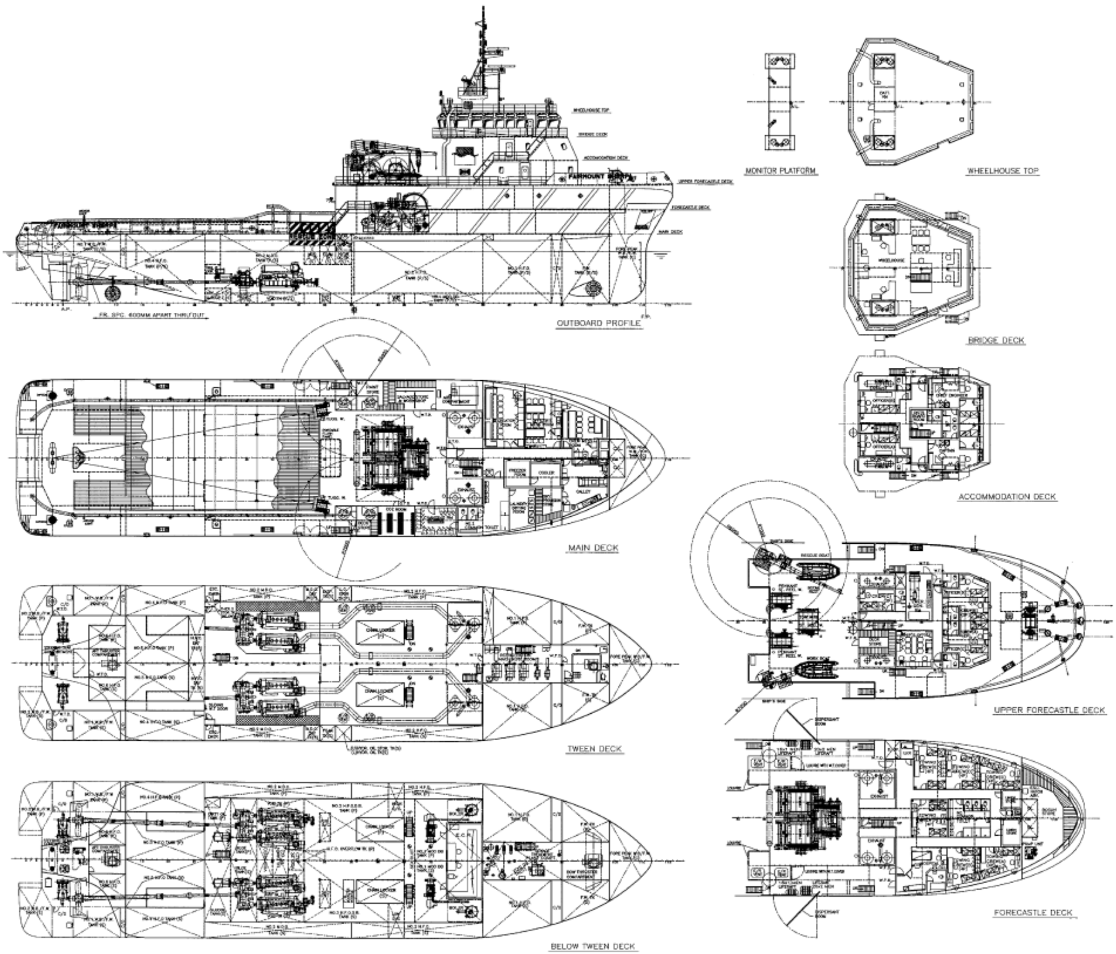


Figure A.3: Power system of Fairmount vessel

A.3 Power Plant Outline

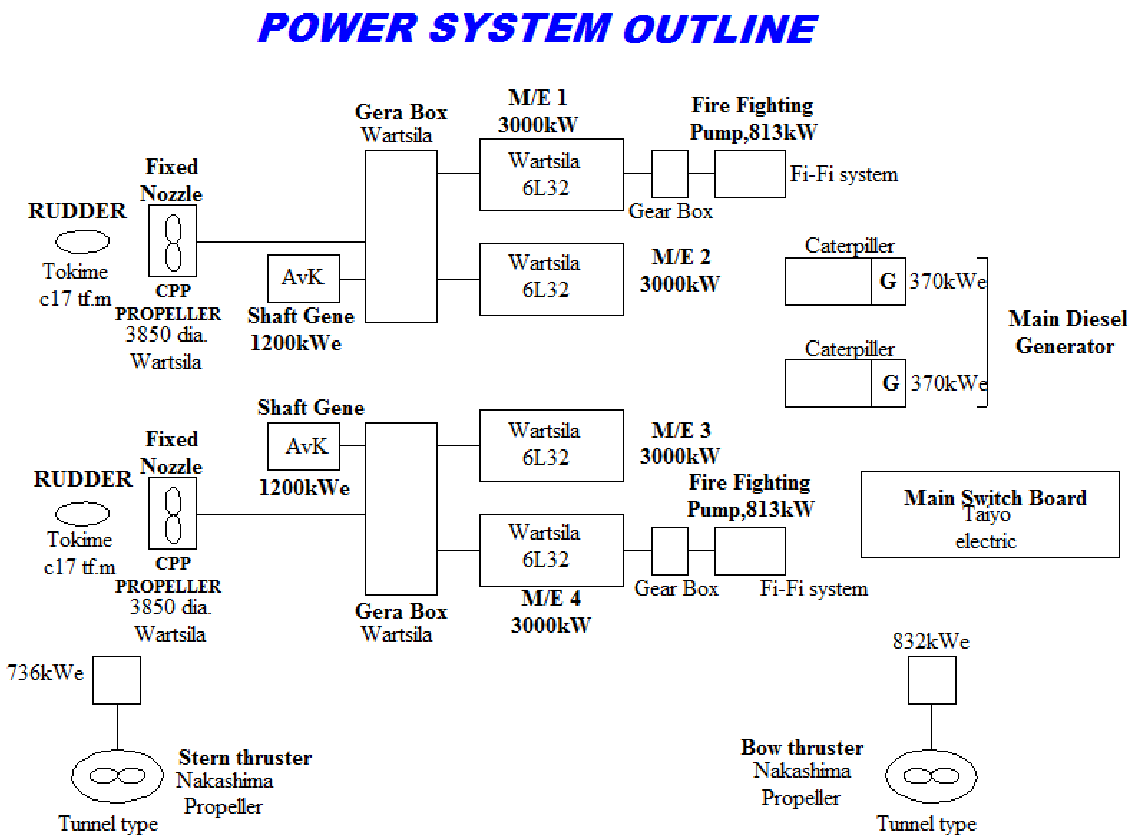


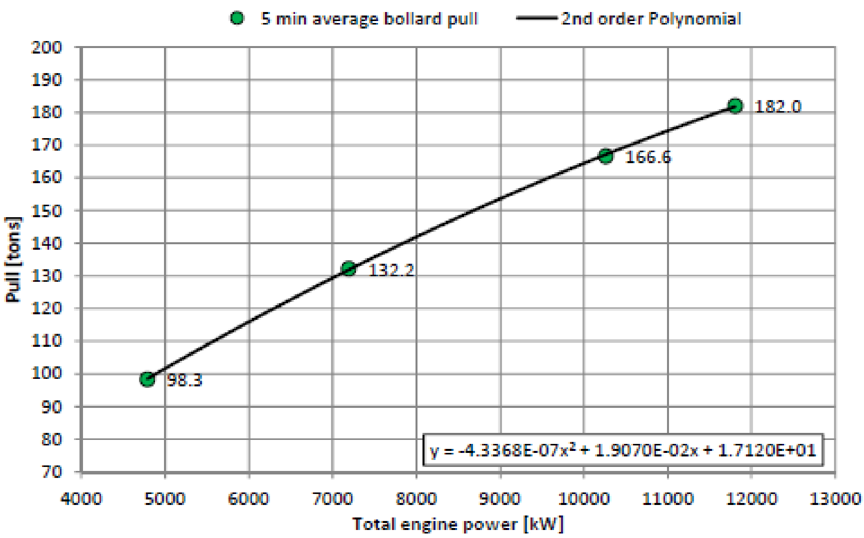
Figure A.4: Power system of Fairmount vessel

A.4 Bollard pull trail results of MARIN

31659-1-TM Boka Alpine Bollard Pull Trial report International Standard For Bollard Pull Trials

Mean values over 5min period of highest bollard pull

	Parameter	Unit	Test 1	Test 2	Test 3	Test 4
	Load setpoint	[%]	100	85	60	40
	Test direction (over bow / stern)	[bow, stern]	Stern			
	Start time	[hh:mm]	13:56	14:28	14:59	15:20
	Line pull	[Tonne]	182.0	166.6	132.2	98.3
	Engines in operation	[-]	4	4	4	4
PS	Engine power at fly wheel [combined or engine 1 / engine 2]	[kW]	n/a	n/a	n/a	n/a
PS	Engine speed	[RPM]	750	750	750	750
SB	Engine power at fly wheel [combined or engine 1 / engine 2]	[kW]	n/a	n/a	n/a	n/a
SB	Engine speed	[RPM]	750	750	750	750
	Propeller shaft power (PS)	[kW]	5755	5123	3608	2444
	Propeller shaft power (SB)	[kW]	5814	4931	3439	2247
	Combined engine power (PS+SB)/($\eta_{gearbox}$)	[kW]	11805	10259	7191	4787
	Average engine speed	[RPM]	750	750	750	750
	Wind speed	[m/s]	4	3.5	4	4.5
	Wind direction (rel. to bow)	[deg]	-120	-130	-130	-130
	Current speed	[m/s]	-	-	-	-
	Current direction (rel. to bow)	[deg]	-	-	-	-
	Wave height	[m]	0.1	0.1	0.1	0.1



Page | 4

Figure A.5: Bollard pull trial result of Expedition 2019

Appendix B

Business Process Information of Long Distance Towage

B.1 Poster to Explain Business Process Modelling Notation 2.0

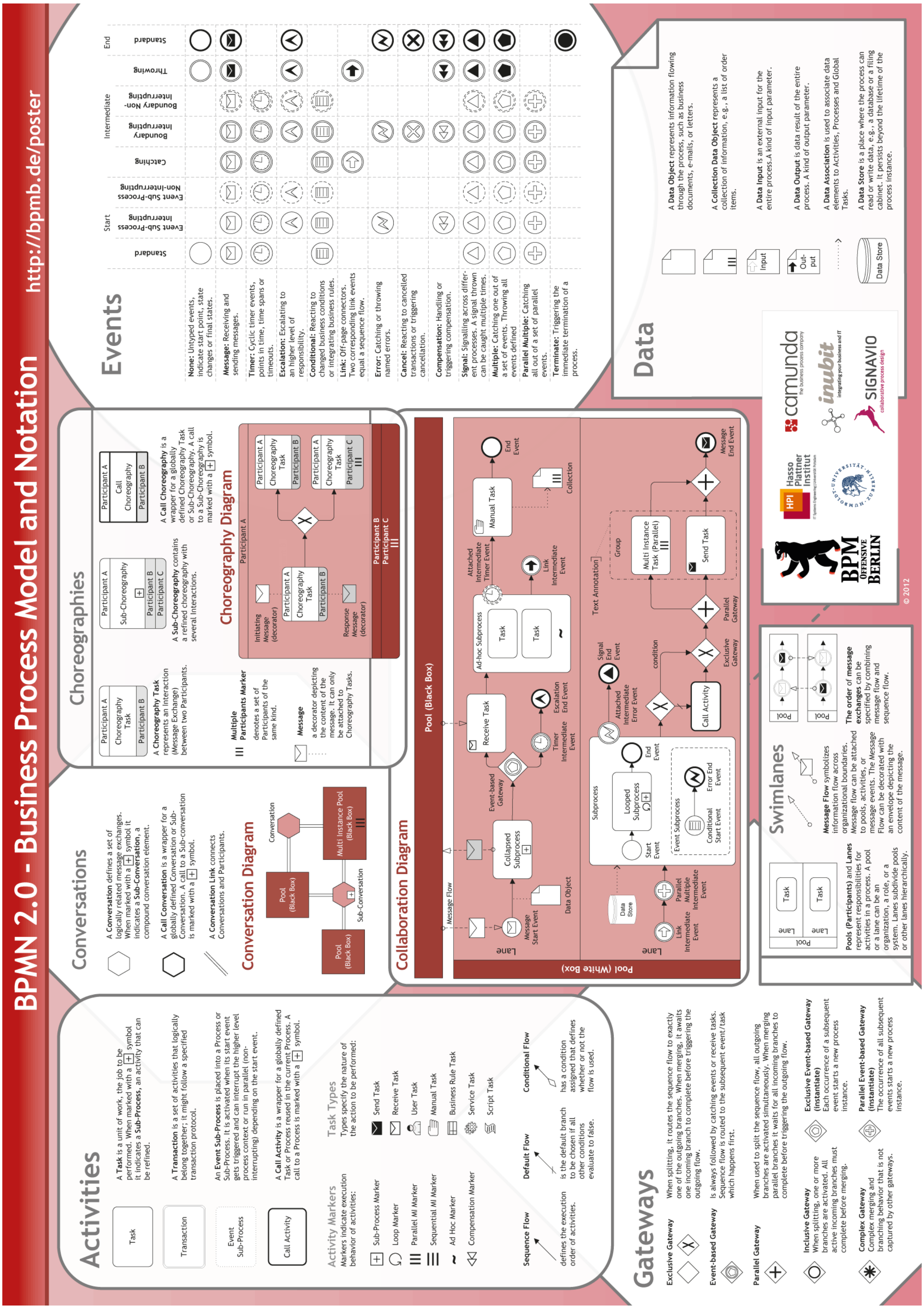


Figure B.1: BPMN 2.0 Poster

B.2 BIMCO Ocean Towage Agreement

BIMCO

TOWCON 2008

INTERNATIONAL OCEAN TOWAGE AGREEMENT (LUMP SUM) **PART I**

1. Date and place of Agreement	
2. Tugowner/place of business (Cl. 1)	3. Hirer/place of business (Cl. 1)
4. Tow (name and type)	5. Gross tonnage/displacement tonnage
6. Maximum length/maximum breadth & towing draught (fore and aft)	7. Flag and place of registry
8. Registered owners	9. Classification society
10. P. & I. liability insurers	11 General condition of tow
12. Particulars of cargo and/or ballast and/or other property on board the tow	
13. Tug (name and type)	14 Flag and place of registry
15. Gross tonnage	16. Classification Society
17. P. & I. liability insurers	
18. Certificated bollard pull (if any)	19. Indicated BHP
20. Estimated daily average bunker oil consumption in good weather and smooth water (a) at full towing power with tow (b) at full sea speed without tow	
21. Winches and main towing gear	
22. Nature of service(s) (Cl. 2)	23. Contemplated route (state restricted waters if any (Cl. 1, 7 and 24)
24. Place of Departure (Cl. 13)	25. Place of Destination (Cl. 14)

Figure B.2: BIMCO TOWCON 2008 for ocean towage

26. Free time at place of departure (Cl. 6(a))	27. Free time at place of destination (Cl. 6(a))
28. Free Time for transiting canals and Restricted Waters (Cl. 6(a))	
29. Notices (Place of Departure) (Cl. 13(c)) (a) Initial departure period (from/to) (b) Initial departure notice (days notice/days period) (c) Final departure period and notice (days notice/days period) (d) Final departure time and date notice (days notice) (e) Notices to be given to	30. Delay payment (Cl. 6, 7, 8(c), 17(b), 24(a), 27(f), 28 and 32(b)) (a) Port rate (b) Sea rate
	31. Riding crew to be provided by (also state number to be provided) (Cl. 15)
	32. If riding crew provided by Tug owner state amount per man per day payable by Hirer (Cl. 15)
33. Lump sum towage price (also state when each instalment due and payable) (Cl. 3) (a) Lump sum towage price (b) amount due and payable on signing Agreement (c) amount due and payable on sailing of tug & tow from place of departure (d) amount due and payable on passing of tug and tow off (e) amount due and payable on arrival of tug & tow at place of destination	34. Payment of lump sum & other amounts (state currency, mode of payment, place of payment and bank account) (Cl. 3)
35. Interest rate (%) per annum to run from (state number of days) after any sum is due (Cl. 11)	36. Security (state sum, by whom to be provided and when) (optional, only to be filled in if expressly agreed) (Cl.12, 23)
37. Current cost of tug's bunker oil (also state type of bunkers) (Cl. 4)	38. Cancelling date (Cl. 5)
39. Termination fee (Cl. 22)	40. Dispute resolution (Cl. 33) (state whether alternative (a), (b) or (c) of Clause 33 agreed); if (c) agreed, also state place of arbitration (if box not filled in, Cl.33(a) shall apply) (Cl.33)
41. Numbers of additional clauses, covering special provisions, if agreed	

It is mutually agreed between the party mentioned in Box 2 (hereinafter called "the Tugowner") and the party mentioned in Box 3 (hereinafter called "the Hirer") that the Tugowner shall, subject to the terms and conditions of this Agreement which consists of PART I including additional clauses, if any agreed and stated in Box 41, and PART II and Annex A, use his best endeavours to perform the towage or other service(s) as set out herein. In the event of a conflict of terms and conditions, the provisions of PART I and any additional clauses, if agreed, shall prevail over those of PART II and Annex A to the extent of such conflict but no further.

Figure B.3: BIMCO TOWCON 2008 for ocean towage

Appendix C

Provided Case Study Data

C.1 Provided Data by Boskalis

Daily Position Report (DPR) - Midnight

From: Fairmount Glacier

To: Fairmount Marine B.V.

Fairmount marine

Name Project:	Towing Rasbarge 1	Date (dd/mm/yyyy):	1-Apr-2018
		LT- UTC +/-Hrs:2400	UTC +8
		Project number:	
		Voyage number:	9
Port of Departure:	Batam, Indonesia	Port of Destination:	Qidong, China

	Towing Vessel	(Leading) Tug: Fairmount Glacier		(only when applicable) 2nd Tug or Tow info:
1	Latitude (xx°-xx',x N / S)	31 33.20 N	At anchor north of CJK no.1, 31 mls off Qidong Pstn.	
2	Longitude (xxx°-xx',x E / W)	122 46.30 E		
3	Run (24 hours xx) (NM)			
4	Course (xxx° True) (degrees)			
5	Present Speed (xx,x) (knots)			
6	Log Speed (xx,x) (knots)			
7	Speed 24 hrs (xx,x) (knots)			
8	Total running hours (hrs)			
9	Gen. Av. Speed(xx,x) (knots)			
10	Distance Covered (xxx,x) (NM)			
11	Distance to Go (xxx,x) (NM)			
12	ETA Destination (date)		Based on Gen. Av. Spd. [Local Time]	
13	First Port of Call (F.P.O.C.) (name)			
14	Distance to go F.P.O.C. (NM)			
15	ETA F.P.O.C. (date)			
16	Wind Direction/Windspeed (dir/knots)	SE / 17		
17	Sea Height (x,x) (meters)	1,0		
18	Swell Direction / Height (x,x) (dir/meters)	SE/2		
19	Hours at reduced speed (voyage)			
20	Distance at reduced speed (NM)			
21	Deviations during voyage (NM)			
22	Towing wire length (meters)	60,0		
23	Wire Tension Min/Max (metric tons)			
24	Tow-behaviour (Roll / Pitch) (degrees)			
25	Tow-behaviour (Towing PS/SB) (degrees)			
26	Persons on Board (crew/pax/tow)	12		
27	Consumption IFO 180 cst (xx,x) (MT)			
28	Consumption IFO 380 cst (xx,x) (MT)	12,2		
29	Consumption MGO (xx,x) high S (MT)			
30	Consumption MGO (xx,x) low S (MT)	1,0		
31	Consumption MELO (litres)			
32	Consumption AELO (litres)			
33	Remaining IFO 180 cst (xx,x) (MT)			
34	Remaining IFO 380 cst (xx,x) (MT)	1106,9		
35	Remaining MGO (xx,x) high S (MT)			
36	Remaining MGO (xx,x) low S (MT)	195,0		
37	Remaining MELO (litres)	22.453		
38	Remaining AELO (litres)	1487		
39	Remaining POTABLE WATER (m3-tons)	35		
	REMARKS	0000h-2400h Vessel at stb-bside of Rasbarge 1 maneuvering made to compensate the sear and swell.		

Figure C.1: Example of Daily Progress Report

Daily Technical Report (DTR) - Midnight

From: Fairmount Glacier

To:

Date (dd/mm/yyyy): 1-4-2018

LT= UTC +/- Hrs:

Name Project:

Project number:

Voyage number:

Port of Departure: Batam

Port of Destination: China

<only when applicable>

	Towing Vessel	(Leading) Tug: Fairmount Glacier				2nd Tug or Tow info:
27	Consumption IFO 180 cst (xx,x) (MT)					
28	Consumption IFO 380 cst (xx,x) (MT)	12,2				
29	Consumption MGO (xx,x) high S (MT)					
30	Consumption MGO (xx,x) low S (MT)	1,0				
31	Consumption MELO (litres)					
32	Consumption AELO (litres)					
33	Remaining IFO 180 cst (xx,x) (MT)					
34	Remaining IFO 380 cst (xx,x) (MT)	1106,9				
35	Remaining MGO (xx,x) high S (MT)					
36	Remaining MGO (xx,x) low S (MT)	195,0				
37	Remaining MELO (litres)	22.453				
38	Remaining AELO (litres)	1487				
39	Remaining POTABLE WATER (m3=tons)	95				
40	Bilge tank PS / SB (m3)	1,5		15		
41	Dirty Oil tank PS / Sludge tank SB (m3)	1,69		17,4		
42	Running hours Aux. Eng. PS					
43	Running hours Aux. Eng. SB					
44	Propellers RPM / Pitch (%) for PS # SB	156/7		156/1		
45	Shaft alternator PS # SB (kW)			330		
46	Engine RPM # 1 # 2 # 3 # 4 (rpm)	750		750		
47	Engine Load # 1 # 2 # 3 #4 (%)	22		39		
48	Engine Fuel rack #1#2#3#4 mm	18		24		
49	Engine Exh. temp High/Low #1#2#3#4 (°C)	381 / 349		403 / 388		
50	Engine Exh. before/aft T.C. #1#2#3#4 (°C)	438 / 359		457 / 353		
51	Eng. Charge Airpress./temp #1#2#3#4 (°C)	0,6 / 38		1,21 / 42		
52	Engine TurboCharger M.E. #1#2#3#4 (rpm	15490		19744		
53	Total CO2 output kg/kW/day					
	VORK DONE / MOVEMENTS / REMARKS					

Figure C.2: Example of Daily Technical Report

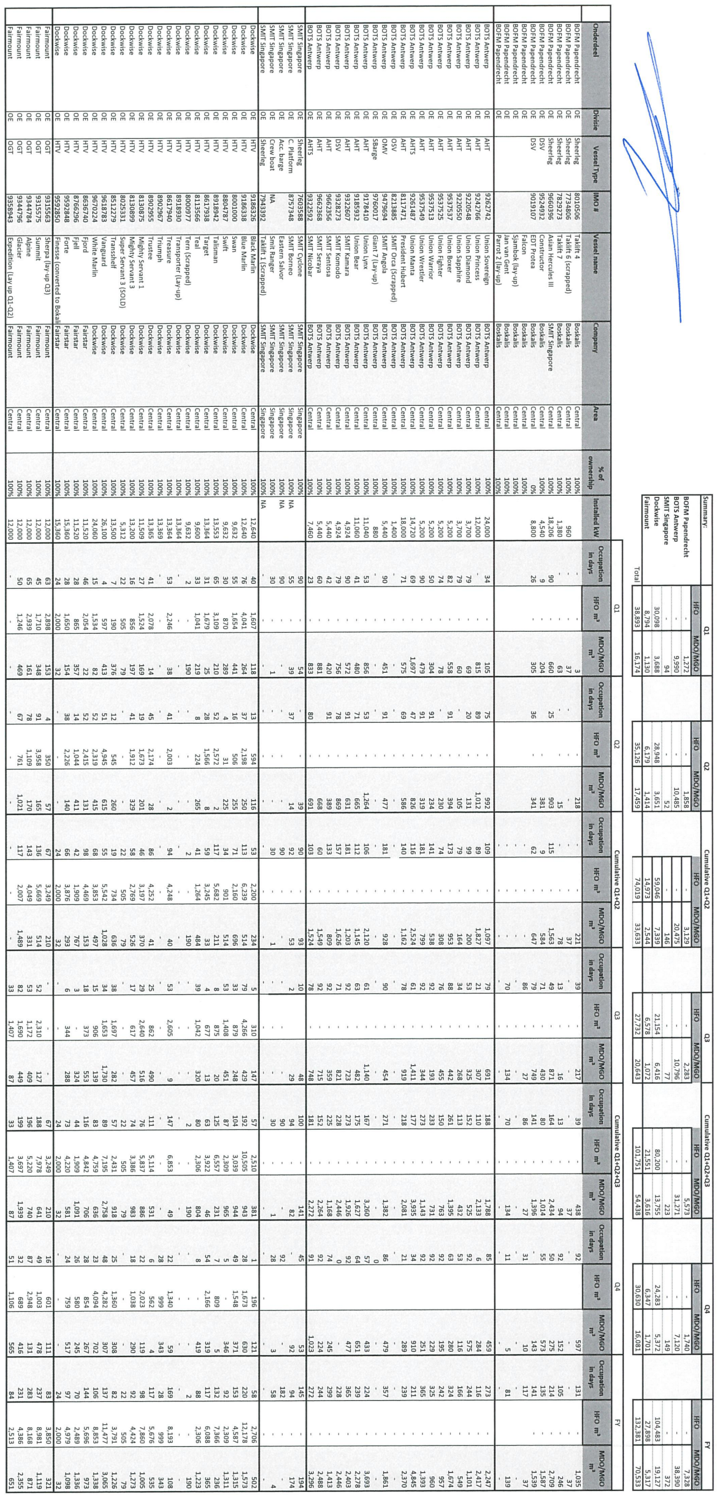
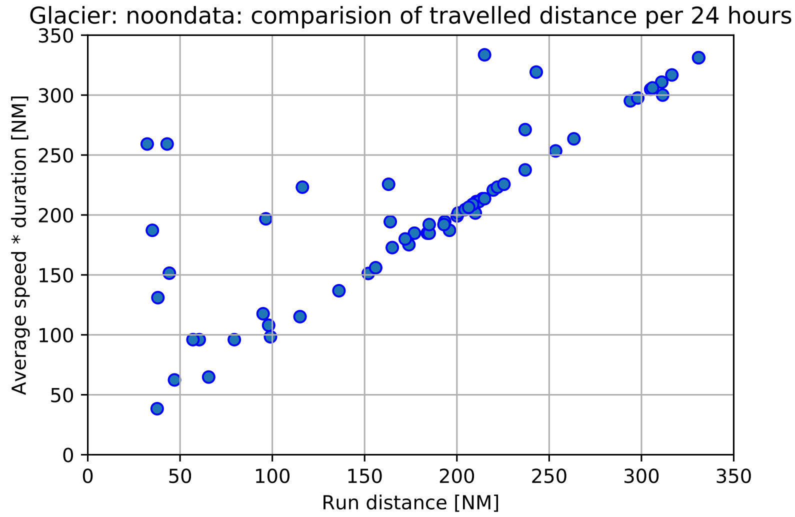
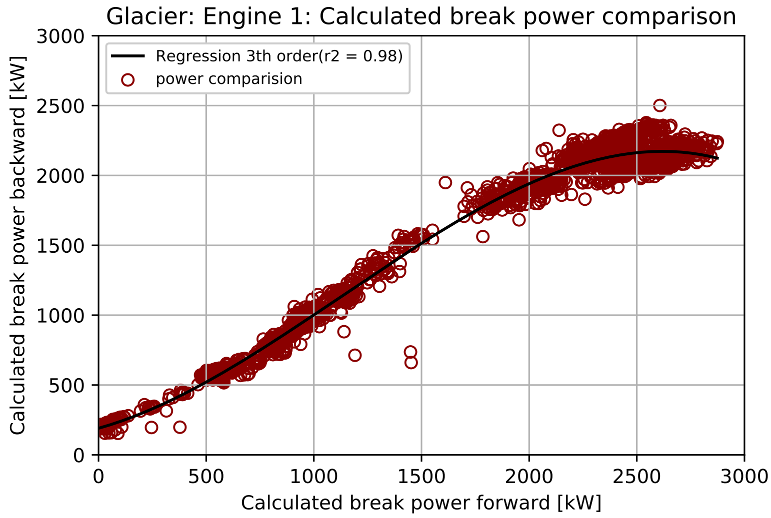


Figure C.3: Example of CSR data sheet

C.2 Visualisation of Data Quality



(a) Travel distance calculation accuracy check



(b) Break power calculation accuracy check

Figure C.4: Data accuracy checks of engine power and travelled distance over 24 hours

Appendix D

Energy Efficiency Improvement Measures

D.1 Long List of Energy Efficiency Improvement Measures

Table D.1: Long list of ideas

Design level			
Idea	Case study scope	Initial investment	Annual Energy Saving
Hull conversion	-	-	-
Propeller & rudder retrofit	-	-	-
WHR-ORC (per 100 kWe)	+	€ 150.000 - 200.000	2-9%
Exhaust to Thermal oil heat exchange	+	€ 4.000 - 6.000 per unit	1-2 %
HT-cooling to fresh water heat exchange	-	€ 1.000 - 2.000 per unit	-
To Hybrid conversion	-	> €250.000	3-42%
Power Management System application	-	€ 80.000 - 100.000	1- 35%
PTO to PTI conversion	-	€ 150.000	-
Variable-frequency drive PTO conversion	-	€ 50.000	-
Propulsion Improvement Device	+	€ 150.000	1-10%
Turbo retrofit	-	€ 600.000	-
Turbo upgrade	+	€ 150.000-200.000	1-3%
Cold ironing	-	-	-
CPP reprogramming (Adaptive)	+		1-15 %
Peak shaving	-	-	-
Solar panel	-	-	1-12%
Flettner Rotors	-	-	-
Kite	-	-	-
Weight of material reduction	-	-	1-21%
frequency controlled electric motors	+	€ 100-200 per kW installed	1%
Air lubrication	-	-	2-17%

Maintenance level			
Idea	Case study scope	Initial investment	Annual Energy Saving
Anti Fouling paint	-	€ 30.000 - 500.000	2-10%
Hull cleaning	+	€ 5.000 - 50.000	1-5%
Propeller polish	+	€ 4.000 - 6.000	3-4%
Engine maintenance optimisation	-	-	1-10%
Efficient auxiliary demand	+	-	1-2%
Efficient hotel demand	+	-	1-2%
Auto pilot upgrade	+	< € 1.000	0.25-1.5%
Purification optimisation	-	-	-

Operational level			
Idea	Case study scope	Initial investment	Annual Energy Saving
Engine & Turbo optimisation (manual)	+	€ 5.000-10.000	1-4%
Engine & Turbo optimisation (automatic)	-	€ 3.000-7.000 per cylinder	1-4%
Combinator mode	+	€ 0 present or € 5.000 to install	1-20%
Awareness Training (crew)	+		1-10%
Weather routing	-	-	-
Trim & draft optimisation	-	-	0-3%
Just-in-time (JIT) routing	+	-	1-50%
Spinning reserve optimisation	-	-	-
Ballast water reduction	-	€ 0	3-8%

D.2 Net Present Value Sheet of Case Study

Cash flow	€ -1.000	€ 103.688	€ 103.688	€ 103.688	€ 103.688	€ 103.688	€ 103.688	€ 103.688	€ 103.688	€ 103.688	€ 103.688
Cum(Cash flow)	€ -1.000	€ 102.688	€ 206.376	€ 310.065	€ 413.753	€ 517.441	€ 621.129	€ 724.818	€ 828.506	€ 932.194	€ 1.035.882
NPV	€ -909	€ 84.784	€ 162.686	€ 233.507	€ 297.889	€ 356.418	€ 409.627	€ 457.998	€ 501.972	€ 541.948	€ **578.290**
Cash flow	€ -10.000	€ 69.125	€ 69.125	€ 69.125	€ 69.125	€ 69.125	€ 69.125	€ 69.125	€ 69.125	€ 69.125	€ 69.125
Cum(Cash flow)	€ -10.000	€ 59.125	€ 128.251	€ 197.376	€ 266.502	€ 335.627	€ 404.753	€ 473.878	€ 543.004	€ 612.129	€ 681.255
NPV	€ -9.091	€ 48.038	€ 99.973	€ 147.186	€ 190.108	€ 229.127	€ 264.600	€ 296.847	€ 326.163	€ 352.814	€ **377.042**
Cash flow	€ -24.000	€ 179.438	€ 179.438	€ 179.438	€ 179.438	€ 179.438	€ 179.438	€ 179.438	€ 179.438	€ 179.438	€ 179.438
Cum(Cash flow)	€ -24.000	€ 155.438	€ 334.875	€ 514.313	€ 693.750	€ 873.188	€ 1.052.625	€ 1.232.063	€ 1.411.500	€ 1.590.938	€ 1.770.375
NPV	€ -21.818	€ 126.477	€ 261.291	€ 383.850	€ 495.266	€ 596.554	€ 688.634	€ 772.343	€ 848.442	€ 917.623	€ **980.514**
Cash flow	€ -150.000	€ 36.484	€ 36.484	€ 36.484	€ 36.484	€ 36.484	€ 36.484	€ 36.484	€ 36.484	€ 36.484	€ 36.484
Cum(Cash flow)	€ -150.000	€ -113.516	€ -77.031	€ -40.547	€ -4.063	€ 32.421	€ 68.906	€ 105.390	€ 141.874	€ 178.359	€ 214.843
NPV	€ -130.435	€ -102.847	€ -78.858	€ -57.998	€ -39.859	€ -24.086	€ -10.370	€ 1.556	€ 11.928	€ 20.946	€ **28.788**
Cash flow	€ -300.000	€ 72.969	€ 72.969	€ 72.969	€ 72.969	€ 72.969	€ 72.969	€ 72.969	€ 72.969	€ 72.969	€ 72.969
Cum(Cash flow)	€ -300.000	€ -227.031	€ -154.063	€ -81.094	€ -8.126	€ 64.843	€ 137.811	€ 210.780	€ 283.749	€ 356.717	€ 429.686
NPV	€ -260.870	€ -205.695	€ -157.717	€ -115.997	€ -79.719	€ -48.172	€ -20.741	€ 3.113	€ 23.855	€ 41.892	€ **57.576**
Cash flow	€ -450.000	€ 115.571	€ 115.571	€ 115.571	€ 115.571	€ 115.571	€ 115.571	€ 115.571	€ 115.571	€ 115.571	€ 115.571
Cum(Cash flow)	€ -450.000	€ -334.429	€ -218.858	€ -103.288	€ 12.283	€ 127.854	€ 243.425	€ 358.996	€ 474.566	€ 590.137	€ 705.708
NPV	€ -391.304	€ -303.916	€ -227.927	€ -161.849	€ -104.389	€ -54.425	€ -10.978	€ 26.803	€ 59.655	€ 88.222	€ **113.064**
Cash flow	€ -700.000	€ 199.256	€ 199.256	€ 199.256	€ 199.256	€ 199.256	€ 199.256	€ 199.256	€ 199.256	€ 199.256	€ 199.256
Cum(Cash flow)	€ -700.000	€ -500.744	€ -301.489	€ -102.233	€ **97.023**	€ 296.279	€ 495.534	€ 694.790	€ 894.046	€ 1.093.301	€ 1.292.557
NPV	€ -608.696	€ -458.030	€ -327.016	€ -213.091	€ -114.025	€ **-27.882**	€ 47.026	€ 112.163	€ 168.804	€ 218.057	€ 260.886
Cash flow	€ -94.500	€ 71.646	€ 71.646	€ 71.646	€ 71.646	€ 71.646	€ 71.646	€ 71.646	€ 71.646	€ 71.646	€ 71.646
Cum(Cash flow)	€ -94.500	€ -22.854	€ 48.791	€ 120.437	€ 192.082	€ 263.728	€ 335.373	€ 407.019	€ 478.664	€ 550.310	€ 621.955
NPV	€ -85.909	€ -26.698	€ 27.130	€ 76.065	€ 120.552	€ 160.994	€ 197.759	€ 231.182	€ 261.567	€ 289.189	€ **314.301**
Cash flow	€ -175.000	€ 20.179	€ 20.179	€ 20.179	€ 20.179	€ 20.179	€ 20.179	€ 20.179	€ 20.179	€ 20.179	€ 20.179
Cum(Cash flow)	€ -175.000	€ -154.821	€ -134.642	€ -114.463	€ -94.284	€ -74.105	€ -53.926	€ -33.747	€ -13.568	€ 6.611	€ 26.790
NPV	€ -159.091	€ -142.414	€ -127.253	€ -113.471	€ -100.941	€ -89.551	€ -79.196	€ -69.782	€ -61.224	€ -53.444	€ **-46.371**
Cash flow	€ -	€ 48.016	€ 48.016	€ 48.016	€ 48.016	€ 48.016	€ 48.016	€ 48.016	€ 48.016	€ 48.016	€ 48.016
Cum(Cash flow)	€ -	€ 48.016	€ 96.032	€ 144.048	€ 192.064	€ 240.081	€ 288.097	€ 336.113	€ 384.129	€ 432.145	€ **480.161**
cash flow	€ -	€ 31.470	€ 31.470	€ 31.470	€ 31.470	€ 31.470	€ 31.470	€ 31.470	€ 31.470	€ 31.470	€ 31.470
Cum(Cash flow)	€ -	€ 31.470	€ 62.941	€ 94.411	€ 125.881	€ 157.351	€ 188.822	€ 220.292	€ 251.762	€ 283.233	€ **314.703**
Cash flow	€ -6.525	€ 1.697	€ 1.697	€ 1.697	€ 1.697	€ 1.697	€ 1.697	€ 1.697	€ 1.697	€ 1.697	€ 1.697
Cum(Cash flow)	€ -6.525	€ -4.829	€ -3.132	€ -1.436	€ 261	€ 1.958	€ 3.654	€ 5.351	€ 7.047	€ 8.744	€ 10.440
NPV	€ -5.932	€ -4.530	€ -3.255	€ -2.096	€ -1.043	€ -85	€ 785	€ 1.577	€ 2.296	€ 2.950	€ **3.545**
Cash flow	€ -59.273	€ 440.733	€ 440.733	€ 440.733	€ 440.733	€ 440.733	€ 440.733	€ 440.733	€ 440.733	€ 440.733	€ 440.733
Cum(Cash flow)	€ -59.273	€ 381.460	€ 822.194	€ 1.262.927	€ 1.703.661	€ 2.144.394	€ 2.585.128	€ 3.025.861	€ 3.466.595	€ 3.907.328	€ 4.348.061
NPV	€ -53.885	€ 310.358	€ 641.488	€ 942.514	€ 1.216.175	€ 1.464.958	€ 1.691.124	€ 1.896.729	€ 2.083.643	€ 2.253.565	€ **2.408.039**

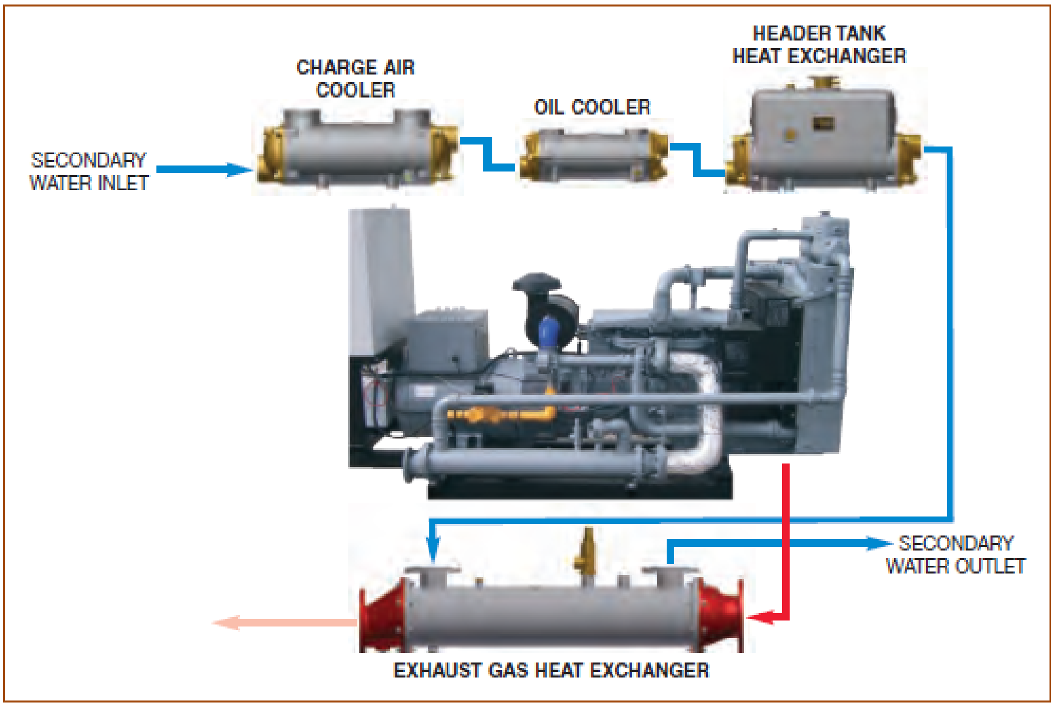
Figure D.1: NPV calculation sheet of case study

D.3 Organic Rankin Cycle Technology Sheets

Combined Heat Recovery

The addition of Bowman exhaust gas heat exchangers enable waste heat recovery from the exhaust gas and can be used on Cogeneration/Combined Heat and Power (CHP) equipment.

Typical configuration for CHP using Bowman Heat Exchangers



Provision should be made for cooling the engine water, oil and gas when heat recovery is not required.

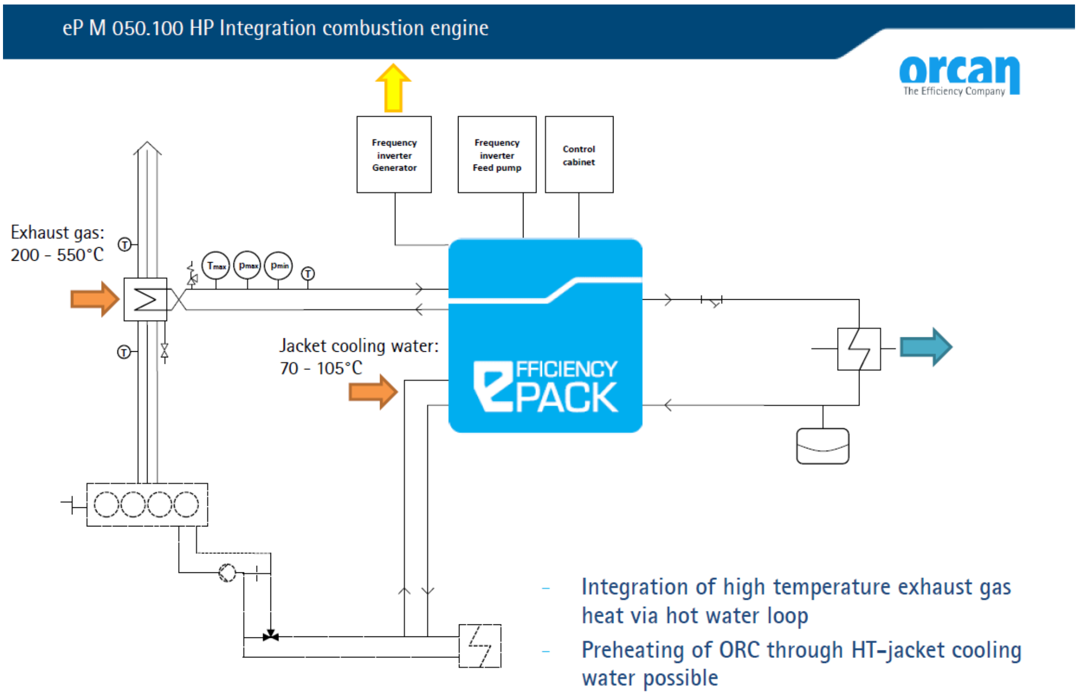
Combined Heat Recovery Performance Table

This table shows the heat that can be removed from each type of heat exchanger as shown in the illustration above.

Type	Engine Power kW	Jacket Water kW	Engine Oil kW	Charge Air Cooler kW	Exhaust Gas kW	Total Reclaimed Energy kW
2"	16	5	2	2.5	11.5	20.5
3"	32	10	4	5	23	41
4"	60	18	7	9	43	77
5"	90	27	10	14	65	115
6"	140	42	15	21	101	179
8"	250	75	28	38	181	321
10"	400	120	44	60	288	512
12"	600	180	66	90	425	761
15"	950	280	104	142	670	1205

The above figures should be used as a guide only, optimised design is available on request.

Figure D.2: Combine heat recovery performance table (provided by bowman)



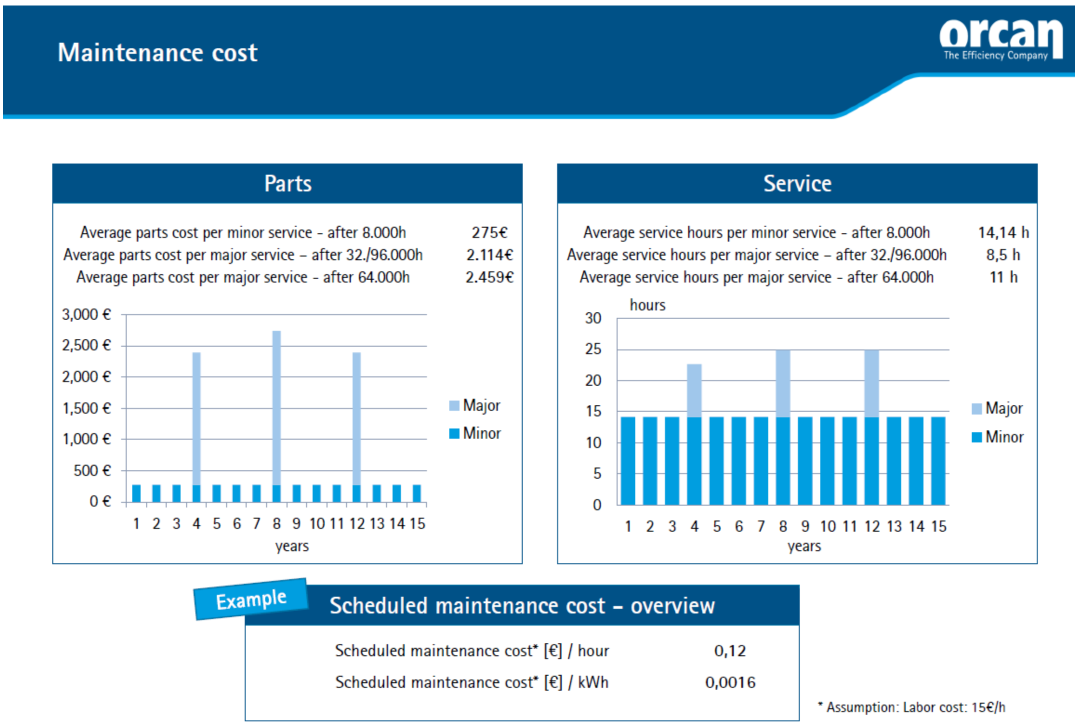


Figure D.3: Orcan efficiency pack working principle and maintenance cost overview

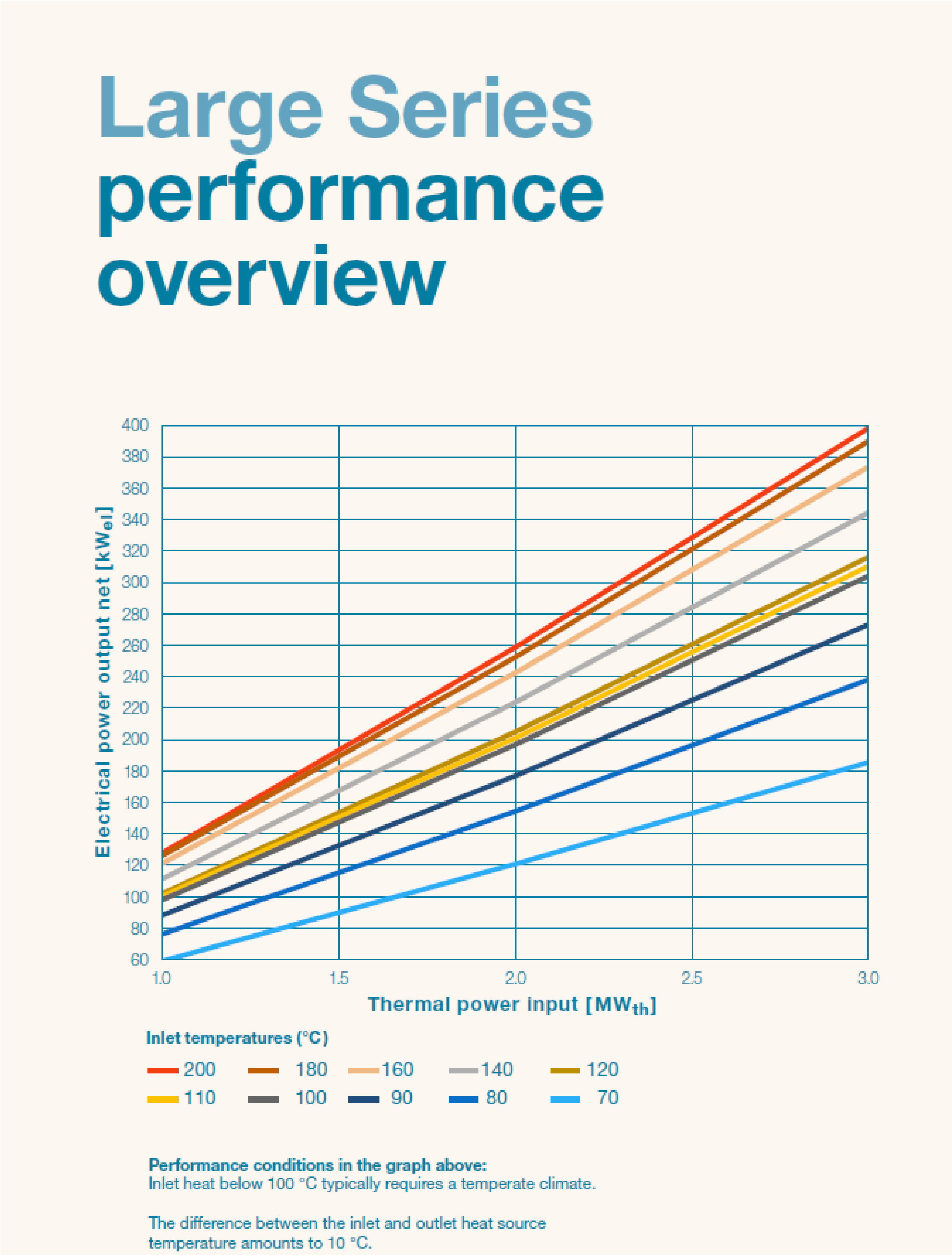


Figure D.4: Organic Rankin Cycle electrical output in relation to thermal power and thermal oil temperatures (provided by Viking heat engines)

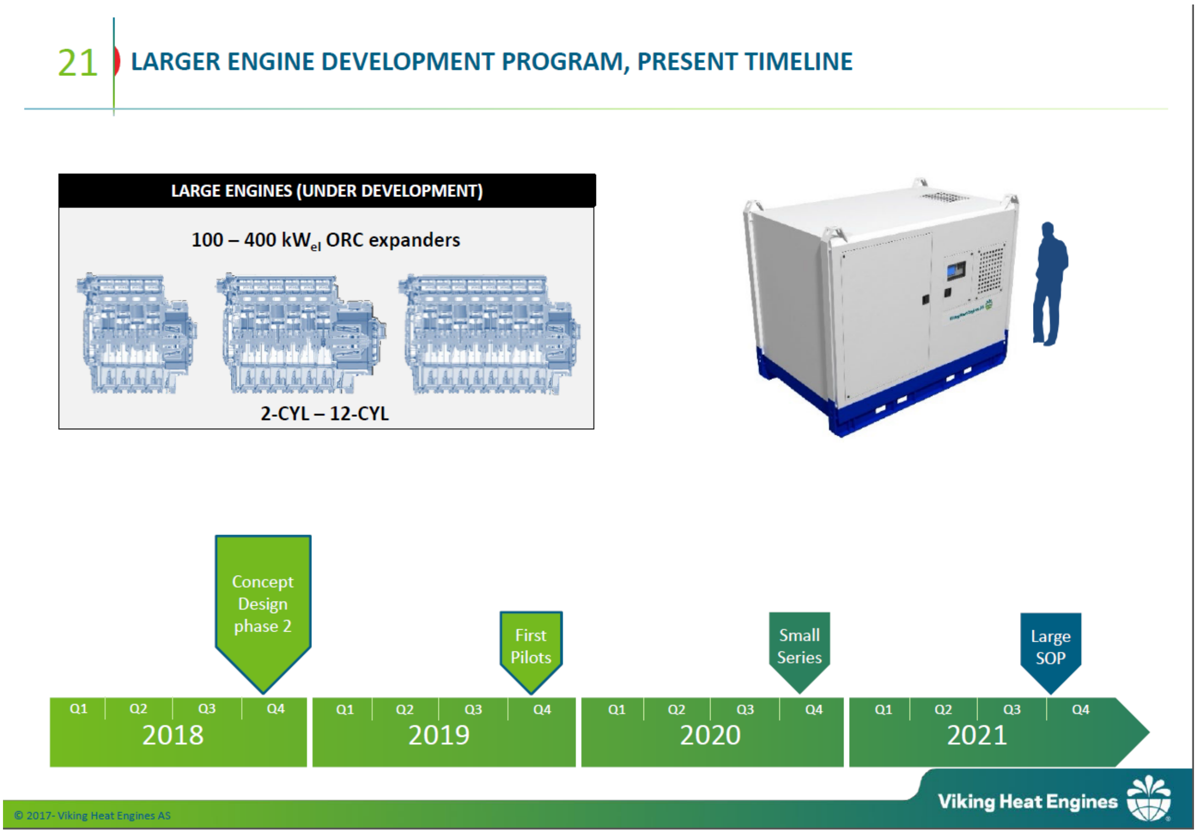


Figure D.5: Organic Rankin Cycle system development timeline (provided by Viking heat engines)

D.4 Cost Overviews of Monitoring Related System

Table D.2: Costs of Performance Monitoring System components according Gaby Steentjes

	Hardware	
Component	Initial Investment	Annual Maintenance cost
GPS logger	€ 3000	€100
Volumetric flow meter	€ 5.000	€1.500
Coriolis flow meter	€ 15.000	€1.500
shaft power meter	€ 25.000	€1.000
Thrust power meter	€ 45.000	€1.500
Electric power meter	€ 5.000	< €100
	Data Transfer	
Remote controlled vessel	€ 150.000 per month (bron)	

Table D.3: Pricelist Marlink data plan

Marlink price list						
	Bandwidth options [kbps]				Lease Period [$ / months]	
Package	MIR Down	MIR Up	CIR Down	CIR Up	36 months	60 months
Standard A+	1024	512	128	64	2.700	2.295
Standard B+	2048	512	256	128	3.900	3.315
Standard C+	3072	512	512	256	7.700	6.545
Standard D+	6144	1024	1024	512	8.800	7.48
Standard E+	6144	1024	2048	1024	16.000	13.600
Standard F+	6144	1024	3072	1024	20.800	17.680

D.5 Corporate Statistic Data of Long Distance Towage

	count	mean	std	min	25%	50%	75%	max
year	20	2.016	1	2.014	2.015	2.016	2.016	2.017
Q1_O	20	59	30	0	43	66	86	91
Q1_HFO	20	1.729	1.142	0	710	1.708	2.540	4.225
Q1_MGO	20	201	117	0	135	165	275	469
Q2_O	20	53	30	0	35	59	78	91
Q2_HFO	20	1.351	1.029	0	796	946	1.988	3.958
Q2_MGO	20	225	232	0	151	167	206	1.021
Q3_O	20	55	29	0	47	60	79	92
Q3_HFO	20	1.363	989	0	403	1.393	2.259	2.960
Q3_MGO	20	256	247	0	124	161	367	1.032
Q4_O	20	45	25	0	32	52	62	87
Q4_HFO	20	1.252	994	0	667	999	1.646	3.212
Q4_MGO	20	215	144	0	135	173	231	565
year_O	20	212	76	20	181	237	258	305
year_HFO	20	5.695	2.397	387	4.287	5.937	7.048	10.022
year_MGO	20	897	536	321	630	699	933	2.354
Q1_HFO_MT	20	1.712	1.130	0	703	1.691	2.515	4.183
Q2_HFO_MT	20	1.337	1.018	0	788	937	1.968	3.919
Q3_HFO_MT	20	1.349	979	0	399	1.379	2.236	2.930
Q4_HFO_MT	20	1.239	984	0	660	989	1.629	3.180
YEAR_HFO_MT	20	5.638	2.373	383	4.244	5.877	6.977	9.922
YEAR_MGO_MT	20	768	460	275	540	599	800	2.018
Q1_BOTH_MT	20	1.884	1.114	0	921	1.918	2.636	4.428
Q2_BOTH_MT	20	1.530	1.053	0	977	1.197	2.227	4.060
Q3_BOTH_MT	20	1.569	1.003	0	706	1.653	2.423	3.047
Q4_BOTH_MT	20	1.424	989	0	800	1.184	1.783	3.296
YEAR_BOTH_MT	20	6.406	2.435	711	4.819	6.480	7.944	10.600
YEAR_HFO_USD	20	2.207.220	929.163	150.019	1.661.653	2.300.937	2.731.580	3.884.377
YEAR_MGO_USD	20	441.265	263.936	157.795	309.809	343.872	459.119	1.158.590
BOTH_FUEL_USD_Q1	20	769.012	434.299	0	400.347	792.605	1.053.968	1.778.214
BOTH_FUEL_USD_Q2	20	634.289	423.161	0	412.611	498.196	898.012	1.615.521
BOTH_FUEL_USD_Q3	20	654.242	403.189	0	351.507	710.266	976.388	1.214.313
BOTH_FUEL_USD_Q4	20	590.987	390.006	0	339.850	497.314	747.504	1.311.707
BOTH_FUEL_USD_Y	20	2.648.486	976.007	338.222	1.991.869	2.764.263	3.295.918	4.273.620
YEAR_MGO_EUR	20	383.901	229.625	137.281	269.534	299.169	399.434	1.007.973
BOTH_FUEL_EUR_Q1	20	669.041	377.840	0	348.302	689.566	916.952	1.547.046
BOTH_FUEL_EUR_Q2	20	551.831	368.150	0	358.972	433.430	781.270	1.405.503
BOTH_FUEL_EUR_Q3	20	569.191	350.775	0	305.811	617.931	849.458	1.056.452
BOTH_FUEL_EUR_Q4	20	514.158	339.305	0	295.669	432.663	650.329	1.141.185
BOTH_FUEL_EUR_YEAR	20	2.304.183	849.126	294.253	1.732.926	2.404.909	2.867.449	3.718.049
Q1_E	20	21.248	12.494	0	10.467	21.667	29.652	49.839
Q2_E	20	17.290	11.846	0	11.061	13.530	25.084	45.653
Q3_E	20	17.739	11.291	0	8.174	18.723	27.288	34.268
Q4_E	20	16.088	11.103	0	9.071	13.402	20.101	37.063
year_E	20	72.363	27.396	8.179	54.436	73.481	89.776	119.366
Q1_BOTH_GHG	20	5.882.539	3.467.844	0	2.887.607	5.994.495	8.218.655	13.810.673
Q2_BOTH_GHG	20	4.782.639	3.282.951	0	3.056.425	3.741.925	6.949.450	12.656.951
Q3_BOTH_GHG	20	4.905.179	3.129.224	0	2.236.227	5.174.172	7.560.241	9.499.789
Q4_BOTH_GHG	20	4.449.997	3.079.992	0	2.505.823	3.704.954	5.565.806	10.275.397
YEAR_BOTH_GHG	20	20.020.354	7.593.583	2.244.068	15.060.561	20.293.107	24.832.611	33.069.729