Goal-based optimization in Arctic offshore support vessel design and fleet composition

Aleksandr Kondratenko
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Aalto University
School of Engineering
Department of Mechanical Engineering
Marine Technology
Supervising professor
Professor Pentti Kujala, Aalto University, Finland

Thesis advisor
Professor Jani Romanoff, Aalto University, Finland

Preliminary examiners
Emeritus Professor Apostolos D. Papanikolaou, National Technical University of Athens, Greece
Professor Stein O. Erikstad, Norwegian University of Science and Technology, Norway

Opponent
Emeritus Professor Apostolos D. Papanikolaou, National Technical University of Athens, Greece
Author
Aleksandr Kondratenko

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Abstract
The goal-based design (GBD) approach is a promising tool, supporting innovative solutions in conceptual ship and fleet design. Unlike traditional ship design methods, GBD aims to quantify different ship performance indicators to avoid prescribed rules and excessive reliance on prototypes, significantly extending the design space.

Although the GBD approach is adapted to solve many ship and fleet design problems, its application for Arctic offshore support vessel design and fleet composition is still limited. Consequently, the thesis aims to advance the existing methods for goal-based optimization of Arctic offshore support vessels and fleets. The proposed approaches and framework consider issues related to the exploration and extraction stages of the development of Arctic offshore oil and gas fields.

The existing methods for optimizing Arctic offshore exploration drilling support fleets rely on external expertise, resulting in limited design space and significant subjectivity of optimization constraints formulation.

The performance of the Arctic offshore support fleet for the exploration stage of oil and gas field development is mainly related to specialized Arctic offshore supply vessels. The holistic ship design optimization approach represents an advanced GBD tool to find effective solutions in the conceptual ship design of complex vessels with a challenging operational context, like Arctic offshore supply vessels. However, it is believed that there is no holistic ship design optimization approach for ice-going vessels. Consequently, an integrated framework, including methods to address these existing gaps in the studied research field, is developed in this thesis.

An Artificial Bee Colony-based approach to optimize Arctic offshore drilling support fleets for cost-efficiency is proposed. The approach provides a quantitative assessment of the versatile functionality of the fleet, considering the combined effect of the expected costs of accidental events, the versatility of individual support vessels, and the management of sea ice. As a result, the proposed method extends the design space and reduces subjectivity in Arctic offshore drilling support fleet optimization.

Furthermore, this thesis proposes an approach for holistic multi-objective optimization of Arctic offshore supply vessels with in-depth consideration of their operational context. The framework scans the feasible design space to find a Pareto front, representing the tradeoffs between the cost and eco-efficiency for a conceptual design of an Arctic offshore supply vessel. The provided case studies and verifications illustrate the validity and reliability of the developed approaches.

Keywords Arctic shipping, goal-based design, holistic ship design, offshore support vessel, multi-objective optimization


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Espoo, 3 September 2021
Aleksandr Kondratenko
Contents

Acknowledgements ........................................................................................................ 1
List of Abbreviations and Symbols ........................................................................... 5
List of Publications ...................................................................................................... 9
Author’s Contribution ................................................................................................. 10
Original features ......................................................................................................... 11

1. Introduction ............................................................................................................. 13
   1.1 Background ....................................................................................................... 13
   1.1.1 Arctic offshore support fleet: purpose and specific ...................................... 13
   1.1.2 Holistic optimization in ship design .............................................................. 15
   1.1.3 Ship performance evaluation ........................................................................ 17
   1.1.4 Optimization algorithms in ship design and fleetcomposition ......................... 19
   1.2 Motivation, objectives, and scope ..................................................................... 21
   1.3 Limitations ....................................................................................................... 24

2. An optimization approach for Arctic offshore drilling support fleet sizing and composition ................................................................................................................. 27
   2.1 Performance modeling of an Arctic offshore drilling support fleet ......................... 27
   2.2 The artificial bee colony algorithm .................................................................... 30
   2.3 Approach applicability assessment: case studies and sensitivity analysis ............. 32
      2.3.1 Case study: Arctic offshore drilling support fleets for the northern and southern Kara Sea ................................................................................................. 34
      2.3.2 Sensitivity analysis .................................................................................... 38

3. A parametric design model of an Arctic Offshore Support Vessel ................................................... 40
   3.1 General description of the model .................................................................... 40
   3.2 Methods for the estimation of ship design qualities ........................................ 42
   3.3 Verification of the design model ....................................................................... 47
4. Holistic multi-objective optimization of Arctic Offshore Supply Vessels: an approach and a framework ..................................................49
   4.1 Description of an optimization process .....................................49
   4.2 Performance assessment model for an Arctic Offshore Supply Vessel ......................................................................................52
   4.3 Optimization of an offshore supply vessel design for the Kara Sea ........................................................................................ 56
5. Discussion ................................................................................... 62
6. Conclusions ................................................................................. 65
References .............................................................................................. 67
### List of Abbreviations and Symbols

<table>
<thead>
<tr>
<th>Abbreviation</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>ABC</td>
<td>Artificial Bee Colony</td>
</tr>
<tr>
<td>AH</td>
<td>Anchor Handling</td>
</tr>
<tr>
<td>AHTS</td>
<td>Anchor Handling Tug Supply</td>
</tr>
<tr>
<td>B</td>
<td>Beam</td>
</tr>
<tr>
<td>BPMN</td>
<td>Business Process Model Notation</td>
</tr>
<tr>
<td>CKPI</td>
<td>Cost-efficiency Key Performance Indicator</td>
</tr>
<tr>
<td>DP</td>
<td>Dynamic Positioning</td>
</tr>
<tr>
<td>ECR</td>
<td>Engine Control Room</td>
</tr>
<tr>
<td>EEDI</td>
<td>Energy Efficiency Design Index</td>
</tr>
<tr>
<td>EKPI</td>
<td>Eco-efficiency Key Performance Indicator</td>
</tr>
<tr>
<td>Fi-Fi</td>
<td>Firefighting</td>
</tr>
<tr>
<td>KPI</td>
<td>Key Performance Indicator</td>
</tr>
<tr>
<td>MCR</td>
<td>Maximum Continuous Rating</td>
</tr>
<tr>
<td>MINLP</td>
<td>Mixed Integer Nonlinear Programming</td>
</tr>
<tr>
<td>MSB</td>
<td>Main Switchboard</td>
</tr>
<tr>
<td>NLP</td>
<td>Nonlinear Programming</td>
</tr>
<tr>
<td>PSV</td>
<td>Platform Supply Vessel</td>
</tr>
<tr>
<td>PW</td>
<td>Present Worth</td>
</tr>
<tr>
<td>RFR</td>
<td>Required Freight Rate</td>
</tr>
<tr>
<td>RIO</td>
<td>Risk Index Outcome</td>
</tr>
</tbody>
</table>

- $A_i, B_i$: Regression coefficients
- $b$: Ice ridging
- $c$: Ice concentration
Cbcl | Block coefficient
---|---
C$_{cap}$ | Cargo capacity parameter for CKPI
C$_{cap}^*$ | Cargo capacity parameter for EKPI
C$_{v,d}^{cr}$ | Charter cost for vessel $v$ to perform duty $d$
C$_{v,d}^f$ | Fuel cost for vessel $v$ to perform duty $d$
C$_{v,d}^{ra}$ | Contribution of vessel $v$ performing duty $d$ to the risk of asset loss
C$_{v,d}^{rh}$ | Contribution of vessel $v$ performing duty $d$ to the risk of human life loss
C$_{ib}^i$ | Contribution of icebreaker $ib$ to the risk of economic loss due to ice presence
$D$ | Required duties to support the platform, indexed by $d$
$E_d^k$ | Consequence of a risk event
FCO | Fuel consumption for cargo operations
$F_d^k$ | Frequency of a risk event
F$_{m,s,i}$ | Fuel consumption in month $m$ for segment $s$ in ice condition $i$
H | Depth
$h_{eq}$ | Equivalent ice thickness
$h_i$ | Level ice thickness
$h_{ice}$ | Icebreaking capability
$h_{ice,j}$ | Icebreaking capability using power output $j$
$h_{sn}$ | Snow thickness
$I$ | Set of feasible fleet configurations, indexed by $i$
i | Number of an ice condition type
$IB$ | Available set of icebreakers, indexed by $ib$
i$_{max}$ | Total number of different types of ice conditions occurring along the segment $s$
j | Current power output
$J$ | Advance ratio of the propeller
$K_Q$ | Torque coefficient of the propeller
$K_r$ | Thrust coefficient of the propeller
$L_{pp}$ | Length between perpendiculars
m  Number of a month
m_{dc}  Average density of the deck cargo
N_{d_{min}}  Set of minimum numbers of vessels to perform duty d, indexed by n_{d_{min}}
N_m  Average number of voyages per month m
N_v  Number of voyages per year
P/D  Pitch ratio of the propeller
P_D  Required power to be delivered
p_{m,s,i}  Probability of occurrence of ice conditions of type i along the route segment s in month m
P_{v,d}  Set of performance capacities to execute duty d by vessel v, indexed by P_{v,d}
r  Transverse metacentric radius
R  Longitudinal metacentric radius
R_d  Set of performance requirements of the fleet for successful performing duty d, indexed by r_d
R_d^k  Risk value
S  Waterplane area
s  Number of a route segment
S_d  Vessel cargo deck area
s_{max}  Number of segments along the route
T  Draft
u_k, v_k, w_k  Regression coefficients
V  Available set of Arctic offshore support vessels, indexed by v
V  Volume displacement
V_{0,j}  Speed corresponding to h_{ice,j}
V_j  Vessel speed in ice with an equivalent ice thickness of h_{eq} using power output j
V_{max,j}  Attained open water speed using power output j
V_s  Design speed in open water
w  Weight factor
X_c  X coordinate of the center of buoyancy
X_f  X coordinate of the center of flotation
$x_k, y_k, z_k$ Regression coefficients

$Z_c$ Z coordinate of the center of buoyancy

$\Delta w$ Weight factor increment

$\Omega$ Wetted surface
List of Publications

This doctoral dissertation consists of a summary of the following publications, which are referred to in the text by their numerals.


Author’s Contribution

**Publication 1:** An Artificial Bee Colony optimization-based approach for sizing and composition of Arctic offshore drilling support fleets considering cost-efficiency.

The author proposed the original idea and further development of the approach and was the main contributor to the article. Bergström contributed to the writing of the Introduction chapter of the manuscript. Bergström, Suominen, and Kujala provided valuable suggestions and comments on the manuscript.

**Publication 2:** Cargo-Flow-Oriented Design of supply vessel operating in ice conditions.

The author conducted the research, designed the coding, and was the main contributor to the article. Tarovik provided valuable suggestions and comments on the original idea and the manuscript.

**Publication 3:** Analysis of the impact of Arctic-related factors on offshore support vessels design and fleet composition performance.

The author collected the data, proposed the original research idea and its implementation, designed the coding, conducted the research, and was the main contributor to the article. Tarovik provided valuable suggestions and comments on the manuscript.

**Publication 4:** A Holistic Multi-Objective Design Optimization Approach for Arctic Offshore Supply Vessels.

The author proposed the original idea and further development of the approach and was the main contributor to the article. Reutskii developed the figures for the ship hulls. Bergström and Kujala provided valuable suggestions and comments on the manuscript.

**Publication 5:** A framework for multi-objective optimization of Arctic offshore support vessels.

The author developed and coded the framework and was the main contributor to the article. Kujala provided valuable suggestions and comments on the manuscript.
The thesis aims to contribute to the theory and methods for the design of Arctic vessels and Arctic fleets. In this respect, the thesis focuses on the development of optimization approaches for goal-based holistic ship design and goal-based fleet design for Arctic offshore support vessels, considering a specific operational context. The existing approaches in these fields are mainly proposed for open water vessels. The following features of this thesis are believed to be original:

1. An approach is developed to optimize the composition of an Arctic offshore drilling support fleet for cost-efficiency, using the Artificial Bee Colony (ABC) algorithm. The approach considers the main types of duties related to Arctic offshore drilling, including supply, towing, anchor handling, standby, oil spill response, firefighting, and ice management. The fleet optimization algorithm considers the risk-related expected costs from accidental events and the versatility of individual support vessels [PI].

2. A parametric design model is proposed for an Arctic offshore support vessel. The model is based on the principles of the holistic ship design approach and considers all the essential ship qualities and related constraints: the hull geometry, hydrostatics, stability, and rolling, resistance and propulsion (in open water and ice), required power plant capacity, general arrangement criteria, estimations of lightweight and deadweight, cargo capacity, and freeboard criteria. The design model is applicable for two major types of offshore support vessels—offshore supply vessels and anchor-handling tug supply vessels—with different ice-breaking capabilities, from open water vessels to icebreakers [PII, PIII].

3. An adaptation of the ABC metaheuristic algorithm is provided for holistic ship design optimization. Holistic ship design optimization represents a highly complex optimization problem and requires maximum performance in the calculation speed and efficiency of the algorithm. The proposed modification of the single-objective ABC algorithm proved to be efficient for the multi-objective Mixed Integer Nonlinear Programming (MINLP) problem in constraints for a wide range of case studies [PI, PIV].

4. A holistic multi-objective design approach and framework are developed for the optimization of Arctic offshore supply vessels for Cost- and Eco-
efficiency. The approach combines a parametric design model of an Arctic offshore supply vessel, performance assessment models for independently operating and icebreaker-assisted Arctic offshore supply vessels, and an adaptation of the ABC metaheuristic algorithm for holistic ship design optimization [PIV, PV].

5. Multi-objective optimization of an offshore supply vessel design is performed for the Kara Sea. The impact of the consideration of icebreaker assistance, the assumed vessel speed profile, and the offshore-specific factors on Arctic offshore supply vessel optimization results is studied [PIV].
1. Introduction

1.1 Background

1.1.1 Arctic offshore support fleet: purpose and specific

In recent decades, there has been broad support for the future transition from fossil fuels to renewable energy sources. Even though significant advances in renewable energy technologies have been made (Ellabban, Abu-Rub and Blaabjerg 2014), it can take more than fifty years before oil and gas are replaced as the primary energy sources (York and Bell 2019). During this period, it is necessary to provide a stable oil and gas supply for a sustainable transition to renewable energy sources. Oil and gas are also expected to play a significant role after this transition as a part of the energy mix (DNV GL 2017; York and Bell 2019).

According to Panichkin (2016), the Arctic shelf contains about 90 billion barrels of oil and 47 trillion cubic meters of natural gas, making it one of the major sources of fossil fuels in the future. Most oil and natural gas fields of the Arctic shelf remain undeveloped. According to the U.S. Energy Information Agency (EIA 2012) and U.S. Geological Survey (2008), the Arctic can account for some 13% of the world’s undiscovered oil and 30% of the world’s undiscovered natural gas.

The Arctic oil and gas fields are mainly located in waters that are ice-infested for most of the year. Their development requires, among other considerations, an ice-strengthened offshore installation and a specialized ice-going offshore support fleet. The duties of an Arctic offshore support fleet could be divided into active duties (e.g., towing and anchor handling (AH) of an installation, supply and crew transportation, ice management, and safety standby) and passive duties (e.g., emergency functions, such as firefighting (Fi-Fi) and oil recovery). Towing and AH duties are aimed at arranging an Arctic offshore installation at a new operating point. Once an Arctic offshore installation is arranged, an Arctic offshore support fleet transports cargoes and crew between the coastal supply base and the Arctic offshore installation. The purpose of ice management in this context is to modify the ice conditions near an Arctic offshore installation to diminish their negative impact on the efficiency and safety of offshore operations. A safety standby duty includes control of the activity of the vessels in the vicinity of an Arctic offshore installation and rescue operations in emergency cases.
The development of an offshore field can be chronologically divided into the following stages: a) exploration drilling to evaluate the size of a deposit and b) extraction of oil or natural gas. In non-Arctic regions with significant offshore activity (e.g., the Norwegian Sea and the North Sea), the distance between installations is minor: an offshore support fleet can serve multiple installations simultaneously. In that case, the field development stage of specific installations has a limited impact on the fleet composition. On the contrary, in remote Arctic regions with no developed offshore activity, the distance between installations can be significant, which requires the organization of a separate support fleet for a specific installation. Besides this, Arctic exploration drilling is limited to the short summer–autumn period of 3–5 months, while oil and gas extraction continues year-round and lasts for decades. To consider this, offshore operators—companies that develop Arctic oil and gas fields—use different approaches to organize offshore support fleets for different stages of an Arctic offshore field development.

The exploration drilling stage can be chronologically divided into mobilization, operation, and demobilization. The primary support fleet duties of mobilization and demobilization include towing and AH, whereas the primary support fleet duty of the operation stage is supply. Because the Arctic exploration drilling season is short, an Arctic drilling support fleet is typically based on multifunctional (versatile) vessels chartered for the whole exploration period (Gauthier and Molyneux 2018). In this regard, the offshore operators need an approach and a decision support tool to optimize an Arctic offshore drilling support fleet for cost-efficiency, considering organizational and ecological aspects, all relevant duties, and potential constraints.

Although the extraction stage of an Arctic offshore field development also includes the mobilization and demobilization of an offshore installation, their total duration and related cost are insignificant compared with that of the operation phase, meaning that supply duty is prioritized. While towing and AH vessels are typically chartered with short-term contracts, Arctic offshore supply vessels are usually bought by an offshore operator for a specific Arctic offshore installation to operate for more than 15–20 years (Tarovik et al. 2018). Thereby, the performance of an Arctic offshore support fleet at the extraction stage is mainly determined by specialized Arctic offshore supply vessels.

The industry of ship design is very competitive; every design of a ship must be modern and effective to be built. The conceptual ship design stage defines the general technical qualities of a vessel. Any suboptimal decision impacts the subsequent stages of ship design, making the conceptual ship design a stage with the most influence on ship performance.

Because an Arctic offshore supply vessel requires increased fuel consumption compared to a conventional open water offshore supply vessel and operates in a fragile Arctic environment for an extended period, the performance analysis must consider both eco-efficiency and cost-efficiency. In this regard, offshore operators need an approach and a decision support tool to optimize a conceptual design of an Arctic offshore supply vessel for cost- and eco-efficiency that considers a specific operational context.
As per Watson (1998), among others, the cost-efficiency of a vessel can be measured by the Required Freight Rate (RFR)—the break-even revenue per transported cargo unit (USD/t). To promote more eco-friendly vessels, the International Maritime Organization introduced the Energy Efficiency Design Index (EEDI) (IMO 2018). The EEDI estimates the amount of CO₂ emissions per unit of transport work, assuming its linear correlation with the capacity of the power plant. According to (Trivyza, Rentizelas, and Theotokatos 2020), a better measure of a vessel’s eco-efficiency can be obtained using nonlinear estimations of the lifetime CO₂ emissions of the vessel.

This study aims to provide approaches and corresponding decision support tools for goal-based optimization in Arctic offshore support vessel design and fleet composition. All algorithms and methods are designed to deal with the relevant issues of the industry related to the main stages of Arctic offshore field development.

1.1.2 Holistic optimization in ship design

The traditional ship design approach relies on statistical data (e.g., parent-hulls data and empirical prescribed rules) to provide a new vessel design concept. As demonstrated by Andrews and Erikstad (2015), the straightforward application of the traditional ship design approach narrows the available design space and often results in a single-point design focus. The goal-based ship design approach aims to quantify different ship performance indicators to avoid prescribed rules when possible, significantly extending the design space and providing more innovative solutions (Tsakalakis, Vassalos, and Puisa 2009; Andrews and Erikstad 2015). Multi-objective optimization effectively applies in goal-based design to find tradeoffs between different ship design qualities (Priftis et al. 2018).

Figure 1 presents the five aspects that determine the efficiency of a ship as stated in Gaspar et al. (2012). Towards the reliable evaluation of a ship design concept, it is necessary to consider its operational context. Besides internal factors that directly determine ship design qualities (i.e., the technical parameters of subsystems and their interrelation), external factors (e.g., ecological, environmental, logistical, and market-driven factors) significantly affect the performance of a ship (Brett et al. 2006).
Figure 1. Five aspects that impact ship efficiency (Gaspar et al. 2012). The structural aspect is related to the internal factors while other aspects are related to the external factors.

Such factors can be considered, among others, by application of the holistic ship design approach (Papanikolaou 2010). In general, the holistic approach to ship design contains (1) a parametric concept design model of the vessel that considers all of the important ship design qualities and related constraints (i.e., internal factors), (2) a model of the performance of a vessel in the operational context that considers the external factors, and (3) an optimization algorithm.

Ship design qualities considered by the parametric concept design model of the vessel are case-specific and can be divided into general and task-related design qualities. As reported by Erikstad and Levander (2012), Figure 2 presents the internal factors considered by a typical concept design model of the multifunctional offshore support vessel.

Table 1 presents some existing holistic ship design approaches for open water ships, which are successfully implemented for a wide range of vessel types. This demonstrates the flexibility of the holistic ship design concept. Most of the approaches deal with multi-objective optimization to avoid a single-point design focus. According to the goal-based design principles, the optimization objectives of the most applied approaches are related to different aspects of ship operation.

According to Table 1, early approaches are often limited to optimization of ship design qualities due to the lack of a vessel performance model. However, recent approaches tend to include a vessel performance assessment model to consider an operational context in-depth.
Figure 2. Systems of an offshore support vessel are divided into task-related systems and general ship systems (Erikstad and Levander 2012).

Table 1. Holistic approaches to open water ship design

<table>
<thead>
<tr>
<th>Publication</th>
<th>Vessel type</th>
<th>Optimization objectives</th>
<th>Vessel performance model (considered factors)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Ray, Gokarn, and Sha (1995)</td>
<td>Container ship</td>
<td>Minimization of power, steel weight, and building costs</td>
<td>not applicable</td>
</tr>
<tr>
<td>Brett et al. (2006)</td>
<td>Open hatch bulk carrier</td>
<td>Profit and service quality indicators</td>
<td>Logistical and market-driven</td>
</tr>
<tr>
<td>Papanikolaou (2010)</td>
<td>High-speed craft</td>
<td>Minimization of the total resistance and wash wave</td>
<td>not applicable</td>
</tr>
<tr>
<td>Papanikolaou (2010)</td>
<td>Ro-Ro (passanger)</td>
<td>Attained subdivision Index, deadweight, and garage deck area</td>
<td>not applicable</td>
</tr>
<tr>
<td>Martins and Burgos (2011)</td>
<td>Oil tanker</td>
<td>Minimization of the cost of ownership and mean oil outflow</td>
<td>not applicable</td>
</tr>
<tr>
<td>Gkochari and Papanikolaou (2010)</td>
<td>Ro-Ro (cargo)</td>
<td>Minimization of time, price, and CO₂ emissions per delivery</td>
<td>Ecological, logistical, and market-driven</td>
</tr>
<tr>
<td>Rehn et al. (2018)</td>
<td>Offshore support vessel</td>
<td>Integral functionality, flexibility to modernization, and minimization of ship cost</td>
<td>Logistical and market-driven</td>
</tr>
<tr>
<td>Mauro, Braidotti, and Trincas (2019)</td>
<td>CNG carrier</td>
<td>Minimization of delivery cost</td>
<td>Ecological, logistical, and market-driven</td>
</tr>
<tr>
<td>Mauro, Braidotti, and Trincas (2020)</td>
<td>Offshore construction vessel</td>
<td>Seakeeping performance</td>
<td>Environmental</td>
</tr>
</tbody>
</table>

1.1.3 Ship performance evaluation

Montreuil (2011) contends that parts of a transportation system must not be designed separately but with an integral, sustainable, and multidisciplinary ap-
Introduction

However, the traditional approach for concept ship design aims to optimize the design qualities of a vessel ship with limited consideration of external factors (e.g., by means of conventional documentation), which can result in suboptimal transportation systems. Some examples of these are presented in Table 2.

The Rhine Line is a bulk cargo transportation system based on multi-purpose open hatch bulk carriers operated between Germany and Norway (Brett et al. 2006). The initially efficient transportation system partly lost its profitability because of a lack of adaptation to the changing circumstances: new vessels built according to the old design concept did not correspond to new logistics and market-driven factors. To mitigate this issue, a study (Brett, et al. 2006) proposed a holistic ship design optimization approach that includes an in-depth model of the Rhine Line. Based on this approach, the authors developed an optimized ship design concept to significantly increase the profitability of the transportation system.

The Prirazlomnaya is an offshore oil platform operated year-round in ice-infested waters. Cargo operations with large ice-class shuttle oil tankers are performed directly from the platform. A combination of drifting ice, wind, and waves makes shuttle tanker loading in the vicinity of the platform risky, resulting in a long-lasting absence of a weather window—a period when weather is acceptable for cargo operations. This decreases the transport efficiency of the system dramatically, which was not accounted for in the concept design of the tankers and fleet sizing. The offshore operator of the Prirazlomnaya platform initiated a study (Tarovik et al. 2018) that provided some successful logistical and organizational solutions to significantly improve the efficiency of the transportation system. Despite these improvements, the expected transport capacity of the transportation system is reduced compared to that assumed in the concept design.

Table 2. Examples of maritime systems with suboptimal efficiency caused by limited consideration of external factors in the concept design stage

<table>
<thead>
<tr>
<th>Maritime system</th>
<th>Primary factors of suboptimal efficiency</th>
<th>Source</th>
</tr>
</thead>
<tbody>
<tr>
<td>The Rhine Line</td>
<td>Logistical, market-driven</td>
<td>Brett et al. 2006</td>
</tr>
<tr>
<td>The Prirazlomnaya platform</td>
<td>Logistical, environmental</td>
<td>Tarovik et al. 2018</td>
</tr>
<tr>
<td>The Crete system</td>
<td>Logistical, market-driven</td>
<td>Gkochari and Papanikolaou 2010</td>
</tr>
<tr>
<td>The Severomut container ship</td>
<td>Ecological, market-driven</td>
<td>Staalesen 2016</td>
</tr>
<tr>
<td>Offshore support</td>
<td>Logistical, market-driven</td>
<td>Gibson 1999</td>
</tr>
</tbody>
</table>

As per (Gkochari and Papanikolaou 2010), the existing system of agricultural goods transportation from Crete to Italy and Germany is suboptimal. The transportation system emerged uncontrolled due to the Breakup of Yugoslavia that blocked the land route between these regions. The cargo in containers is carried by 1) Ro-Pax vessels from Crete to Piraeus, 2) trucks from Piraeus to Patras, 3) Ro-Pax vessels from Patras to an Italian Adriatic port, 4) trucks from an Italian Adriatic port to the final destination. To address this, Gkochari and Papanikolaou (2010) present a holistic optimization approach to concept ship design.
design, which includes the Ro-Pax vessel performance model for the considered line. Furthermore, the authors proposed a new direct sea line between the Crete and Italian Adriatic ports, which is estimated to significantly increase the cost- and time-efficiency of the transportation system due to reduced waiting times.

A nuclear-powered ice-class container ship, Sevmorput, was built in 1988. This unique ship was assumed to be a game-changer in the commercial market due to its significantly reduced CO₂ emissions, high capacity, extended sea endurance, and ability to sail along the Northern Sea Route. However, despite the promising technical characteristics and extended safety precautions, Sevmorput remains unprofitable due to the negative attitude to nuclear energy from the international community and stakeholders (Staalesen 2016). The actual ecological impact of this ship is disputable, but its negative image can result in significant economic losses to potential stakeholders. Such an external factor was not appropriately considered in the conceptual ship design stage.

An offshore support vessel design in the 20th century is mainly developed by the trial-and-error approach (Gibson 1999). In this approach, support vessels are built based on the established design despite the changing external factors. When the established design is tested, and its weaknesses are revealed in new practical circumstances, a new, better design is created to replace the established design. Consequently, the development of offshore support vessels was discrete, resulting in many suboptimal vessels (Gibson 1999).

The external factors that significantly affected the offshore industry include new types of offshore installations (e.g., jack-up rigs and semi-submersible rigs) and new regions of operation (e.g., the North Sea, the Norwegian Sea, and Brazilian deepwater fields).

In 1974, the Norwegian Ulstein ship design bureau proposed a new UT 704 design of an offshore support vessel that finished the era of the trial-and-error approach. Since then, this design bureau gradually developed UT 704 into a large UT design family, proactively considering the dynamics of the industry, which sets the highest offshore support vessel design standards. Furthermore, researchers from the Norwegian University of Science and Technology significantly contributed to the development of performance assessment models for open water offshore support vessel design (Gaspar et al. 2012; Rehn et al. 2018).

The five presented examples of real-world maritime systems demonstrate the necessity of the in-depth study of external factors in the concept ship design. This is much easier and more cost-efficient than fixing an already existing suboptimal maritime system. Such a study is especially advantageous when a vessel is a part of a complex and dynamic system, e.g., systems operated in ice-infested waters.

Incorporated in a holistic ship design approach, the performance assessment model of a vessel estimates the optimization objectives functions, considering the ship design qualities of a vessel in a specific operational context.

1.1.4 Optimization algorithms in ship design and fleet composition

According to Huang et al. (2015) and Ray et al. (1995), the ship design and fleet composition problems, as well as the similar engineering applied problems, are
the most complex to solve for optimization algorithms. This complexity is caused by 1) a nonlinear black-box model of the optimized object; 2) the need for global optimization due to a large number of local optima; 3) a well-developed system of constraints; and 4) the significant size of the design space (i.e., a high number of potential candidate solutions). A black-box model does not provide access to its internal calculation process and related metadata for an optimization algorithm, which requires an algorithm that can deal with any model.

Holistic ship design is the most complex ship design optimization problem as it simultaneously considers many design issues. In general, this can be formulated as a multi-objective mixed integer nonlinear programming (MINLP) problem with constraints. Optimization of such a problem requires maximum performance in the calculation speed and efficiency of the algorithm.

As noted by Fagerholt and Lindstad (2000), Aas et al. (2007), and Halvorsen-Weare et al. (2012), some early attempts to apply straightforward optimization algorithms, such as brute force search as well as commercial nonlinear problem solvers, required significant model simplifications for the complex system optimization to keep the calculation time reasonable. As a result, the practical utility and value of the approaches are assumed to be limited.

Table 3 presents some approaches that successfully applied different optimization algorithms to ship design and fleet composition problems. Most of these optimization algorithms are metaheuristics that have been demonstrated to enable fast and reliable optimization without significant model simplifications. Metaheuristics are universal and able to work with limited information about the studied model.

Applied metaheuristics (see Table 3) include single- and multi-objective methods based on the principles of biological evolution (e.g., Genetic and Differential evolution algorithms) or swarm intelligence (e.g., Artificial Bee Colony or Particle Swarm algorithms). The Genetic algorithm is one of the oldest metaheuristics and is implemented in many programming languages and research software (e.g., MATLAB), which explains its higher popularity than other metaheuristics.

Any multi-objective optimization approach is an adaptation of a single-objective optimization algorithm (Peri 2020). Usually, the result of multi-objective optimization is a set of Pareto-optimal solutions; for each of them, the improvement of one objective results in the deterioration of another objective.
Table 3. Optimization algorithms applied to ship design and fleet composition problems

<table>
<thead>
<tr>
<th>Publication</th>
<th>Problem scope</th>
<th>Optimization algorithm</th>
<th>Algorithm group</th>
</tr>
</thead>
<tbody>
<tr>
<td>Papanikolaou (2010)</td>
<td>Holistic approach</td>
<td>Multi-objective Genetic algorithm</td>
<td>Metaheuristic</td>
</tr>
<tr>
<td>Martins and Burgos (2011)</td>
<td>Holistic approach</td>
<td>Multi-objective Genetic algorithm</td>
<td>Metaheuristic</td>
</tr>
<tr>
<td>Choi, Rehn, and Erikstad (2017)</td>
<td>Modular ship design</td>
<td>Genetic algorithm</td>
<td>Metaheuristic</td>
</tr>
<tr>
<td>Ehlers et al. (2019)</td>
<td>Fleet composition</td>
<td>Particle Swarm algorithm</td>
<td>Metaheuristic</td>
</tr>
<tr>
<td>Peri (2020)</td>
<td>Hull form (resistance) and propulsion</td>
<td>Multi-objective Genetic and Particle Swarm algorithm</td>
<td>Metaheuristic</td>
</tr>
</tbody>
</table>

1.2 Motivation, objectives, and scope

The general aim of this dissertation is to develop a decision support framework for goal-based optimization of an Arctic offshore support fleet. This framework must consider the exploration drilling stage and the extraction stage of Arctic offshore oil and gas field development.

As noted in Section 1.1.1, a decision support tool for the exploration drilling stage is required to consider the issue of fleet sizing and composition of a chartered Arctic offshore drilling support fleet to perform several duties. Existing approaches, e.g., Fagerholt and Lindstad (2000), Halvorsen-Weare et al. (2012), and Borthen et al. (2018), are mainly applied for open water regions with significant offshore activity, and they consider the issue of monofunctional fleet optimization. The first attempts to develop methods for the optimization of an Arctic offshore support fleet are made in studies (Gauthier and Molyneux 2018; Ehlers et al. 2019) using a simplified formulation; a quantitative assessment is only provided for the transportation function (i.e., supply and crew delivery). The functionality requirements (i.e., towing, AH, safety standby, and ice management) in these models are assumed to be provided by an expert as inputs limited to simplified constraints; the fleet must have one or more vessels with specific functionality. Such experts have no consolidated opinion on the issue at hand, which can result in subjective and suboptimal assessments that do not correspond to the principles of goal-based optimization.

The development of an approach for optimization of a multifunctional Arctic offshore drilling support fleet, which includes quantitative assessment of its versatile performance in a specific operational context, is well-motivated by the highlighted research gap and the needs of the industry (RAO/CIS Offshore 2019; Gauthier and Molyneux 2018).

As noted in Section 1.1.1, the cost- and eco-efficiency of an Arctic offshore support fleet for the extraction stage of an Arctic offshore field development are mainly associated with the performance of specialized supply vessels.

Operation in ice-infested waters is related to ice resistance and corresponding loads, significantly affecting the speed and performance of a ship (Kujala et al. 2019). For that reason, the temporal and spatial dynamics of ice conditions on
a specific route make it challenging to maintain stable year-round cargo trans-
portation. Thus, even though some ship design measures (e.g., ice strengthening
of a hull, icebreaking hull form, and extra engine power) can reduce the negative
ice impact, they also can result in undesired consequences (e.g., increased light-
weight, open water resistance, building and operating costs, and reduced cargo
capacity and seakeeping performance). Another way to reduce the negative ice
impact—using icebreaking assistance, which results in extra cost (i.e., ice-
breaker fees). The conceptual design of an Arctic offshore supply vessel aims to
identify tradeoffs between different design qualities, considering internal and
external factors.

As demonstrated in Sections 1.1.2–1.1.3, the holistic approach to conceptual
ship design provides advanced and effective tools for the goal-based optimiza-
tion of vessels with different purposes. Its application is especially advantageous
for complex vessels with sophisticated operation profiles, e.g., Arctic offshore
supply vessels. However, to the author’s knowledge, there is no such approach
applicable to Arctic vessels.

An Arctic offshore support fleet optimization for the exploration drilling stage
and holistic optimization of an Arctic offshore supply vessel are mathematical
problems of significant complexity. In both cases, the objective function is com-
plex, nonlinear, highly constrained, replete with logical operators, and as a re-
sult, discontinuous and non-differentiable. Multiple local optima of the objec-
tive function further complicate the optimization process. Therefore, the stud-
ied objective function must be operated as a black box by an optimization algo-
rithm with no information about the target function. Classic optimization ap-
proaches (e.g., the simplex method and gradient descent method) can not be
applied for this optimization problem at hand, which can, however, be effi-
ciently solved by a metaheuristic optimization algorithm, as discussed in Sec-
tion 1.1.4.

Although it is known that metaheuristics are preferable for the optimization
of support vessels and fleets, there are different opinions as to which metaheu-
ristic is the most efficient for this task. A study by Karaboga and Basturk (2007)
demonstrated significant computational performance of the Artificial Bee Col-
ony (ABC) metaheuristic optimization algorithm and its ability to avoid local
minima for different multi-variable functions. The study also indicates that ABC
can outperform the Genetic Algorithm and Particle Swarm Algorithm, which are
usually applied for ship design optimization and fleet composition. Thus, there
is a strong motivation to apply the ABC algorithm for the studied optimization
problems as a viable alternative to the already applied methods.

The objectives of the thesis are as follows:

**Objective 1:** to adapt the ABC algorithm to the studied problems [PI, PIV],
including

1) the development of the ABC algorithm for a constrained integer non-
linear programming (NLP) problem [PI] and
2) the development of the multi-objective ABC algorithm for a mixed in-
teger nonlinear programming (MINLP) problem [PIV].
**Objective 2:** to develop an optimization approach for Arctic offshore drilling support fleet sizing and composition [PI, PII, PIII]. The corresponding research questions to be addressed are as follows:

1) Does a quantitative assessment of fleet functionality contribute to a systemic and integrated search for an optimal Arctic offshore drilling support fleet?
2) Does the consideration of the expected costs of accidental events significantly impact the choice of support fleet composition?
3) Is it economically beneficial to invest in safety?
4) Is it feasible to apply an ABC algorithm to optimize an Arctic offshore drilling support fleet?

**Objective 3:** to propose a parametric design model of an Arctic offshore support vessel, including

1) the development of an integrated approach to determine the ship design qualities of an Arctic offshore support vessel [PII, PIII] and
2) the verification of the developed approach using data of existing vessels [PIII].

**Objective 4:** to develop an approach and framework for holistic multi-objective optimization of Arctic offshore supply vessels [PIV, PV]. The corresponding research questions to be addressed are as follows:

1) How does the consideration of icebreaker assistance affect the optimization of an Arctic offshore supply vessel?
2) How does the assumed speed profile of an Arctic offshore supply vessel affect the outcome of the vessel optimization process?
3) How do variations in the cargo capacity parameters (e.g., deadweight or cargo deck area), discount rate, or operation period affect the optimization results?
4) Is it feasible to apply the ABC algorithm for the holistic multi-objective optimization of an Arctic vessel?

Figure 3 presents the logical connections between the aims of the thesis, publications, and objectives. The general aim of the thesis is divided into two parts: to develop a decision support framework for goal-based optimization of ① an Arctic offshore drilling support fleet and ② an Arctic offshore supply vessel. To this end, PI and PIV contribute to Objective 1 (O1) by the proposed adaptations of the ABC algorithm. Objective 2 (O2) is supported by PI, where the corresponding approach is proposed. This approach utilizes some technical ship design methods from PII and PIII. PII and PIII presented a parametric design model to achieve Objective 3 (O3). Objective 4 (O4) is supported by PIV and PV, where the corresponding approach and framework are proposed. PI also provided a basic method and a program code to adapt the ABC algorithm for multi-objective optimization in PIV. Moreover, a parametric design model from PII and PIII is included in the approach and framework presented in PIV and PV.
1.3 Limitations

The thesis scope is limited to the early conceptual stage of Arctic offshore support vessel design and fleet composition.

The Arctic offshore supply vessel optimization approach is designed to consider a vessel on a general level as a complex system operating in an external context. Thus, the design qualities of a vessel should be additionally studied in the following design stages using specialized in-depth methods for all the essential subsystems of each vessel.

Similarly, after applying the Arctic drilling support fleet optimization approach, the key performance indicators (KPIs) of the optimized fleet should be assessed by an industry expert considering specific practices and circumstances relevant to a specific offshore project. This statement is in line with the following principle: a decision support tool may not strictly determine the engineering solution, but it can provide advice.

The presented approaches assume regular Arctic offshore cargo logistics: a vessel transports supplies between a supply base and an offshore installation. Non-classic solutions (e.g., arrangement of a floating storage between a supply base and an offshore installation, service for multiple installations, or usage of a supply hovercraft in shallow water) are not considered. Long-term changes in ice conditions (e.g., due to climate change) are not specifically considered.

An optimization approach for Arctic offshore drilling support fleet sizing and composition is based on the current practice of exploration drilling only in a summer–autumn navigation period when ice conditions are the most favorable. The model considers the possibility of the interaction of an offshore installation with ice but assumes that vessels generally operate in open water. An extension
of an approach to account for year-round exploration drilling requires additional consideration of possible risks and expected costs due to damage caused by ship-ice interaction.

The hull form variation in the parametric design model of an Arctic offshore support vessel is limited to interpolation between the prototype hulls, specified for vessels depending on icebreaking capabilities. Instead, using a parametric CAD model of a hull surface for high ice-classed vessels makes it possible to optimize some local hull characteristics (e.g., the stem rake and waterline entrance angle) to improve their icebreaking performance. The parametric vessel model is applicable for vessels with the total machinery power of up to 25 000 kW. This does not include highly powerful specialized icebreakers, whose layout significantly differs from that of support vessels.

The developed design and performance models are deterministic. With this, there are promising signs of extending the functionality and reliability of the models with the introduction of stochastic models and risk-based design elements into the approach for Arctic offshore drilling support fleet sizing and composition, a parametric design model of an Arctic Offshore Support Vessel, and a model of the performance of a vessel in its operational context.
2. An optimization approach for Arctic offshore drilling support fleet sizing and composition

2.1 Performance modeling of an Arctic offshore drilling support fleet

Even though Arctic offshore exploration drilling is typically performed from July to November when ice conditions are mild, it is associated with safety, environmental, and economic risk. This is mainly related to the possibility of ice occurrence, the complexity of the operations, and the fragility of the Arctic environment. A drilling support fleet as a critical element for the development of an Arctic offshore field has a significant impact on the reliability and cost of the operations. The risks associated with Arctic offshore exploration drilling can be managed by chartering an extensive and high-quality support fleet, resulting in high fleet-related costs. In this regard, the optimal Arctic offshore drilling support fleet is a tradeoff between the risks and cost-efficiency.

An Arctic offshore drilling installation is not designed to withstand any possible ice condition in the intended region of operation during the drilling season; this would make it heavy ice-strengthened, technically complex, and very expensive. Furthermore, the installation cannot avoid ice by maneuvering in its daily operation. Ice management is provided by Arctic offshore support vessels to diminish an ice impact on an offshore drilling installation. This assistance is especially relevant at the beginning and end of a drilling period when the possibility of thick ice and iceberg occurrence is the highest.

Any offshore installation has a specified limit for the ice conditions in which it can operate. If worse ice conditions are forecasted, the installation must be relocated in advance from the drilling area to a safe location with the assistance of tugs and icebreakers. This relocation is related to significant financial loss because the exploration drilling must be repeated from the beginning. The safe operation period can be extended by chartering a high-numbered fleet of high ice-class icebreakers to improve the local ice condition around the installation (El Bakkay, Coche, and Riska 2014), which is subject to additional cost. In this regard, the optimal ice management solution is a tradeoff between the relocation consequences cost and fleet chartering cost, estimated by considering the possible ice conditions and characteristics of the installation (Keinonen 2008).
A new Artificial Bee Colony-based approach for optimizing an Arctic offshore drilling support fleet is proposed in PI. This approach utilizes a quantitative assessment of the functionality of a fleet, considering well-established offshore operation practices. The approach is based on a novel formulation of the optimization problem in hand that includes estimating the expected costs from accidents and modeling the multifunctionality (versatility) of a support vessel. It also considers offshore operation statistics and current offshore regulations and guidelines.

To the author’s knowledge, there is no existing method for Arctic offshore support fleet sizing and composition, which is able to assess its versatility (e.g., considering ice management).

The proposed approach contributes to a consistent search for an Arctic offshore drilling support fleet configuration to minimize the total expected costs, considering safety and performance constraints. This requires a limited amount of input data that is typical for the offshore operator’s practice. Thus, the study in PI aims to diminish the level of subjectivity in Arctic offshore support fleet optimization.

The mathematical problem of Arctic offshore drilling support fleet optimization is formulated in PI as follows.

Sets:

- $V$ the available set of Arctic offshore support vessels, indexed by $v$;
- $IB$ the available set of icebreakers, indexed by $ib$;
- $D$ the required duties to support the platform (i.e., towing, anchor handling, supply, firefighting, safety standby, and oil recovery), indexed by $d$;
- $N_{d}^{\min}$ the set of minimum numbers of vessels to perform duty $d$, indexed by $n_{d}^{\min}$;
- $P_{v,d}$ the set of performance capacities to execute duty $d$ by vessel $v$, indexed by $p_{v,d}$; and
- $R_{d}$ the set of performance requirements for the fleet for the successful performance of duty $d$, indexed by $r_{d}$.

Parameters:

- $C_{v,d}^{r}$ the charter cost for vessel $v$ to perform duty $d$;
- $C_{v,d}^{f}$ the fuel cost for vessel $v$ to perform duty $d$;
- $C_{v,d}^{\alpha}$ the contribution of vessel $v$ performing duty $d$ to the risk of asset loss;
- $C_{v,d}^{h}$ the contribution of vessel $v$ performing duty $d$ to the risk of human life loss; and
- $C_{ib}^{i}$ the contribution of icebreaker $ib$ to the risk of economic loss due to ice presence.

$$\alpha_{v,d} = \begin{cases} 1, & \text{if vessel } v \text{ is specified to perform duty } d \\ 0, & \text{otherwise.} \end{cases}$$
An optimization approach for Arctic offshore drilling support fleet sizing and composition

The Risk Index Outcome to consider limitations for operations in ice.

Variables:

\[ x_{v,d} = \begin{cases} 1, & \text{if vessel } v \text{ performs duty } d \\ 0, & \text{otherwise.} \end{cases} \]

\[
\min \sum_{v \in V} \sum_{d \in D} x_{v,d} (C_{v,d}^{cr} + C_{v,d}^{f} + C_{v,d}^{rh}) + \sum_{ib \in IB} C_{ib}^{ri}, \tag{1}
\]

\[
x_{v,d} \neq 1 \text{ if } \alpha_{v,d} \neq 1, v \in V, d \in D, \tag{2}
\]

\[
\sum_{v \in V} x_{v,d} \geq n_{d}^{min}, d \in D, n_{d}^{min} \in N_{d}^{min} \tag{3}
\]

\[
\sum_{v \in V} x_{v,d} P_{v,d} \geq r_{d}, v \in V, d \in D, P_{v,d} \in P_{v,d}, r_{d} \in R_{d}. \tag{4}
\]

\[
RIO_{v} \geq 0, v \in V. \tag{5}
\]

Eq. (1) estimates the total costs of operations—the objective function of fleet optimization that is minimized. The Artificial Bee Colony (ABC) algorithm (see Section 2.2) selects candidate vessels from the vessel set \( V \), containing a certain number of vessels of each predefined vessel type. A vessel is selected for a fleet configuration if it performs one duty at least.

Eq. (1) includes different risk-associated costs, the charter costs \( C_{v,d}^{cr} \), and fuel costs \( C_{v,d}^{f} \), calculated for the various duties performed by each vessel. Risks are divided into asset risks \( C_{v,d}^{ra} \), human life risks \( C_{v,d}^{rh} \), and risks related to the ice presence \( C_{ib}^{ri} \). Constraint (2) determines that every vessel \( v \) aiming to execute duty \( d \) must be able to do so.

Constraint (3) requires the minimum number of vessels \( n_{d}^{min} \) to perform a duty \( d \), and Constraint (4) defines the minimum fleet capabilities to perform a duty \( d \). Constraint (5) is introduced to consider ice-class requirements for a vessel to operate in ice using the Risk Index Outcome (RIO) (IMO 2016). Only RIO values corresponding to the “normal operation mode” (RIO \( \geq 0 \)) are accepted by default.

Constraints (3–5) represent the lower acceptable boundary of performance and safety of a fleet. The most cost-efficient fleet is selected by the ABC algorithm among the feasible solutions \( i \in I \) (\( I \) is the set of feasible fleet configurations) that satisfy the constraints, considering the expected costs from risk events. In general, the impact of the inclusion of any vessel \( v \) in \( i \) is different for various \( i \). In the provided formulation (1–5), risk management measures do not only result in additional expenses but also contribute to cost savings by avoidance of the consequences of risk events. The approach considers only risks dependent on the fleet configuration \( i \).

Risk is calculated as \( R_{i}^{k} = F_{d}^{k} E_{d}^{k} \), where \( F_{d}^{k} = f(i) \) is the frequency of a risk event and \( E_{d}^{k} = f(i) \) is the consequence of a risk event in US dollars (USD). The
individual risk contribution $C_{v,d}^k$ of an offshore support vessel or $C_{lb}^l$ of an ice-breaker in (1) is calculated as $R_d^k / \sum_{v \in V} x_{v,d}$.

The considered risks can be divided into the following: risks of asset losses, lost profit and expenses related to unscheduled operational shutdown due to ice presence, and risks to human life. Risks of asset losses are measured in repair costs or cost of new assets. Risks associated with the presence of ice are calculated as lost profit and wasted expenses due to unscheduled operational shutdown. The economics-based approach is applied to consider the risks to human life (Viscusi and Gayer 2002), which assumes that a risk management measure is motivated if the cost of preventing a fatality or injury is below their statistical values in USD, specified individually depending on the type of professional activity of an individual.

PI presents the methods to define each member of mathematical formulation (1). The developed approach considers recommendations from classification societies (Russian Maritime Register of Shipping 2014), best practices of offshore operations (Gibson 1999), offshore accident statistics for regions of operation with a harsh environment (Oil & Gas UK 2009), and descriptions of individual accidents (Health and Safety Executive 2019). Fuel consumption of vessels and parameters of supply cargo operations are calculated as per the methodologies presented in PII and PIII.

The prevailing ice condition is specified using the equivalent ice thickness ($h_{eq}$), which is determined as per Eq. (6) (CNIIMF 2014) as a function of the ice concentration ($c$), level ice thickness ($h_i$), ice ridging ($b$) (represented by the integer values from 0 to 5 that shows the share of ridged ice from 0% to 100% correspondingly), and snow thickness ($h_{sn}$):

$$h_{eq} = c (h_i + 0.25bh_i + k_{sn}h_{sn}) ,$$

where $k_{sn}$ is 0.33 if $h_{sn} < 0.5$ and 0.5 otherwise.

The approach applies different possible ice condition scenarios considering the probability of their occurrence.

### 2.2 The Artificial Bee Colony algorithm

Motivation to apply the Artificial Bee Colony (ABC) algorithm for the studied optimization problems (see Sections 2.1 and 4.1) is discussed in Sections 1.1.4 and 1.2. A novel adaptation of the ABC algorithm for the multi-objective holistic Pareto optimization of a vessel is presented in Section 4.1.

The ABC stochastic algorithm is initially proposed in a study (Karaboga and Basturk 2007) to resolve a mixed integer unconstrained optimization problem with multi-variable functions. Mixed integer optimization in the ABC algorithm applies real variables as optimization parameters when an unconstrained objective function is defined over its entire domain.

The ABC algorithm reproduces the foraging behavior of a natural honeybee colony (Tereshko and Loengarov 2005) and includes the following elements:

1. Potential food sources (passive elements),
2. Employed bees,
3. Temporary unemployed onlooker bees, and
4. Scout bees.

Each employed bee (2) moves to a random food source (1) and provides information about its quality to other bees. The quality of a food source is a complex function of the distance from the hive, calorific value, taste, and amount of energy that is necessary to expend to obtain the food. Thereafter, onlooker bees (3) aim to locate a new food source from (1) using the information acquired by the employed bees. In contrast, scout bees aim to independently find new food sources without any assistance from other bees. The activity of an onlooker or scout bee is successful when it finds a food source of better quality than that of the employed bee. In that case, the new food source replaces the original one, and an employed bee from the abandoned source becomes an onlooker bee or a scout bee correspondingly. The combined representation of the behavior of employed bees, onlooker bees, and scout bees provides the ABC algorithm with local and global search, resulting in improved optimization efficiency.

Optimization of an Arctic offshore drilling support fleet can be formulated as an integer nonlinear programming problem in constraints. Integer optimization applies integer variables as optimization parameters. Some fleet configurations can be unfeasible in constraint optimization, meaning that a function under optimization is not defined over its entire domain. To consider these features, an adaptation of the ABC algorithm to the studied optimization problem is provided in PI, where an additional penalty function is utilized to avoid undesired solutions.

Figure 4 presents a general flow chart of the ABC algorithm. A detailed description of each step of the adapted optimization process and corresponding formulas are provided in PI.

![Figure 4. A general flow chart of the Artificial Bee Colony algorithm (PIV).](image-url)
In Arctic offshore drilling support fleet optimization, each solution (i.e., an analog of a food source) consists of several non-negative integer values, representing the number of vessels of each possible type in a specific fleet configuration.

The performance model of an Arctic offshore drilling support fleet (see Section 2.2) includes a description of the function under optimization. The adapted ABC algorithm utilizes the function as a black box, which provides information about the quality and feasibility of the solution. This function estimates the quality of a specific solution in terms of cost-efficiency. A solution is considered unfeasible if the applied constraints are not satisfied. In this case, the penalty function adds extra cost to the initial cost estimation, which is much higher than the cost of any possible feasible solution. In this formulation, the ABC algorithm avoids unfeasible solutions as inefficient. Some equations of the original ABC algorithm are also modified to use non-negative integer variables instead of real variables to produce a solution.

The applied penalty function is efficient for an Arctic offshore drilling support fleet because the design space is dominated by feasible solutions. Otherwise (e.g., in holistic ship design optimization), this method can significantly reduce the optimization performance. The maximum number of vessels of a specific type is limited based on real operational practice in order to improve the efficiency of the optimization process.

The calculation stop criterion can be determined in terms of the maximum number of cycles, calculation time, or specific function value. The optimization process continues until the criterion of the calculation stop is met.

2.3 Approach applicability assessment: case studies and sensitivity analysis

An applicability assessment for the developed approach (PI) includes two case studies based on real-world offshore projects with available data on the fleet configuration obtained from (Kjøl 2014; Staalesen 2019). Case study 1 corresponds to the drilling of the Universitetskaya-1 well in 2014 in the northern Kara Sea, where ice presence is significant. Case study 2 considers drilling the Leninogradskoe oil field in 2017 in the southern Kara Sea with moderate ice. For each case study, three possible ice condition scenarios (i.e., mild, average, and severe) and two scenarios of the probability of their occurrence are considered. The first probability scenario (i.e., statistical ice conditions) assumes that the frequencies of ice conditions scenarios correspond to historical data from the period 1939–2012 (Dumanskaya 2014). The second probability scenario (i.e., mild ice conditions) considers the trend of diminishing Arctic ice conditions in the 21st century, assuming that the ice condition scenario is always mild. Besides case studies, a sensitivity analysis of the influence of specific input parameters on the optimal fleet configuration is provided.

The ABC algorithm selects the optimal fleet configurations for each case study based on detailed descriptions of 27 predefined vessel types, corresponding to the data of real-world vessels. The vessel data is manually collected using an
open-source database (Russian Maritime Register of Shipping 2020). The maximum number of vessels in the entire fleet per one vessel type is limited to ten to improve computational efficiency. The input data for the case studies are provided in PI.

The performance of the optimized fleet configurations is analyzed using spider diagrams with normalized values for the specific key performance indicators (KPIs): duty-related KPIs (i.e., towing, supply, ice management, and Fi-Fi) that represent the capacity of a fleet to perform corresponding duties, and auxiliary KPIs (i.e., DP class, fleet age, ice class, and environmental friendliness) that provide additional information on the functionality of a fleet. The values of the KPIs are calculated as per Table 4.

The towing, ice management, Fi-Fi, and dynamic positioning class (DP class) KPIs represent the capacity of a fleet to manage related risks. The fleet age and ice class KPIs reflect the average values of corresponding characteristics for a fleet configuration. The environmental friendliness KPI is the total amount of expended fuel, assumed to reflect the amount of CO₂ produced. A detailed description of the methods to calculate KPIs values is provided in PI. A KPI value above 100 indicates redundancy that cannot be utilized.

Table 4. Normalization of fleet KPIs (adapted from PI)

<table>
<thead>
<tr>
<th>KPI</th>
<th>Explanation</th>
</tr>
</thead>
<tbody>
<tr>
<td>Supply</td>
<td>A performance of 100 means that the supply-demand is fully satisfied.</td>
</tr>
<tr>
<td>DP class</td>
<td>This corresponds to the average DP class of the fleet divided by three (e.g., an average DP class value of 2 corresponds to a DP class performance of 2/3 * 100).</td>
</tr>
<tr>
<td>Ice class</td>
<td>This corresponds to the average ice class of the fleet normalized as per Table 5 (e.g., a fleet consisting of two PC 4 ships and two PC 5 ships have an ice class KPI of 68.2).</td>
</tr>
<tr>
<td>Fleet age</td>
<td>This reflects the average vessel age (assumed to reflect the operational reliability of the vessels, among others). A fleet consisting of brand-new ships would have a KPI value of 100. Each added year of age reduces the KPI value by two (e.g., an average age of 10 years corresponds to a KPI value of 80).</td>
</tr>
<tr>
<td>Environmental friendliness</td>
<td>This reflects the total amount of expended fuel, which is directly proportional to the amount of CO₂ produced. A KPI value of 100 corresponds to a reference fuel consumption of 4200 tonnes. For each additional 165 tonnes of fuel consumed, the KPI value drops by one.</td>
</tr>
<tr>
<td>Ice management</td>
<td>This corresponds to the achievable ice management strategy. A value of 1/3 * 100 corresponds to passive ice management—the installation leaves the drilling location in advance if ice forecasts indicate that a specific upper limit value of the equivalent ice thickness will be exceeded. A value of 2/3 * 100 corresponds to active ice management—reasonable measures to reduce the equivalent ice thickness are applied. A value of 100 corresponds to complete ice management—the fleet protects the drilling rig from ice and icebergs in all possible scenarios.</td>
</tr>
<tr>
<td>Towing</td>
<td>This corresponds to the expected consequences from a towing accident. A value of 1/3 * 100 indicates that any fault disabling the single tug will result in a loss of control of the installation. A value of 2/3 * 100 indicates that the fleet can prevent the complete loss of control of an installation, but a fault may nevertheless result in minor damage. A value of 100 indicates that a towing accident results in insignificant damage.</td>
</tr>
<tr>
<td>Fi-Fi</td>
<td>This corresponds to the achievable firefighting scenario. A value of 100 indicates that fire can be suppressed in the initial stage. A value of 2/3 * 100 indicates that the fire escalation can be prevented until the arrival of specialized firefighting vessels. A value of 1/3 * 100 indicates that rapid fire escalation is unavoidable, resulting in substantial damage to the installation and crew.</td>
</tr>
</tbody>
</table>

Table 5. Normalization of ice class values (PI)

<table>
<thead>
<tr>
<th>Ice class</th>
<th>Normalized value</th>
<th>Ice class</th>
<th>Normalized value</th>
</tr>
</thead>
<tbody>
<tr>
<td>PC1</td>
<td>100</td>
<td>PC7</td>
<td>100*(5/11)</td>
</tr>
<tr>
<td>PC2</td>
<td>100*(10/11)</td>
<td>IA Super</td>
<td>100*(4/11)</td>
</tr>
<tr>
<td>PC3</td>
<td>100*(9/11)</td>
<td>IA</td>
<td>100*(3/11)</td>
</tr>
<tr>
<td>PC4</td>
<td>100*(8/11)</td>
<td>IB</td>
<td>100*(2/11)</td>
</tr>
<tr>
<td>PC5</td>
<td>100*(7/11)</td>
<td>IC</td>
<td>100*(1/11)</td>
</tr>
<tr>
<td>PC 6</td>
<td>100*(6/11)</td>
<td>Below IC</td>
<td>0</td>
</tr>
</tbody>
</table>
2.3.1 Case study: Arctic offshore drilling support fleets for the northern and southern Kara Sea

Case study 1 deals with optimizing a support fleet for conditions corresponding to the drilling at the Universitetskaya-1 well. Ice conditions in the northern Kara Sea during a drilling season can be challenging: ice is often thick, and the iceberg occurrence probability is up to 0.3 (PI).

Optimization of the drilling support fleet is performed separately for the ice-going offshore support fleet and ice management fleet to increase computational efficiency. The optimization results of the fleet are presented respectively in Table 6 and Table 7. The reference ice-going offshore support fleet (see Table 6) consists of one vessel with ice class PC 3 (for safety standby) and five vessels without ice class for other duties. The optimal solution for the statistical ice conditions includes one vessel with ice class PC 3 (for safety standby), two vessels with ice class PC 4 (for anchor handling, towing, and supply), and two vessels with ice class PC 5 (for supply and firefighting).

The higher number of support vessels in the reference fleet is explained by the high redundancy of supply capacity, which is typical for the industry. The considerable difference in vessel ice class is caused by the conservative assumption of the ice conditions and conservative RIO constraint (RIO ≥ 0).

<table>
<thead>
<tr>
<th>Vessel type</th>
<th>Ice class</th>
<th>Solution 1 (statistical ice)</th>
<th>Solution 2 (mild ice)</th>
<th>Solution 3 (no ice, supply redundancy)</th>
<th>Reference</th>
</tr>
</thead>
<tbody>
<tr>
<td>Type 1</td>
<td>PC 3</td>
<td>1</td>
<td>1</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>Type 10</td>
<td>PC 4</td>
<td>2</td>
<td>1</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Type 11</td>
<td>PC 5</td>
<td>2</td>
<td>2</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Type 16</td>
<td>No</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>2</td>
</tr>
<tr>
<td>Type 17</td>
<td>No</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>2</td>
</tr>
<tr>
<td>Type 18</td>
<td>No</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Type 19</td>
<td>IC</td>
<td>0</td>
<td>1</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Type 23</td>
<td>No</td>
<td>0</td>
<td>0</td>
<td>1</td>
<td>0</td>
</tr>
<tr>
<td>Type 27</td>
<td>No</td>
<td>0</td>
<td>0</td>
<td>3</td>
<td>1</td>
</tr>
</tbody>
</table>

The second solution is optimized with the assumption of mild ice conditions and non-conservative RIO constraint (RIO > -10), meaning that elevated operational risk is acceptable. Based on these assumptions, the optimal fleet configuration includes one vessel with ice class PC 3 (for safety standby), one vessel with ice class PC 4 (for anchor handling, towing, and supply), two vessels with ice class PC 5 (for supply and firefighting), and one vessel with ice class IC (for anchor handling, towing, and supply). It is noted that even while applying non-conservative assumptions, vessels without ice class are not feasible because of the RIO constraint. The reference ice-going offshore support fleet based on vessels without ice class is appropriate for the considered case only if a reliable ice forecast predicts no ice in the area of operation. This is possible if drilling is limited to one or two of the warmest months or occurs in a year with atypically mild ice conditions in the studied location.

To better demonstrate the merits of the developed method, the optimization process is repeated using assumptions similar to those applied in practice for the real reference fleet: ice is not considered, and a specific supply redundancy
An optimization approach for Arctic offshore drilling support fleet sizing and composition

is required. Some level of supply redundancy is often considered in practice to avoid unnecessary operational downtime. The minimum supply redundancy of the reference fleet is estimated at 17%, corresponding to the supply KPI of 117 (see Table 4). Based on the applied assumptions, the optimal fleet has no ice class and consists of one vessel of Type 23 (for safety standby), two vessels of Type 18 (for towing, anchor handling, and supply), and three vessels of Type 27 (for supply and firefighting). The obtained fleet is identical to the reference fleet in terms of ice class and number of vessels.

The optimized solutions for the ice management fleet, assuming statistical and mild ice conditions (RIO > -10), and the reference fleet are presented in Table 7. The ice management fleet optimization cannot be provided for the case of no ice (solution 3), as ice management would require ice to be reasonable. However, for further analysis, the ice management fleet for solution 3 is conservatively assumed to be the same as that of optimized solution 2 (i.e., mild ice conditions) to compare the fleets consistently.

**Table 7. Reference and optimized fleet configurations of the ice management support fleet for case study 1 (adapted from PI)**

<table>
<thead>
<tr>
<th>Vessel type</th>
<th>Ice class</th>
<th>Solution 1 (statistical ice)</th>
<th>Solution 2 (mild ice)</th>
<th>Solution 3 (no ice, supply redundancy, assumed fleet)</th>
<th>Reference</th>
</tr>
</thead>
<tbody>
<tr>
<td>Type 1</td>
<td>PC 3</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>Type 7</td>
<td>PC 5</td>
<td>4</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Type 10</td>
<td>PC 4</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Type 12</td>
<td>IA Super</td>
<td>0</td>
<td>0</td>
<td>1</td>
<td>2</td>
</tr>
<tr>
<td>Type 13</td>
<td>IA</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>Type 15</td>
<td>IB</td>
<td>0</td>
<td>4</td>
<td>4</td>
<td>0</td>
</tr>
</tbody>
</table>

Two optimized ice management solutions and the reference fleet consist of five vessels, including a lead vessel with ice class PC 3. The ice classes of the auxiliary vessels are different: the fleet optimized for the statistical ice conditions has the auxiliary vessels of high ice class PC 5; the fleet optimized for the mild ice conditions has the auxiliary vessels of low ice class IB; the reference fleet is a compromise with auxiliary vessels of ice class IA–PC 4. As per PI, such fleet configurations provide the maximum protection of the drilling rig from impacts with ice and icebergs with no need to relocate the drilling rig in the assumed ice conditions.

The following analysis of the functionality of a support fleet for the four considered fleet configurations (see Figure 5) is provided for the complete support fleet (i.e., ice-going offshore support & ice management).
Figure 5. Case study 1. The functionality of the optimized fleet: a) spider diagram for the optimized fleet, solution 1; b) spider diagram for the optimized fleet, solution 2; c) spider diagram for the reference fleet; d) spider diagram for the optimized fleet, solution 3; e) the chart demonstrates the optimization progress for solution 1 (i.e., ice-going offshore support fleet). Figure 5 is adapted from PI.

The three considered fleets differ in total cost and functionality, represented by KPIs (Figure 5).

Solution 1 has a better firefighting capability, higher average ice class, and reduced CO₂ emissions than the reference fleet, but it is worse in terms of supply performance and average fleet age. Solution 2 is close to the reference fleet in KPIs but has some advantages in firefighting capability and higher average ice class; however, it is worse in terms of supply performance and average fleet age. The spider diagrams in Figure 5c and Figure 5d are identical, indicating that the optimized solution 3 and the reference fleet are equal in functionality.

The estimated total cost of the reference fleet is USD 55.1 million. Meanwhile, the total cost for solution 1 (i.e., statistical ice conditions) and solution 2 (i.e., mild ice conditions) are correspondingly estimated at USD 49.3 million (10% lower than that of the reference fleet) and USD 46.0 million (16% lower than that of the reference fleet). The total cost estimate for solution 3 (i.e., no ice, supply redundancy) is USD 48.9 million per drilling season, i.e., 11% lower than
the reference fleet, although it provides the same level of functionality. Thus, the optimized fleets provide improved cost-efficiency in all the considered cases.

Figure 6 presents the contributions of different cost categories to the objective function for optimized solution 1. Simultaneous application of the proposed spider diagrams and the total cost estimation provides useful information for decision-making that helps identify a fleet performance-to-costs tradeoff.

The chart in Figure 5e shows the optimization progress for solution 1 (i.e., ice-going offshore support fleet). Here, the ABC algorithm found the optimal solution in 21 steps, demonstrating high optimization efficiency considering a significant number of potential solutions, estimated at $6^{11} = 362797056$ based on the number of possible combinations per one vessel type (from 0 to 5) and the number of feasible vessels that satisfy the constraints (11).

![Figure 6. Contribution of different cost categories to the objective function, case study 1, optimized solution 1 (statistical ice conditions) (PI)](image)

Case study 2 (see PI) deals with optimizing a drilling support fleet for conditions corresponding to the drilling season at the Leningradskoe oil field. Ice conditions in the southern Kara Sea during a drilling season are significantly milder than those of case study 1; high concentrated thick ice is rare, and the probability of iceberg occurrence is insignificant.

The ice-going offshore support fleet optimization results for case study 2 show similar patterns to that of case study 1. The fleet optimized for the conservative statistical ice conditions has a much higher average ice class and less supply redundancy than the reference fleet. The fleet optimized for the mild ice conditions is close to the reference fleet in terms of ice class but also has less supply redundancy. An optimal fleet identical to the reference fleet in terms of ice class and functionality is obtained for the mild ice conditions when supply redundancy is required.

Ice management fleet optimization resulted in solutions similar to the reference fleet: minimum ice management with no active measures to affect the ice condition. One vessel with a high ice class provides icebreaking assistance to
safely relocate the drilling rig if ice conditions are forecast to exceed the specified limit (PI).

The estimated total cost for the reference fleet is USD 30.2 million; for the statistical ice conditions, it is USD 29.4 million; and for the mild ice conditions, it is USD 22.1 million—around 25% lower than the other considered alternatives. The total cost for the fleet with the same functionality as the reference fleet optimized for the mild ice condition is estimated at USD 24.5 million, or around 19% lower than the costs of the reference fleet.

Case studies 1 and 2 demonstrate the ability of the proposed approach to significantly optimize the cost of a fleet, assuming reliable input data, e.g., ice prognosis.

### 2.3.2 Sensitivity analysis

A sensitivity analysis for the ice-going offshore support fleet optimization is executed by varying the value of input parameters within a specific range, defined in percent of the default values (see Table 8). Each range is assumed based on the minimum and maximum feasible (realistic) value of each parameter. Different optimal solutions $s$ are indexed by $s_n$, where $n$ is the order number of a solution. A description of the input data, the vessels included in each optimal solution, and a sensitivity analysis for the ice management fleet are provided in PI.

The sensitivity analysis for the ice-going offshore support fleet assumes no sea ice because its impact on optimization results is studied in cases 1 and 2. This makes all of the 27 predefined candidate vessel types (see PI) feasible due to the absence of the constraints for operations in ice.

The sensitivity analysis results from 30 optimization experiments are provided in Table 8 and Table 9. Table 9 presents the percentual variation of the total cost of the optimal solution due to a variation in a single parameter, where 100% corresponds to the total cost of the default optimal solution.

<table>
<thead>
<tr>
<th>Value, %</th>
<th>0</th>
<th>50</th>
<th>100</th>
<th>150</th>
<th>200</th>
<th>400</th>
</tr>
</thead>
<tbody>
<tr>
<td>Risk consequences, USD</td>
<td>S2</td>
<td>S1</td>
<td>S1</td>
<td>S3</td>
<td>S3</td>
<td>-</td>
</tr>
<tr>
<td>Price of fuel, USD</td>
<td>-</td>
<td>S3</td>
<td>S1</td>
<td>S1</td>
<td>S4</td>
<td>-</td>
</tr>
<tr>
<td>Daily charter rate, USD</td>
<td>-</td>
<td>S4</td>
<td>S1</td>
<td>S1</td>
<td>S1</td>
<td>-</td>
</tr>
<tr>
<td>Cargo consumption rate, m²/month</td>
<td>-</td>
<td>S6</td>
<td>S1</td>
<td>S6</td>
<td>S7</td>
<td>-</td>
</tr>
<tr>
<td>Time of operation, days</td>
<td>-</td>
<td>S1</td>
<td>S1</td>
<td>S1</td>
<td>S4</td>
<td>-</td>
</tr>
<tr>
<td>Distance to the supply port, NM</td>
<td>-</td>
<td>S5</td>
<td>S1</td>
<td>S1</td>
<td>S1</td>
<td>S8</td>
</tr>
<tr>
<td>Cargo deck area of the installation, m²</td>
<td>-</td>
<td>S9</td>
<td>S1</td>
<td>S5</td>
<td>S5</td>
<td>-</td>
</tr>
</tbody>
</table>

### Table 8. Optimal fleet configurations ($S$) for different input parameters. The table shows the sensitivity of the optimization results to variations in parameter values (marked from green to grey—from the most sensitive to the least sensitive parameter) (adapted from PI)

<table>
<thead>
<tr>
<th>Value, %</th>
<th>0</th>
<th>50</th>
<th>100</th>
<th>150</th>
<th>200</th>
<th>400</th>
</tr>
</thead>
<tbody>
<tr>
<td>Risk consequences, USD</td>
<td>-14</td>
<td>-2</td>
<td>0</td>
<td>+1</td>
<td>+3</td>
<td>-</td>
</tr>
<tr>
<td>Price of fuel, USD</td>
<td>-9</td>
<td>0</td>
<td>+9</td>
<td>+18</td>
<td>+36</td>
<td>-</td>
</tr>
<tr>
<td>Daily charter rate, USD</td>
<td>-40</td>
<td>0</td>
<td>+39</td>
<td>+78</td>
<td>-</td>
<td></td>
</tr>
<tr>
<td>Cargo consumption rate, m²/month</td>
<td>-12</td>
<td>0</td>
<td>+13</td>
<td>+25</td>
<td>-</td>
<td></td>
</tr>
<tr>
<td>Time of operation, days</td>
<td>-41</td>
<td>0</td>
<td>+41</td>
<td>+81</td>
<td>-</td>
<td></td>
</tr>
<tr>
<td>Distance to the supply port, NM</td>
<td>-15</td>
<td>0</td>
<td>+2</td>
<td>+5</td>
<td>+32</td>
<td>-</td>
</tr>
<tr>
<td>Cargo deck area of the installation, m²</td>
<td>+16</td>
<td>0</td>
<td>-12</td>
<td>-12</td>
<td>-</td>
<td></td>
</tr>
</tbody>
</table>

### Table 9. Percentual variation of the total cost due to a variation in a single parameter (adapted from PI)
As per Table 8, the cargo consumption rate impacts the optimization results the most, followed by the fuel price, cargo deck area of the installation, risk consequences, and distance to the supply port. On the contrary, the optimization results are the least susceptible to the daily charter rate of the vessel and operation time of the installation.

Some parameter variations (e.g., the daily charter rate and time of operation) may impact the total costs significantly but have a limited effect on the optimal fleet configuration. For the default input data, charter costs are the most significant cost category. Therefore, a further increase in charter costs insignificantly affects the optimization results. A significant decrease in charter rates, on the other hand, would make other cost factors more important, resulting in a different optimal solution. The time of operation equally affects the most important components of the total cost—the fleet charter and fuel costs. As a result, time increasing up to 150% does not change the optimal fleet. Further increasing the time of operation improves the importance of other factors (e.g., the role of risk-related components), resulting in a different optimal solution.

Some parameters (e.g., the cargo deck area of the installation and voyage distance) appear to have a nonlinear effect on the estimated total costs. For the cargo deck area of the installation, this effect is the following: if the cargo deck area of the installation is higher than the maximum cargo deck area of the candidate vessels, the impact on the estimated total costs is constant. This is related to the following logistics factor: the cargo deck area of the installation limits the maximum useful cargo deck area of a vessel. For the voyage distance, the nonlinear effect may be associated with the complex interaction of the applied constraints and algorithms.

Table 8 shows that variations in risk consequences have a noticeable influence on the optimal fleet configuration. Changes in the values of the risk consequences from 0 to 200% result in various optimal fleets (e.g., S2, S1, S3). A spider diagram with safety-related KPIs is presented in Figure 7, demonstrating that S3 has a significantly higher level of safety than S2. That observation indicates that extra safety investments might be cost-effective.

![Figure 7. Safety-related KPIs for fleet configuration S1–S3 (PI).](image-url)
As demonstrated by the case studies and sensitivity analysis in Section 2.3, the presented approach may provide realistic and cost-effective solutions corresponding to the real-life Arctic offshore practice.

3. A parametric design model of an Arctic offshore support vessel

3.1 General description of the model

As demonstrated in the literature review (Chapter 1), there is no existing parametric design model for Arctic offshore support vessels. A proposed parametric design model of an Arctic offshore support vessel (see PII and PIII) calculates ship design qualities based on the set of input parameters, considering a vessel as a complex system with in-depth modeling of the performance and interaction of the subsystems. The model is developed for offshore supply vessels and anchor handling tug supply vessels with different icebreaking capabilities: from open water vessels to icebreakers.

The model considers all of the essential ship qualities and related constraints, including the following: hull geometry, hydrostatics and stability, resistance and propulsion in open water and ice, required power plant capacity, general arrangement criteria, estimations of lightweight and deadweight, cargo capacity and cargo deck area, freeboard criteria, and maximum tolerated vessel rolling in adverse weather and sea conditions.

Figure 8 presents a general flow chart of the parametric design model of an Arctic offshore support vessel. The calculation methods for phases 1–17 are presented in PII and PIII and briefly described in Section 3.2. The model combines numerical, semi-empirical, and empirical methods with preference given to the former when possible.

In order to develop the model, a support vessel database (Kondratenko and Tarovik 2020) is collected for further analysis, which contains more than 100 parameters for 115 projects of platform supply vessels and anchor-handling tug supply vessels built in 1997–2017. The database was collected from 2014 to 2018 during the author’s research study at State Maritime Technical University of St. Petersburg. The database is complemented by general arrangement drawings and lines drawings for individual open water and ice-going vessels, and other drawings of vessel subsystems. The primary sources for the data were the official websites of shipping companies, shipyards, ship equipment manufacturers, and the register of ships (Russian Maritime Register of Shipping 2020). Although
usually inaccessible for most vessels, the obtained ship design information is available for offshore support vessels. The offshore market is highly competitive and client-oriented. The detailed information on most vessels is usually deposited online to attract potential stakeholders and customers. An analysis of the database provided the necessary insight to develop a reliable model according to the modern practice of offshore support vessel design.

The assumed minimum and maximum feasible values of the input parameters provided in Table 10 are based on the database data. According to Tarovik et al. (2018), the performance and safety of an Arctic offshore vessel significantly deteriorate if its length between perpendiculars exceeds the typical linear dimensions of an offshore installation (around 100 m), which supports the applied limit. This negative effect is related to the combination of the following factors: 1) the consequences of a potential vessel-platform collision are proportional to the size of a vessel; 2) the larger ship has considerably more inertia and an increased chance of colliding the platform while maneuvering; 3) the weather window constraints for cargo operations are stricter in the case of a larger vessel to provide the same level of safety, which deteriorates the transportation efficiency. The effect of these factors is further exaggerated by the presence of ice.

The maximum draft limit corresponds to the relatively shallow water along the Northern Sea Route.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Symbol</th>
<th>min</th>
<th>max</th>
</tr>
</thead>
<tbody>
<tr>
<td>Ship type</td>
<td>-</td>
<td>Offshore supply vessel or anchor handling tug supply vessel</td>
<td></td>
</tr>
<tr>
<td>Length between perpendiculars, m</td>
<td>L&lt;sub&gt;pp&lt;/sub&gt;</td>
<td>50</td>
<td>100</td>
</tr>
<tr>
<td>Beam, m</td>
<td>B</td>
<td>13</td>
<td>25</td>
</tr>
<tr>
<td>Draft, m</td>
<td>T</td>
<td>3.5</td>
<td>9</td>
</tr>
<tr>
<td>Depth, m</td>
<td>H</td>
<td>5</td>
<td>13.5</td>
</tr>
<tr>
<td>Speed in open water, knots</td>
<td>V&lt;sub&gt;s&lt;/sub&gt;</td>
<td>6</td>
<td>25</td>
</tr>
<tr>
<td>Ice class</td>
<td>-</td>
<td>No ice class</td>
<td>Arc8</td>
</tr>
<tr>
<td>Icebreaking capability, m</td>
<td>h&lt;sub&gt;ice&lt;/sub&gt;</td>
<td>0</td>
<td>2.8</td>
</tr>
<tr>
<td>Block coefficient</td>
<td>C&lt;sub&gt;bwl&lt;/sub&gt;</td>
<td>0.57</td>
<td>0.78</td>
</tr>
</tbody>
</table>

A specific feasible range of icebreaking capability for each ice class is specified in Table 11 as per Sazonov (2010). The ice classes are defined according to the Russian Maritime Register of Shipping (RS 2015).

<table>
<thead>
<tr>
<th>Ice class</th>
<th>h&lt;sub&gt;ice&lt;/sub&gt; min</th>
<th>h&lt;sub&gt;ice&lt;/sub&gt; max</th>
</tr>
</thead>
<tbody>
<tr>
<td>No</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Ice 1</td>
<td>0</td>
<td>0.15</td>
</tr>
<tr>
<td>Ice 2</td>
<td>0</td>
<td>0.3</td>
</tr>
<tr>
<td>Ice 3</td>
<td>0</td>
<td>0.5</td>
</tr>
<tr>
<td>Arc 4</td>
<td>0.4</td>
<td>0.8</td>
</tr>
<tr>
<td>Arc 5</td>
<td>0.55</td>
<td>1.2</td>
</tr>
<tr>
<td>Arc 6</td>
<td>0.7</td>
<td>1.5</td>
</tr>
<tr>
<td>Arc 7</td>
<td>0.9</td>
<td>2</td>
</tr>
<tr>
<td>Arc 8</td>
<td>1.1</td>
<td>2.8</td>
</tr>
</tbody>
</table>

The parametric model is verified for vessels with installed machinery power of up to 24 700 kW (see Section 3.3). Estimations of the required hull volume and lightweight for vessels with an installed machinery power exceeding 24 700 kW.
A parametric design model of an Arctic offshore support vessel are not reliable enough as the layouts of very powerful vessels (e.g., specialized icebreakers) may differ from that of conventional offshore support vessels.

Figure 8. A general flow chart of the parametric design model for an Arctic offshore support vessel (PIII).

3.2 Methods for the estimation of ship design qualities

The methods for the evaluation of specific ship design qualities are described as per Figure 8. Before calculations (phases 1–2), the input parameters are checked for correspondence to (1) the feasible ranges provided in Tables 10–11 and (2) the Load Line Regulations (IMO 1966) with amendments introduced by 01.2015. All checkings in the model are implemented as constraints.

In phase 3, the ship lines drawing is obtained by linear interpolation between the parent hulls offsets based on the block coefficient as per PII. Figure 9 presents the parent hull lines drawings assumed in the model for vessels with different icebreaking capabilities. Thus, the model can create an unlimited number of different hulls, but their geometry is obtained by processing a pair of existing hulls (see PII). To the author’s knowledge, the proposed model is the first to consider the parametric hull lines variation for an ice-going vessel.
The compliance of the obtained hull form with the requirements for ice-going vessels is checked according to the Russian Maritime Register of Shipping (2015) in phases 4–5, which is applied for vessels of ice class higher than Arc 4. The checking includes a comparison of specific angles of the hull surface to the corresponding feasible value ranges.

Phase 6 calculates the hydrostatic curves (i.e., the volume displacement V, waterplane area S, transverse metacentric radius r, longitudinal metacentric radius R, the center of buoyancy coordinates Xc and Zc, the center of flotation Xf, and the wetted surface Ω) using numerical integration of the ship hull surface based on the obtained offsets as per PII. An example of the hydrostatic curves calculation result provided by the model is shown in Figure 10.

The initial selection of steering, propulsion, and thrusters configurations is provided in phase 7. The empirical equations and logical conditions are presented in PIII to define the following characteristics: the number and diameter of propellers, type of propeller (fixed or controllable pitch), type of power transmission (electric or mechanical shaft transmission), propeller arrangement (azimuth thrusters vs. conventional; with or without a Kort nozzle); and tunnel thrusters configuration. These characteristics are defined based on the data from Kondratenko and Tarovik (2020) as a function of the input parameters considering the results of the preceding calculations (phases 1–6). The propulsion configuration is considered in the estimations of propeller-hull performance and required power plant capacity.
Phase 8 estimates the towing resistance of a vessel in open water at speed $V_s$: different methods are applied depending on its ice class. For vessels of ice class up to Arc 4, Holtrop and Mennen’s method (Holtrop 1984) is used and is believed to be well suited for the corresponding hull form with a bulbous bow. Some test calculations for icebreaker-shaped hulls demonstrated that Holtrop and Mennen’s method systematically underestimates the towing resistance by 15–25%. In contrast, Dubrovin’s method (Kashtelyan et al. 1972) to estimate the towing resistance of an icebreaker is believed to be more reliable for icebreaker-shaped hulls and is applied for vessels of ice class higher than Arc 4. A novel adaptation of Dubrovin’s method is developed in PIII using regression analysis. Unlike the original method requiring manual graph processing, the obtained formulas can be effectively utilized in software for automated calculation.

The total resistance of a vessel in open water is calculated for all vessels by adding the missing components of the residual resistance to the towing resistance as per Holtrop (1984).

An algorithm to select the optimal four-bladed propeller (Phase 9) based on a three-propeller series is described in PIII. A propeller is optimized for the open-water efficiency $\eta_0$ with a constraint on the minimum propeller blade area ratio to avoid excessive cavitation in accordance with Voitkunsky (1985). The assumed vessel speed for the propeller optimization is $V_s$ (see Table 10).

The conventional series M-65 and M-85 (Voitkunsky 1985) are applied for vessels of ice class up to Arc 4. The series designed for ice-going vessels (Kaprantsve et al. 2012) is applied for vessels with an ice class higher than Arc 4. The performance estimation of a serial propeller requires calculating its thrust coefficient $K_T$ and torque coefficient $K_Q$ as a function of the advance ratio $J$ and the pitch ratio $P/D$. Corresponding equations are provided for M-65 and M-85 in Voitkunsky (1985) but are lacking for the ice-going vessel propeller series. Thus, the ice propeller performance characteristics were approximated in this study as per Eqs. (7–8) using regression analysis, where $u_s$, $v_k$, $w_k$, $x_k$, $y_k$, $z_k$, $A_i$, and $B_i$ are regression coefficients. The approximation results are shown in

**Figure 10.** A demonstration result of the hydrostatic curves calculation provided by the model. Scale: $V$, m$^3$ (1:200); $S$, m$^2$ (1:50); $r$, m (1:1); $R$, m (1:10); $X_c$, m (1:1); $Z_c$, (1:1); $X_f$, m (1:1); $\Omega$, m$^2$ (1:50).
Figure 11, where the specific points are obtained from Eqs. (7–8) are added to the original charts from Kaprantsev et al. (2012).

\[
K_T = \sum_{k=1}^{25} u_k \left( \frac{P}{D} \right)^{w_k} (J)^{w_k} + A_1 \left( \frac{P}{D} \right) + A_2 J + A_3 \tag{7}
\]

\[
K_Q = \sum_{k=1}^{25} x_k \left( \frac{P}{D} \right)^{y_k} (J)^{y_k} + B_1 \left( \frac{P}{D} \right) + B_2 J + B_3 \tag{8}
\]

\[a)\]

\[b)\]

Figure 11. The characteristics approximation of a propeller: a) for the thrust coefficient \(K_T\) and b) for the torque coefficient \(K_Q\). The calculated red points are added to the original charts adapted from Kaprantsev et al. (2012).

Eqs. (7–8) and similar equations for the conventional propeller series can be utilized to estimate the efficiency of a propeller in open water at any speed.
A parametric design model of an Arctic offshore support vessel

In phase 10, the model calculates the required power to be delivered \( (P_D) \) to propellers for the specific modes of operation: navigation in open water, navigation in limit ice conditions, and anchor handling (only for the anchor handling tug supply vessel). Ship resistance in ice conditions is estimated according to Lindqvist (1989), followed by the \( P_D \) estimation as per Sazonov (2010). A corresponding expression for the anchor handling mode is obtained in PIII.

The required capacity of a power plant is determined to provide the maximum \( P_D \) obtained for the operational modes, considering different energy consumers of a vessel. The methods included in the model can estimate the fuel consumption of a vessel for the considered operational modes.

Twenty-five general arrangement drawings of existing offshore support vessels are analyzed to obtain empirical expressions to calculate the required volumes of specific non-cargo compartments (see Figure 12): the engine room, engine control room (ECR), main switchboard (MSB), propulsion/steering gear compartment, thruster room, volume of the stern roller (for AHTS), and other spaces for auxiliary purposes. Similarly, expressions to estimate the occupied deck area by non-cargo elements (e.g., forecastle, winches and related equipment for anchor handling and towing, passages in double bulwarks, and other deck equipment) are obtained. All the volumes and areas are expressed as functions of the parameters of the corresponding vessel subsystems.

In phase 11, the cargo capacity and cargo deck area are calculated by subtracting the non-cargo elements from the total hull capacity and total deck area correspondingly.

Phases 12–13 include an algorithm to estimate the lightweight and deadweight components and corresponding gravity center coordinates based on the empirical data (i.e., 12 existing offshore support vessels).

---

**Figure 12.** Typical general arrangement of an offshore support vessel assumed in the model (PIII).
A numerical stability check is provided in phase 14 for the worst loading case: the maximum possible cargo is arranged on a deck. The iterative heuristic algorithm is used for the optimization of vessel ballasting. The model applies the constraints on near-zero trim and the minimum value of the transverse metacentric height. The final constraint (phase 16) checks the vessel rolling parameters to correspond to the requirements for operation in adverse weather and sea conditions according to IMO (2007).

### 3.3 Verification of the design model

Some performance indicators (i.e., cargo deck area, cargo capacity, deadweight, and power plant capacity) of existing vessels are compared with their estimations to verify the parametric design model of an Arctic offshore support vessel. These performance indicators are well suited to evaluate the holistic vessel design model because many vessel subsystems impact their values. The considered vessels differ significantly in size, ice class, and icebreaking capability (see Table 12), where PSV is a platform supply vessel and AHTS is an anchor handling tug supply vessel. The comparison results are presented in Table 13 and Figure 13.

#### Table 12. Parameters of the existing vessels considered in verification

<table>
<thead>
<tr>
<th>Vessel</th>
<th>Type</th>
<th>Ice class</th>
<th>Displacement, t</th>
<th>Icebreaking capability, m</th>
</tr>
</thead>
<tbody>
<tr>
<td>Bourbon Liberty 151</td>
<td>PSV</td>
<td>No ice class</td>
<td>3010</td>
<td>0</td>
</tr>
<tr>
<td>Havila Foresight</td>
<td>PSV</td>
<td>No ice class</td>
<td>8040</td>
<td>0</td>
</tr>
<tr>
<td>Normand Skipper</td>
<td>PSV</td>
<td>No ice class</td>
<td>10950</td>
<td>0</td>
</tr>
<tr>
<td>Vos Hermes</td>
<td>AHTS</td>
<td>No ice class</td>
<td>2770</td>
<td>0</td>
</tr>
<tr>
<td>Maersk Handler</td>
<td>AHTS</td>
<td>No ice class</td>
<td>5910</td>
<td>0</td>
</tr>
<tr>
<td>Normand Prosper</td>
<td>AHTS</td>
<td>No ice class</td>
<td>11400</td>
<td>0</td>
</tr>
<tr>
<td>Maersk Dispatcher</td>
<td>AHTS</td>
<td>IC</td>
<td>9420</td>
<td>0.4</td>
</tr>
<tr>
<td>Aleut</td>
<td>AHTS</td>
<td>Arc 5</td>
<td>6650</td>
<td>1.2</td>
</tr>
<tr>
<td>Yury Topchev</td>
<td>PSV</td>
<td>Arc 6</td>
<td>9600</td>
<td>1.7</td>
</tr>
<tr>
<td>Vitus Bering</td>
<td>AHTS</td>
<td>Arc 6</td>
<td>10700</td>
<td>1.5</td>
</tr>
</tbody>
</table>

#### Table 13. Results of the model verification presented as ‘actual value / estimated value’

<table>
<thead>
<tr>
<th>Vessel</th>
<th>Cargo deck area, m²</th>
<th>Cargo capacity, m³</th>
<th>Deadweight, t</th>
<th>Power plant capacity, kW</th>
</tr>
</thead>
<tbody>
<tr>
<td>Bourbon Liberty 151</td>
<td>40 / 390</td>
<td>2450 / 2460</td>
<td>1700 / 1690</td>
<td>3700 / 1800</td>
</tr>
<tr>
<td>Havila Foresight</td>
<td>1045 / 1050</td>
<td>6770 / 6750</td>
<td>4790 / 4800</td>
<td>8800 / 8400</td>
</tr>
<tr>
<td>Normand Skipper</td>
<td>1220 / 1170</td>
<td>8150 / 8130</td>
<td>6400 / 6170</td>
<td>8400 / 7500</td>
</tr>
<tr>
<td>Vos Hermes</td>
<td>340 / 310</td>
<td>1930 / 2170</td>
<td>1370 / 1410</td>
<td>3800 / 4600</td>
</tr>
<tr>
<td>Maersk Handler</td>
<td>526 / 530</td>
<td>3980 / 3580</td>
<td>2620 / 2500</td>
<td>12900 / 13000</td>
</tr>
<tr>
<td>Normand Prosper</td>
<td>760 / 870</td>
<td>7900 / 7430</td>
<td>4710 / 4500</td>
<td>24700 / 24100</td>
</tr>
<tr>
<td>Maersk Dispatcher</td>
<td>755 / 840</td>
<td>6370 / 6300</td>
<td>4050 / 4720</td>
<td>13400 / 16000</td>
</tr>
<tr>
<td>Aleut</td>
<td>600 / 600</td>
<td>6370 / 5400</td>
<td>2600 / 2700</td>
<td>14000 / 13000</td>
</tr>
<tr>
<td>Yury Topchev</td>
<td>750 / 730</td>
<td>6210 / 6190</td>
<td>3860 / 3730</td>
<td>22500 / 22200</td>
</tr>
<tr>
<td>Vitus Bering</td>
<td>710 / 840</td>
<td>no data</td>
<td>4160 / 4150</td>
<td>18000 / 18500</td>
</tr>
</tbody>
</table>

In Figure 13, the model complies with the modern offshore support design practice. The comparison shows the reasonable correspondence of the estimated performance indicators with the actual values for the considered vessels. The best agreement is noted for the deadweight parameter where the mismatch is less than 5%. The power estimation is proved to be acceptable for all vessels besides Bourbon Liberty 151, where the estimated plant capacity is more than...
A parametric design model of an Arctic offshore support vessel

twice less than the actual value. This mismatch might be explained by the atypical design of the vessel, where the significant extra power is arranged. It is noted that the general arrangement of Bourbon Liberty 151 also differs from the assumed in Figure 12: the main generators are placed in the forecastle.

Figure 13. Verification results: comparison of the parameters of existing vessels with their model estimations. Charts (a)–(c) are adapted from PIII.
4. Holistic multi-objective optimization of Arctic Offshore Supply Vessels: an approach and framework

4.1 Description of an optimization process

As demonstrated in the literature review (Chapter 1), no existing approach applies the holistic ship design optimization to Arctic vessels (e.g., Arctic offshore support vessels). In Chapter 4, an approach for holistic multi-objective design optimization of Arctic offshore supply vessels for cost- and eco-efficiency (PIV) and the corresponding framework (PV) are described. The approach includes a parametric design model of an Arctic offshore support vessel (see Chapter 3), performance assessment models for icebreaker-assisted and independently operating Arctic offshore supply vessels (see Section 4.2), and an adaptation of the single-objective ABC algorithm for holistic multi-objective ship design optimization based on the method and program code described in Section 2.1.

The optimization of an Arctic offshore supply vessel is formulated as a multi-objective mixed integer nonlinear programming (MINLP) problem. The objective of the optimization algorithm is to maximize the cost- and eco-efficiency of an Arctic offshore supply vessel. Cost-efficiency is measured using a cost-efficiency key performance indicator (CKPI)—an adapted and simplified version of RFR; eco-efficiency is measured using a novel eco-efficiency key performance indicator (EKPI)—an adapted version of EEDI (see Section 4.2). The optimization results are represented in a Pareto front: a set of Pareto-optimal vessel designs—different tradeoffs between cost- and eco-efficiency.

The quality of the Pareto optimization is usually measured by its ability to represent all design space equally. A Pareto front must be informative for a decision-maker or, in mathematical terms, homogenous with minor variations in the distances between consecutive points on the Pareto front.

A Pareto front is not sufficiently homogeneous if the value ranges of the optimization objectives differ significantly; in that case, the concentration of the Pareto points is unevenly distributed in favor of the objective with higher values.

Furthermore, a straightforward scalarization of several objective functions, meaning the step-wise solution of a single-objective optimization problem using the weighted sum method, can only result in the convex hull of the Pareto front that is not usually homogenous. Thus, the optimization algorithm must be able to find the non-convex regions of a Pareto front.
The multi-objective ABC algorithm to overcome these issues is developed in PIV. A general flow chart of the algorithm is presented in Figure 14, which includes the two main steps: a) a step-wise scalarized bi-objective optimization with a normalized objective function to provide a homogeneous convex hull of the Pareto front and b) processing non-convex regions to provide the missing points of the Pareto front, ensuring its homogeneity.

Each run of the ABC algorithm (see Figure 4) results in a Pareto front point representing a single optimal solution. The algorithm presented in Section 2.1 is adapted to the studied problem: the integer and double optimization variables are considered, and the penalty function is omitted. The problem of an Arctic offshore supply vessel optimization is highly constrained, meaning the design space is dominated by non-feasible solutions. Applying the penalty function for such a design space may result in significant time loss, searching among the unfeasible solutions.

The ABC algorithm operates the parametric design and performance assessment models of a vessel as a black box that provides data on the feasibility of a solution (i.e., the constraints check result) and estimates the cost- and eco-efficiency of the solution (see Section 4.2) for each set of inputs.

Step (a) starts from searching the values of $\text{CKPI}_{\text{min}}$ and $\text{EKPI}_{\text{min}}$ through two optimization runs with CKPI and EKPI as the optimization objective correspondingly, which results in two boundary points of the Pareto front. These values are utilized in PIV to normalize the objective function as per Eq. (9).

$$\text{Objective function} = \frac{w \cdot \text{CKPI}}{\text{CKPI}_{\text{min}}} + \frac{(1 - w) \cdot \text{EKPI}}{\text{EKPI}_{\text{min}}},$$  \ \ (9)

where $w$ is a weight factor with a value in a range from 0 to 1.
Step (a) continues with the step-wise scalarized bi-objective optimization: starting from \( w = 0 \), the algorithm adds to \( w \) the default value \( \Delta w \) step-by-step and finds an optimal solution (i.e., a new Pareto front point) while \( w < 1 \).

Step (b) of the algorithm is applied if the distance between two consecutive Pareto front convex hull points exceeds a specific limit value (i.e., the average distance + specific percentage \( \times \) average distance). In this case, optimization is repeated for non-convex regions of the Pareto front; an additional constraint for either of the objectives is introduced to consider only the range between the points. The algorithm divides the range into two halves and optimizes the unconstrained objective for each half of the range, resulting in two new Pareto front points. This process is repeated to provide an informative Pareto front until the distance between all the points within the initial range is acceptable.

A novel object-oriented framework for the multi-objective optimization of Arctic offshore supply vessels (see PV) applies the approach presented in Chapter 4. A Business Process Model Notation 2.0 (BPMN) diagram is presented in Figure 15, illustrating the optimization process implemented in the framework. The parametric model of a vessel (Chapter 3) creates its information model—an object of class named TVessel with all the necessary data stored to use in the following calculation steps. As per Figure 15, the ABC processes only feasible solutions that satisfy the constraints imposed by the parametric model and performance assessment models of a vessel.

![Figure 15. A BPMN process diagram for the object-oriented vessel optimization framework (adapted from PV).](image-url)
4.2 Performance assessment model for an Arctic Offshore Supply Vessel

A novel performance assessment model for an Arctic offshore supply vessel presented in PIV evaluates the cost- and eco-efficiency of a vessel according to the flow chart provided in Figure 16. The module decomposition of the model is presented in Figure 17. Based on an estimate of the ship design qualities of a vessel provided by the parametric vessel design model (see Section 3), the performance assessment model calculates the vessel key performance indicators (KPIs) considering a specific operational context defined by the parameters presented in Figure 17.

![Figure 16](image1.png)

Figure 16. A flow chart of the vessel evaluation process (PIV).

![Figure 17](image2.png)

Figure 17. A module decomposition of the performance assessment model (PIV) of a vessel. The color reflects the module category: gray—technical, red—safety, green—environment and emissions, and blue—economics. A bold frame highlights the modules of most importance for the model.

CKPI is calculated as per Eq. (10) (PIV) when an Arctic offshore supply vessel is assumed to operate year-round with the option to call for icebreaker assistance in challenging ice conditions. The present worth (PW)—the value of future cash
flows discounted to the present (see PIV)—in Eq. (10) is calculated with the following assumptions: 1) a vessel is bought at the beginning of the offshore project and 2) a vessel is sold at the end of the offshore project considering its decreased price due to aging.

Consideration of the resale value of a vessel significantly impacts its overall cost efficiency as a part of the offshore project. An offshore supply vessel is usually sold many times during the lifecycle at a reasonable price. Unconsidered size-dependent cost categories, such as insurance, maintenance, and port fees, are assumed to have limited influence on the optimization results because of the size constraints of an offshore support vessel (see Table 10).

\[
\sigma \left( \sum_{n} \left( \text{PW(Operating costs)} + \text{PW(Ship acquisition costs)} - \text{PW(Ship sale income)} \right) \right)
\]

\[
\sum_{n} \left( N_v C_{\text{cap}} \right)
\]

where \( n \) is the operation period (years); \( N_v \) is the number of voyages per year; and \( C_{\text{cap}} \) is the cargo capacity parameter (tonnes).

The operating costs are calculated as the sum of the fuel and icebreaker assistance costs. The price of icebreaker assistance per nautical mile is calculated according to the Federal Tariff Service (2014) with an inflation adjustment.

A novel feature of the developed performance assessment model is that two different options for a cargo flow structure are considered. The cargo flow structure significantly impacts the efficiency of supply transportation. If most of the cargo is deck cargo (transported on the cargo deck of a vessel), the cargo capacity parameter \( C_{\text{cap}} = S_d \cdot m_{dc} \), \( S_d \) (m²) is the vessel cargo deck area, and \( m_{dc} \) is the average density of the deck cargo (tonnes/m²). If most of the cargo is carried within the hull (e.g., when a supply vessel delivers the fuel for an installation), the cargo capacity parameter is \( C_{\text{cap}} = \text{deadweight} \).

EKPI—a novel adaptation of the original EEDI formula by the IMO (2018) proposed in PIV and calculated as per Eq. (11)—unlike the original EEDI formula, does not consider ship size-specific coefficients and calculates the fuel consumption of a vessel as a nonlinear function of the total installed power.

In contrast, the performance assessment model calculates the fuel consumption of a vessel by considering its total lifecycle and corresponding engine loads. The approach described below makes it possible to define EKPI and CKPI across different vessel sizes.

\[
\text{EKPI} = \frac{\text{Fuel consumption per hour} \cdot C_F}{C_{\text{cap}} \text{ Average speed}},
\]

where \( C_F \) is the coefficient that converts the fuel consumption to CO₂ emissions; \( C_{\text{cap}}^* \) is the cargo capacity parameter for EKPI (tonnes); and \( C_{\text{cap}}^* = S_d \cdot m_{dc} \) if most of the cargo is deck cargo and \( C_{\text{cap}}^* = f_i \cdot \text{deadweight} \) if most of the cargo is carried within the hull, \( f_i \) is the correction factor for ice-classed ships (IMO 2018).

The so-called h-v curve is often applied to model vessel speed in level ice as a function of ice thickness at constant engine load (Bergström, Erikstad, and Ehlers 2016). This curve is usually specified for the maximum continuous rating.
Holistic multi-objective optimization of Arctic Offshore Supply Vessels: an approach and framework

(MCR) of a vessel, corresponding to its maximum attainable speed in specific ice conditions. The assumption of moving at MCR in any possible ice condition results in an acceptable estimation of the speed profile and fuel consumption for vessels with power plant capacity determined for open water operation mode (e.g., low ice-class vessels, large high-speed and high ice-class vessels, including Arctic LNG carriers or containerships). For these vessels, the power consumption at cruising speed in open water is close to the maximum continuous rating.

On the contrary, small- and medium-sized vessels with a high ice class, such as Arctic offshore supply vessels, have a significant power reserve for icebreaking: the capacity of their power plant is significantly higher than required for a reasonable speed in open water. Therefore, assuming continuous operations as per an h-v curve specified for the MCR for such vessels can result in an unrealistic speed profile and overestimated fuel consumption.

A novel alternative approach to model the speed profile and fuel consumption of an Arctic supply vessel is proposed in PIV. The approach is based on applying a dimensionless quadratic polynomial approximation of an h-v curve (Eq. 12) derived using the data provided in Brovin and Klyachkin (1997). This approximation provides an h-v curve for any specific power output j based on three parameters: attained open water speed $V_{\text{max},j}$, icebreaking capability $h_{\text{ice},j}$, and the speed $V_{0,j} = 2$ knots corresponding to $h_{\text{ice},j}$. The prevailing ice conditions are modeled in terms of an equivalent ice thickness $h_{\text{eq}}$ as per Eq. (6). $V_{\text{max},j}$ and $h_{\text{ice},j}$ for the power output j are calculated according to the methods developed in PII and PIII (see Section 3).

$$V_l = V_{0,j} + \left(1 - 1.7306 \left(\frac{h_{\text{eq}}}{h_{\text{ice},j}}\right) + 0.7306 \left(\frac{h_{\text{eq}}}{h_{\text{ice},j}}\right)^2\right) (V_{\text{max},j} - V_{0,j}), \quad (12)$$

where $V_l$ is a vessel speed in ice with an equivalent ice thickness of $h_{\text{eq}}$ using the power output j.

The approach applies a heuristic algorithm (see Figure 18) and the dimensionless approximation of an h-v curve to model the speed profile of a vessel.
Holistic multi-objective optimization of Arctic Offshore Supply Vessels: an approach and framework

Figure 18. The algorithm to model the speed profile of a vessel in a voyage (PIV).

As per the algorithm, the maximum attainable speed (at MCR) for a vessel without icebreaking assistance is evaluated at every change in ice condition. If the attainable speed is lower than its open water cruising speed, the vessel moves at the maximum attainable speed at MCR. Otherwise, a new h-v curve specified for a lower engine load—i.e., the required power for operating at the cruising speed in open water—is drawn, and the vessel sails at the attainable speed as per the updated h-v curve in the prevailing equivalent ice thickness. According to the proposed algorithm, the vessel utilizes MCR only in heavy ice conditions, enabling moderate speed and reduced fuel consumption in ice and open water.

The algorithm is assumed to provide realistic fuel consumption estimations for a fair comparison of vessels with different icebreaking capabilities. The vessel cruising speed in open water is included among the optimization parameters, which customizes the algorithm for a specific vessel.

The performance assessment model for a vessel considers the possibility of obtaining icebreaking assistance in difficult ice conditions to extend the design space by vessels with moderate icebreaking capabilities. An icebreaker helps a vessel to break through extreme ice conditions and to increase the speed of a vessel using the constant power output.

The speed of an icebreaker-assisted vessel is calculated as in Buzuev et al. (1988) as a function of the attainable speed of an icebreaker, approximated by Eq. (12), the navigational season (summer–autumn/winter–spring), and the ice class of the assisted vessel. This applied methodology (Buzuev, et al. 1988) is based on the experience of icebreaking assistance along the Northern Sea Route.

Due to limited number of icebreakers, it is not relevant to assume year-round icebreaking assistance of all considered Arctic offshore supply vessels. The optimization of icebreaking assistance in a voyage for cost-efficiency is provided...
in the model: its optimal level depends on the icebreaking capability of a vessel. The eco-efficiency is not considered in this optimization because icebreakers are assumed to be nuclear-powered with limited CO₂ emissions, meaning that a EKPI optimized solution is always year-round icebreaker-assisted. The algorithm decides whether a ship calls for icebreaker assistance for each voyage based on an assessment of the total operating costs (i.e., the sum of the fuel and icebreaker assistance costs).

The important outcome of the model that impacts cost- and eco-efficiency is an estimate of the total annual fuel consumption of a vessel (Eq. 13).

\[
\text{Fuel consumption} = \sum_{m=1}^{12} N_m \left( \sum_{s=1}^{s_{\text{max}}} \sum_{i=1}^{i_{\text{max}}} F_{m,s,i} P_{m,s,i} + F_{\text{CO}} \right),
\]

where \( m \) is the month number; \( N_m \) is the average number of voyages per month \( m \); \( s \) is the number of a route segment; \( s_{\text{max}} \) is the number of segments along the route; \( i \) is the ice condition type number corresponding to the equivalent ice thickness range; \( i_{\text{max}} \) is the number of different types of ice conditions occurring along the segment \( s \); \( F_{m,s,i} \) is the fuel consumption in month \( m \) for segment \( s \) in ice condition \( i \); \( P_{m,s,i} \) is the probability of occurrence of ice conditions of type \( i \) along the route segment \( s \) in month \( m \); and \( F_{\text{CO}} \) is the fuel consumption for cargo operations. An example of the input data for the calculation is presented in Section 4.3.

The values of \( N_m \) and \( F_{m,s,i} \) are evaluated using the proposed approach to model the speed profile of an Arctic supply vessel, considering the results of the ice-breaking assistance optimization. The total duration of offshore cargo operations is calculated as per PIII. The fuel consumption per hour (see Eq. 11) is calculated by dividing the annual fuel consumption (see Eq. 13) by the total annual operating hours.

### 4.3 Optimization of an offshore supply vessel design for the Kara Sea

The series of optimization studies presented in PIV demonstrates the applicability and merits of the approach in optimizing an Arctic offshore supply vessel for year-round operation in the northern Kara Sea. The supply is assumed to be transported from the port of Murmansk to the undeveloped Pobeda field located in harsh ice conditions (see Figure 19). The corresponding route in ice is divided into segments less than 100 nautical miles in length to consider the spatial heterogeneity of the ice condition. This spatial resolution is believed to be detailed enough to reliably estimate the performance of a supply vessel in the studied region.

The equivalent ice thickness for each segment is modeled as per Eq. (6) based on historical ice data (Arctic and Antarctic Research Institute 2020; Shalina and Sandven 2018; Dumanskaya 2014), accounting for the period 1998–2020 with a temporal resolution of one month.
Holistic multi-objective optimization of Arctic Offshore Supply Vessels: an approach and framework

Figure 19. The assumed route between the supply port Murmansk to the Pobeda field (a) and an example of the corresponding monthly ice chart (b). Graph (c) presents the probability distribution of equivalent ice thickness per different ranges for the route segment 4–5 in March (PIV).

The data on prevailing ice conditions are derived by the manual processing of the ice charts for each segment, assuming that vessels can make minor deviations from the initial route to avoid the most challenging local ice conditions. The ice thickness probability distributions for each month and route segment \( p_{m,s,i} \) (see Eq. 13) are determined based on the processed ice data. An example of such distribution for the segment 4–5 in March is presented in Figure 19 (c). The performance of a vessel at each segment is calculated based on the average ice thickness of a thickness range.

The case studies analyze the sensitivity of the Pareto front vessels to the following settings: 1) cargo capacity parameter (i.e., cargo is mainly carried on deck or within the hull); 2) algorithm to control the speed profile of a vessel (activated/deactivated); 3) availability of icebreaking assistance (Yes/No); 4) discount rate (%); and 5) operation period (years). It is assumed that the icebreaking capability \( h_{icw} \) of a vessel limits the maximum equivalent ice thickness in which it can operate.

The optimization results for case study 1 (i.e., the cargo is mainly carried on deck; the speed control is active; an icebreaker is available; the discount rate is 12%; and the operation period is 20 years) and case study 2 (i.e., the same as case 1, but the cargo is mainly carried within the hull) are presented in Figure 20. In this and other conducted case studies, the Pareto front is smooth, non-convex in general, and close to equidistant (for the convex and non-convex regions of the Pareto front).
Holistic multi-objective optimization of Arctic Offshore Supply Vessels: an approach and framework

The characteristics of the boundary solutions (Min CKPI and Min EKPI) and the intermediate solution for case studies 1–2 are presented in Tables 14–15. The parametric vessel design model determines the waterline length as a function of $L_{pp}$ and a hull form. The utilization of IB assistance is the ratio of the total distance covered with the icebreaker to the total covered distance.

The vessels in Table 14 (case study 1) have a similar waterline length, block coefficient, and ice class, while other characteristics are different. It is noted that the constraint on the maximum $L_{pp}$ (see Table 10) restricts the waterline length, while ice conditions on the route limit the minimum value of ice class. The algorithm determined the block coefficient as a tradeoff between the icebreaking performance and deadweight of a vessel.

![Figure 20. Optimization results for case study 1 (a) and 2 (b). The black points represent the Pareto front; the blue points represent other feasible solutions; and the yellow points present the performance of the Pareto front vessels if the vessels operate at maximum speed (PIV).](image)

**Table 14.** Characteristics of selected vessels from the Pareto front, case study 1 (adapted from PIV)

<table>
<thead>
<tr>
<th>Case study 1:</th>
<th>Cargo is mainly carried within the hull</th>
</tr>
</thead>
<tbody>
<tr>
<td>Caption</td>
<td>Min CKPI</td>
</tr>
<tr>
<td>Waterline length, m</td>
<td>110.5</td>
</tr>
<tr>
<td>B, m</td>
<td>18.4</td>
</tr>
<tr>
<td>T, m</td>
<td>7</td>
</tr>
<tr>
<td>Displacement, t</td>
<td>9230</td>
</tr>
<tr>
<td>$C_b$</td>
<td>0.635</td>
</tr>
<tr>
<td>Power plant capacity, kW</td>
<td>6070</td>
</tr>
<tr>
<td>$V_s$, kn</td>
<td>13.4</td>
</tr>
<tr>
<td>Ice class</td>
<td>Arc 5</td>
</tr>
<tr>
<td>$h_{ice}$, m</td>
<td>0.84</td>
</tr>
<tr>
<td>Utilization of IB assistance</td>
<td>0.034</td>
</tr>
<tr>
<td>Deadweight, t</td>
<td>4860</td>
</tr>
<tr>
<td>Cargo deck area, m²</td>
<td>850</td>
</tr>
</tbody>
</table>

The increased weight of EKPI for the objective function naturally results in solutions with lower fuel consumption per unit of transported cargo for all the case studies. The corresponding vessel designs are more expensive and significantly larger, measured in B, T, Dw, and displacement. EKPI-oriented supply vessels also have lower cruising speeds that reduce emissions in open water and most ice conditions as per the applied speed control algorithm.
Figure 21 demonstrates how the monthly utilization of IB assistance is changing throughout the year for two specific vessels optimized for Min CKPI and Min EKPI correspondingly.

Table 15. Characteristics of selected vessels from the Pareto front, case study 2 (adapted from PIV)

<table>
<thead>
<tr>
<th>Case study 2:</th>
<th>Cargo is mainly carried on deck</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Caption</strong></td>
<td><strong>Min CKPI</strong></td>
</tr>
<tr>
<td>Waterline length, m</td>
<td>109.6</td>
</tr>
<tr>
<td>B, m</td>
<td>18.3</td>
</tr>
<tr>
<td>T, m</td>
<td>4.6</td>
</tr>
<tr>
<td>Displacement, t</td>
<td>5930</td>
</tr>
<tr>
<td>Cbwl 0.625</td>
<td>0.625</td>
</tr>
<tr>
<td>Power plant capacity, kW</td>
<td>6520</td>
</tr>
<tr>
<td>Vm, kn</td>
<td>14.5</td>
</tr>
<tr>
<td>Ice class</td>
<td>Arc 5</td>
</tr>
<tr>
<td>hice, m</td>
<td>0.92</td>
</tr>
<tr>
<td>Utilization of IB assistance</td>
<td>0.027</td>
</tr>
<tr>
<td>Deadweight, t</td>
<td>2670</td>
</tr>
<tr>
<td>Cargo deck area, m²</td>
<td>840</td>
</tr>
</tbody>
</table>

The maximum utilization of icebreaker assistance is applied from February to May for both vessels corresponding to the most challenging ice conditions. The vessel optimized for CKPI has a higher ice-breaking capability (hice) and uses the icebreaker assistance less frequently to diminish costs for icebreaker assistance. The eco-efficient vessel (Min EKPI) has a more frequent need for the icebreaker to save fuel and limit the capacity of its power plant, resulting in a lower light-weight and increased Dw.

The cargo capacity parameter has a significant impact on the optimization results. The optimal vessels in case study 2 are significantly smaller and flatter, with lower deadweight, hull cargo capacity (m³), draft, and block coefficient than in case study 1. The cargo deck area of a supply vessel is associated mainly with the waterline length and beam. Thus, in case 2, the optimization algorithm minimizes other particulars while design constraints are satisfied. Figure 22 presents the optimal hulls developed by the model for the intermediate solutions of case studies 1 and 2 (see Tables 14–15).

The optimal supply vessels in case 2 mainly have ice class Arc 5, except for Arc 8 vessels with an icebreaking capability near 2.5 m and a cruising speed of less than 6.5 knots. They are obtained by assuming the objective function with a high
weight of EKPI (e.g., Min EKPI vessel in Table 15, marked in yellow). These theoretical solutions must be excluded from the Pareto front as their power plant capacities significantly exceed the verified range of the model for reliable layout estimations (see 3.1). However, their further study is helpful to analyze how the algorithm controlling the speed profile of a vessel impacts the optimization results.

The obtained Arc 8 vessels have a high icebreaking capability, resulting in low power consumption in ice for independent operation and operation under icebreaker assistance. The algorithm significantly constrained the maximum operation speed to decrease fuel consumption in open water and ice. This strategy provides the best EKPI values in case study 2, but the corresponding CKPI values are extremely high. Therefore, these designs form a separate group of points in the Pareto front, standing far from the other vessels in the right-down corner of the chart (see Figure 20).

Additional calculations are conducted for all the Pareto optimal vessels in case studies 1 and 2 (black points in Figure 20) to demonstrate how the algorithm to control the speed profile of a vessel impacts their efficiency. New EKPI and CKPI values (yellow points in Figure 20) are calculated for these solutions, assuming that speed control is deactivated, meaning that all vessels operate at the maximum attained speed regardless of the ice conditions.

Figure 20 shows that the yellow points are located much higher than the original Pareto front, indicating a significant efficiency reduction for both case studies. Besides this, the shape of the curve formed by the yellow points is different from the shape of the Pareto front, meaning that some vessels are less efficient than others while operating at maximum speed: they would be compared unfairly without the power control algorithm. This conclusion is especially relevant for vessels of ice class Arc 8, which have a very high machinery power to provide the required icebreaking capability, resulting in significant fuel consumption if the vessels operate at maximum speed. Thus, optimizing an Arctic offshore supply vessel with the assumption of operating at the maximum attainable speed is not reasonable as the optimal speed in specific conditions is significantly different for different vessels.
Case 3 is calculated using the inputs of case 2 but assuming that the icebreaker is unavailable. The optimization results are shown in Figure 23; some optimal vessels (e.g., Min CKPI, Min EKPI, and intermediate) are presented in Table 16. The optimal vessels have ice class Arc 7 and Arc 8 because vessels of lower ice classes do not guarantee safe year-round, independent operation in the considered ice conditions.

Figure 23. Optimization results for Case 3 (where icebreaking assistance is not available). The black points show the Pareto front; the blue points show other feasible solutions (PIV).

Table 16. Characteristics of selected vessels from the Pareto front, case study 3 (adapted from PIV)

<table>
<thead>
<tr>
<th>Case study 3: Icebreaking assistance is not available</th>
<th>Min CKPI</th>
<th>Intermediate</th>
<th>Min EKPI</th>
</tr>
</thead>
<tbody>
<tr>
<td>Caption</td>
<td>Waterline length, m</td>
<td>108.8</td>
<td>106.4</td>
</tr>
<tr>
<td></td>
<td>B, m</td>
<td>20</td>
<td>24.7</td>
</tr>
<tr>
<td></td>
<td>T, m</td>
<td>5</td>
<td>6.7</td>
</tr>
<tr>
<td></td>
<td>Displacement, t</td>
<td>6867</td>
<td>10833</td>
</tr>
<tr>
<td></td>
<td>Cbw1</td>
<td>0.617</td>
<td>0.597</td>
</tr>
<tr>
<td></td>
<td>Power plant capacity, kW</td>
<td>21082</td>
<td>23869</td>
</tr>
<tr>
<td></td>
<td>V, kn</td>
<td>15</td>
<td>13</td>
</tr>
<tr>
<td></td>
<td>Ice class</td>
<td>8</td>
<td>8</td>
</tr>
<tr>
<td></td>
<td>hice, m</td>
<td>1.84</td>
<td>1.87</td>
</tr>
<tr>
<td></td>
<td>Utilization of IB assistance</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td></td>
<td>Deadweight, t</td>
<td>1801</td>
<td>3187</td>
</tr>
<tr>
<td></td>
<td>Cargo deck area, m²</td>
<td>991</td>
<td>1408</td>
</tr>
</tbody>
</table>

Compared with Case 2, the Pareto-optimal vessels in case 3 have significantly reduced efficiency in terms of CKPI and EKPI, highlighting the importance of icebreaking assistance. As demonstrated in Figure 21, the optimal amount of icebreaking assistance is different for different vessels, highlighting the importance of icebreaking assistance optimization to ensure fair consideration of all feasible vessel designs.

Optimization experiments with variations of the discount rate and operation period (see PIV) demonstrated their moderate impact on the characteristics of the Pareto optimal vessels. The discount rate variation resulted in up to a 6% average change in some vessel design characteristics. The variation of the period of operation resulted in up to 13% of the corresponding change. The presented change values are averaged for all the Pareto front vessels, but it is noted that the boundary solutions are affected the least.
The thesis aims to advance the existing methods for goal-based optimization of an Arctic fleet, specifically an Arctic offshore support fleet. The proposed approaches and framework consider issues related to the exploration and extraction stages of the development of Arctic offshore oil and gas fields. A review of the state-of-the-art methods to optimize the ice-going offshore support fleet is presented in Chapter 1, where the corresponding research gaps and needs of the industry are identified.

The existing methods for offshore support fleet sizing and composition as well as for the goal-based design and optimization of offshore support vessels are mainly limited to open water application.

As demonstrated in the literature survey (see Chapter 1), a few methods (Gauthier and Molyneux 2018; Ehlers et al. 2019) are applicable for Arctic offshore support fleet optimization with its unique technical and organizational features of operation in ice-infested waters with undeveloped infrastructure.

These methods assume that the expert from the industry provides most fleet functionality requirements as input data in the form of simplified constraints (i.e., minimum required number of vessels with specific characteristics), which mainly reduces the problem to the optimization of a monofunctional supply fleet in constraints. Although such approaches can provide satisfactory solutions, the results might be suboptimal due to significant subjectivity in the constraints formulation and limited design space.

The proposed goal-based method for Arctic offshore drilling support fleet sizing and composition (Chapter 2) provides for optimization of an Arctic offshore drilling support fleet based on a quantitative assessment of its multifunctional performance. In the proposed method, a fleet is optimized for cost-efficiency, considering the versatility of support vessels and the expected costs of accidental events. The method considers all essential duties of the Arctic offshore support fleet, including ice management. The applied system of constraints is case-sensible and represents the lower acceptable boundary of performance and safety of a fleet, while the need for additional performance is decided in the optimization routine.

The presented case studies showed the significant capability of the approach to reduce the fleet operation cost compared to the reference solution. They also demonstrate the significant impact of the risk-related cost consideration on the obtained optimal solution. In this respect, we found that there is often an economic motivation to invest in a fleet with good safety performance. The high
performance, efficiency, and robustness of the ABC algorithm for an Arctic offshore drilling support fleet optimization are demonstrated in several case studies of significant complexity.

As a result, the novel goal-based method extends the design space and reduces subjectivity in Arctic offshore drilling support fleet optimization. To the author's knowledge, the present study is the first to apply the Artificial Bee Colony algorithm to the offshore support fleet sizing and composition problem (Section 2.2).

As discussed in Chapter 1, the holistic ship design optimization approach is an advanced tool to find effective solutions in conceptual ship design. The advantages of its application rise proportional to the complexity of a vessel and its operational context. Applying the holistic ship design optimization approach to Arctic offshore supply vessels is promising due to their significant complexity caused by offshore- and ice-related challenges. Again, to the author’s knowledge, there is no holistic ship design optimization approach for Arctic (ice-going) vessels.

Offshore field development in the Arctic is associated with high cost and ecological concerns. In this regard, the holistic multi-objective design approach and framework for the optimization of Arctic offshore supply vessels for cost- and eco-efficiency are developed (in Chapter 4), including a parametric model of a corresponding vessel (in Chapter 3), performance assessment models, and a novel adaptation of the single-objective ABC algorithm for the optimization problem at hand.

As demonstrated in the literature review (Chapter 1), there is no existing parametric design model for Arctic offshore support vessels. The model to estimate ship design qualities of an Arctic offshore support vessel is proposed in Chapter 3. The proposed model is believed to be the first to consider the parametric hull lines variation for an ice-going vessel in the optimization context.

An extensive database of existing offshore support vessel characteristics and drawings (Kondratenko and Tarovik 2020) was collected to support the reliability and validity of a parametric design model for an Arctic offshore support vessel. The novel database provides information on different ship design qualities that helped develop a parametric design model for an offshore support vessel in line with modern design practice.

The novel adaptations of two existing Arctic vessel design methods, namely Dubrovin’s method to estimate towing resistance and the Krylov State Research Centre’s ice-going propeller design method, are provided. The original versions of the methods only support manual application, meaning that they can not be applied in automatic calculations. The presented adaptations can be effectively used in holistic optimization with a significant number of considered vessel designs.

EEDI is widely applied to measure the ecological efficiency of vessels, estimating CO₂ emissions of a vessel as a linear function of its total installed power. However, according to Trivyza, Rentizelas, and Theotokatos (2020), CO₂ emission estimations based on direct calculations of the lifetime fuel consumption of a vessel are more accurate. Furthermore, EEDI might significantly overestimate
CO₂ emissions for vessels with a high reserve capacity power plant, such as with medium- and small-size ice-going vessels. For this reason, a novel Eco-efficiency Key Performance Indicator measuring the amount of lifetime CO₂ emissions per unit of transport work is proposed as one of the optimization objectives in Section 4.2.

Although an assumption that a vessel is moving at the maximum attainable speed is often applied in Arctic transportation research (Bergström, Erikstad, and Ehlers 2016; Topaj et al. 2019), it is not reasonable for use with Arctic support vessels that mainly operate at speeds almost twice lower than the maximum attainable speed. A novel approach to model the speed profile and fuel consumption for an independent and icebreaker-assisted Arctic offshore supply vessel is presented in Section 4.2. The approach applies a dimensionless quadratic polynomial approximation of an h-v curve, which, when combined with the parametric vessel design model, can calculate fuel consumption at any speed for different ice conditions.

Vessel operation parameters must be considered in optimization alongside its design parameters to provide a holistic optimization of an Arctic offshore support vessel. For that reason, optimization of vessel speed and icebreaking assistance for each voyage is provided, and different methods of cargo arrangement on a vessel are considered in Chapter 4. The proposed model is believed to be the first to consider optimization of speed profile and icebreaking assistance in the conceptual design of Arctic ships.

As the case studies demonstrate, the optimal speed and amount of icebreaking assistance are different for different vessels. Together with a preferred method of cargo arrangement, they significantly affect the optimal vessel design and motivate the holistic optimization of Arctic offshore supply vessels. The Artificial Bee Colony algorithm applied in holistic ship design for the first time in the present study (Section 4.1) demonstrated high efficiency and performance for the multi-objective optimization problem at hand.

The reliability and validity of the developed approaches are supported by verifications and sensitivity analyses provided in Section 2.3, 3.3, and 4.3. The derived models and findings can be utilized to develop new holistic optimization models for similar Arctic and open water vessels, e.g., wind farm service vessels, offshore construction vessels, and diving support vessels.

However, the presented models have some limitations: 1) all the proposed algorithms are deterministic, meaning that they do not consider the influence of the stochastic weather factors on the optimization results; 2) the consequences of potential ice damage to ships and installations are not considered; 3) the algorithms are based on conventional Arctic offshore supply logistics, namely supply transportation between the supply base and an installation by a conventional Arctic supply vessel. Moreover, potential alternatives are not considered; 4) the functionality of a drilling support fleet is assessed using discrete scenario-based models that, to some degree, limit the practical value of the approach; and 5) the proposed EKPI is a simplified cost-efficiency indicator that does not consider some cost and income components.
6. Conclusions

The presented approaches and framework for goal-based optimization of Arctic offshore support vessels and fleets contribute to developing competitive solutions in conceptual design.

An Artificial Bee Colony-based cost-efficiency optimization approach for Arctic offshore drilling support fleet sizing and composition is proposed. The approach provides a quantitative assessment of the functionality of a fleet. It considers the combined effect of (1) the expected costs of accidental events (i.e., the equivalent costs related to human injuries and loss of life and direct economic losses due to production downtime and asset damages), (2) the versatility of individual support vessels, and (3) the management of sea ice. As per the conducted case studies and sensitivity analysis, the approach provides a systematic and objective search for a support fleet configuration that minimizes the overall expected costs while meeting set system criteria.

An approach and framework for holistic multi-objective optimization of Arctic offshore supply vessels are also proposed. The approach combines a parametric design model of an Arctic offshore support vessel, performance assessment models for independently operating and icebreaker-assisted Arctic offshore supply vessels, and a novel adaptation of the single-objective ABC algorithm for holistic multi-objective ship design optimization. The framework scans the feasible design space to find a Pareto front, representing the tradeoffs between cost- and eco-efficiency for the conceptual design of an Arctic offshore supply vessel. Verification is provided for the parametric design model of an Arctic offshore support vessel.

The proposed adaptation of the ABC algorithm proved to be highly efficient for the holistic multi-objective optimization of an Arctic offshore supply vessel. The algorithm is fast and productive in dealing with highly complex multi-dimensional optimization problems. The obtained Pareto fronts are smooth, non-convex in general, and informative for a wide range of case studies.

The case studies demonstrate that the consideration of icebreaker assistance and the assumed speed profile in the optimization of an Arctic offshore supply vessel significantly extends the feasible design space. It is noted that disregarding such considerations often results in a suboptimal solution. A conducted sensitivity analysis indicates the significant impact that the cargo capacity parameter has on the optimization results.

Future studies could address the limitations of the presented approaches. Stochastic simulations can be included in the models to study how the stochastic nature of weather factors, such as ice, wind, and waves, impact the optimization
results. The combined impact of different stochastic factors might be significant. It is noted that weather-related factors can significantly influence the weather windows for specific cargo operations.

Another potential direction of future research is to consider the consequences of potential ice damage to ships and installations in optimization models and to study how these impact the ice class of an optimal vessel and the utilization of icebreaker assistance.

Non-conventional solutions for Arctic offshore supply logistics (e.g., using a floating supply storage between the supply base and an installation or replacing a conventional Arctic supply vessel with ice-going hovercraft in shallow water conditions) can be considered in performance models.

The developed discrete scenario-based models for the quantitative assessment of a drilling support fleet functionality might be evolved into continuous algorithms that would significantly improve the validity and utility of the method.

The applied supply vessel performance model could be further developed to consider additional optimization objectives (e.g., RFR instead of EKPI, safety, ergonomics, and recyclability) and economic aspects in greater detail.
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