Norwegian School of Economics
Bergen, Autumn 2023

Scheduling Support Vessels In Antarctic Krill Fishing

A Mixed-Integer Linear Programming Model With A Rolling Horizon Approach

Kristian Stenmark and Sebastian Smeby

Supervisor: Julio Goez

Master thesis, Economics and Business Administration

Major: Business Analytics

NORWEGIAN SCHOOL OF ECONOMICS

Acknowledgements

We would like to start by thanking our supervisor Julio Goez for his guidance, valuable feedback and drive to connect us to a relevant contact person in the industry. We would also like to thank Julie Schasler at Dataloy for taking the time to meet us and inform us about the daily fishing operation of Aker BioMarine.

Further, we would like to acknowledge our friends, family and Sebastians dog Ekko for their support and encouragement.

Norwegian School of Economics

Bergen, December 2023

Kristian Stenmark

Sebastian Smeby

Abstract

Increasing food prices in Europe demands a heightened attention to resource utilisation. This leads to a great potential to better utilize one of the most abundant biomasses on earth: krill. These tiny crustaceans consist of more than 25% lipids containing omega-3 fatty acids and more than 60% high quality proteins (Tou et al., 2007). Today krill products are produced both for pets and humans, and it is especially popular in aquaculture feed. There is, however, still a great potential for this resource to be utilized better and in an even more effective way.

This thesis aims to optimize the supply chain, and more specifically the fishing operation in the Antarctic krill fishing business. A case study of the Aker BioMarine fishing operation is conducted for a single season where a schedule is created for their support vessel, a vessel used to transport krill, crew, fuel, and equipment between the fishing vessels in the Antarctic Ocean and the shore of South America, to maximize the total krill harvested while keeping costs down. This was done using a mixed integer linear programming model with a rolling horizon approach. In addition to using the numbers from the 2021 season, the model was also tested on two scenarios: one where the fishing rates were increased by 50%, and one where the travelling times between all locations were increased. This was to see the model's performance under more lucrative seasons, and seasons with bad weather.

The base case findings show that the MILP approach effectively schedules the season so that the support vessel has as few trips as possible, while allowing the fishing vessels to have no ineffective days. This was also the case in the scenario with the increased travelling times. The results for the scenario with increased fishing rates were slightly worse. The support vessel still had no problem managing to deliver all krill while keeping the fishing vessels active every day. It used unnecessarily many trips to do so. We allocate this inefficiency to problems related to the rolling horizon approach.

This study shows the effectiveness in using mathematical modelling to schedule support vessels in fishing operations to keep the operation effective while cutting unnecessary costs.

Keywords – MILP, Antarctic Krill, Support Vessel, Scheduling, Optimization

Contents

Appendices

List of Figures

List of Tables

1 Introduction

1.1 Scope of Research

The Antarctic, a remote and icy wilderness located at the south pole of the Earth, is home to a great variety of species that make out the Antarctic ecosystem. One of the cornerstones of this ecosystem is the Euphausia Superba, commonly known as the Antarctic Krill (Nicol and Endo, 1997). Being one of the most abundant biomasses on the Earth (Aker BioMarine, 2023a), Antarctic Krill is an important source of food to larger species such as whales, seals, penguins, and birds (WWF Australia, 2022). Since the early 1960s, Antarctic Krill has also become a valuable resource for production of various human-made products such as aquaculture feed, pet feed and dietary supplements. The demand for these products has created business opportunities in the Antarctic Ocean, where krill fisheries have emerged. In a competition mostly dominated by Norwegian, Russian, Japanese, and South Korean companies, the industry together sold for around 500 million US dollars in 2019 (ASOC, 2021).

Running krill fisheries in the Antarctic comes with a lot of challenges. The cold climate and icy waters, in addition to the considerable distance to the closest ports, makes the fishing operations unique. Because of the distances in the Antarctic Ocean, some of the krill fisheries rely on using support vessels in addition to the fishing vessels. The support vessels are used to transfer cargo, fuel and personnel between the fishing grounds and the closest ports, so that the fishing vessels can stay in the Antarctic for longer periods and thus have more fishing days. The use of the support vessels creates the need for logistical planning of when the vessel should be present in the Antarctic, available to the fishing vessels, and when it should be scheduled to go back and forth to the ports.

In this thesis we will investigate the logistical planning of such support vessels in Antarctic fishing operations. We will study a case of Aker BioMarine, the largest krill harvesting and processing companies in the world. Aker BioMarine relies on their support vessel, Antarctic Provider, to transport krill between the fishing vessels and an onshore logistics hub located in Montevideo, Uruguay. We have formulated the following thesis statement:

> *We intend to study the use of optimization techniques in planning a support vessel's schedule in an Antarctic krill fishing operation. The goal is to maximize the amount of krill delivered to the onshore hub, while keeping the number of voyages to a minimum.*

We will approach this problem by creating a mixed integer linear programming (MILP) model in A Mathematical Programming Language (AMPL) taking into account the voyages needed in order to transport krill to Montevideo, while facilitating for crew changes on the fishing vessels by picking up and delivering personnel at another port located in Puerto Williams, Chile. By use of this model and a rolling horizon approach, we will search for an optimal way to allocate the support vessel to reach our goals. We will also implement a scenario analysis to examine the effects of changing fishing rates and sailing times, as these may vary vastly during the course of the fishing season.

1.2 Structure of the Thesis

This thesis consists of 9 distinct sections. It will continue with section 2 with some brief background information about the Antarctic krill industry and Aker BioMarines operation. In section 3 we will study the current litterature on relevant topics for this thesis. In section 4, we will introduce the problem more thoroughly, before we in section 5 introduce and discuss the data that were used in the model. Section 6 will be a review of the methods that were used to solve the problem as well as a walkthrough of the MILP model. Section 7 will present and analyse the results from all three scenarios. In section 8, all these results will be discussed, before we in section 9 add our concluding remarks for the thesis.

2 Background

2.1 History of Antarctic Krill Fishing

Krill fishing in the Antarctic Ocean has existed since the Soviet Union launched their first experimental operations in the early 1960s. Throughout this decade they carried out preparatory work such as mapping the best fishing grounds and developing and improving necessary equipment to both catch and process krill. This resulted in a small annual catch of a few tens of tons. The Soviets set up the first permanent Antarctic krill fishery in 1972, which resulted in a catch of 7 500 metric tons (mt) the following year. These catch numbers expanded quickly (McElroy, 1984).

Since then, there has become more competition for the Antarctic krill, with Japan starting their full-scale commercial operation in 1975. During the 1980s Poland, Chile, and South Korea also started operating in the area. The Soviet Union still had the largest share of production by far. In the peak year of 1982, the Soviet Union had a share of 93% of the total production of 528 000 mt (CCAMLR, 2021). After the downfall of the Soviet Union, Russia and Ukraine took over the Soviet operation. Russia later abandoned their operation in 1993. In the years after, Japan was one of the top producers. After year 2000 the South Korean operation has expanded considerably. In addition to this, a U.S. based company entered the market in 2001 and the Norwegian company Aker BioMarine entered the market in 2003. They quickly expanded their operations and is today the largest producer of Antarctic krill products in the world (Krafft et al., 2023).

2.2 Aker Biomarine

Aker BioMarine is the largest krill harvesting and processing company in the world. In 2022 they were responsible for over 65% of the global krill catch. They also have an annual expected krill meal production of over 55 000 mt, which is used as both an animal and human nutrition ingredient (Aker BioMarine, 2022).

The krill is harvested in subarea 48 of the Antarctic Ocean which is located east and north-east of the Antarctic Peninsula on the South American side of Antarctica. This area is further separated into 6 smaller zones. A figure of the area is included below. The South

Orkney Islands located in zone 48.2 is an especially important area for Aker BioMarine, as they use Signy Island to shelter from weather when transferring krill between the fishing vessels and their support vessel (J. Schasler, personal communication, September 21, 2023).

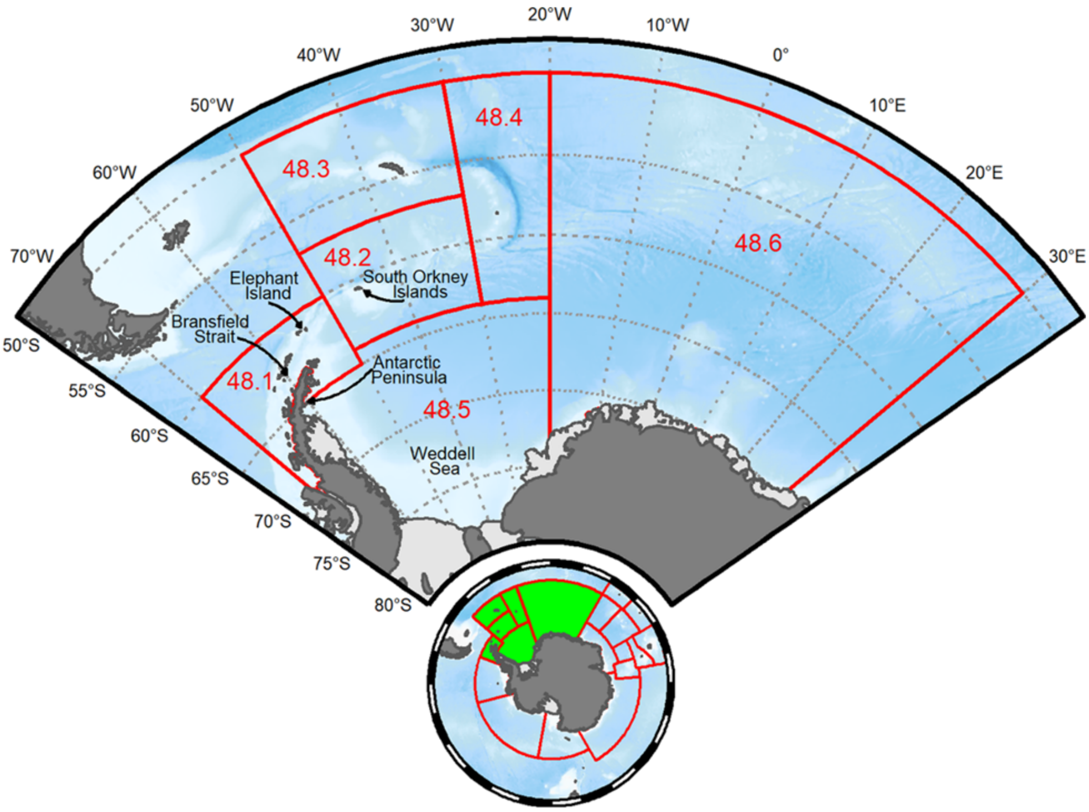


Figure 2.1: Area 48 in the Antarctic Ocean. Retrieved from: (Meyer et al., 2020)

The krill they harvest is used to produce both products for humans, like the Superba Krill range, pets, like Qrill Pet, and aquaculture, like the QrillAqua range (Aker BioMarine, 2022). In 2020 alone, they sold 1.6 billion doses of Superba Krill, and Aker BioMarine estimates that their krill products contributed to the production of 410 million extra servings of fish Aker BioMarine, 2023b).

They are the only krill supplier that controls their entire harvesting and production operation. After their three custom built krill fishing vessels Antarctic Endurance, Antarctic Sea, and Saga Sea has harvested the krill in the Antarctic Ocean, they process the raw krill into krill meal immediately after it is brought onboard. After that, their support vessel, Antarctic Provider, brings the krill meal to their logistics hub in Montevideo. From there, it is transported further to their manufacturing plant in Houston, Texas, where some of the krill is processed further into Superba Krill and QrillAqua, and some is sold directly to customers around the world (Aker BioMarine, 2023c). The figure below gives a visual representation of the production process and which products Aker BioMarine produces.

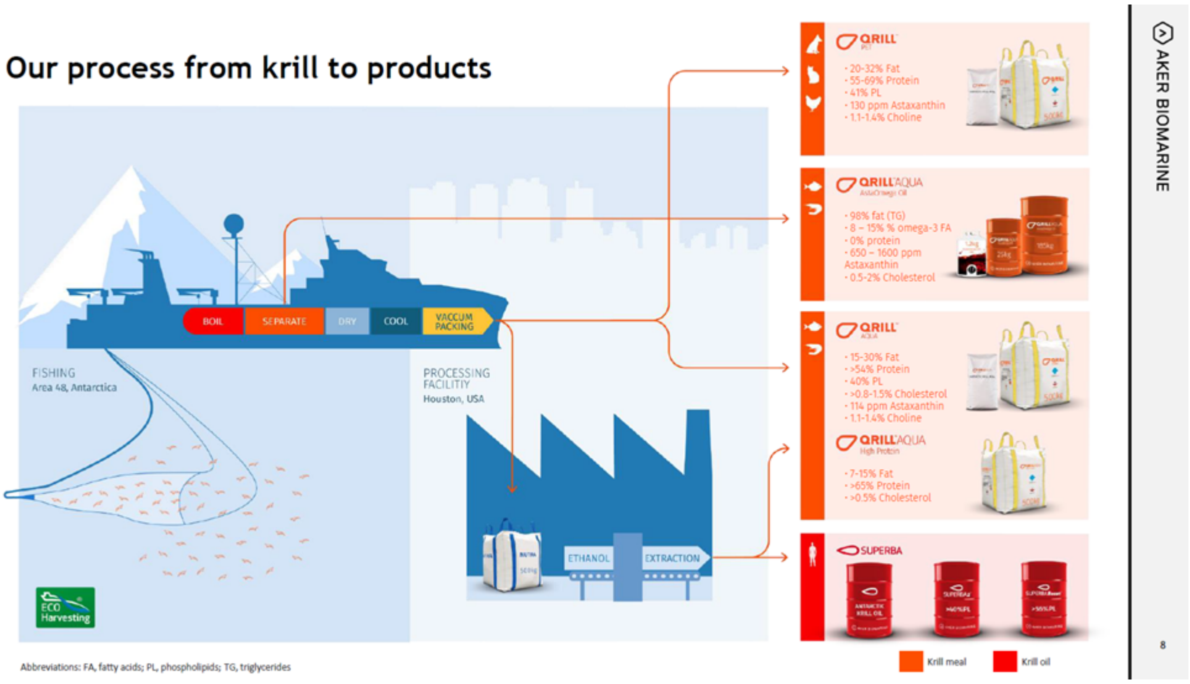


Figure 2.2: The Production process of Aker BioMarine. Retrieved from: (Aker BioMarine, 2022)

2.3 Conservation

To ensure that the natural resources of the Antarctic Ocean are not over-exploited, The Commission for the Conservation of Antarctic Marine Living Resources (CCAMLR) was established by international convention in 1982. This was a response to the increasing interest in Antarctic krill and the history of over-exploitation of several other species of the Antarctic Ocean (CCAMLR, 2023a).

To support the conservation of Antarctic marine living resources, CCAMLR implements a comprehensive set of measures. These measures are reviewed and developed once a year at their annual meeting of the Commission (CCAMLR, 2023b). According to the website of Aker BioMarine, the krill quotas set by CCAMLR are very precautionary. In their sustainability brochure from 2018 they claim that:

> "The annual precautionary quota for Antarctic Krill set by CCAMLR is 5.61 million tonnes and amounts to approximately 10 percent of the total estimated

> biomass in area 48 of 60.3 million tonnes. The catch is further limited to 620,000 tonnes in any one season. For the 2015/2016 season the recorded krill catch for all vessels fishing for krill was 225,646 tonnes and only 0.3 percent of the total biomass of krill in the South Atlantic." (Nicol, 2018).

The Norwegian Institute of Marine Research also concluded that the Antarctic krill fisheries were managed sustainably during their 10-year monitoring period of the krill population from 2011 to 2020 (Skaret et al., 2023).

This indicates that the quotas set by CCAMLR are highly precautionary compared to other fisheries. It is also not necessarily a constraining quota, as the total catch of the 2015/2016 season amounted to only around a third of the total quota. Because of this, we will not consider the possibility of exceeding the quota when formulating our model. It is, however, worth noting that it can become a constraining quota in the future.

3 Literature Review

In the following section we will investigate the current state of research in maritime logistics, with an emphasis on two areas that are especially important for the problem that later will be outlined in detail in section 4: the scheduling of support vessels and the coordination of crew changing schedules.

3.1 Support Vessel Scheduling

Data driven optimization in maritime logistics is a field that is receiving an increased amount of interest (Fagerholt et al., 2023), however, the research is mostly focused on applications in the shipping, oil and aquaculture industries. In our research we found that the specific case of using optimization techniques to schedule support vessels in fishing operations is a field that has received little to no attention in scientific research. Because our specific case is relatively unexplored, we have made use of similar cases and models in the literature to find inspiration.

A key finding in the literature is that one of the areas where using optimization to schedule actions of vessels is common is within the sea-borne trade industry, where liner shipping plays a pivotal role. In the article Containership Routing and Scheduling in Liner Shipping: Overview and Future Research Directions (Meng et al., 2014) it is stated that in the industry, a schedule design is important to plan port arrival and departure times, as well as, when transshipment of cargo should occur. An example where mathematical programming is used for this purpose can be found in the article Cargo Allocation and Vessel Scheduling on Liner Shipping with Synchronization of Transshipments (Ozcan et al., 2020). The study presents a mixed integer linear programming (MILP) model for optimizing the allocation of cargo and vessel scheduling in liner shipping. With focus on a Turkish company, the model includes port-stay lengths, transit times, and transshipment processes between vessels. After testing the model on real life cases, the authors conclude that the model is able to improve operational efficiency in liner shipping. Although the article presents a case that is different from the one who is to be considered in this thesis, there are elements of resemblance. Both the need for planning vessel actions in terms of voyages, and handling cargo are common considerations needed in the model formulation.

An industry that has a supply chain comparable to the one of Antarctic Krill fishing is the liquid natural gas (LNG) industry. The supply chain consists of producing LNG at liquefaction plants before it is shipped at sea to a destination where the LNG is regasified, stored and consumed U.S. Department of Energy, 2020). Similar to the Antarctic Krill fishing industry, all parts of the supply chain are then limited to a specific storage capacity, with ships being the mode of transporting cargo from production to consumption. In the book Energy, Natural Resources and Environmental Economics (Andersson et al., 2010) a mixed integer model is introduced planning the voyages of each ship, and minimizing the cost related to these voyages. Because of the complexity of such real-world problems, they can be difficult to solve and require high computational power and long running times. Two solution approaches are discussed to deal with this; reducing the number of path variables that the ship can take, or using a rolling horizon heuristic where the planning horizon is split into smaller intervals and solved one at the time.

Another area that receives great attention in the literature on vessel scheduling is decisions regarding vessel routing. In the article Supply Vessel Routing and Scheduling under Uncertain Demand (Kisialiou et al., 2019) an arc-flow model is built with the intent of delivering demanded number of products to ports around Europe within specific time windows and minimizing the involved costs. Here the model has to make decisions on where and when the vessel should go, depending on costs and uncertain demand.

Notably, the literature shows that using optimization in the form of scheduling logistics in maritime companies has the potential to serve as a cost saver. In the paper Optimization in offshore supply vessel (OSV) planning Halvorsen-Weare and Fagerholt (2017) outline a voyage-based model where the fleet size and number of trips to offshore oil installations was planned, scheduled, and later implemented by Statoil. The cost reductions from implementing the model were estimated to be around 3 million USD/year. Although the case studied by Halvorsen-Weare and Fagerholt differs the study in this thesis in the way that the OSV are supplying offshore installations, rather than collecting cargo from fishing vessels, the research proves that effective scheduling the use of supply vessels in maritime logistics can reduce costs.

3.2 Crew Changes

One of the problems we will try to solve is scheduling crew changes for the different fishing vessels. Comparable to the situation with krill pickups and deliveries, the crews are also retrieved and delivered by the support vessel, Antarctic Provider, so that the fishing vessels will not have to stop fishing for several days to change crew. Although we have not found this exact example in the literature, there are some very comparable problems that have been examined already. One example of this is scheduling air transport for offshore oil rig crews. This problem is not the same as ours, but consists of some of the same aspects, where a vessel brings the crew from shore to the operation and brings the old crew back to shore. Some of the notable differences are that in this case the crew are usually brought by multiple helicopters rather than one large ship. In addition to this, the helicopters do not have the same importance to the supply chain as Antarctic Provider, as they are not bringing the main product to shore in addition to bringing crew.

Optimizing transport of crew to and from offshore oil rigs has been studied since the late 1980s, when Galvão and Guimarães (1987;1990) created a heuristic algorithm and decision support system to optimally transport personnel to oil rigs from the coast of Brazil, and back. Later, Sierksma and Tijssen (1998) came out with the first mathematical model for operational planning of crew transport by helicopters between onshore heliports and offshore oil platforms with their linear programming approach.

Among several newer articles we found on this subject, this 2021 article was the most relevant to our problem: An exact solution method for a rich helicopter flight scheduling problem arising in offshore oil and gas logistics (Nafstad et al., 2021). In this paper, they use a rich vehicle routing problem with pickup and delivery structure for creating an optimal flight schedule for a heterogenous fleet of helicopters tasked with transporting personnel to, from, and between offshore installations.

4 Problem Description

In the following chapter, we will describe the underlying details of Aker BioMarines fishing operation. The optimization model is based on these descriptions. Although much of the information was retrieved from Aker BioMarines website, we also had a lot of help from Julie Schasler from Dataloy (a company providing a global technology platform for the commercial maritime industry) who informed us about the harvesting operation of Aker BioMarine.

4.1 Vessels

Aker BioMarine have three fishing vessels: Antarctic Endurance, Antarctic Sea, and Saga Sea, that operate in the Antarctic Ocean during the krill season. The fishing vessels historically has between 260 and 300 fishing days per year. On these fishing days they harvest krill by use of a fine mesh net. After harvesting, the krill is boiled, cleaned, frozen, and packed on ship so that it keeps fresh and is ready to be transported to shore Aker BioMarine, 2022). The processed krill is then transported to Montevideo to be transported further to Aker BioMarines facility in Texas or sold directly to customers. The problem with this is that it is very time-consuming to sail all the way from the Antarctic Ocean to Montevideo to unload every time the storage capacity of a fishing vessel is full. To account for this problem and optimize efficiency, they use a large support vessel, Antarctic Provider, to both transport krill from the fishing vessels to Montevideo as well as to bring supplies from shore to the fishing vessels. When Antarctic Provider is not on a specific task, it is preferred that it is located by the fishing vessels to offer support in daily operation (J. Schasler, personal communication, September 21., 2023).

4.2 Transfer of Cargo

The transshipment of krill is done by ship to ship transfer so that the support vessel Antarctic Provider can receive the packed krill from the fishing vessels and at the same time resupply the fishing vessels with necessities like food, water, fuel, and fresh crew, all without the fishing vessels leaving the Antarctic Ocean. This allows the fishing vessels to have more active fishing days per year, as they do not need to sail to Montevideo every time they have filled their storage capacity. Now they can simply transfer their cargo to Antarctic Provider and continue fishing while Antarctic Provider delivers the cargo to Montevideo. At the same time as facilitating for more fishing time, this can also be a great cost saver, as only one ship would need to make the trip to Montevideo instead of three.

The transshipment can, however, be a time-consuming process, as the open sea can be a risky location for such a task. Because of risk of harsh weather and large waves, the transshipment is usually completed in the shelter of Signy Island, an island located near the fishing grounds in area 48.2. This means that the fishing vessels will use additional time to sail here when they must transfer their cargo to Antarctic Provider. This additional sailing time will vary depending on which area they are currently fishing.

4.3 Crew

In addition to transporting krill from the fishing vessels to Montevideo, Antarctic Provider is also used to transport crew to (from) the support vessels from (to) shore. This is however from another port that is located in Puerto Williams, in the south of Chile. Puerto Williams is much further south than Montevideo, and thus a shorter sail from the fishing operation. Antarctic Provider can carry and house crew for one fishing vessel at a time in addition to its own crew (J. Schasler, personal communication, November 13, 2023). This way, Antarctic Provider could allow the fishing vessels to have more fishing days a year compared to if they had to retrieve their own crew in Puerto Williams.

4.4 Fishing Operation

In the fishing operations in the Antarctic, it is important to make the most out of each fishing day, by raising the average daily krill catch. This is an area where Aker BioMarine uses a lot of resources in research and development of methods of harvesting as much as possible. For instance, they newly introduced an autonomous boat which gathers data on where to find abundances of krill, and they use machine learning to reduce the time in which they are searching for areas to fish (Aker BioMarine, 2023d). With years of experience, they have also gathered insight into the patterns of the Antarctic Ocean, and usually fish in different areas throughout the year, as the krill schools change areas with the seasons. This way the fishing rates can be more predictable than earlier as they now can make more educated decisions of where to fish at a given time.

5 Data

In this section we will discuss how we obtained the data used to create our model, and which assumptions and simplifications were made. We will also present our data and explain the methods that were used to calculate it.

5.1 Data Description

We will investigate the data used in our optimization model. We had to identify what data was available and the credibility of the data. In some areas we had to acknowledge that when modelling real world scenarios, some simplification of reality is needed in order to secure a functional model. Further in this section, our data gathering process along with choices and assumptions will be discussed.

5.1.1 Scheduling Period

The scheduling period corresponds to a regular fishing season which lasts from January to October (J. Schasler, personal communication, September 21, 2023). This results in a scheduling period of approximately 300 days. To facilitate the scheduling model, we have chosen to use one day intervals. This allows the model to determine what are the optimal actions of the different vessels during each day. For fishing vessels this may vary between fishing, transferring cargo or being inactive, while for the support vessel this can vary between being in the Antarctic, Montevideo, Puerto Williams or on transit between any of the locations.

5.1.2 Fleet Size

In the context of Antarctic krill operations, different companies within the industry will differ both in how they organize their operations, and the resources available. As we specifically focused on the operations of Aker BioMarine, we used their real-life fleet which consists of one support vessel, Antarctic Provider, and three fishing vessels, Antarctic Endurance, Antarctic Sea, and Saga Sea (Aker BioMarine, 2022).

5.1.3 Fishing Rates and Capacity

An influential part of the problem is deciding at what rate krill is harvested on the different fishing vessels. In our model, we decided to take a deterministic approach, with fishing rates being constant. The data is based on the average daily krill production of each fishing boat in 2021 (Aker BioMarine, 2022). There are quotas set by CCAMLR to ensure that krill fishing is not over exploited. As stated in section 2, the annual krill catch is far below this quota, and we therefore ignore the quota in the model formulation.

It is important to keep in mind that in reality, the amount of krill harvested for each fishing vessel can fluctuate significantly from day to day and may also vary throughout the fishing season. Weather conditions, krill abundance, scheduled ship maintenance or other factors may influence the daily krill catch.

How much krill the respective vessels may hold is also highly relevant for the problem solution and how many trips the support vessels need to make to port. Aker BioMarine uses large fishing vessels that are used to harvest, process and store krill, in addition to a large support vessel with a high storage capacity. The capacity used in the problem was derived from a company presentation published by Aker BioMarine (Aker BioMarine, 2022).

5.1.4 Cargo Transfer

In order to operate within the capacity limits, the fishing vessels need to transfer their accumulated krill to the Antarctic Provider. The transshipment operation between the fishing vessels and Antarctic Provider often happens in shelter of Signy Island. As the fishing vessels harvest krill in different parts of the Antarctic Ocean, some travel might be necessary to conduct a transfer of cargo. Because of this, we assume that an average transshipment takes one day and only one fishing vessel can transfer krill, in addition to this, the fishing vessels cannot both fish and transfer cargo at the same day. We also assume that a fishing vessel will transfer all its inventory to Antarctic Provider when conducting a cargo transfer. This is to prevent old krill from spoiling due to the last-in-first-out nature of a storage room.

5.1.5 Crew

We must ensure that the work times of the crews of all vessels are respected and that we are able to produce a plan for when the crews are to be changed for each vessel. From a document retrieved from Aker BioMarines website, the workers are on the ships for four to five months at a time (Aker BioMarine, 2020). A crew change consists of a pickup of fresh crew in Puerto Williams, a switch of the crews in the Antarctic Ocean, and a delivery of the old crew in Puerto Williams. Antarctic Provider can only carry one additional crew at a time, meaning it cannot change crew for more than one fishing vessel at a time (J. Schasler, personal communication, November 13, 2023). The time span assures that Antarctic Provider has time to change crew for all three ships for the first rotation, as it takes several days to change one crew because of the necessary roundtrip to Puerto Williams. Antarctic Provider is handled separately from the fishing vessels in the model formulation. As Antarctic Provider is responsible for carrying out the crew changes for the fishing vessels, they have many trips to Puerto Williams and can there change their own crew as well. The crew changes of Antarctic Provider are therefore not considered in the model but assumed to be carried out during their stays in Puerto Williams.

5.1.6 Voyages

In our problem we have four different locations in which the Antarctic Provider might be: the Antarctic, Montevideo, Puerto Williams, or on transit between locations. We allow the Antarctic Provider to travel freely between all locations. This way it is possible to combine a shipment of krill with either a crew pickup or a crew delivery and be able to save time compared to if Antarctic Provider had to perform both these tasks separately. In addition to this we assume that stopping in either Montevideo or Puerto Williams requires one day.

An aspect that has great influence on the optimal solution of the problem is how much time Antarctic Provider uses to sail between locations. A deterministic approach is used, meaning that the travel time stays constant throughout the scheduling period. In reality, one must assume that this is not the case, as weather conditions and other factors will influence the speed at which Antarctic Provider might sail. To calculate the travel time between locations, we have used a nautical distance calculator (bednblue, 2023) and the average sailing speed of the Antarctic Provider which is 13.3 knots according to Marine Traffic (Marine Traffic, 2023). When using a distance calculator some error margin must be assumed, as the calculator relies on pinning a start/end point on a map.

5.1.7 Costs

As this thesis is written without cooperation with Aker BioMarine, we have little insight into the actual costs associated with sailing between the different locations, lying in port, or paying crew. We also have little insight into the actual monetary value of krill to Aker BioMarine, as the krill is turned into many different products of which we do not know how much is sold. Therefore, we have chosen to base our model on tons of krill instead of money gained. The costs in the model for sailing and being in port are therefore also not displayed in monetary currency, but rather a symbolic sum to specify that there is a cost related to sailing and being in port.

5.2 Used Data

In the used data section, we will present and explain the data that was used in the model. Not all the data was straight forward to acquire. Much of the information had to be interpreted and calculated based on information found on for example Aker BioMarines website.

5.2.1 Fishing Rates and Capacity

The data for the storage capacities and fishing rates are retrieved from the company presentation of Aker BioMarine (Aker BioMarine, 2022). Most of the capacities were originally given in cubic meters. We were able to convert it to metric tons, as one cubic meter contains approximately half a metric ton of krill (Hansen, 2019). The storage capacities of the vessels are given as follows:

Vessel	Storage capacity
Antarctic Provider	20 000 mt
Antarctic Endurance	3 200 mt
Antarctic Sea	3 660 mt
Saga Sea	1 930 mt

Table 5.1: Storage capacity for all vessels

The daily fishing rates correspond to the 2021 average daily catch of the fishing vessels measured in metric tons (mt). The fishing rate of the vessels are presented in the table below:

Vessel	Fishing rate
Antarctic Endurance	80 mt
Antarctic Sea	70 mt
Saga Sea	50 mt

Table 5.2: Fishing rate for fishing vessels

5.2.2 Travel Time

The calculated nautical distance and travelling time using an average speed of 13.3 knots is summarized in the table below.

Voyage	Nautical Miles	Travelling Time	Travelling Time rounded
Antarctic ↔ Montevideo	1 613.9	5 days, 1 hour, 21 minutes	5 days
Antarctic ↔ Puerto Williams	784.1	2 days, 10 hours, 57 minutes	2 days
Montevideo ↔ Puerto Williams	1 371.1	4 days, 7 hours, 5 minutes	4 days

Table 5.3: Travelling routes and travelling times

As the time interval used in the model is entire days, the travelling time between locations is rounded off to the closest day. As a result of this, Antarctic Provider uses 5 days travelling between the Antarctic and Montevideo, 4 days travelling between Montevideo and Puerto Williams, and 2 days travelling between the Antarctic and Puerto Williams. This is consistent with information given by Dataloy (J. Schasler, personal communications, September 21, 2023). A round trip from the Antarctic to Montevideo and back to the Antarctic takes a total of 11 days, and a round trip back and forth to Puerto Williams takes a total of five days. A visual presentation of the locations and the distances measured in travelling days are given below:

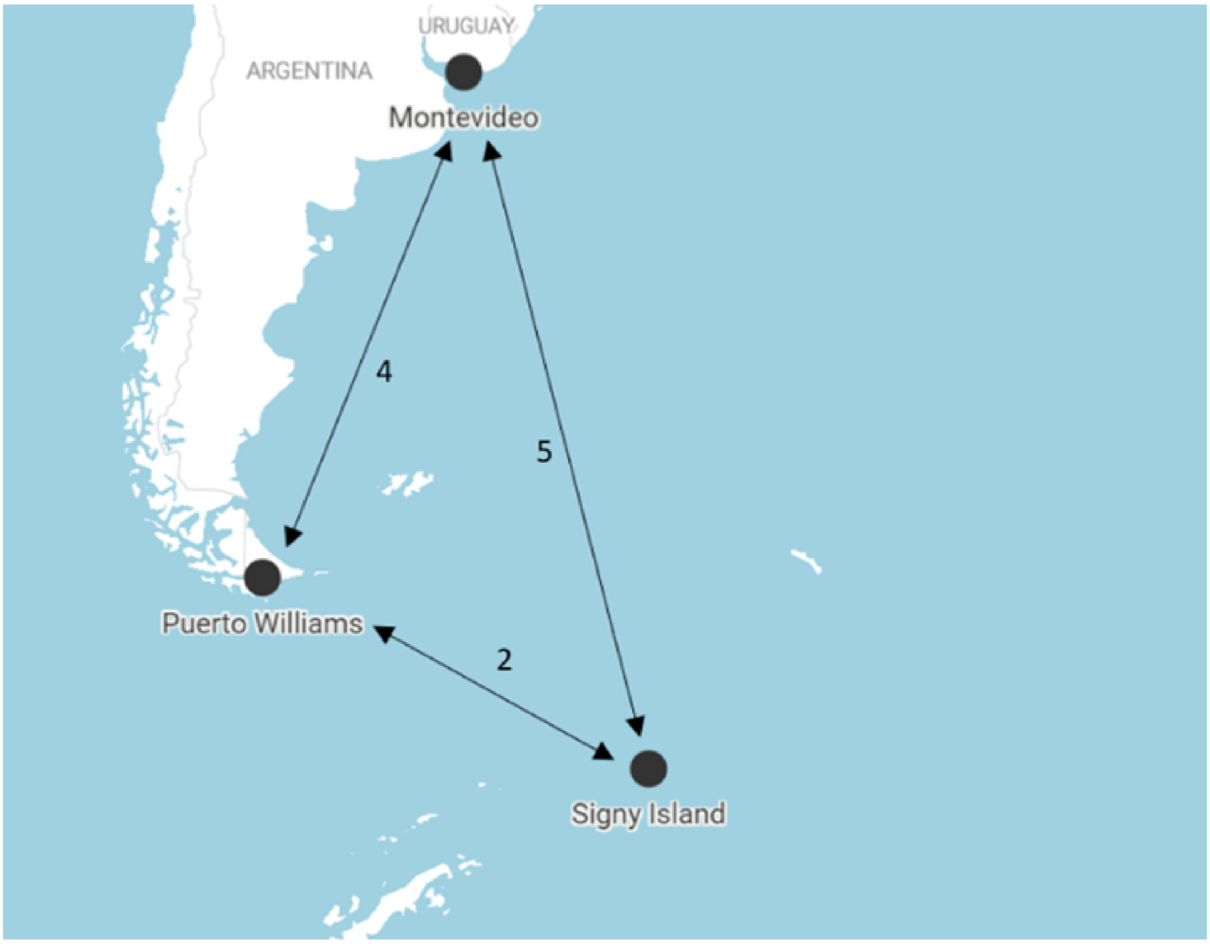


Figure 5.1: Travel routes and travel times

6 Methodology

In this part of the thesis, we will outline the methodology adopted for developing the optimization model, which is used to solve the problem specified in Section 4. First, the theory behind the mathematical programming will be described before the actual solution model will be formulated and explained.

6.1 Mathematical Programming

Mathematical programming is often referred to as mathematical optimization and is a tool used in decision making processes. According to Dantzig and Thapa (1997) mathematical programming can be defined as "the branch of mathematics dealing with techniques for maximizing or minimizing an objective function subject to linear, non-linear, and integer constraints on the variables". Yang Huang, Yue Lai and Cheng (2009) gives a general problem expression of mathematical programming problems:

$$\text{Minimize (or maximize) } f(x);$$

$$\text{Subject to } X = \{x \mid g_i(x) \leq b_i, i = 1, \ldots, m\}$$

where

$x = (x_1, \ldots, x_n)$ are optimization (or decision variables),

$f : \mathbb{R}^n \to \mathbb{R}$ is the objective function, and

$g_i : \mathbb{R}^n \to \mathbb{R}$ and $b_i \in \mathbb{R}$ form the constraints for the valid values of x

A general process to solving optimization problems is given in the book Optimization (Lundgren et al., 2010). The process starts with identifying a real problem needed to be solved. Thereafter, the real problem is often too complex and needs to be simplified to achieve a solution. After simplifying the problem, an optimization model in the form of a mathematical expression with decision variables, an objective function, and constraints, is built. The model is then solved using an algorithm. Examples of commercially available software algorithms are CPLEX, Gurobi and OSL. Finally, the resulting optimal solution(s) are evaluated.

Based on the types of decision variables and constraints used in the mathematical expression of the problem, mathematical programming can be divided into several types. Linear programming, non-linear programming, integer programming or a mix of these are the most common. In this thesis we have opted to use a mixed integer linear programming model (MILP). We used a linear approach because the this requires less computing power compared to solving a non-linear model.

Mixed-integer linear programming can be defined as an optimization problem with continuous and integer variables, influencing a linear objective function and restricted by linear constraints (Rambau, 2023).

6.2 Rolling Horizon

When optimizing over a large timespan, the number of variables and constraints may become so great that the model cannot be solved without running for a very long time using great computing power. When increasing the number of variables and especially integer variables, the computation time needed in order to solve the problem can increase significantly (Marquant et al., 2015). In these cases, a rolling horizon approach is common. In the article *A Rolling Horizon Approach For Multi Period-Optimization* (Glomb et al., 2022), a general framework for the rolling horizon approach is presented. The overall optimization problem is divided into a finite sequence of optimization problems $\{P_0, \ldots, P_T\}$ where each problem belongs to a time period $\{0, \ldots, T\}$. To connect the periods together, start- and end-state variables are used, where the end-state of a period t becomes the start-state of period $t + 1$. To connect the periods together one makes use of start- and end-state variables, where the previous period decides the start-state value of the variables in the next period.

In order to smooth the transitions between periods and increase the accuracy of the model it is common to use overlaps between periods. The authors represent this technique with the parameter μ. For instance, with $\mu = 2$, the optimization includes the current period and the entire next period as an overlap. Using a rolling horizon approach in optimization helps with reducing the computational effort compared to solving the original problem because it reduces the number of scenarios by dividing the problem into smaller pieces. However, the approach comes with the risk of deteriorating the quality of the solution as the as the model assumes a reduced time horizon for each period it is optimizing. This is known as the end-of-horizon effect (Cavagnini et al., 2022).

6.3 Model Formulation

In this section, the model used will be mathematically expressed. The parameters and variables are given descriptive names in order to improve readability.

6.3.1 Sets

V : Set of vessels

L : Set of locations

T : Set of days

6.3.2 Parameters

FishingRate_v : The daily fishing rate of vessel v

StorageCapacity_v : The storage capacity (mt) on vessel v

StorageAP : The storage capacity (mt) on Antarctic Provider

MaxStay : The maximum time between a crew change

MinStay : The minimum time between a crew change

6.3.3 Binary Variables

$$\text{Fishing}_{v,t} = \begin{cases} 1 & \text{if vessel } v \text{ is fishing on day } t \\ 0 & \text{otherwise} \end{cases}$$

$$\text{CargoTrans}_{v,t} = \begin{cases} 1 & \text{if fishing vessel } v \text{ is transferring cargo to AP on day } t \\ 0 & \text{otherwise} \end{cases}$$

$$\text{TripIni}_{f,d,t} = \begin{cases} 1 & \text{if vessel AP initiates a trip from location } f \text{ to destination } d \text{ on day } t \\ 0 & \text{otherwise} \end{cases}$$

$$\text{APLoc}_{l,t} = \begin{cases} 1 & \text{if Antarctic Provider is at location } l \text{ on day } t \\ 0 & \text{otherwise} \end{cases}$$

$$\text{ChangeCrew}_{v,t} = \begin{cases} 1 & \text{if fishing vessel } v \text{ has its crew changed on day } t \\ 0 & \text{otherwise} \end{cases}$$

$$\text{CrewPickup}_{v,t} = \begin{cases} 1 & \text{if AP picks up crew for vessel } v \text{ in PW on day } t \\ 0 & \text{otherwise} \end{cases}$$

$$\text{CrewDeliver}_{v,t} = \begin{cases} 1 & \text{if AP delivers crew for vessel } v \text{ in PW on day } t \\ 0 & \text{otherwise} \end{cases}$$

6.3.4 Continuous Variables

$\text{KrillInv}_{v,t}$: Amount of krill stored on vessel v on day t

$\text{KrillHarv}_{v,t}$: Amount of krill harvested by vessel v on day t

$\text{KrillTrans}_{v,t}$: Amount of krill transferred from vessel v to AP on day t

KrillOSH_{t} : Amount of krill transferred to onshore hub in Montevideo by AP on day t

KrillInvAP_{t} : Amount of krill stored on AP on day t

$\text{Timer}_{v,t}$: The number of days the crew of vessel v has worked since last change on day t

6.3.5 Objective Function

$$\max : \sum_{v \in V} \sum_{t \in T} (\text{KrillOSH}_t - (\text{APLoc}_{\text{Transit},t} + \text{APLoc}_{\text{Mont},t} + \text{APLoc}_{\text{PW},t}) \times 100)$$

The objective function seeks to maximize the krill transferred to the onshore hub in Montevideo minus the days AP must spend on transit and in the ports of Montevideo and Puerto Williams. This way the model is incentivized to bring as much krill as possible to Montevideo, while taking as few trips to Montevideo and Puerto Williams as possible. We have multiplied the costs by 100 to ensure that the cost of sailing and lying in port is not negligibly small.

6.3.6 Constraints

The objective function is subject to the following constraints:

6.3.6.1 Non-Negativity Constraint

$$\text{KrillInv}_{v,t}, \text{KrillHarv}_{v,t}, \text{KrillTrans}_{s,t}, \text{KrillOSH}_t, \text{KrillInvAP}_t, \text{Timer}_{v,t} \geq 0 \quad \forall v \in V, t \in T \tag{6.1}$$

All continuous variables must be larger than or equal to zero.

6.3.6.2 Fishing Constraints

$$\text{KrillHarv}_{v,t} + \text{Fishing}_{v,t} = 0 \quad \forall v \in V, t \in T, t < 1 \tag{6.2}$$

No vessel v can fish before day 1, so both KrillHarv and fishing is zero before day 1.

$$\text{KrillHarv}_{v,t} = \text{Fishing}_{v,t} \times \text{FishingRate}_{v,t} \quad \forall v \in V, t \in T \tag{6.3}$$

The amount of krill harvested for a vessel v on a given day t equals the fishing rate for that vessel multiplied with the binary variable for if the vessel fished on that day.

$$\text{Fishing}_{v,t} + \text{CargoTrans}_{v,t} \leq 1 \quad \forall v \in V, t \in T \tag{6.4}$$

A vessel v cannot fish on the same day that it transfers cargo, so the binary variables for fishing and transfer must be less than or equal to 1

6.3.6.3 Storage Constraints

$$\text{KrillInv}_{v,t} + \text{KrillInvAP}_{t} + \text{KrillOSH}_{t} + \text{KrillTrans}_{v,t} + \text{CargoTrans}_{v,t} = 0 \quad \forall v \in V, t \in T, t < 1 \tag{6.5}$$

The initial values for storage and transfer variables are zero.

$$\text{KrillInv}_{v,t} \leq \text{StorageCapacity}_{v} \quad \forall v \in V, t \in T \tag{6.6}$$

A vessel v cannot store more krill than the maximum capacity for the given vessel v.

$$\text{KrillInvAP}_{t} \leq \text{StorageAP} \quad \forall t \in T \tag{6.7}$$

AP cannot store more krill than its maximum capacity on any day t.

$$\text{KrillInvAP}_{t} = \text{KrillInvAP}_{t-1} + \sum_{v \in V} \text{KrillTrans}_{v,t} - \text{KrillOSH}_{t} \quad \forall t \in T, t > 0 \tag{6.8}$$

The inventory on Antarctic Provider equals the inventory from the day before, minus the krill that is sold on this day, plus any krill transferred from any of the fishing vessels.

$$\text{KrillInv}_{v,t} = \text{KrillInv}_{v,t-1} + \text{KrillHarv}_{v,t} - \text{KrillTrans}_{v,t} \quad \forall v \in V, t \in T, t > 0 \tag{6.9}$$

The inventory on a fishing vessel v equals the inventory from the day before, plus the krill that is harvested on that day t, minus the krill that is transferred to AP on this day t.

6.3.6.4 Transfer Constraints

$$\sum_{v \in V} \text{CargoTrans}_{v,t} \leq 1 \quad \forall t \in T \tag{6.10}$$

Maximum one vessel v can transfer krill to AP on a given day t, so the sum of cargo transfers for the vessels must be less than or equal to one.

$$\text{KrillTrans}_{v,t} \leq \text{CargoTrans}_{v,t} \times M \quad \forall v \in V, t \in T \tag{6.11}$$

A vessel v can only transfer krill when the binary variable CargoTrans is 1. Krill trans will be zero, unless the CargoTrans variable is one, where it is multiplied with big M allowing KrillTrans to be larger than zero.

$$\text{KrillOSH}_t \leq \text{APLoc}_{\text{Mont},t} \times M \quad \forall l \in L, t \in T, t > 0 \tag{6.12}$$

AP can only transfer krill to the onshore hub if it is in Montevideo on day t. Works the same way as the previous constraint where big M allows KrillOSH to be large if APLoc is 1 for Montevideo on the day.

$$\text{KrillTrans}_{v,t} \geq \text{KrillInv}_{v,t-1} - (1 - \text{CargoTrans}_{v,t}) \times M \quad \forall v \in V, t \in T, t > 0 \tag{6.13}$$

A vessel v must transfer all its inventory if it transfers cargo on day t. This is upheld saying that krill transfer must be greater or equal to krill inventory the day before, minus a large negative number. If a cargo transfer happens then the part of the equation that gives a negative number becomes zero, meaning that the krill transfer must be greater or equal to krill inventory.

$$\text{KrillOSH}_t \geq \text{KrillInvAP}_{t-1} - (1 - \text{APLoc}_{\text{Mont},t}) \times M \quad \forall t \in T, t > 0 \tag{6.14}$$

AP must transfer all inventory when it transfers cargo to the onshore hub. Has the same logic as constraint 6.13.

$$\sum_{v \in V} \text{CargoTrans}_{v,t} \leq \text{APLoc}_{\text{Ant},t} \quad \forall l \in L, t \in T \tag{6.15}$$

Vessels v can only transfer krill to AP when APLoc has a location in the Antarctic Ocean.

6.3.6.5 Crew Constraints

$$\text{ChangeCrew}_{v,t} + \text{CrewDeliver}_{v,t} + \text{CrewPickup}_{v,t} + \text{Timer}_{v,t} = 0 \quad \forall v \in V, t \in T, t < 1 \tag{6.16}$$

Initial values for crew variables are 0 before day 1.

$$\text{Timer}_{v,t} \leq M \times (1 - \text{ChangeCrew}_{v,t}) \quad \forall v \in V, t \in T, t > 0 \tag{6.17}$$

$$\text{Timer}_{v,t} \geq \text{Timer}_{v,t-1} + 1 - M \times \text{ChangeCrew}_{v,t} \quad \forall v \in V, t \in T, t > 0 \tag{6.18}$$

$$\text{Timer}_{v,t} \leq \text{Timer}_{v,t-1} + 1 \quad \forall v \in V, t \in T, t > 0 \tag{6.19}$$

Constraints 6.17, 6.18, and 6.19 ensures that the timer for vessel v is one more than the day before unless it is a crew change for the given vessel v on day t. If a crew change occurs for the given vessel v on day t, the timer for the vessel v is reset to 0.

$$\text{Timer}_{v,t-1} \geq \text{MinStay} \times \text{ChangeCrew}_{v,t} \quad \forall v \in V, t \in T \tag{6.20}$$

Timer must be larger than MinStay (119 days) to change crew. This means that a crew must work at least 120 days before being changed.

$$\text{Timer}_{v,t} \leq \text{MaxStay} \quad \forall v \in V, t \in T \tag{6.21}$$

Timer must at all times be smaller than MaxStay (149 days). This means that a worker cannot work more than 149 days in a row.

$$\text{ChangeCrew}_{v,t} \leq \text{CrewPickup}_{v,t-3} \quad \forall v \in V, t \in T, t > 0 \tag{6.22}$$

For a crew to be changed for vessel v on day t, the crew must have been picked up in PW 3 days ago.

$$\text{CrewDeliver}_{v,t} = \text{ChangeCrew}_{v,t-3} \quad \forall v \in V, t \in T, t > 0 \tag{6.23}$$

After changing a crew for vessel v, the crew must be delivered in PW 3 days after.

$$\text{ChangeCrew}_{v,t} \leq \text{APLoc}_{\text{Ant},t} \quad \forall v \in V, l \in L, t \in T \tag{6.24}$$

Crew can only be changed when AP is located in the Antarctic Ocean.

6.3.6.6 Travel and Location constraints

$$\text{TripIni}_{f,d,t} = 0 \quad \forall f \in L, d \in L, t \in T, t < 1 \tag{6.25}$$

No trips can be initiated before day 1.

$$\text{APLoc}_{\text{Ant},t} = 1 \quad \forall l \in L, t \in T, t < 1 \tag{6.26}$$

The starting location of AP is in the Antarctic Ocean.

$$\sum_{l \in L} \text{APLoc}_{l,t} = 1 \quad \forall t \in T \tag{6.27}$$

AP can only be at one location at a time, so the sum of locations must be 1 at all times.

$$\text{TripIni}_{f,d,t} \leq \text{APLoc}_{f,t-1} \quad \forall f \in L, d \in L, t \in T, t > 0 \tag{6.28}$$

AP can only initiate a trip from the current position of AP (We use t-1 in APLoc as AP will be in transit the first day of the trip).

$$\text{TripIni}_{f,d,t} = 0 \quad \forall f \in L, d \in L, t \in T, f = d \tag{6.29}$$

AP cannot initiate a trip that ends at the start location.

$$\text{TripIni}_{\text{Transit},d,t} = 0 \quad \forall f \in L, d \in L, t \in T \tag{6.30}$$

AP cannot initiate a new trip when it is already in transit. So if APLoc is transit, the TripIni variable must be 0.

$$\text{TripIni}_{f,\text{Transit},t} = 0 \quad \forall f \in L, d \in L, t \in T \tag{6.31}$$

“Transit” cannot be the end destination of a trip.

$$\sum_{v \in V} \text{CrewPickup}_{v,t} \leq \text{APLoc}_{\text{PW},t} \quad \forall l \in L, t \in T \tag{6.32}$$

AP can only pick up crew when it is located in Puerto Williams.

$$\sum_{v \in V} \text{CrewDeliver}_{v,t} \leq \text{APLoc}_{\text{PW},t} \quad \forall l \in L, t \in T \tag{6.33}$$

AP can only deliver crew when it is located in Puerto Williams.

$$\text{APLoc}_{\text{Mont},t} + \text{APLoc}_{\text{Mont},t-1} \leq 1 \quad \forall l \in L, t \in T, t > 0 \tag{6.34}$$

AP can only stay one day in a row in Montevideo.

$$\text{APLoc}_{\text{PW},t} + \text{APLoc}_{\text{PW},t-1} \leq 1 \quad \forall l \in L, t \in T, t > 0 \tag{6.35}$$

AP can only stay one day in a row in Puerto Williams.

$$\text{APLoc}_{\text{transit},t} \geq \text{TripIni}_{\text{Ant},\text{Mont},t-i} \quad \forall l \in L, f \in L, d \in L, t \in T, i \in \{0, \ldots, \min(t, 4)\} \tag{6.36}$$

When AP initiates a trip from the Antarctic Ocean to Montevideo, it will be in transit for the current day and following 4 days. This constraint works as a loop in the model formulation in AMPL, where one secures that after a trip is initiated the constraint is valid for t-i, where i goes from 0 to 4 (5 days in total).

$$\text{APLoc}_{\text{Mont},t} \leq \text{TripIni}_{\text{Ant},\text{Mont},t-5} + \text{TripIni}_{\text{PW},\text{Mont},t-4} \quad \forall l \in L, f \in L, d \in L, t \in T, t > 0 \tag{6.37}$$

The only possible reasons for AP to be in Montevideo is if it either started a trip there from Antarctic Ocean 5 days ago or if it started a trip to Montevideo from Puerto Williams 4 days ago.

$$\text{APLoc}_{\text{Transit},t} \geq \text{TripIni}_{\text{Mont},\text{Ant},t-i} \quad \forall l \in L, f \in L, d \in L, t \in T, i \in \{0, \ldots, \min(t, 4)\} \tag{6.38}$$

When AP initiates a trip from Montevideo to the Antarctic Ocean, it will be in transit for the current day and following 4 days. Similar loop constraint as was the case in constraint 6.36.

$$\text{APLoc}_{\text{Transit},t} \geq \text{TripIni}_{\text{Ant},\text{PW},t-i} \quad \forall l \in L, f \in L, d \in L, t \in T, i \in \{0, \ldots, \min(t, 1)\} \tag{6.39}$$

When AP initiates a trip from the Antarctic Ocean to Puerto Williams, it will be in transit for the current day and the following day. Similar loop constraint as was the case in constraint 6.36, but i is now from 0 to 1, giving a total of two days in transit.

$$\mathrm{APLoc}_{\mathrm{PW},t} \leq \mathrm{TripIni}_{\mathrm{Ant,PW},t-2} + \mathrm{TripIni}_{\mathrm{Mont,PW},t-4} \quad \forall l \in L, f \in L, d \in L, t \in T, t > 0 \tag{6.40}$$

The only possible reasons for AP to be in Puerto Williams is if it either started a trip there from Antarctic Ocean 2 days ago or if it started a trip to Montevideo from Puerto Williams 4 days ago.

$$\mathrm{APLoc}_{\mathrm{Transit},t} \geq \mathrm{TripIni}_{\mathrm{PW,Ant},t-i} \quad \forall l \in L, f \in L, d \in L, t \in T, i \in \{0, \ldots, \min(t, 1)\} \tag{6.41}$$

When AP initiates a trip from Puerto Williams to the Antarctic Ocean, it will be in transit for the current day and the following day. Similar loop constraint as was the case in constraint 6.36.

$$\mathrm{APLoc}_{\mathrm{Transit},t} \geq \mathrm{TripIni}_{\mathrm{Mont,PW},t-i} \quad \forall l \in L, f \in L, d \in L, t \in T, i \in \{0, \ldots, \min(t, 3)\} \tag{6.42}$$

When AP initiates a trip from Montevideo to Puerto Williams, it will be in transit for the current day and the following 3 days. Similar loop constraint as was the case in constraint 6.36, but i is now 0 to 3, giving a total of 4 days on transit.

$$\mathrm{APLoc}_{\mathrm{Transit},t} \geq \mathrm{TripIni}_{\mathrm{PW,Mont},t-i} \quad \forall l \in L, f \in L, d \in L, t \in T, i \in \{0, \ldots, \min(t, 3)\} \tag{6.43}$$

When AP initiates a trip from Puerto Williams to Montevideo, it will be in transit for the current day and the following 3 days. Similar loop constraint as was the case in constraint 6.36.

$$\begin{aligned}\text{APLoc}_{\text{Ant},t} = \text{APLoc}_{\text{Ant},t-1} - \sum_{d \in L} \text{TripIni}_{\text{Ant},d,t} + \text{TripIni}_{\text{Mont},\text{Ant},t-5} \\ + \text{TripIni}_{\text{PW},\text{Ant},t-2} \quad \forall l \in L, f \in L, d \in L, t \in T, t > 0 \quad (6.44)\end{aligned}$$

AP will be located in the Antarctic Ocean if it was located there the day before and it has not initialized a trip to anywhere the current day t. It can also be in the Antarctic Ocean if there was initiated a trip to there from Montevideo 5 days ago or from Puerto Williams 2 days ago.

6.4 Model Implementation

The developed model was integrated into AMPLs optimization framework. For solving the formulated MILP problem, we selected Gurobi as our solver engine. Because of the great number of variables needed to be decided over the 300 days in the problem, Gurobi were unable to solve the problem even after running the model for over 30 hours. To account for this, we thought of several ways to test our model without incurring this problem. After testing the model on shorter timespans and with altered parameters, we decided that we wanted to keep both the timespan and parameters as in the real world to ensure that the results would be as relevant to the real-life case as possible.

For this to be possible we landed on using an overlapping rolling horizon approach. In our implementation of the rolling horizon approach, we adjust for the model complexity by splitting the 300-day timespan (technically 306 days, as we allow for 300 days of fishing, and 6 days for Antarctic Provider to reach Montevideo after the last day of fishing) into 10 distinct periods P_T: $\{P_1, \ldots, P_{10}\}$, where each of these periods has a corresponding time interval T: $\{1, \ldots, 10\}$ of 30 days each. The end state variable values are taken at day 30 and used as the start-state variable values for the next optimization. This means that the starting values for krill inventory for all vessels and location for Antarctic Provider in period two, are equal to these values at day 30 in in the previous optimization, in this case optimization one. The same applies to all periods. In addition to this, we started all optimizations from day $t = -5$ to allow for our travelling constraints to make sense and to be able to accurately set the location of Antarctic Provider if it started a voyage right before day 30 in the previous optimization period. We will, however, not refer to these negative days when we speak of the optimization periods.

The rolling horizon optimization periods of 30 days is also the reason we set the MinStay and MaxStay parameters to 119 and 149 days, instead of choosing a round number of days. This is because a MaxStay of 150 would fall exactly in the seam between two periods allowing optimization period 6 to be run without the model having to account for crew changes in the overlapping period as all timers would end on 150 exactly. This would cause problems for the next period as the model does not account for the necessary crew changing trips to Puerto Williams. A MaxStay of 149 fixes this, as the model now has to initiate crew changes for all vessels in the overlapping period of optimization period 5 to keep the solution feasible.

Each optimization period has an overlap to the next period of $\mu = 2$. This results in the model optimizing 60 days at a time, where the first 30 days are the actual optimization period, and the last 30 days are considered an overlap to the next period. The exception to this is the last two periods where we optimize for both in one run. This means that the last run contains 66 days (in addition to the negative ones), as we have included an opportunity for Antarctic Provider to reach Montevideo after the 300-day fishing season. An illustration of the first two optimization periods can be found below.

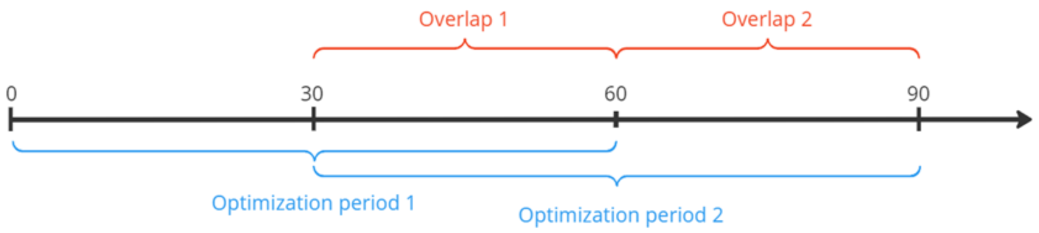


Figure 6.1: Visualization of rolling horizon approach

When implementing the rolling horizon, there were made changes to the objective function. This was to ensure that the model worked as intended and optimized for the entire period instead of prioritizing short-term krill brought to Montevideo in each optimization period on expense of the total optimal solution for the entire season. An example of this happening is if the start state inventory of Antarctic Provider is large enough that it must make two voyages to Montevideo during one optimization period. Because of the objective function being set up the way it is, Antarctic Provider will always bring krill to Montevideo on the very last day of the optimization period. For the other trip it is, however, not necessarily that important exactly which day it initiates the trip. In this case, it would usually not matter if it travelled before day 30, or after day 30. If the model chooses to travel before day 30, we will end up with a trip to Montevideo where Antarctic Provider would not necessarily be close to its storage capacity. To avoid this happening, and incentivize the model to postpone those trips, the objective function was altered to add a penalty cost for initiating a trip to Montevideo before day 31. This way the trips were postponed to after day 30 unless they were necessary. The altercation to the objective function is shown below.

$$\begin{aligned} \max \quad & \sum_{v \in V} \sum_{t \in T} (\mathrm{KrillOSH}_{v,t} - (\mathrm{APLoc}_{\mathrm{Transit},t} + \mathrm{APLoc}_{\mathrm{Mont},t} + \mathrm{APLoc}_{\mathrm{PW},t}) \times 100) \\ & - \sum_{f \in L} \sum_{d \in L} \sum_{t \in T : t < 31} \mathrm{TripIni}_{f,d,t} \end{aligned} \tag{6.45}$$

In a rolling horizon approach it is important that we change the ingoing values so that it matches the ones at day 30 on the previous optimization period. When Antarctic Provider is located in the Antarctic Ocean on day 30, this is fairly simple. Then the only constraints that need to be changed are the ingoing inventory values for all four vessels and the ingoing values for the crew timers. This means that we remove KrillInv and KrillInvAP from constraint 6.5 and make new initial values for each vessel. Timer is removed from constraint 6.16 and given a new initial constraint for each vessel. An example of which constraints must be added for an optimization period can be seen below.

$$\mathrm{KrillInvAP}_t = 10000 \quad \forall t \in T, t < 1 \tag{6.46}$$

$$\mathrm{KrillInv}_{\text{Antarctic Endurance},t} = 2000 \quad \forall t \in T, t < 1 \tag{6.47}$$

$$\mathrm{KrillInv}_{\text{Antarctic Sea},t} = 1800 \quad \forall t \in T, t < 1 \tag{6.48}$$

$$\text{KrillInv}_{\text{Saga Sea},t} = 1500 \quad \forall t \in T, t < 1 \tag{6.49}$$

$$\text{Timer}_{\text{Antarctic Endurance},t} = 10 \quad \forall t \in T, t < 1 \tag{6.50}$$

$$\text{Timer}_{\text{Antarctic Sea},t} = 16 \quad \forall t \in T, t < 1 \tag{6.51}$$

$$\text{Timer}_{\text{Saga Sea},t} = 22 \quad \forall t \in T, t < 1 \tag{6.52}$$

If Antarctic Provider is located any other place than in the Antarctic Ocean on day 30 in the optimization period, it becomes more complicated to initiate the next optimization period. This is because even more constraints must be altered or added to allow for the location of Antarctic Provider to be somewhere else than The Antarctic Ocean. There are also very many different scenarios that can happen. Antarctic Provider can be in Montevideo, Puerto Williams, the Antarctic Ocean, or anywhere between these three locations. How many days ago the voyage started is also relevant, as this will influence which day Antarctic Provider reaches its destination in the current optimization period. We will not include every possible combination but will provide an example where Antarctic Provider started a voyage to Montevideo on day 30 in the previous optimization period.

$$\text{APLoc}_{\text{Ant},t} = 1 \quad \forall l \in L, t \in T, t < 0 \tag{6.53}$$

$$\text{APLoc}_{\text{Mont},t} = 1 \quad \forall l \in L, t \in T, t = 5 \tag{6.54}$$

$$\text{TripIni}_{\text{Ant,mont},t} = 1 \quad \forall f \in L, d \in L, t \in T, t = 0 \tag{6.55}$$

7 Results

In this section, the results of the optimizations will be presented and analyzed. The results will focus on detailing the operations of Antarctic Provider, specifically its voyage schedule, krill inventory levels and the required number of voyages to facilitate the fishing vessels activity in the Antarctic Ocean. Additionally, an overview of the fishing vessels' activity will be presented and analyzed.

7.1 Base Case Results

7.1.1 Antarctic Provider

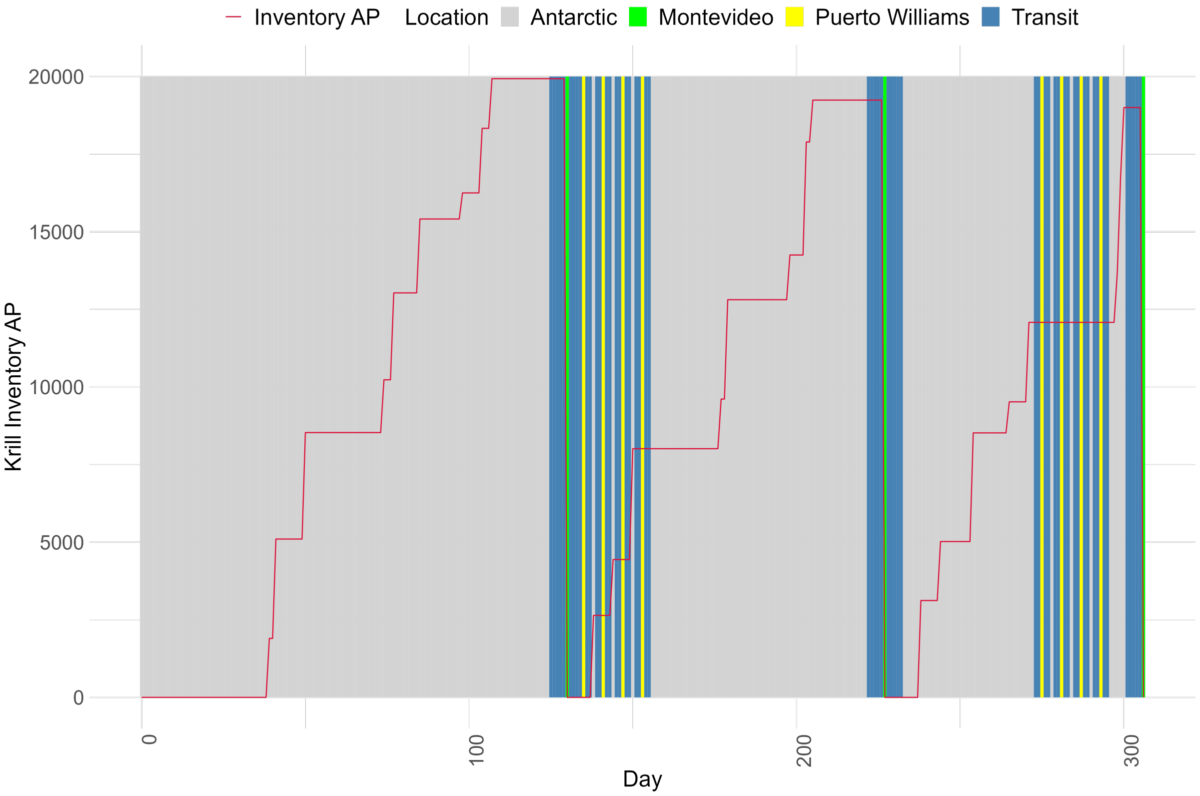


Figure 7.1: Storage and location of Antarctic Provider in the base case

In the figure above, we can see the schedule for Antarctic Provider for the entire optimization period. The colors indicate the location of the Antarctic Provider, with gray vertical lines indicating it is in the Antarctic Ocean, blue lines indicating it is on transit, green lines indicating Antarctic Provider being in Montevideo, and yellow lines when it is in Puerto Williams. The red line shows the krill inventory of Antarctic Provider at any given point in time.

The optimization model was designed to maximize krill transfer to the onshore hub in Montevideo, while minimizing the number of voyages to Montevideo and Puerto Williams. The model's optimal solution directed the Antarctic Provider to transfer 58 170 mt krill to the onshore hub in Montevideo. This was achieved over three voyages, with an average amount of 19 390 mt carried by the Antarctic Provider which is an average of 96.95% of its maximum capacity. Antarctic Provider takes eight trips to Puerto Williams, facilitating two crew changes for each of the fishing vessels.

In addition to the last, season-ending trip, one of the voyages to Montevideo are straight back and forth from the Antarctic, while one of the voyages is combined with changing crew in Puerto Williams. In this case, Antarctic Provider delivers krill to Montevideo and goes via Puerto Williams on the way back to pick up a crew. This starts a cycle where it continuously changes crew for all fishing vessels, resulting in a total of four trips to Puerto Williams before it has a longer period stationary in the Antarctic Ocean.

7.1.2 Fishing Vessels

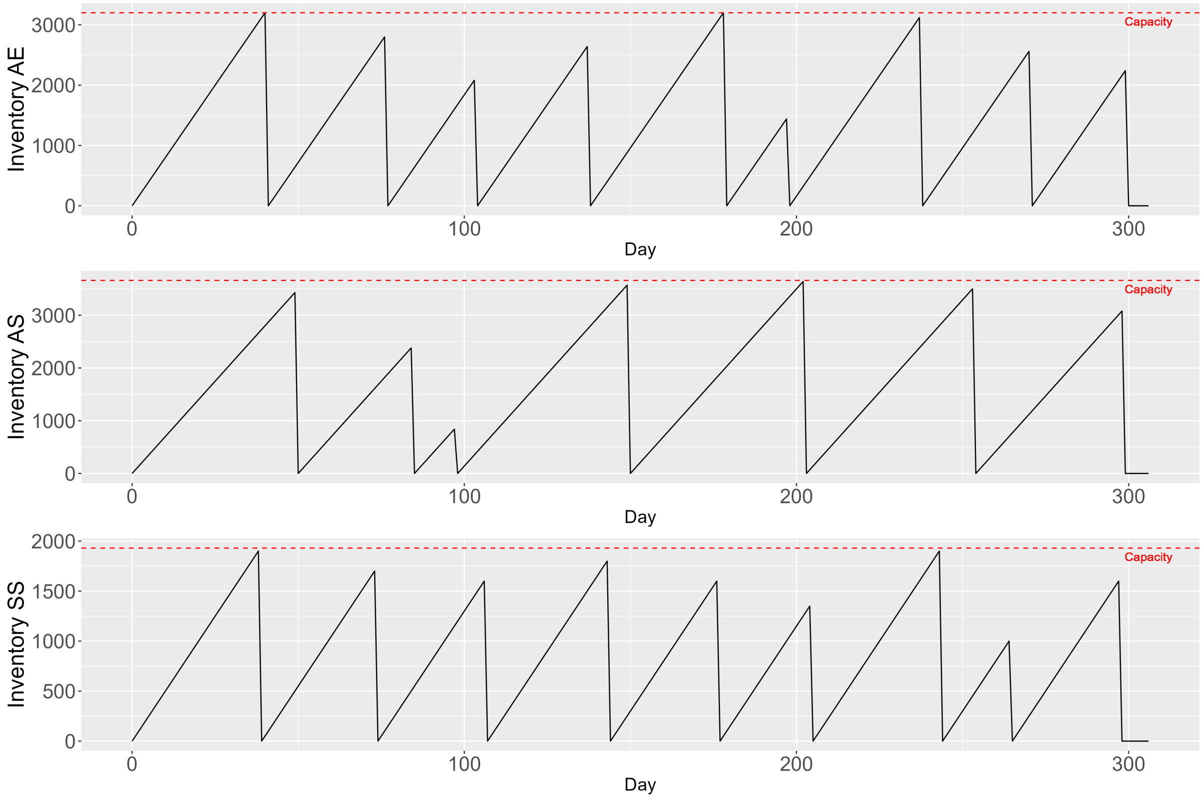


Figure 7.2: Storage of fishing vessels in the base case

In the figure above, the inventory of all three fishing vessels during the entire optimization period is presented. The diagonal lines show periods where the vessel is fishing without transferring the krill to Antarctic Provider. When the krill is transferred, we can see it by the vertical line bringing the inventory for the respective vessel back down to zero. As expected, all vessels usually fill their inventory relatively close to capacity before transferring to Antarctic Provider because every day spent transferring is a day they cannot fish. There are some exceptions to this, where they transfer smaller amounts to match the timing with Antarctic Providers deliveries to Montevideo.

Vessel	Days fishing	Days transferring	Days inactive	Total catch
AE	291	9	0	23 280 mt
AS	292	7	1	20 440 mt
SS	289	9	2	14 450 mt

Table 7.1: Key numbers for fishing vessels in base case

The table above shows how the fishing vessels operate in the Antarctic throughout the fishing season. The fishing vessels are maximizing the krill harvesting throughout the fishing season by only having inactive days after their last cargo transfer at the end of the season. Because only one vessel can transfer krill during a day, the fishing vessels must take turns to transfer their last krill. For example, Saga Sea, having the lowest fishing rate, will transfer first, on day 298, and therefore be inactive on day 299 and 300.

Antarctic Endurance has 291 total fishing days, 9 days transferring cargo, without any inactive days and a total of 23 280 mt krill catch. Antarctic Sea has 292 days of fishing, 7 days of transferring inventory and 1 inactive day, resulting in 20 440 mt krill harvested during the 300-day season. Saga Sea has the least amount of fishing days with 289, while transferring inventory 9 days, this results in a total catch of 14 440 mt krill. This means that the vessels are fishing every day, pausing only the days when it is necessary to transfer krill inventory to the Antarctic Provider and achieving an average daily catch of 193.9 mt against a potential of 200 mt.

7.1.3 Base Case Analysis

From the results we see that Antarctic Provider only needs three trips to Montevideo in the base case. On every trip to Montevideo the inventory is almost completely full, with an average of 96.95% of its maximum capacity. There is not a single day where any vessel is neither fishing nor transferring krill to Antarctic Provider except for the mandatory end-of-season days. This indicates that the model successfully manages to optimize the use of the support vessel despite the rolling horizon approach. One can also see that the fishing vessels are usually almost at full capacity when transferring their krill to Antarctic Provider. All three vessels have an average transfer of around 80% of total capacity (80.83%, 79.78%, and 83.18% for Antarctic Endurance, Antarctic Sea, and Saga Sea, respectively). This indicates that the fishing vessels are utilized relatively efficiently, as the fewer transfer days they have, the more days they can spend on fishing. There are, however, some exceptions to this, like Antarctic Sea transferring under a quarter (840 tons) of its capacity right before day 100. The main reason is that we decided a fishing vessel must transfer all their krill when it starts a transfer. By transferring earlier when Antarctic Seas inventory is low, Antarctic Provider can reach closer to their maximum capacity, as it could not have taken a large transfer when it is almost at full capacity.

Another aspect we can observe is that Antarctic provider chooses to wait several days after filling its capacity before it goes on the first trip to Montevideo. This way it could combine the trip to Montevideo with a necessary trip to Puerto Williams, saving a total of 3 days away from the Antarctic Ocean compared to if it had to go on both trips separately. After it returns to the Antarctic Ocean, we can see it getting filled quickly back up while it changes the crews of the fishing vessels, as the fishing vessels have had ample time to fill their respective storages with krill.

It seems that the resources possessed by Aker BioMarine are utilized very effectively in this case, where no trips are wasted, and Antarctic Provider even saves a couple of days of travelling when it can combine a krill delivery in Montevideo with a crew related trip to Puerto Williams.

7.2 Scenarios

To test the robustness of the model and examine the effects of changing parameters, we want to run our model on two different scenarios in addition to the base case. Even though we have found average numbers for fishing rates and travelling times, we find it interesting to see how the optimal schedule would change if any of these parameters are increased. This is especially relevant considering how fishing rates and travelling times can vary greatly both during a fishing season and from year to year, depending on krill abundance and weather conditions. In this section, we will present both scenarios, go through which changes we implemented to the model, present and analyze the results from the scenarios.

7.2.1 Scenario 1

The first scenario is a good season with increased fishing rates. It is difficult to predict what fishing rate Aker BioMarine can expect in the future, but with new research and development, like the recent investment in autonomous boats to search for krill, it is not unrealistic that the fishing rates can increase going forward. To examine if Antarctic Provider is ready for such future development, we have increased the fishing rate by 50%. With a higher fishing rate, Antarctic Provider needs to conduct more frequent cargo transfers with the fishing vessels as well as more voyages to Montevideo. This increased frequency will of course also need to be planned around the necessary crew change trips to Puerto Williams to make sure the workers rotations are respected.

7.2.1.1 Changes to Model

The changes to the model in scenario 1 are very simple. The model works in the same way as in the base case. The only difference is that fishing rates have now increased by 50%. This was done by simply changing the fishing rate parameters for all fishing vessels. The new fishing rates are presented in the table below.

Vessel	Fishing Rate Base Case	Fishing Rate Scenario 1
Antarctic Endurance	80 mt	120 mt
Antarctic Sea	70 mt	105 mt
Saga Sea	50 mt	75 mt

Table 7.2: Fishing rate changes in Scenario 1

7.2.1.2 Scenario 1 Results

Antarctic Provider

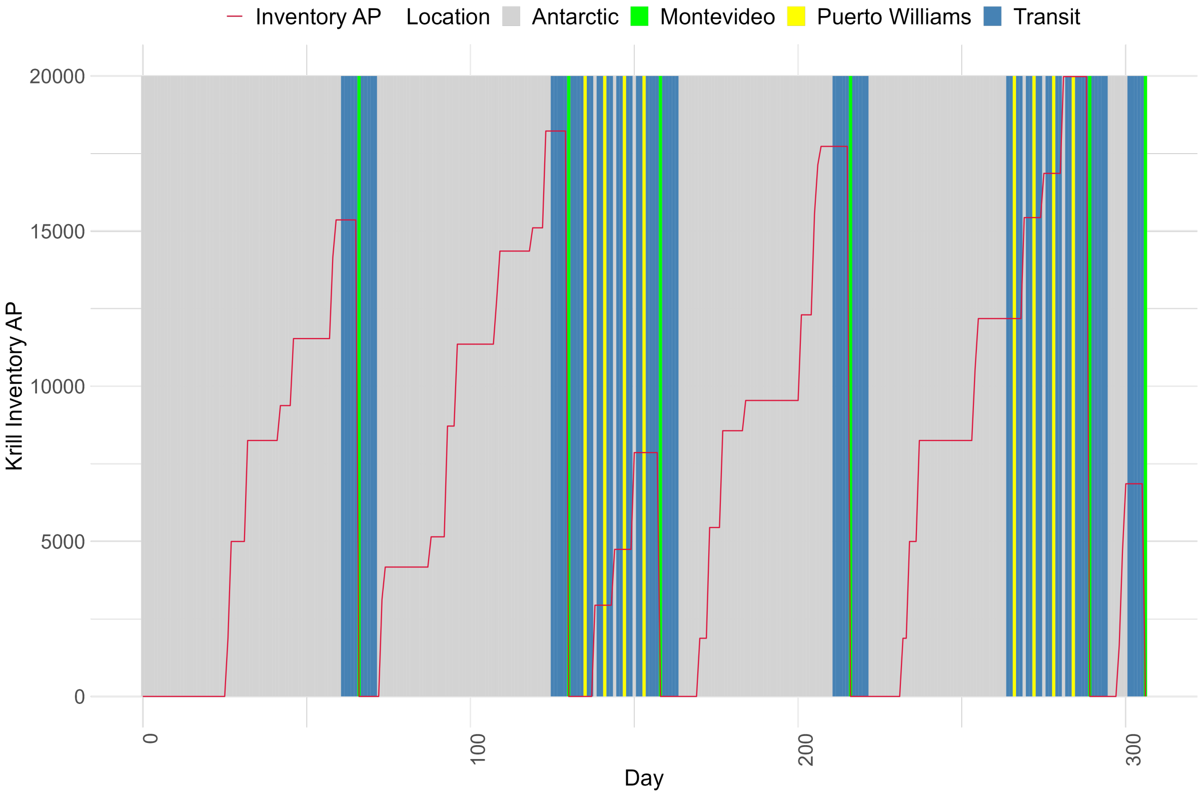


Figure 7.3: Storage and location of AP in scenario 1

After adjusting the fishing rate parameter by 50%, a new optimization was conducted. This adjustment resulted in the Antarctic Provider successfully transferring a total of 86

010 mt krill to the onshore hub in Montevideo, distributed over six voyages. This is an increase in harvested krill of 47.86%, compared to the base case. It makes sense that this number is not exactly 50%, as the fishing vessels now must use more days to transfer the extra krill. Antarctic Provider has an average load of 14 335 mt krill (71.68% of the total capacity) transferred per voyage to Montevideo, a substantial decrease in the average load compared to the base case.

During scenario 1, Antarctic Provider, conducted the eight mandatory trips to Puerto Williams, allowing each fishing vessel to change crew twice throughout the fishing season. Both times Antarctic Provider were in the process of picking up and delivering crew in Puerto Williams it was combined with a trip to Montevideo to offload krill at the same time.

Fishing Vessels

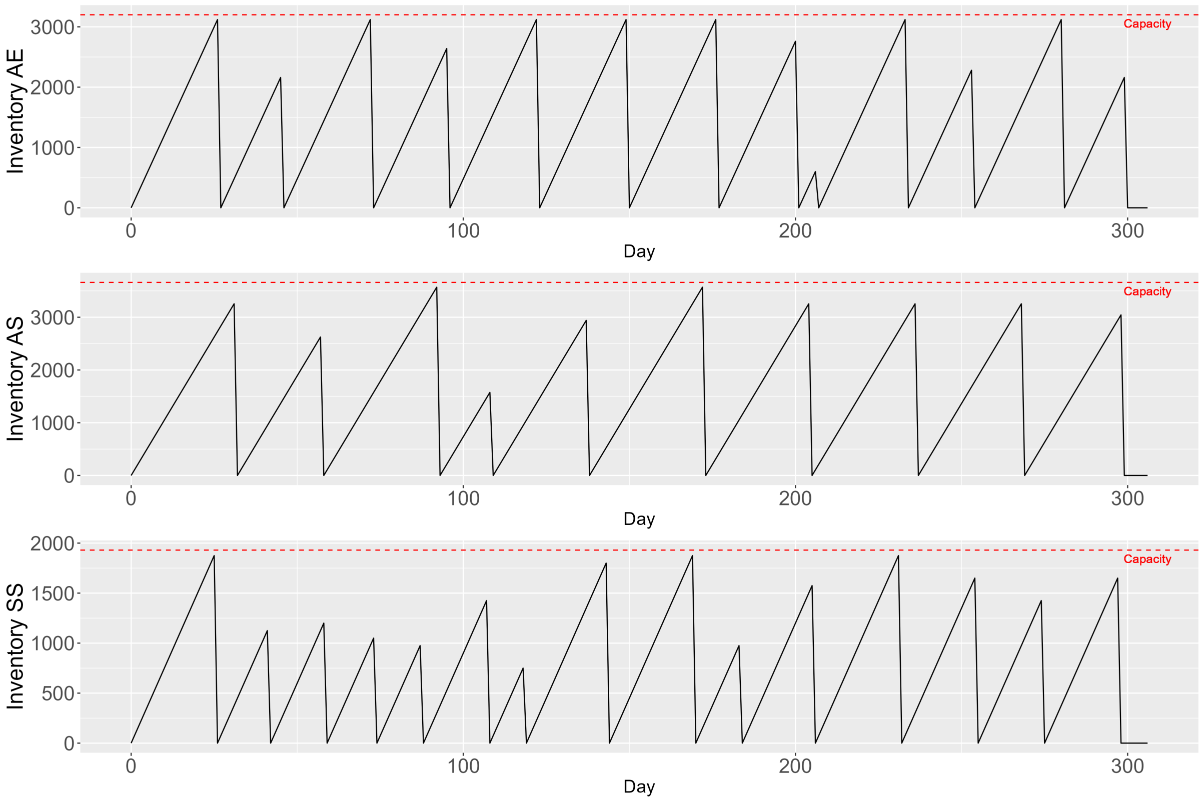


Figure 7.4: Storage of fishing vessels in scenario 1

The impact of the increased fishing rate naturally affected the fishing operations. The higher fishing activity led to an increased number of transfers needed as storage filled up quicker. Notably, Antarctic Endurance and Antarctic Sea often approach their maximum storage limits just prior to initiating a transfer. However, there are some instances coinciding with Antarctic Providers voyages to Montevideo where a transfer was conducted with lower inventory levels. Saga Sea typically initiated its transfers either when the inventory level was full or just over halfway filled.

Vessel	Days fishing	Days transferring	Days inactive	Total catch
AE	287	13	0	34 440 mt
AS	289	10	1	30 345 mt
SS	283	15	2	21 225 mt

Table 7.3: Key numbers for fishing vessels in scenario 1

The table above presents a summary of the activities of the fishing vessels under scenario 1. Antarctic Endurance completed 287 fishing days and 13 days of transferring inventory, harvesting a total of 34 440 mt krill. Antarctic Sea had 289 fishing days and 10 days of transferring, catching a total of 30 345 mt krill. Saga Sea had 283 active days of fishing, with 15 days of transferring inventory, resulting in a total catch of 21 225 mt krill. Naturally, the increased fishing rate results in higher total krill catches and thus, the need for more transferring days compared to the base case. Although the fish rate increased significantly, the efficiency of the vessels did not suffer. All three fishing vessels use the days throughout the fishing season to either fish, or to transfer cargo, meaning that there are no days where their storage was full at the same time as Antarctic Provider was unavailable for transfer. The data shows that the vessels together had a daily average catch of 286.7 mt out of a possible 300 mt.

7.2.1.3 Scenario 1 Analysis

In scenario 1, the fishing rates of all vessels was increased by 50% to see how the schedule would be affected, and if Antarctic Provider could keep up with a year with an exceptional abundance of krill without it forcing the fishing vessels to cease fishing. According to our results, an increase in fishing rates of 50% would not be a problem for Antarctic Provider to handle. It would only mean that it would take additional trips to Montevideo to keep up with the new fishing rates.

From the graph in figure 7.3, we can see that this is managed by taking six trips to Montevideo instead of the three trips in the base case. It is also apparent in the graph that on both trip three and trip six, Antarctic Provider has an inventory below half of the maximum capacity. Antarctic provider had an average transfer of 71.68% of its maximum capacity compared to 96.95% in the base case. This indicates that the schedule is not optimized completely for the entire optimization period because of the rolling horizon approach. The altercations that were made to the objective function worked very good in the base case. In scenario 1, on the other hand, it seems that the model is not as successful. This is because all fishing vessels now harvest at a higher rate. In turn, this increases the probability of the model having to deliver krill during the first 30 days to allow for the fishing vessels to continue fishing, because of the optimization period starting with high values for storage on the vessels. The result is that Antarctic Provider can deliver smaller amounts of krill because there is no penalty cost to delivering small amounts, only to delivering before day 31 in the optimization period.

As for the graphs of the fishing vessels, the first obvious difference is that they are much steeper because they now accumulate krill much faster than in the base case. They also have many more transactions, as they now have to get rid of their krill at a faster rate. Their average transaction is still relatively high, but there are quite a few transactions of lower amounts of krill. Saga Sea especially has many transactions where the inventory is only about halfway full. Both Antarctic Endurance and Antarctic Sea transfers a higher average percentage of maximum capacity compared to the base case with a percentage of 82.79% and 82.91%, respectively. Saga Sea, on the other hand, has an average transfer of 73.32% of maximum capacity, which is a decrease of approximately 10 percentage points compared to the base case.

7.2.2 Scenario 2

The second scenario we want to run is a season with exceptionally bad weather influencing travel times. Because the model uses a deterministic approach with constant travelling times, it is difficult to vary the time needed on voyages within a single optimization. We chose to represent the increased travelling time by adding two days on transit between the Antarctic Ocean and Montevideo, two days between Montevideo and Puerto Williams, and one day between the Antarctic Ocean and Puerto Williams. A summary is given below.

Voyage	**Base Case**	**Scenario 2**
Antarctic ↔ Montevideo	5 days	7 days
Antarctic ↔ Puerto Williams	2 days	3 days
Montevideo ↔ Puerto Williams	4 days	6 days

Table 7.4: Travel times comparison between base case and scenario 2

The thought behind this is studying the effects of increased travel times due to bad weather. This will not be extensive research of all possible outcomes of bad weather but will give a certain insight into how the model would plan around a relatively small inconvenience by weather.

7.2.2.1 Changes to Model

Some small adjustments to the model were necessary to run scenario 2. As the travelling time required to reach Montevideo now is 7 days, we adjust the last optimization period to contain 308 days, so that the number of potential fishing days remains at 300. Further adjustments that were made were that we added additional negative days in the set of days to allow us to control the starting position of Antarctic Provider, and to ensure it could start a trip on day one. We also added two additional days at the end of the last optimization period to ensure that the fishing vessels would have an equal amount of potential fishing days before Antarctic Provider must initiate its final trip to Montevideo for the season.

After this was done, the actual travel constraints were changed so that Antarctic Provider uses the intended amount of time for all trips. This was handled by making these adjustments to the following constraints model (the original constraint numbers are included to the right of the reformulated constraints):

$$\text{APLoc}_{\text{transit},t} \geq \text{TripIni}_{\text{Ant,Mont},t-i} \quad \forall l \in L, f \in F, d \in D, t \in T, i \in \{0, \dots, \min(t, 6)\} \tag{6.36}$$

When AP initiates a trip from the Antarctic Ocean to Montevideo, it will be in transit for the current day and following 6 days.

$$\text{APLoc}_{\text{Mont},t} \leq \text{TripIni}_{\text{Ant,Mont},t-7} + \text{TripIni}_{\text{PW,Mont},t-6} \quad \forall l \in L, f \in L, d \in L, t \in T, t > 0 \tag{6.37}$$

The only possible reasons for AP to be in Montevideo is if it either started a trip there from Antarctic Ocean 7 days ago or if it started a trip to Montevideo from Puerto Williams 6 days ago.

$$\text{APLoc}_{\text{Transit},t} \geq \text{TripIni}_{\text{Mont,Ant},t-i} \quad \forall l \in L, f \in L, d \in L, t \in T, i \in \{0, \dots, \min(t, 6)\} \tag{6.38}$$

When AP initiates a trip from Montevideo to the Antarctic Ocean, it will be in transit for the current day and following 6 days.

$$\text{APLoc}_{\text{Transit},t} \geq \text{TripIni}_{\text{Ant},\text{PW},t-i} \quad \forall l \in L, f \in L, d \in L, t \in T, i \in \{0, \ldots, \min(t, 2)\} \tag{6.39}$$

When AP initiates a trip from the Antarctic Ocean to Puerto Williams, it will be in transit for the current day and the following 2 days.

$$\text{APLoc}_{\text{PW},t} \leq \text{TripIni}_{\text{Ant},\text{PW},t-3} + \text{TripIni}_{\text{Mont},\text{PW},t-6} \quad \forall l \in L, f \in L, d \in L, t \in T, t > 0 \tag{6.40}$$

The only possible reasons for AP to be in Puerto Williams is if it either started a trip there from Antarctic Ocean 3 days ago or if it started a trip to Montevideo from Puerto Williams 6 days ago.

$$\text{APLoc}_{\text{Transit},t} \geq \text{TripIni}_{\text{PW},\text{Ant},t-i} \quad \forall l \in L, f \in L, d \in L, t \in T, i \in \{0, \ldots, \min(t, 2)\} \tag{6.41}$$

When AP initiates a trip from Puerto Williams to the Antarctic Ocean, it will be in transit for the current day and the following 2 days.

$$\text{APLoc}_{\text{Transit},t} \geq \text{TripIni}_{\text{Mont},\text{PW},t-i} \quad \forall l \in L, f \in L, d \in L, t \in T, i \in \{0, \ldots, \min(t, 5)\} \tag{6.42}$$

When AP initiates a trip from Montevideo to Puerto Williams, it will be in transit for the current day and the following 5 days.

$$\text{APLoc}_{\text{Transit},t} \geq \text{TripIni}_{\text{PW},\text{Mont},t-i} \quad \forall l \in L, f \in L, d \in L, t \in T, i \in \{0, \ldots, \min(t, 5)\} \tag{6.43}$$

When AP initiates a trip from Puerto Williams to Montevideo, it will be in transit for the current day and the following 5 days.

$$\text{APLoc}_{\text{Ant},t} = \text{APLoc}_{\text{Ant},t-1} - \sum_{d\in L} \text{TripIni}_{\text{Ant},d,t} + \text{TripIni}_{\text{Mont},\text{Ant},t-7} + \text{TripIni}_{\text{PW},\text{Ant},t-3} \quad \forall l \in L, f \in L, d \in L, t \in T, t > 0 \quad (6.44)$$

AP will be located in the Antarctic Ocean if it was located there the day before and it has not initialized a trip to anywhere the current day t. It can also be in the Antarctic Ocean if there was initiated a trip to there from Montevideo 7 days ago or from Puerto Williams 3 days ago.

7.2.2.2 Scenario 2 Results

Antarctic Provider

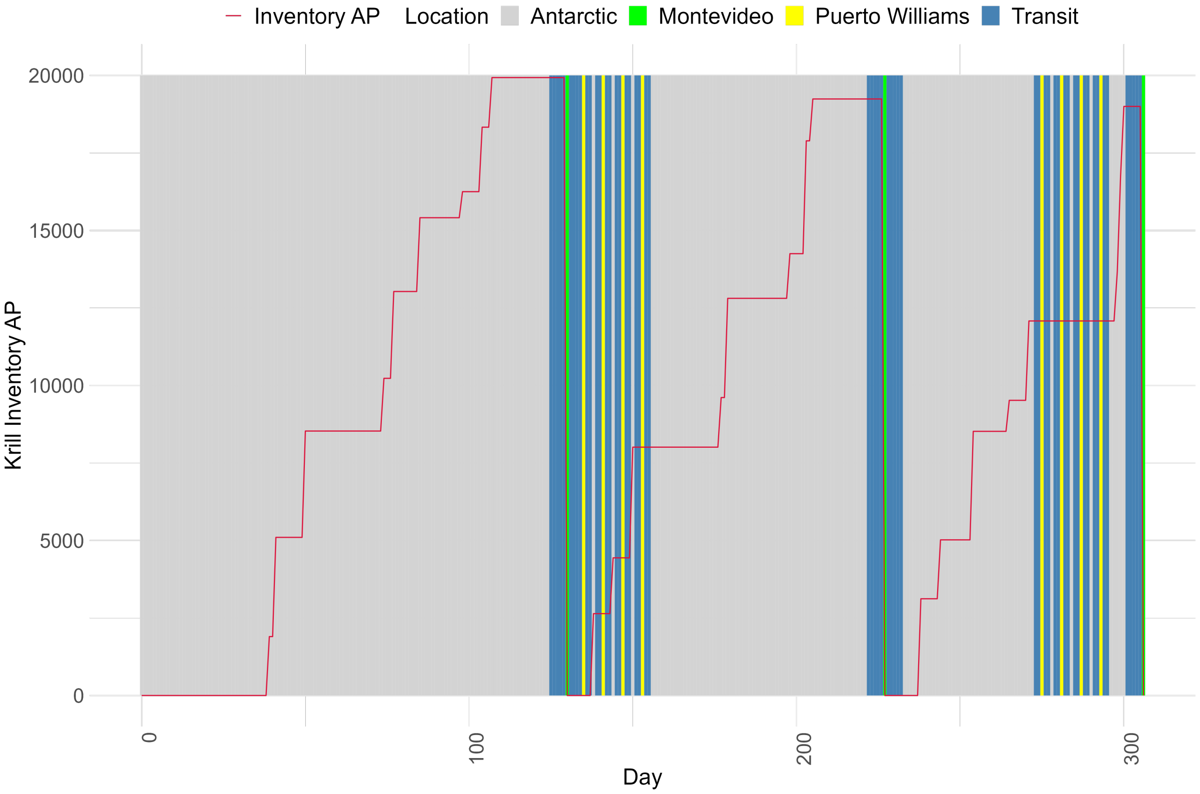


Figure 7.5: Storage and location of AP in scenario 2

The longer travel times resulted in Antarctic Provider transferring a total of 58 120 mt krill to the logistics hub in Montevideo. This was transported from the Antarctic to

Montevideo over three voyages, with an average krill load of 19 373.33 mt krill which is 96.87% of the vessel's capacity. Scenario 2 looks really similar to the base case, with three trips to Montevideo where the cargo was relatively close to maximum capacity on every trip. The scenario greatly resembles the base case in the performance, except for a marginally lower total krill harvested.

Fishing Vessels

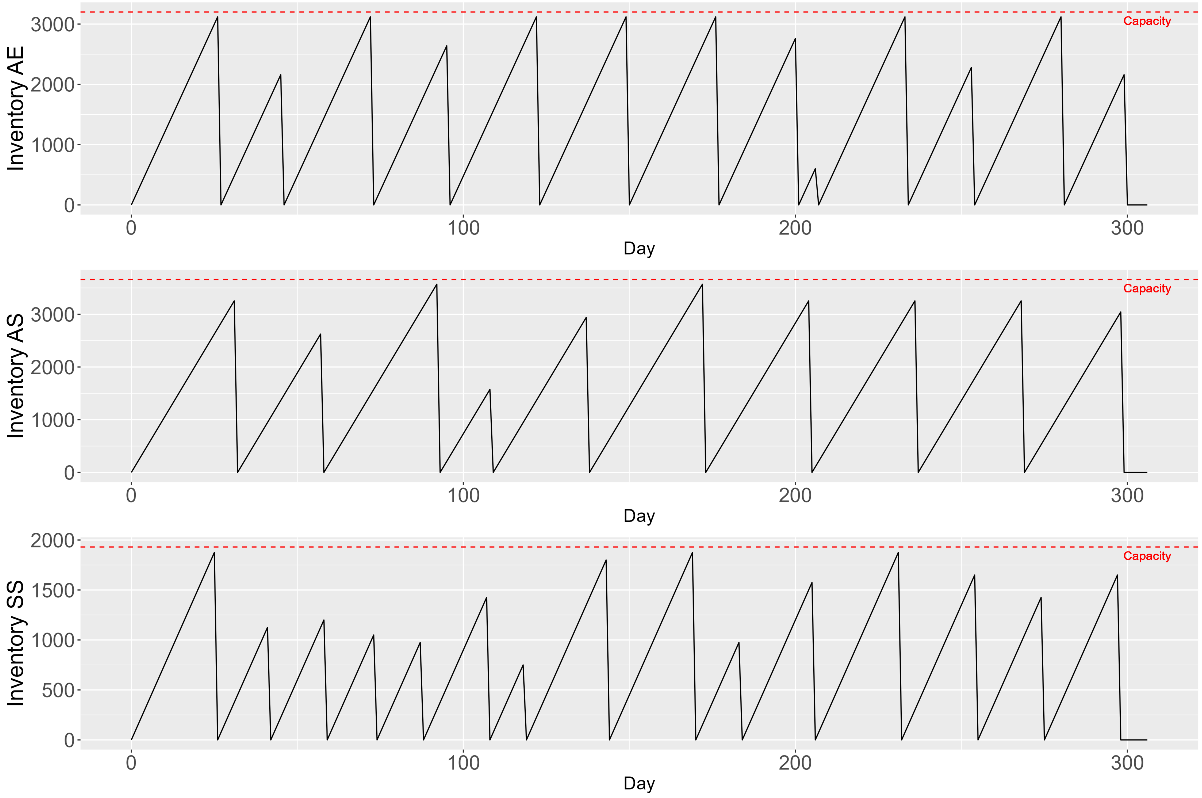


Figure 7.6: Storage of fishing vessels in scenario 2

The storage capacities of the fishing vessels also greatly resemble the base case. The fishing vessels generally are close to maximum capacity when transferring, but they have some smaller transfers as well to ensure that Antarctic Provider can be filled closer to its capacity.

Vessel	Days fishing	Days transferring	Days inactive	Total catch
AE	291	9	0	23 280 mt
AS	292	7	1	20 440 mt
SS	288	10	2	14 400 mt

Table 7.5: Key numbers for fishing vessels in scenario 2

By looking at the total days fishing compared to the total days of transferring inventory it also becomes apparent why this scenario performed slightly worse than the base case. It is because Saga Sea has one more transfer day, resulting in it harvesting 50 mt less during the entire fishing season. Other than that, the numbers for the fishing vessels are identical to the ones in the base case.

7.2.2.3 Scenario 2 Analysis

From the graphs in the results, it is obvious that Antarctic Provider still takes three trips to Montevideo, which is the same as in the base case. It does, however, transfer marginally less krill to Montevideo with a total amount of 58 120 mt compared to 58 170 mt in the base case. This is because Saga Sea has an extra transfer day, leaving it one less day to fish. The reason for this might be that Antarctic Provider now takes longer time to reach Montevideo, which gives fewer days for the fishing vessels to transfer krill, which results in them having to choose less optimal times.

8 Discussion

In this chapter, we will discuss the results for all three scenarios and evaluate the performance of the model in optimizing the scheduling period. We will also discuss limitations to this thesis and suggest potential for further research.

8.1 Discussion of Results

After running all three scenarios, it is apparent that the model performs good in optimizing the use of Antarctic Provider to transport as much krill as possible from the Antarctic Ocean to Montevideo on as few trips as possible. It also manages to do this while still planning this around the crew changes for all vessels so that the crew rotations are respected. In both the base case and scenario 2, the model manages to transport all the krill to Montevideo on only three trips, with an almost full capacity on all three occasions without having any inefficient days for any of the fishing vessels. In scenario 1, however, Antarctic Provider uses six trips to Montevideo to transport the krill. An increase in the number of trips is to be expected, as the fishing rates are now raised by 50% and the capacity was almost full on all three trips in the base case. The number of voyages required is unproportionally large, increasing 100%, compared to the 50% increase in fishing rates.

In all scenarios, Antarctic Provider has a considerable amount of time where it is just waiting for the fishing vessels to fill their storages so they can transfer their krill. Scenario 1 and 2 shows that this is also the case when raising the fishing rates and when the travel times increase. This is a part of the operation where the resources might not be utilized as effectively as they could be. Having a large ship like Antarctic Provider with its full crew laying idle in the Antarctic is a costly procedure. These periods could potentially be used to earn additional income by Antarctic Provider doing alternative work in the area. This is, of course, dependent on there actually being alternative work in the area, like freight jobs for scientists in Antarctica. It is also dependent on the additional income being worth the lower presence of Antarctic Provider for the fishing vessels.

Although our model produces a schedule where the vessels are utilized effectively, it is important to note that this is under perfect conditions with constant harvesting rates for all vessels and a constant travel speed for all voyages. The two scenarios test this somewhat, but in a real-world scenario factors like weather and krill abundance are volatile and hard to predict. This could result in it being smarter on a practical operational level to not fill Antarctic Providers' storage rooms quite as full on every trip, but rather have more trips to allow for some more leeway room in case of unforeseen events.

8.2 Cost Saving

Although we in this thesis do not have the information on the exact cost structure of Aker BioMarines operations in the Antarctic Ocean, one would assume that travelling back and forth between South America and the Antarctic comes with large expenses, especially for vessels of the size of Antarctic Provider. Reducing the number of voyages, even by just one, could therefore lead to great cost reductions for Aker BioMarine.

The base case optimization results offer an insight into the cost saving opportunities for Aker BioMarine. In this model, Antarctic Provider operates near its full capacity at 95.96% in its voyages to offload krill at the logistics hub in Montevideo. By carrying large amounts on each voyage, Antarctic Provider minimizes the number of trips to Montevideo, and could hardly transfer any more krill, without increasing the number of voyages. At the same time, Antarctic Provider is able to facilitate the fishing operations for the fishing vessels. There are no instances where the vessels cannot fish because of storage limitations and being unable to transfer their cargo to Antarctic Provider. These two factors combine for an efficient model, where the fishing vessels can fish as much as possible, while the number of trips to Montevideo is kept to a minimum.

There are, however, some concerns raised when comparing the base case model with the outcomes under scenario 1. When increasing the fish rate by 50%, the model is no longer able to keep the average amount transferred by the Antarctic Provider close to its capacity, with an average carried load of 71.68% of the full capacity. One could argue that this raises questions about the scalability of the model and the potential need for additional resources in order to account for potential changes in krill abundance. Although the results from scenario 1 underline this kind of argumentation, it seems that the increased fishing rate works worse with the rolling horizon approach. The problem is that the model needs to consider going on voyages to Montevideo more often, because its capacity fills quicker. With the heightened fishing rates, the probability increases for Antarctic Provider having to go to Montevideo before day 30 to avoid prohibiting the fishing vessels from fishing because of full storages. If this is the case, there is no extra cost of taking this trip early during those 30 days instead of later, leaving it up to chance.

8.3 Limitations

There are several aspects of this thesis where assumptions and simplifications have been made to be able to build a mathematical model that is able to produce usable results. These limitations and assumptions will be discussed in the paragraphs below.

8.3.1 Rolling Horizon

One of the most prominent limitations of this study is that we had to implement a rolling horizon to be able to produce results for the entire fishing season. Even though this is a great tool to be able to produce results at all, it still compromises the optimal solution because we can no longer optimize for the entire period. This makes it so that the model must make decisions without having the entire assessment basis. For example, the model will want to deliver krill to Montevideo at the end of each optimization period because this way it will have as much time as possible to gather krill, and the delivered krill to Montevideo is the metric we want to optimize. A potential fault of this is that the model might deliver krill to Montevideo at suboptimal times to prepare for the final delivery on day 60. An example of this is if it must deliver krill one time prior to day 60, this may be done on any given day without it having much effect on the optimal solution. The altercations made to the objective function solved this problem in the base case and scenario 2 but was less successful in scenario 1. If the model had more information to make its decisions on, this trip to Montevideo might have been done in conjunction with a crew related trip to Puerto Williams, an option not necessarily available in the 60-day optimization time because of the strict constraints related to the working times of the crews.

8.3.2 Time Increment

Another limitation is that we have simplified the model significantly by using time increments of entire days. For the model to be more accurate, one could make it so that it runs on an hourly basis. This would, however, make it exponentially harder to run the model as it would need much more computing power to make all the extra decisions associated with the smaller increments of time. We therefore decided to make the model as simple as possible, while keeping it relevant, and found the one-day increment to be a reasonable trade-off between processing time and accuracy. This means that any action that can be made, like transferring krill to AP or from AP to Montevideo, must take at least one day or a multiple of whole days. This is not necessarily the case in real life, where one could operate on a more precise schedule.

8.3.3 Antarctic Providers' Responsibilities

Antarctic Provider is used for other tasks than only transporting krill and crew, like transporting equipment and fuel (Aker BioMarine, 2022). This is not included in our model as we did not find any data for fuel consumption or fuel capacity for the different vessels. Additionally, we assumed that necessary fuel and equipment can be brought while Antarctic Provider is in either Montevideo to deliver krill, or in Puerto Williams to either pick up or deliver crew (or both). We do not know exactly how often AP is required to sail to shore to bring equipment for the fishing vessels. Another reason not to bring equipment into our modelling is that it is hard to predict what equipment will need replacement and at which times. Our goal is to produce a base schedule to help make decisions. We can, however, not plan for every unforeseeable event by having a fixed time for when AP should retrieve equipment from Montevideo, Puerto Williams, or any other port. One could make the point that our model makes Antarctic Provider prepared to handle these unforeseen events, by making Antarctic Provider stay in the Antarctic Ocean if there is no reason for it to be elsewhere. This way it will always be close to the fishing vessels and can help if there is anything that needs to be done. It can also carry the basic necessities of equipment in case any of the fishing vessels has a malfunction.

8.3.4 Weather

The model assumes that the weather stays constant throughout the entire season. This is reflected in the model by having the travel times between the different locations being constant in the entire period and that the fishing vessels can fish on any given day. Antarctica is a harsh place with a rough climate. The warmest month, January, typically has an average temperature of zero degrees Celsius. In the other months the average temperature can range between -10 to -60 degrees Celsius depending on where on the continent you are located. Temperature is not the only challenge in Antarctica. Wind is also a large factor. Gusts in Antarctica regularly reach 100km/h, and it is not unusual to see speeds of up to 160 km/h. This also means that the sea will get increasingly difficult to travel. Not only can this make the sail to Montevideo or Puerto Williams take longer time, but it may also render it impossible at certain times due to the dangers presented by the weather conditions. On the website of Hurtigruten it is stated that:

> “If anyone is in Antarctica once winter comes, they’re staying until summer returns. Flights and ships cease travel to and from Antarctica once the weather starts to turn, as conditions become too treacherous for travel. Typically, researchers are the only people who brave the Antarctic night” (Hurtigruten, 2023).

It is thus obvious that weather plays an important role in the daily operation of Antarctic krill harvesting. As was the case with the equipment malfunctions, it is a hard, if not impossible, task to predict the weather in advance when planning for the entire season. Because of this, we chose to run our optimization model without considering weather conditions.

To somewhat account for the possibility of longer travelling times during rough weather, scenario 2 uses increased travelling times. This will not give a full picture of how the weather affects the ability to travel, and at what speed Antarctic Provider can travel, but showcases how the model responds to constant longer travel times between locations.

8.3.5 Fishing Rates

Keeping fishing rates constant means that there were only two outcomes for a fishing vessel for a given day: it could either not fish, which would result in gathering zero krill, or they could fish, which would result in a catch of 80, 70 and 50 metric Tons for Antarctic Endurance, Antarctic Sea, and Saga Sea, respectively. In a real-life situation, one would expect the fishing rates to fluctuate from day to day and also during the season according to how well the fishermen predicts the migratory patterns of the krill shoals. Our numbers are based on average fishing rates, but the daily catch might deviate from this average throughout the fishing season. With the newly implemented autonomous boats that track the migrations of krill, it is likely to both increase the average fishing rates and make the fishing rates more predictable as they might have a higher success rate of finding krill. It is, however, still a stretch to assume fishing rates to be strictly constant.

Another factor which can also affect the fishing rates is the weather. As previously discussed, the weather in Antarctica can be extremely harsh, especially during the winter months. This can not only lower the fishing rates, as operations may take longer during harsh weather, but may also halt the operation entirely as the fishing vessels may need to seek shelter rather than fish. To keep our model simple, and due to lack of data on the distributions of fishing rates during the season, we have chosen the fishing rates to be constant. We did, however, study the effect of an increased fishing rate to determine how it would affect the optimal solution.

8.3.6 Location of the Fishing Vessels

The model is based on Antarctic Provider being in either The Antarctic Ocean, Montevideo, Puerto Williams, or in transit between two of these locations. This is also a simplification of reality. Our model treats The Antarctic Ocean as a single location, when there in reality are vast areas in which the fishing vessels can fish. As described in section 2, the fishing vessels change locations during the season to accommodate the migratory tendencies of the krill. This means that there, depending on the locations of the fishing vessels, will be variable time consumptions related to for example transshipment of krill or crew changes. This is because they often seek shelter in the South Orkney Islands to avoid strong waves while the ships are laying side by side. The farther they are from the

South Orkney Islands, the more time they will use to reach there in order to link up to Antarctic Provider.

From some locations in the Antarctic Ocean the Antarctic Provider might use longer time to Montevideo and Puerto Williams. Some locations might lead to Antarctic Provider needing less time to reach Montevideo or Puerto Williams. We have not accounted for this in our model as we thought it hard to predict the locations of the krill so far in advance. In our model, transshipment of krill is always set to one day, meaning that a vessel cannot fish on the same day as a transshipment. We found this to be a fair assumption, as the fishing vessel this way has a whole day to both reach a suitable location for the transshipment as well as perform the transshipment itself.

8.3.7 Crew

Another assumption we made to simplify our model is that the entire crew of a vessel will be changed at once. We have found no documentation for how the crew changes are performed by Aker BioMarine and what the rotation of the workers really is like. We do, however, know that the workers are brought from Puerto Williams by Antarctic Provider, and that Antarctic Provider has room for one additional crew at a time (J. Schasler, personal communication, September 21, 2023). Because of our lack of insight into the rotations of the different types of workers, we chose to simplify this by having the entire crew of a vessel changed at the same time. Even though this might not be the case in reality, we believe that it should be possible to use our schedule as a base to work around planning which workers should be changed at certain times. Antarctic Provider's general presence in the Antarctic Ocean also makes it possible to make decisions on short notice if it should be necessary to bring out workers or put in workers for example because of special expertise.

8.4 Further Research

As indicated by the limitations, there are several potentially interesting altercations that can be made to our model to make it represent reality better. An interesting study would be to cooperate with Aker BioMarine to make all parameters and assumptions as close to reality as possible, both fishing rates, locations during the season, and the rotation of the crews for all ships. With their cooperation one could also include fuel and equipment transportation into the problem to fully plan for every possible task for Antarctic Provider. One would of course still not be able to plan for unforeseen events but could plan for any routine trips. With a cooperation with Aker BioMarine, one could also get a better insight into their cost structure. This would make it easier to validate the performance of the model in monetary terms such as how much costs one would be able to cut through a mathematical optimization approach to scheduling the operation. Further research could also consist of testing the model on other krill fishing companies. Adjusting the model for other companies' approach to krill fishing operations would help to evaluate the model robustness in different scenarios and cases.

Another interesting study would be to examine different setups for the rolling horizon to see how the different setups can affect the optimal solution. Optimally, one could try to run the model on a powerful computer to see how much better the result would be after running the model for the entire 300-day season. This way one would also be able to compare the rolling horizon optimal solutions to the solution of a model that does not use a rolling horizon approach.

Further one could study the robustness of the schedule by trying to simulate the operation. With more data on day-to-day catches, as well as the effects of weather on both fishing and travel, one could find probable distributions for fishing rates and travel times. These can again be used to create a simulation model to examine if the schedule still is realistic when accounting for more volatile fishing rates and changing weather conditions.

9 Conclusion

This study aims to investigate how optimization can be used in scheduling the use of support vessels in Antarctic Krill fishing operations. Using Aker BioMarine's operations as a case, the goal was to maximize krill harvested and delivered to an onshore logistics hub in Montevideo, while keeping the number of voyages to a minimum.

The mixed integer linear programming model can effectively manage decisions around the actions of a support vessel in Antarctic fishing operations. This was tested in three different scenarios: one based on the actual values from the 2021 season, one where the fishing rates were increased by 50%, and one where travel times were increased. The results of these scenarios show that Aker BioMarine has a capacity to handle both increases in fishing rates and occasional bad weather without the fishing vessels experiencing days when storage reaches capacity without being able to transfer their cargo. The support vessel is able to facilitate fishing vessels, while keeping the number of trips to port as few as possible, waiting to voyage before cargo is close to capacity.

Although this thesis scenario analysis suggests that in most instances the model remains robust when increasing parameters, there are some concerns raised about the potential for sub-optimal solutions when fishing rates are increased. When increasing the fishing rate parameters, the model suggests more voyages with a lower average capacity load. This is likely due to the implemented rolling horizon approach where each optimization period has to consider more voyages as the storage of the vessels fill up faster.

We conclude that mathematical programming can be a great tool to help schedule support vessels in an Antarctic krill fishing operation. The model built in our case study successfully scheduled both crew changes and support vessel voyages to allow for a maximum amount of krill delivered to the onshore hub.

References

Aker BioMarine. (2020, May). *Meet our people: The fisherman.* https://www.akerbiomarine.com/blog/meet-our-people-the-fisherman?fbclid=IwAR1nE-7u4DcpjK_kk5lJLGtYjSslvwebzbUGodv9iK8-b2vsnOAj8m5N5vM

Aker BioMarine. (2022, August). *Company presentation.* https://www.akerbiomarine.com/hubfs/Aker%20BioMarine%20-%20Company%20presentation%20%20-%20August%202022.pdf

Aker BioMarine. (2023d, October). *Innovation is in our nature.* https://www.akerbiomarine.com/innovation

Aker BioMarine. (2023a, October). *The power of tiny krill.* www.akerbiomarine.com/what-is-krill

Aker BioMarine. (2023c, December). *Our operation from catch to product.* https://www.akerbiomarine.com/operations

Aker BioMarine. (2023b, December). *Who we are.* https://www.akerbiomarine.com/who-we-are

Andersson, H., Christiansen, M., & Fagerholt, K. (2010). Transportation planning and inventory management in the lng supply chain. In E. Bjørndal, M. Bjørndal, P. Pardalos, & M. Rønnqvist (Eds.), *Energy, natural resources and environmental economics* (pp. 427–439). Springer.

ASOC. (2021). *Evaluating the economics of the antarctic krill fishery* (Report). CCAMLR.

bednblue. (2023, November). *Sailing distance calculator.* https://www.bednblue.com/sailing-distance-calculator?cruisingSpeed=13.3

Cavagnini, R., Bertazzi, L., & Maggioni, F. (2022). A rolling horizon approach for a multi-stage stochastic fixed-charge transportation problem with transshipment. *European Journal of Operational Research*, 912–922.

CCAMLR. (2021, July). *Krill fisheries.* https://www.ccamlr.org/en/fisheries/krill

CCAMLR. (2023b, October). *About ccamlr.* https://www.ccamlr.org/en/organisation

CCAMLR. (2023a, October). *History.* https://www.ccamlr.org/en/organisation/fishing-ccamlr

Dantzig, G., & Thapa, M. (1997). *Linear programming 1: Introduction.* Springer-Verlag.

Fagerholt, K., Heilig, L., Lalla-Ruiz, E. M., & Wang, S. (2023). Data-driven optimization and analytics for maritime logistics. *Flexible Services and Manufacturing Journal*, 1–4.

Galvão, R., & Guimarães, J. (1987). An algorithm for helicopter routing in the support of offshore oil exploration. *Proceedings of the XX Brazilian OR Symposium*, 96–108.

Galvão, R., & Guimarães, J. (1990). The control of helicopter operations in the brazilian oil industry: Issues in the design and implementation of a computerized system. *European Journal of Operational Research*, 266–270.

Glomb, L., Liers, F., & Rosel, F. (2022). A rolling horizon approach for multi-period optimization. *European Journal of Operational Research*, 189–206.

Halvorsen-Weare, E. E., & Fagerholt, K. (2017). Optimization in offshore supply vessel. *Optimization and Engineering*, 317–341.

Hansen, K. (2019, January). *Aker biomarine christens new krill catcher.* https://mag.hookandnet.com/2019/01/18/2019-01antarcticend/pugpig_index.html

Huang, C.-Y., Lai, C.-Y., & Cheng, K.-T. (2009). Fundamentals of algorithms. In *Electronic design automation* (pp. 173–234). Science Direct.

Hurtigruten. (2023, December). *Weather and seasons in antarctica.* https://global.hurtigruten.com/destinations/antarctica/inspiration/weather-in-antarctica/

Kisialiou, Y., Gribkovskaia, I., & Laporte, G. (2019). Supply vessel routing and scheduling under uncertain demand. *Transportation Research Part C*, *104*, 305–316.

Krafft, B., Pedersen, R., Zhang, G., Menze, S., Rasmussen, A. F., Skaar, H., et al. (2023). Antarctic krill and ecosystem monitoring survey off the south orkney islands in 2023. *Norwegian Institute of Marine Research.*

Lundgren, J., Ronnqvist, M., & Varbrand, P. (2010). *Optimization.* Studentlitteratur.

Marine Traffic. (2023, November). *Antarctic provider voyage information.* https://www.marinetraffic.com/en/ais/details/ships/shipid:6483647/mmsi:257621000/imo:9886160/vessel:ANTARCTIC_PROVIDER

Marquant, J., Elvins, R., & Carmeliet, J. (2015). Reducing computation time with a rolling horizon approach applied to a milp formulation of multiple urban energy hub system. *Procedia Computer Science*, 2137–2146.

McElroy, J. K. (1984). Antarctic fisheries: History and prospects. *Marine Policy*, 239–258.

Meng, Q., Wang, S., Andersson, H., & Thun, K. (2014). Containership routing and scheduling in liner shipping: Overview and future research directions. *Transportation Research Part E: Logistics and Transportation Review*, *48*(2), 265–280.

Meyer, B., Atkinson, A., Bernard, K. S., Brierley, A. S., Driscoll, R., Hill, S. L., et al. (2020). Successful ecosystem-based management of antarctic krill should address uncertainties in krill recruitment, behaviour and ecological adaptation. *Communications Earth & Environment.*

Nafstad, G. M., Haugseth, A., Høyland, V., & Stålhane, M. (2021). An exact solution method for a rich helicopter flight scheduling problem arising in offshore oil and gas logistics. *Computers & Operations Research.*

Nicol, S. (2018). *Antarctic krill sustainability.* Aker Biomarine.

Nicol, S., & Endo, Y. (1997). *Krill fisheries of the world.* Food; Agriculture Organization of the United Nations.

Ozcan, S., Eliiyi, D. T., & Reinhardt, L. B. (2020). Cargo allocation and vessel scheduling on liner shipping with. *Applied Mathematical Modelling*, *77*, 235–252.

Rambau, J. (2023, December). *Mixed-integer linear programming.* https://www.modus.uni-bayreuth.de/en/competences/optimization/milp/index.html

Sierksma, G., & Tijssen, G. A. (1998). Routing helicopters for crew exchanges on off-shore locations. *Annals of Operations Research*, 261–286.

Skaret, G., Macaulay, G. J., Pedersen, R., Wang, X., Klevjer, T. A., Krag, L. A., et al. (2023). Distribution and biomass estimation of antarctic krill (euphausia superba) off the south orkney islands during 2011–2020. *Ices Journal of Marine Science*, 1472–1486.

Tou, J. C., Jaczynski, J., & Chen, Y.-C. (2007). Krill for human consumption: Nutritional value and. *Nutritional Reviews*, 63–77.

U.S. Department of Energy. (2020, October). *Liquefied natural gas value chain.* https://www.energy.gov/fecm/articles/liquefied-natural-gas-value-chain-fact-sheet

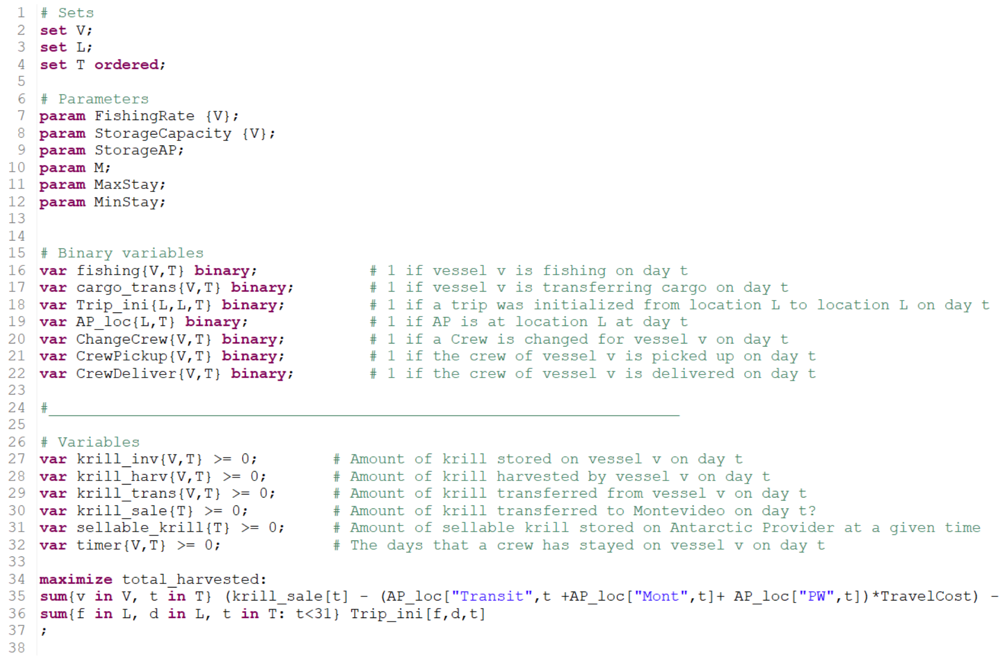
WWF Australia. (2022). *Antarctic krill* (Report). WWF Australia. https://wwfwhales.org/resources/wwf-report-antarctic-krill-powerhouse-of-the-southern-ocean

Appendices

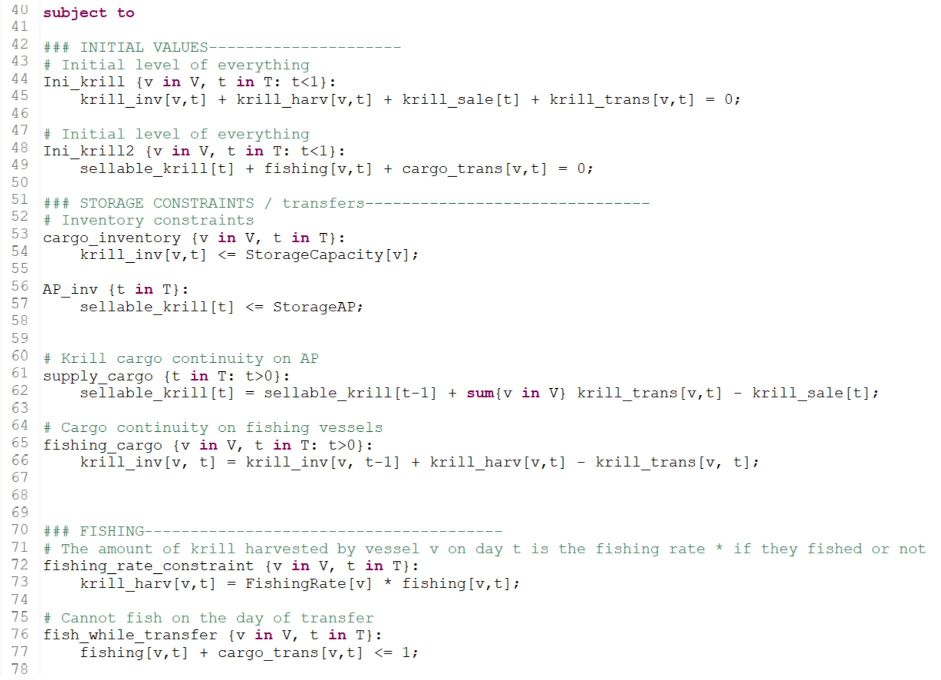
A AMPL Data File

```
data;
# Sets
set V := "Antarctic Endurance", "Saga Sea", "Antarctic Sea";
set T := -5, -4, -3, -2, -1, 0, 1, 2, 3, 4, 5, 6, 7, 8, 9, 10,
         11, 12, 13, 14, 15, 16, 17, 18, 19, 20,
         21, 22, 23, 24, 25, 26, 27, 28, 29, 30,
         31, 32, 33, 34, 35, 36, 37, 38, 39, 40,
         41, 42, 43, 44, 45, 46, 47, 48, 49, 50,
         51, 52, 53, 54, 55, 56, 57, 58, 59, 60;


set L := "Mont", "PW", "Ant", "Transit";

# Parameters
param FishingRate := # the rate of fishing on vessel v
"Antarctic Endurance" 120
"Saga Sea" 75
"Antarctic Sea" 105
;

param StorageCapacity := # the storage avaliable on vessel v
"Antarctic Endurance" 3200
"Saga Sea" 1930
"Antarctic Sea" 3660
;

param StorageAP := 20000;
param M := 999999;
param MaxStay := 149;
param MinStay := 119;
```

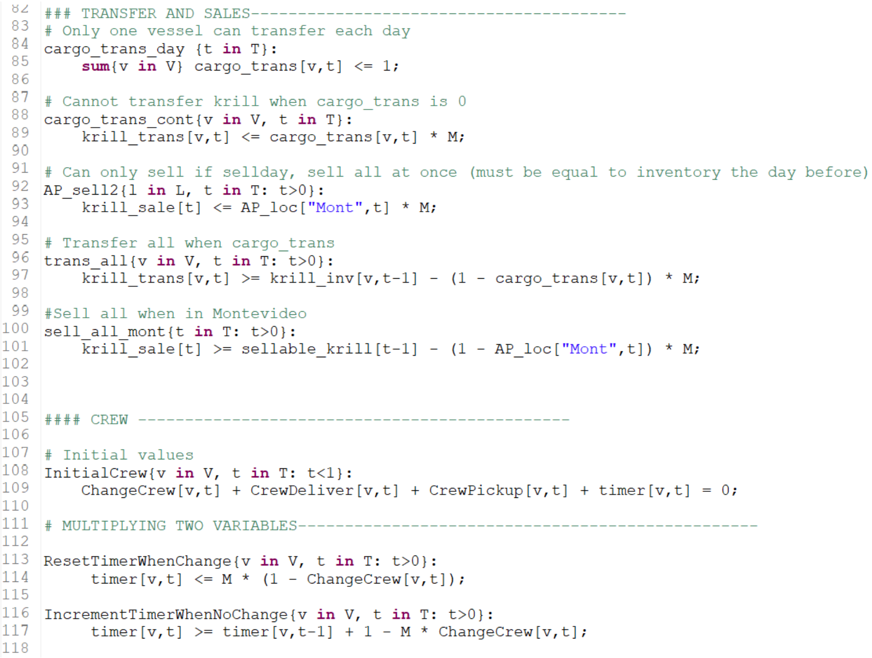
B AMPL Model File



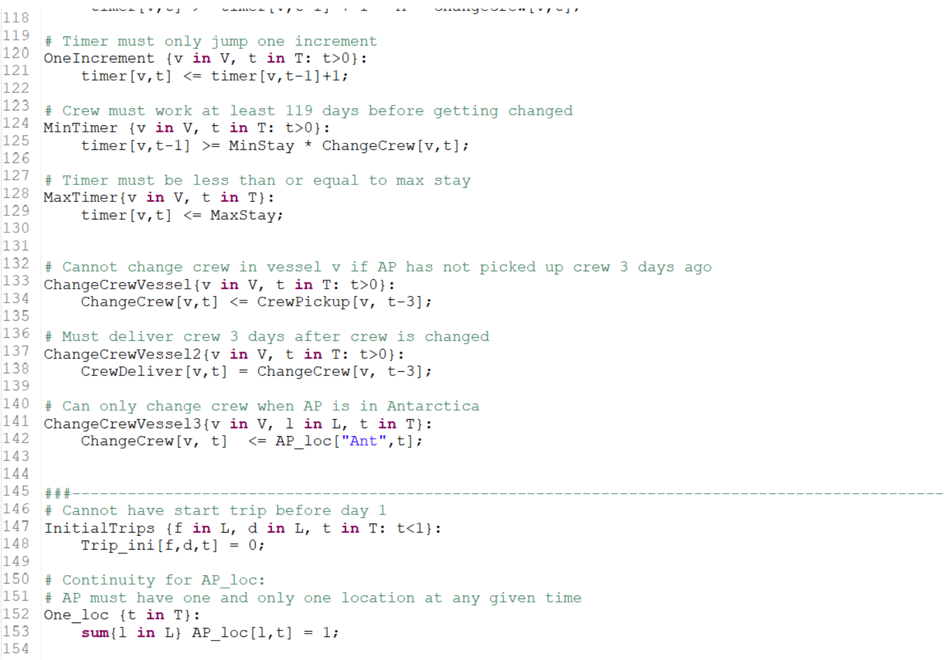
```
# Sets
set V;
set L;
set T ordered;

# Parameters
param FishingRate {V};
param StorageCapacity {V};
param StorageAP;
param M;
param MaxStay;
param MinStay;


# Binary variables
var fishing{V,T} binary;            # 1 if vessel v is fishing on day t
var cargo_trans{V,T} binary;        # 1 if vessel v is transferring cargo on day t
var Trip_ini{L,L,T} binary;         # 1 if a trip was initialized from location L to location L on day t
var AP_loc{L,T} binary;             # 1 if AP is at location L at day t
var ChangeCrew{V,T} binary;         # 1 if a Crew is changed for vessel v on day t
var CrewPickup{V,T} binary;         # 1 if the crew of vessel v is picked up on day t
var CrewDeliver{V,T} binary;        # 1 if the crew of vessel v is delivered on day t

#______________________________________________________________________

# Variables
var krill_inv{V,T} >= 0;        # Amount of krill stored on vessel v on day t
var krill_harv{V,T} >= 0;       # Amount of krill harvested by vessel v on day t
var krill_trans{V,T} >= 0;      # Amount of krill transferred from vessel v on day t
var krill_sale{T} >= 0;         # Amount of krill transferred to Montevideo on day t?
var sellable_krill{T} >= 0;     # Amount of sellable krill stored on Antarctic Provider at a given time
var timer{V,T} >= 0;            # The days that a crew has stayed on vessel v on day t

maximize total_harvested:
sum{v in V, t in T} (krill_sale[t] - (AP_loc["Transit",t +AP_loc["Mont",t]+ AP_loc["PW",t])*TravelCost) -
sum{f in L, d in L, t in T: t<31} Trip_ini[f,d,t]
;

```



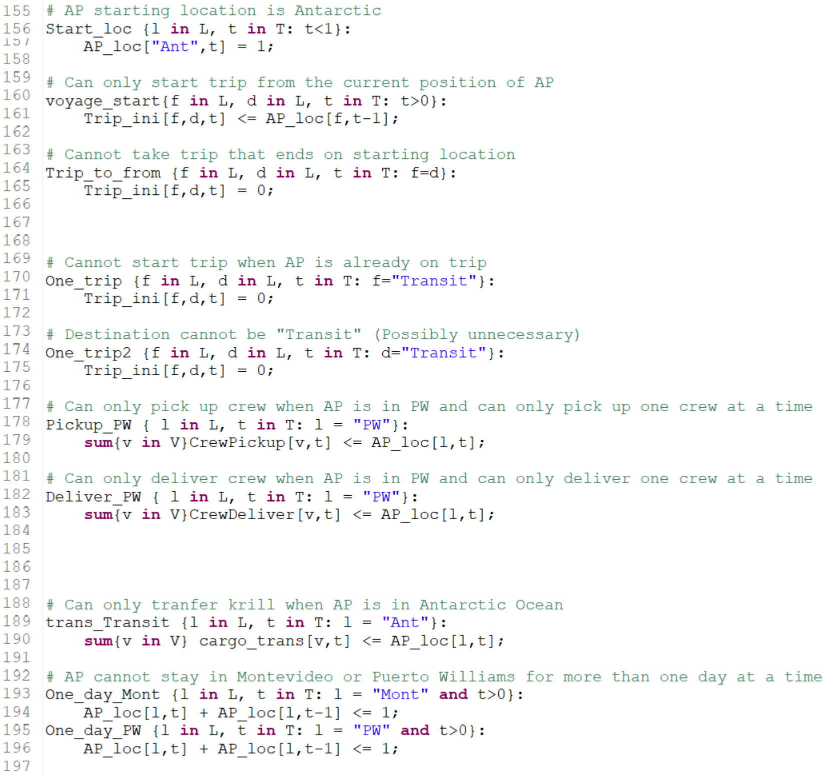
```
subject to

### INITIAL VALUES--------------------
# Initial level of everything
Ini_krill {v in V, t in T: t<1}:
    krill_inv[v,t] + krill_harv[v,t] + krill_sale[t] + krill_trans[v,t] = 0;

# Initial level of everything
Ini_krill2 {v in V, t in T: t<1}:
    sellable_krill[t] + fishing[v,t] + cargo_trans[v,t] = 0;

### STORAGE CONSTRAINTS / transfers------------------------------
# Inventory constraints
cargo_inventory {v in V, t in T}:
    krill_inv[v,t] <= StorageCapacity[v];

AP_inv {t in T}:
    sellable_krill[t] <= StorageAP;


# Krill cargo continuity on AP
supply_cargo {t in T: t>0}:
    sellable_krill[t] = sellable_krill[t-1] + sum{v in V} krill_trans[v,t] - krill_sale[t];

# Cargo continuity on fishing vessels
fishing_cargo {v in V, t in T: t>0}:
    krill_inv[v, t] = krill_inv[v, t-1] + krill_harv[v,t] - krill_trans[v, t];



### FISHING-------------------------------------
# The amount of krill harvested by vessel v on day t is the fishing rate * if they fished or not
fishing_rate_constraint {v in V, t in T}:
    krill_harv[v,t] = FishingRate[v] * fishing[v,t];

# Cannot fish on the day of transfer
fish_while_transfer {v in V, t in T}:
    fishing[v,t] + cargo_trans[v,t] <= 1;

```



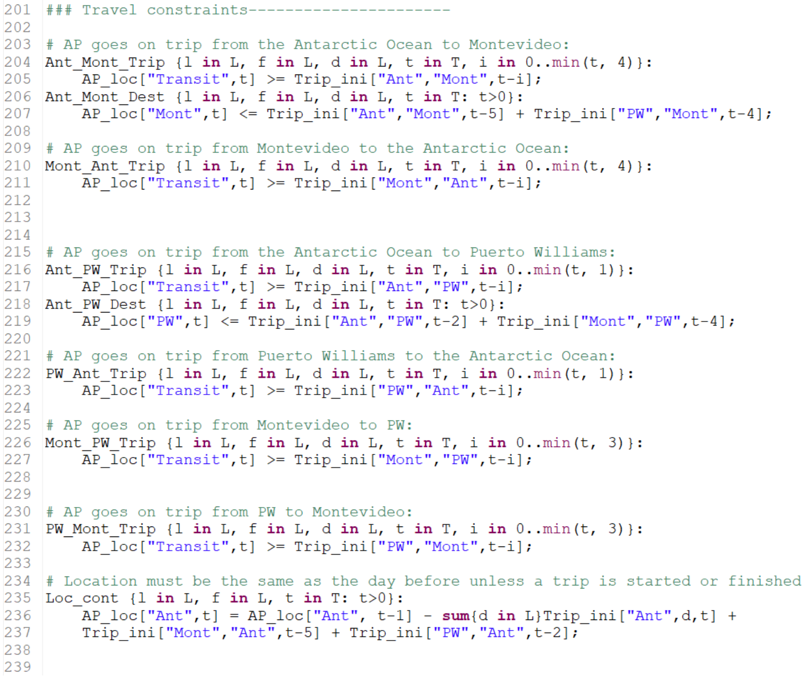
```
### TRANSFER AND SALES----------------------------------------
# Only one vessel can transfer each day
cargo_trans_day {t in T}:
    sum{v in V} cargo_trans[v,t] <= 1;

# Cannot transfer krill when cargo_trans is 0
cargo_trans_cont{v in V, t in T}:
    krill_trans[v,t] <= cargo_trans[v,t] * M;

# Can only sell if sellday, sell all at once (must be equal to inventory the day before)
AP_sell2{l in L, t in T: t>0}:
    krill_sale[t] <= AP_loc["Mont",t] * M;

# Transfer all when cargo_trans
trans_all{v in V, t in T: t>0}:
    krill_trans[v,t] >= krill_inv[v,t-1] - (1 - cargo_trans[v,t]) * M;

#Sell all when in Montevideo
sell_all_mont{t in T: t>0}:
    krill_sale[t] >= sellable_krill[t-1] - (1 - AP_loc["Mont",t]) * M;



#### CREW ----------------------------------------------

# Initial values
InitialCrew{v in V, t in T: t<1}:
    ChangeCrew[v,t] + CrewDeliver[v,t] + CrewPickup[v,t] + timer[v,t] = 0;

# MULTIPLYING TWO VARIABLES-------------------------------------------------

ResetTimerWhenChange{v in V, t in T: t>0}:
     timer[v,t] <= M * (1 - ChangeCrew[v,t]);

IncrementTimerWhenNoChange{v in V, t in T: t>0}:
     timer[v,t] >= timer[v,t-1] + 1 - M * ChangeCrew[v,t];

```



```

# Timer must only jump one increment
OneIncrement {v in V, t in T: t>0}:
    timer[v,t] <= timer[v,t-1]+1;

# Crew must work at least 119 days before getting changed
MinTimer {v in V, t in T: t>0}:
    timer[v,t-1] >= MinStay * ChangeCrew[v,t];

# Timer must be less than or equal to max stay
MaxTimer{v in V, t in T}:
    timer[v,t] <= MaxStay;


# Cannot change crew in vessel v if AP has not picked up crew 3 days ago
ChangeCrewVessel{v in V, t in T: t>0}:
    ChangeCrew[v,t] <= CrewPickup[v, t-3];

# Must deliver crew 3 days after crew is changed
ChangeCrewVessel2{v in V, t in T: t>0}:
    CrewDeliver[v,t] = ChangeCrew[v, t-3];

# Can only change crew when AP is in Antarctica
ChangeCrewVessel3{v in V, l in L, t in T}:
    ChangeCrew[v, t]  <= AP_loc["Ant",t];


###---------------------------------------------------------------------------------------------
# Cannot have start trip before day 1
InitialTrips {f in L, d in L, t in T: t<1}:
    Trip_ini[f,d,t] = 0;

# Continuity for AP_loc:
# AP must have one and only one location at any given time
One_loc {t in T}:
    sum{l in L} AP_loc[l,t] = 1;

```



```
# AP starting location is Antarctic
Start_loc {l in L, t in T: t<1}:
    AP_loc["Ant",t] = 1;

# Can only start trip from the current position of AP
voyage_start{f in L, d in L, t in T: t>0}:
    Trip_ini[f,d,t] <= AP_loc[f,t-1];

# Cannot take trip that ends on starting location
Trip_to_from {f in L, d in L, t in T: f=d}:
    Trip_ini[f,d,t] = 0;



# Cannot start trip when AP is already on trip
One_trip {f in L, d in L, t in T: f="Transit"}:
    Trip_ini[f,d,t] = 0;

# Destination cannot be "Transit" (Possibly unnecessary)
One_trip2 {f in L, d in L, t in T: d="Transit"}:
    Trip_ini[f,d,t] = 0;

# Can only pick up crew when AP is in PW and can only pick up one crew at a time
Pickup_PW { l in L, t in T: l = "PW"}:
    sum{v in V}CrewPickup[v,t] <= AP_loc[l,t];

# Can only deliver crew when AP is in PW and can only deliver one crew at a time
Deliver_PW { l in L, t in T: l = "PW"}:
    sum{v in V}CrewDeliver[v,t] <= AP_loc[l,t];




# Can only tranfer krill when AP is in Antarctic Ocean
trans_Transit {l in L, t in T: l = "Ant"}:
    sum{v in V} cargo_trans[v,t] <= AP_loc[l,t];

# AP cannot stay in Montevideo or Puerto Williams for more than one day at a time
One_day_Mont {l in L, t in T: l = "Mont" and t>0}:
    AP_loc[l,t] + AP_loc[l,t-1] <= 1;
One_day_PW {l in L, t in T: l = "PW" and t>0}:
    AP_loc[l,t] + AP_loc[l,t-1] <= 1;
```



```
### Travel constraints----------------------

# AP goes on trip from the Antarctic Ocean to Montevideo:
Ant_Mont_Trip {l in L, f in L, d in L, t in T, i in 0..min(t, 4)}:
    AP_loc["Transit",t] >= Trip_ini["Ant","Mont",t-i];
Ant_Mont_Dest {l in L, f in L, d in L, t in T: t>0}:
    AP_loc["Mont",t] <= Trip_ini["Ant","Mont",t-5] + Trip_ini["PW","Mont",t-4];

# AP goes on trip from Montevideo to the Antarctic Ocean:
Mont_Ant_Trip {l in L, f in L, d in L, t in T, i in 0..min(t, 4)}:
    AP_loc["Transit",t] >= Trip_ini["Mont","Ant",t-i];



# AP goes on trip from the Antarctic Ocean to Puerto Williams:
Ant_PW_Trip {l in L, f in L, d in L, t in T, i in 0..min(t, 1)}:
    AP_loc["Transit",t] >= Trip_ini["Ant","PW",t-i];
Ant_PW_Dest {l in L, f in L, d in L, t in T: t>0}:
    AP_loc["PW",t] <= Trip_ini["Ant","PW",t-2] + Trip_ini["Mont","PW",t-4];

# AP goes on trip from Puerto Williams to the Antarctic Ocean:
PW_Ant_Trip {l in L, f in L, d in L, t in T, i in 0..min(t, 1)}:
    AP_loc["Transit",t] >= Trip_ini["PW","Ant",t-i];

# AP goes on trip from Montevideo to PW:
Mont_PW_Trip {l in L, f in L, d in L, t in T, i in 0..min(t, 3)}:
    AP_loc["Transit",t] >= Trip_ini["Mont","PW",t-i];


# AP goes on trip from PW to Montevideo:
PW_Mont_Trip {l in L, f in L, d in L, t in T, i in 0..min(t, 3)}:
    AP_loc["Transit",t] >= Trip_ini["PW","Mont",t-i];

# Location must be the same as the day before unless a trip is started or finished
Loc_cont {l in L, f in L, t in T: t>0}:
    AP_loc["Ant",t] = AP_loc["Ant", t-1] - sum{d in L}Trip_ini["Ant",d,t] +
    Trip_ini["Mont","Ant",t-5] + Trip_ini["PW","Ant",t-2];
```