LUT University

UTILIZING ARTIFICIAL INTELLIGENCE IN CUTTING PLAN GENERATION OF SHIP STRUCTURE IN SHIP RECYCLING PROCESS

Lappeenranta–Lahti University of Technology LUT

Master's Programme in Mechanical Engineering, Master's thesis

2024

Mahshad Keshtiarast Esfahani

Examiners: Professor Heikki Handroos

Ming Li, D.Sc. (Tech.)

ABSTRACT

Lappeenranta–Lahti University of Technology LUT

LUT School of Energy Systems

Mechanical Engineering

In co-operation with partner university: Polytechnic University of Milan

Mahshad Keshtiarast Esfahani

Utilizing artificial intelligence in cutting plan generation of ship structure in ship recycling process

Master's thesis

2024

78 pages, 51 figures, 7 tables

Examiners: Professor Heikki Handroos and D.Sc.(Tech) Ming Li

Keywords: ship recycling, artificial intelligence algorithms, optimization, cutting plan

Traditional ship dismantling in developing countries endangers workers, environment, and social safety as it involves intensive manual labour. While use of dry dock method is a safer method of vessel dismantling, due to higher costs of the green yards, ship owners deny selling their vessels to them. Use of innovative artificial intelligence algorithms in generation of cutting plan for ship hull which involves most of the steel mass of a vessel can aim to pave the way for green yards to lower their costs. That is because in current practice, cutting plan for a vessel is generated by human expertise which is costly, subjective, and time-consuming. Utilizing AI algorithms can lower the need for human expertise while ensuring that the plan is optimized and feasible. As the plan is optimized, cutting operations become more efficient and the emissions reduce. The feasibility of plan is considered by imposing constraints of the shipyard facility such as lifting and transportation capacity and consideration of stability while the cuts are performed. To implement AI algorithms, a set of reliable data from digital model of a vessel would be needed to ensure that the generated plan is not artificial. Since the needed data as input for AI algorithm is impossible to be achieved by interacting with user interface of CAD software, application programming interface is used instead to automatize the process. Different algorithms have different characteristics that the proposed problem needs to be defined such that the objectives can be realized. After deploying AI algorithms, their achieved solution can be validated by analysis of convergence and comparison of different algorithm solutions. Finally, a discussion on performance of algorithms and their adequacy for this specific problem is done.

SYMBOLS AND ABBREVIATIONS

Roman characters

A	area	[cm^2]
COM	center of mass	[cm]
m	mass	[kg]
T	temperature	[K]
t	time	[S]

Dimensionless quantities

c	crossover point
child	offspring
g	global position
E	energy function
exp	exponential function
Indpb	mutation probability
k	bias factor
l	length of chromosome
N	number of cuts
p	probability
p1, p2	parent individuals
r	random number between 0 and 1
s	state
v	particle velocity

x	gene / particle position
α	cooling rate
σ	sigmoid function
φ	inertia weight

Subscripts

0	initial
f	final
i	individual/iteration/particle
j	gene
x,y,z	directional indices

Superscripts

$'$	transitioned state/muted gene
old	refers to previous values
new	refers to updated values

Abbreviations

AI	Artificial Intelligence
API	Application Programming Interface
CAD	Computer Aided Design
EVS	Economic Value Streams
EU	The European Union
GA	Genetic Algorithm

ILP	Integer Linear Programming
LDT	Light Displacement Tonnage
NEVS	Non-economic Value Stream
PCB	Polychlorinated Biphenyls
PSO	Particle Swarm Optimization
SA	Simulated Annealing

Table of contents

1 Introduction

In this section first some background information about the ship recycling industry is given. This includes various techniques of vessel recycling, and the problems we face in this industry. After that the research objective, the scope and limitations, and the methodology of the work are discussed.

1.1 Background information

Ship recycling means disassembly of a ship, storage and processing of these materials for reusing in a recycling facility (European Union, 2013, p. 4). Therefore, many parts of the ship, from ship hull to the machinery, can be recycled, and reused. This process feeds construction industry by recycled scrap steels as well as homes and small businesses by electronic equipment. While recycling steel can benefit the environment as it eliminates the need for extraction of iron which is energy intensive, in case it is not done in a safe manner, it can impose hazards. (Gourdon, 2019, pp. 11-21.) Therefore, dismantling an end-of-life ship in substandard conditions can have detrimental effects on environment, and labour (Solakivi, 2021, pp. 1-4).

Despite the basic constructional components of dismantled ships that are safe steel components, the process may generate hazardous materials like mineral wool (such as asbestos), polychlorinated biphenyls (PCBs), glass fibre, paints, waste oil, and solid foam. The listed materials can lead to environmental pollution and contaminations, fire and explosions, and human health issues such as cancer and immune system damage. Different locations of the vessel can contain these materials, such as the engine room, insulations and coatings, and fuel system. (Du, 2018, pp. 158-171; Zakaria, 2012, pp. 98-100.)

More than environmental hazards and health issues that ship recycling practice by beaching can bring about, some social issues are present as well. Most workers in shipyards have not been formally trained to deal with toxic materials. Many workers die or get injured because of falling from heights, or explosions. (Kusumaningdyah, 2012, pp. 88-94.)

In 2017, since labour costs in Bangladesh, Pakistan, India, and China are lower, 91% of demolition of vessels were done in these countries. While there are several regulations which aim to enhance health and environmental standards in ship recycling industry, many of them have not been put into force in these countries. Some of these regulations are Basel Convention (1989), Hong Kong Convention (2009), and European Union ship recycling regulations (2013). For enhancing standards in this industry, EU is establishing a list of facilities that comply with its regulations. It also requires that all EU-flagged ships should be demolished at a facility mentioned in the list (Gourdon, 2019, pp. 11-21). In 2009, EU flagged ships represented a volume of more than 0.81 million Light Displacement Tonnage (LDT) while the existing dismantling capacity (aligned with EU regulations) is only one quarter of that. This shows that there is an urgent need for environmentally safe ship recycling facilities. (European Commision, 2012.)

Ship dismantling can be carried out using various techniques, but a common traditional approach in Asia is the beaching method. In this process, once the ship owner selects a buyer and completes all necessary inspections and certifications, the ship is brought ashore using high tidal variations and a gently sloping shoreline. After salvaging any reusable or partially used materials, the ship is cut into smaller sections using gas cutting. The process lacks a structured cutting sequence and involves minimal safety precautions or technological expertise during the recycling phase. (Zakaria, 2012, pp. 98-100.) A general description of the steps taken would be as follows. 1) preparation of ship for dismantling, 2) pre-cleaning and removal of hazardous materials, 3) block cutting, 4) secondary cutting, sorting and site cleaning (Zhou, 2021, pp. 2-5). Small investment, large amount of manual labour, and less electricity provides economic opportunities for developing countries (Kusumaningdyah, 2012, pp. 88-94).

A variation of beaching method in which low level of tide difference is needed is called slipway. The ship in this method is docked to shore or a slipway extended to the sea. The other method which is believed to be the most environmentally friendly method is dry-docking because of works being carried out in an enclosed area and post-cleaning of the dock before re-flooding. The process, therefore, is done in a dock which has a lock gate and impermeable floor. (Qyuen, 2019, p. 89.) Dry-docking as a green facility should adopt advance technology and equipment with less human labour yet more skilful. That is why this green capacity tends to be more costly and therefore ship owners who try to maximize their profit prefer beaching method (Kusumaningdyah, 2012, pp. 88-94). However, it should be noted that based on EU regulations, beaching ships for demolition is no longer possible (Merisaari, 2024, 80 p).

1.2 Research objective

The overall goal of the project is to adopt and integrate innovative artificial intelligence systems into the ship recycling industry. As current ship recycling procedures involve intensive manual labour in operations and human expertise in generation of cutting plan, adopting AI algorithms aims in eliminating this necessity while ensuring that safety and operational capabilities are considered.

A ship recycling plan that needs to be developed by the operator of the ship recycling facility, contains the necessary procedures that need to be followed such as preparation works of the ship, labelling the hazardous materials based on the inventory of hazardous materials provided by the ship owner, further evaluation of inventory of hazardous material by yard authorized personnel and finally cutting plan (IMO, 2011, pp. 1-8).

The aim of the project is to reduce the amount of time needed to cut the ship hull into large blocks by optimizing the cutting plan based on the digital model of the ship that is available. In current ship recycling processes though, a cutting master generates the cutting plan based on experience on similar vessels and expertise. This is why explosions, blocks falling, and hazardous material exposures are probable. Cutting the ship hull into large blocks shall be translated as primary cutting plan. For Autonomous generation of the cutting plan of the ship hull, it is needed that necessary data on geometry and properties of the digital model are derived and given to appropriate artificial intelligence algorithms to produce a plan which is optimized. This eliminates the need for intervention of human expertise, which is time-consuming and pricy in generation of cutting plan. It makes the process faster, more efficient with the cutting process, and less costly. Therefore, the project can pave the way for more economical ship recycling by environmentally friendly approaches that are deprioritized because of their higher costs.

With realization of the goal of this project, not only the amount of time spent for generation of cutting plan significantly reduces, but also by minimizing the total cutting area, the time for cut and the emissions made by it significantly reduce. This enables green shipyards to compete with their less-environmentally-friendly counterparts despite their higher costs of labour. More than economic and environmental advantages that the outcome of this project brings about, social safety increases as stability of the ship hull during cutting has been considered. This prevents unexpected falls and injuries of the workers throughout the process. The cutting plan also needs to be feasible to be operated which is realized by consideration of typical transportation and lifting capacities.

1.3 Scope and limitations

As generation of a cutting plan for a super structure like a vessel for all the involved stages and all the structures is not achievable at once, the main concern of this project is to generate the primary cutting plan for the ship hull. That is why secondary cutting and sorting plan have not been analysed. Cutting the ship hull into large blocks, is inspired by ship recycling practice at city of Raahe with diamond wire cutting instead of gas cutting in dry dock. Therefore, prior to this step, ship’s machinery and superstructures are detached.

It is assumed that the disposal of hazardous materials is done before the start of cutting phase and therefore presence of any cross sections of the ship that cannot be cut because of presence of these materials has not been considered. This assumption is close to reality as the focus of project is cutting the ship hull which can be made free of hazardous materials as most of them are in engine room.

Drawings, and digital models of vessels are confidential documents that are not easily accessible. Therefore, a simplified digital model of a vessel is utilized which represents a container ship. Ship recycling plan and to be more exact, the cutting plan, is ship specific. Consequently, the results obtained correspond to this type of vessel.

Deployed artificial intelligence algorithms are metaheuristic approaches that do not guarantee reaching a global optimum. Instead, they might converge to a sub-optimum solution. However, with analysis of convergence and comparison of results from genetic and simulated annealing algorithms, it is ensured that the solutions are reliable.

1.4 Methodology

In this section, the approach with which the problem of generation of an optimized primary cutting plan for ship hull is solved, is discussed.

1.4.1 Literature review

Initially the general ambition of the project was to improve the industry of ship recycling by utilizing innovative methods of artificial intelligence, which can make environmentally friendly dismantling of vessels feasible. However, the constraints present in the problem and the exact objective that is specifically addressed for this problem, and the general scheme of the work was not identified. That is why an extensive literature review was conducted to find about general procedures that are taken for ship dismantling in traditional and greener methods. That could help to find out about the general steps from preparation works of the vessel and disposal of hazardous materials to primary and secondary cutting phases. Moreover, the problems in industry ranging from health issues and environmental hazards to loss of stability of the vessel during the cut and potential fall of blocks were identified.

For detection of objectives and constraints of the optimization problem, it was necessary to address what the reasons are that ship owners deny selling their vessels to green shipyards. Solving this problem could set a solid goal for the algorithms. Therefore, the available literature in this concern helped in pinpointing the constraints that limit the cutting phase, and the requirements of the process. Respecting the recognized constraints and requirements lead to generation of a plan that is doable in practice.

After getting an overview of the general process and the goals to achieve, the method of solving the problem was the concern. That is why the literature concerning disassembly sequence generation and optimization were gone through. When it comes to disassembly/dismantling of a superstructure, finding the sequence of disassembly and the optimized solution can be a problem that needs a tremendous computational effort. Consequently, the literature helped in detection of approaches that can manage the size of the problem. (Kongar, 2006, pp. 497-506; Kizilay, 2022, pp. 1-10; Tseng, 2011, pp. 1183-1197.)

1.4.2 CAD model data derivation

For realization of the aim of the project, it was necessary to start from a set of data on a vessel. However, this data was not available which made us pursue methods of accessing data on ship hull. Firstly, a simplified CAD model of a vessel was retrieved. It should be noted that as the ship hull is a huge structure with many details, it was impossible to derive the necessary data using the user-interface of CAD software. This means that the CAD model data derivation should have been done automatically with the use of application programming interface using Python script. The obtained data aimed in ensuring that what the algorithms generate as a result in the end, is not artificial.

Based on the goal of the optimization algorithms that were previously identified, this set of data had to be about physical properties of the ship hull such as material, density, area, and mass and some geometric data such as centre of mass coordinates for all the bodies generated by the cuts. The physical data is needed for applying the mass constraint of each cut block that should not exceed the transportation and lifting capacity of shipyard, and for minimization of total cutting area. Centre of mass coordinates are necessary for applying a constraint on stability of the remaining ship after each cut. Before utilizing the optimization algorithms, it is also needed to perform some calculations to prepare the input.

1.4.3 AI algorithm implementation

When the necessary data was available, it was time to use them as inputs of artificial intelligence algorithms. There are several meta-heuristic approaches that can be implemented for generation of an optimized cutting plan. However, not all suit the characteristics of the problem and the type of data that was available. Therefore, genetic algorithm, particle swarm optimization method, and simulated annealing (along with linear programming for initial state generation) were adopted which are suggested by literature for such purpose. Python modules were utilized for this purpose such that the identified constraints are respected, and objective are achieved. Different parameters of each algorithm were fine-tuned to ensure reaching best solution. Finally, the optimized sequences obtained were verified using convergence analysis and by comparison of different algorithms. In the end, a discussion over adequacy of each adopted algorithm for this specific problem was done.

2 Recycling procedures

Although some general guidelines exist on how the procedure of ship dismantling should be done, each plan needs to be ship specific. Some ships, like bulk carrier, general cargo, and container ships have similar hull structural elements which are truss-like elements. This means that their dismantling procedure is almost the same. One traditional method in ship recycling is beaching method. In this method, the ship beaches during high-tide period, while the cutting process occurs during low-tide period as it could be observed in Figure 1. (M. Hiremath, 2016, pp. 279-298.)

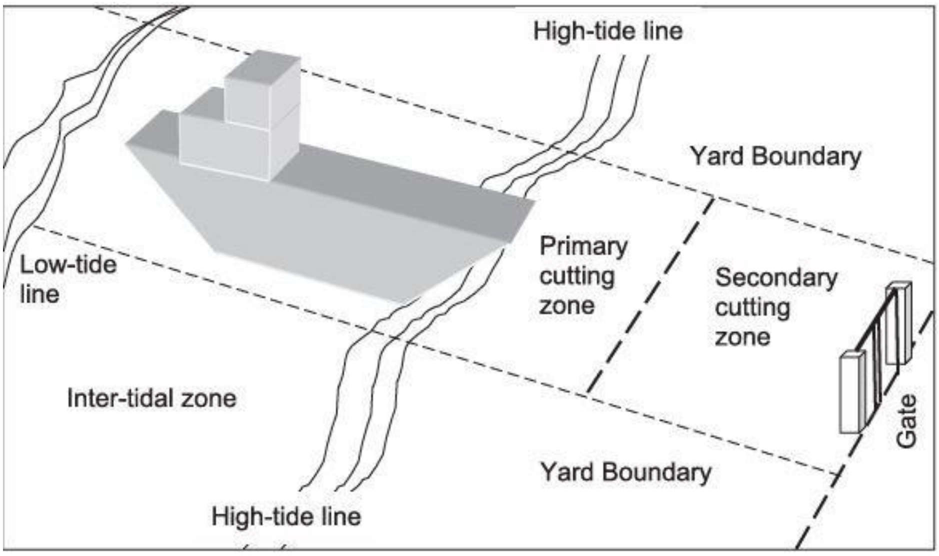

Figure 1. Schematic representation of a typical yard with notational yard boundaries, gate, and the beached ship between the high-tide and low-tide lines (M. Hiremath, 2016, p. 282).

Different zones of a shipyard are illustrated in Figure 1. Intertidal zone is a wet area in which large pieces of ships are cut. Primary cutting zone though, is a semi-wet area that large cut blocks of ships are dragged toward by the help of winches. After that, in this area the blocks are cleaned up, fragmented and transferred to the gate. The secondary zone is used for further processes like further cuts. The cutting process normally has some general steps that can be observed in Figure 2. First, the bow of the ship is cut so that the workers can enter the first hold of the ship. Then, the front wall of the ship is cut followed by cutting the side-walls.

When the bow is cut, holds of the ship can be reached. During the process, stability and structural integrity of the ship should be also taken care of. That is why when some holds and the hull beneath them are cut, it could happen that the remaining ship goes in deep water losing its balance. Using winches, the remaining ship is dragged towards primary zone to prevent loss of balance of the ship. More than this, filling the ballast tank at some stages can help with maintenance of balance. High tide can also assist dragging by winches. When large parts of steel are cut in the primary stage, they are lifted and transported for further cuts and sorting to end up in re-rolling mills, electric arc furnaces, or waste yards. This depends on what application the recovered material is appropriate for. The last step would be about cutting the cabin, galley and the engine room. Engine room cutting process is the most challenging step in ship dismantling which requires precise commitment to guidelines as follows: 1) hazardous waste location marking 2) cutting out the openings to act as windows for ventilation purposes 3) small equipment separation from flanged joints 4) draining fuel lines and taking parts to the secondary zone. As there could be oil in pipes of the engine, in gas cutting process a helper should pour water continuously onto cutting zone to prevent fire. (M. Hiremath, 2016, pp. 279-298.)

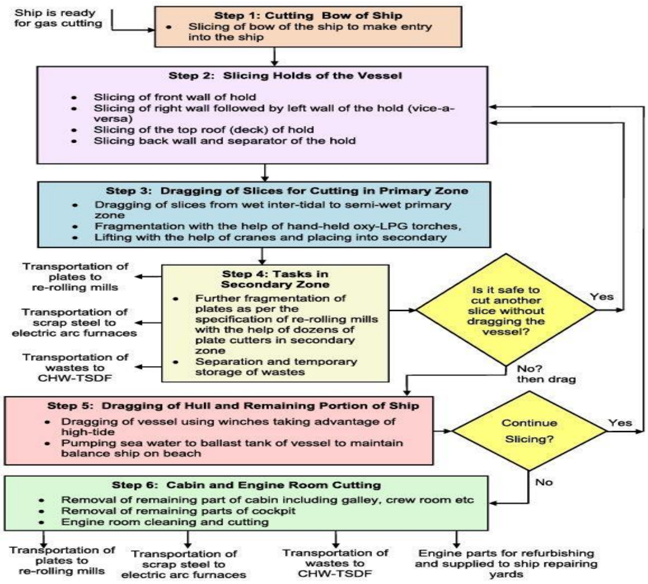

Figure 2. Typical steps followed in breaking bulk carrier ships in recycling yards (M. Hiremath, 2016, p. 283).

2.1 Material flow analysis

Previously, a general overview of cutting steps of the ship was discussed. In this section, we aim to focus on flow of all the materials found on a vessel from the primary stage of preparation works up to last stage. It should be noticed that before cutting process begins, several steps are mandatory. According to (K.P.Jain, 2017, pp. 674-677), “the entire recycling process can be divided into three main phases of pre-cutting, cutting, and post-cutting as in **Error! Reference source not found.**. The pre-cutting process involves various surveys and hull preparations for gas cutting. The cutting process is the process where actual cutting of steel hull and machinery into small pieces takes place. The post-cutting process involves sorting and segregation of materials. All material streams originating from each process are categorized into two major streams, economic value stream (EVS) and non-economic value stream (NEVS). Economic value stream is the stream having the products which can either be sold for reuse or recycling, resulting in cash in-flow for the recycling yard. Non-economic value stream is the stream having the products which needs to be disposed of either at a waste treatment facility or at landfill sites resulting in cash out-flow for the recycling yard.” As it can be seen in **Error! Reference source not found.**, all three stages of pre-cutting, cutting and post-cutting will result in flow of materials that do not have any economic value. The reason why NEVS from pre-cutting and cutting first goes to post-cutting rather than going to landfills is that an initially recognized NEVS of material, may need more sorting and involve EVS. The total LDT percentage of recovered material of a vessel is estimated as 96.595% which proves that this industry is profitable. (K.P.Jain, 2017, pp. 674-683.)

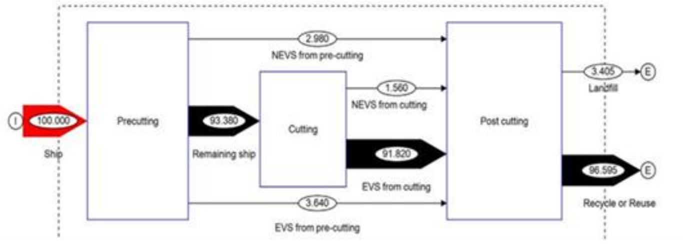

Figure 3. Ship recycling process showing quantities of material flow in terms of percentage of LDT (K.P.Jain, 2017, p. 678).

It should be noted that according to (shipbreaking, 2024), “light displacement tonnage (LDT) is defined as the weight of the ship with all its permanent equipment, excluding the weight of cargo, fuel, water, ballast, stores, and crew”.

2.1.1 Pre-cutting

According to (K.P.Jain, 2017, p. 678), “pre-cutting consists of various sub-processes such as the removal of loose items, removal of liquids, removal of hazardous materials, removal of insulation, flooring and tiling, and removal of cables and electrical equipment. These are directly sent to post-cutting in which further separation and sorting takes place”. In Figure 3, the flow of materials in pre-cutting stage can be observed.

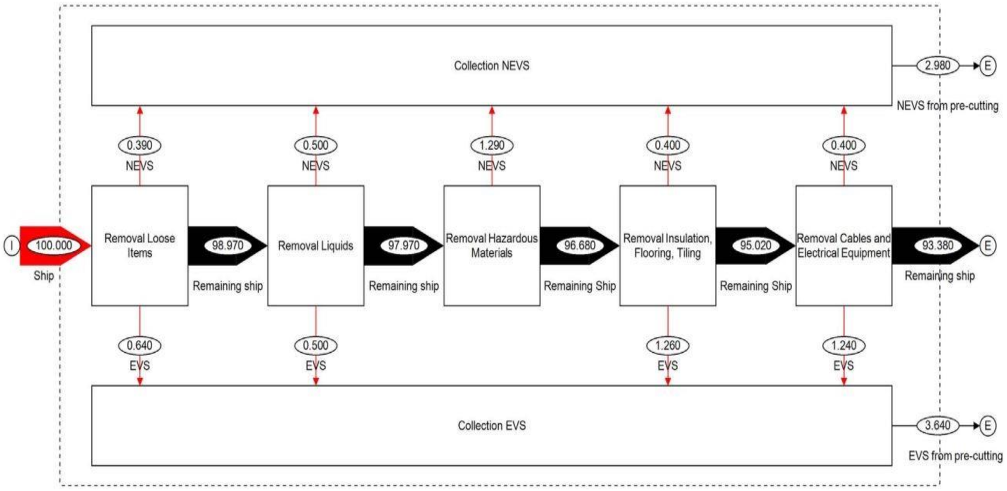

Figure 3. Pre-cutting process of ship showing the quantities of material flow in terms of percentage of LDT (K.P.Jain, 2017, p. 678).

2.1.2 Cutting

After pre-cutting stage is over, ship’s hull is cut into ferrous blocks, and non-ferrous items are extracted. The machinery is then segregated to reusable and scrap machinery. The ferrous scrap machinery is cut further in the secondary cutting step. Non-ferrous items though are small enough not to need the secondary cut. (K.P.Jain, 2017, p. 679.) As evident in Figure 4, the cut blocks are mostly Ferrous ones which need to go through secondary cutting as well. The extracted machinery is either reusable or is cut to form scrap for recycling and waste to be directed toward landfills.

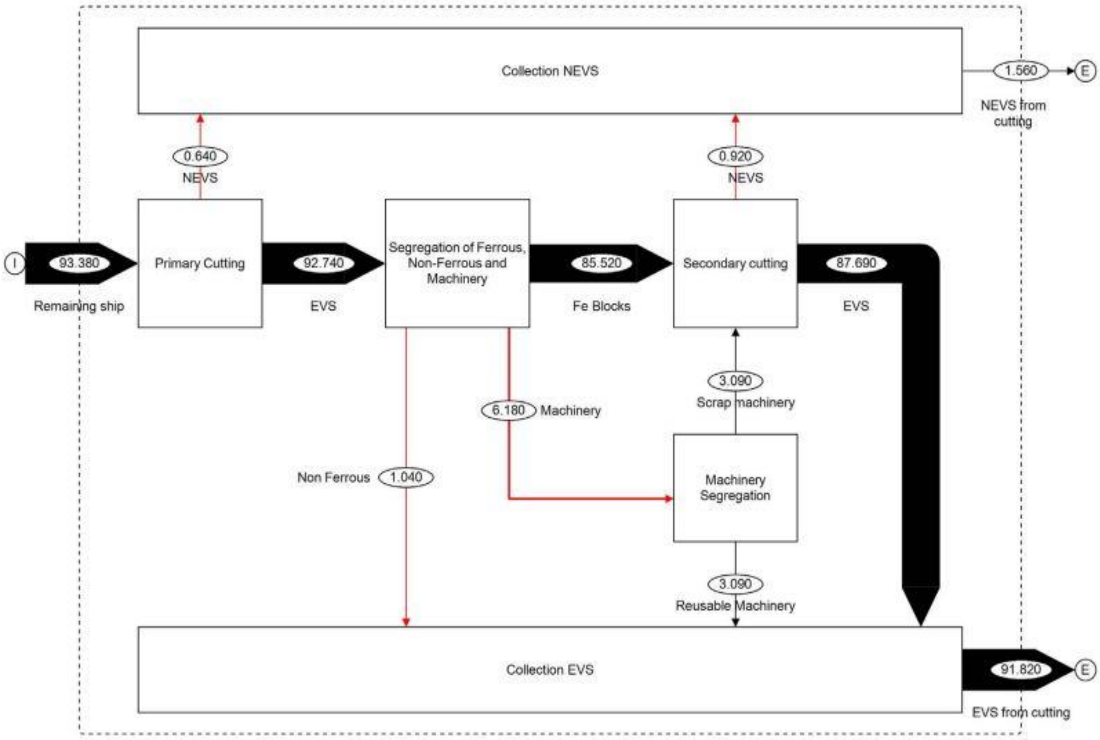

Figure 4. Cutting process of ship showing quantities of material flow in terms of percentage of LDT (K.P.Jain, 2017, p. 679).

2.1.3 Post-cutting

In post-cutting, three steps of 'pick-up and storage', separation' and 'segregation and transport' take place. Firstly, both streams of material are picked up from their sources to be stored. Then, EVS should be segregated and transported to be reused or recycled. However, NEVS should further be processed by separation because some initially non-value recognized streams can contain valuable objects. For instance, a valve insulated with asbestos may be considered NEVS initially while it can be separated into metal and asbestos.

This happens because of large amount of waste that exists in ship recycling procedures. Overall, all streams of materials can be listed as in Figure 5 which is generated for an 11044T lightweight handymax bulk carrier. (K.P.Jain, 2017, p. 677.) Therefore, more than 80% of the stream of material in a ship is due to steel which is dominant in ship hull structure. This is the main reason why in this project, primary cut of ship hull is analyzed.

S.no.	Material Streams	Quantity (% of LDT)
1.	Ferrous scrap	84.60
2.	Non-ferrous scrap	1.04
3.	Machinery	6.18
4.	Electrical and electronic waste	1.24
5.	Minerals	2.52
6.	Plastics	1.19
7.	Liquids, chemicals and gases	1.03
8.	Joinery	1.28
9.	Miscellaneous	0.92

Figure 5. Material composition of an 11044T lightweight handymax bulk carrier (K.P.Jain, 2017, p. 677).

2.2 General steps in ship recycling

Beside the material flow attitude toward ship recycling procedures, a general view over steps can be beneficial. Ship recycling plan which should be developed prior to anchoring of the vessel, includes all the actions needed to be taken that are brought in Figure 6. This means that before the vessel anchors to the dock or beach, the ship recycling plan should already be prepared. One prevalent method of ship dismantling after separation of loose items and cleaning is cutting all holds and superstructures while leaving the ship keel for the last step of cutting. When all the stages are over, the site needs to be cleaned and a report should be written about the recycling. (Zhou, 2021, pp. 2-5.)

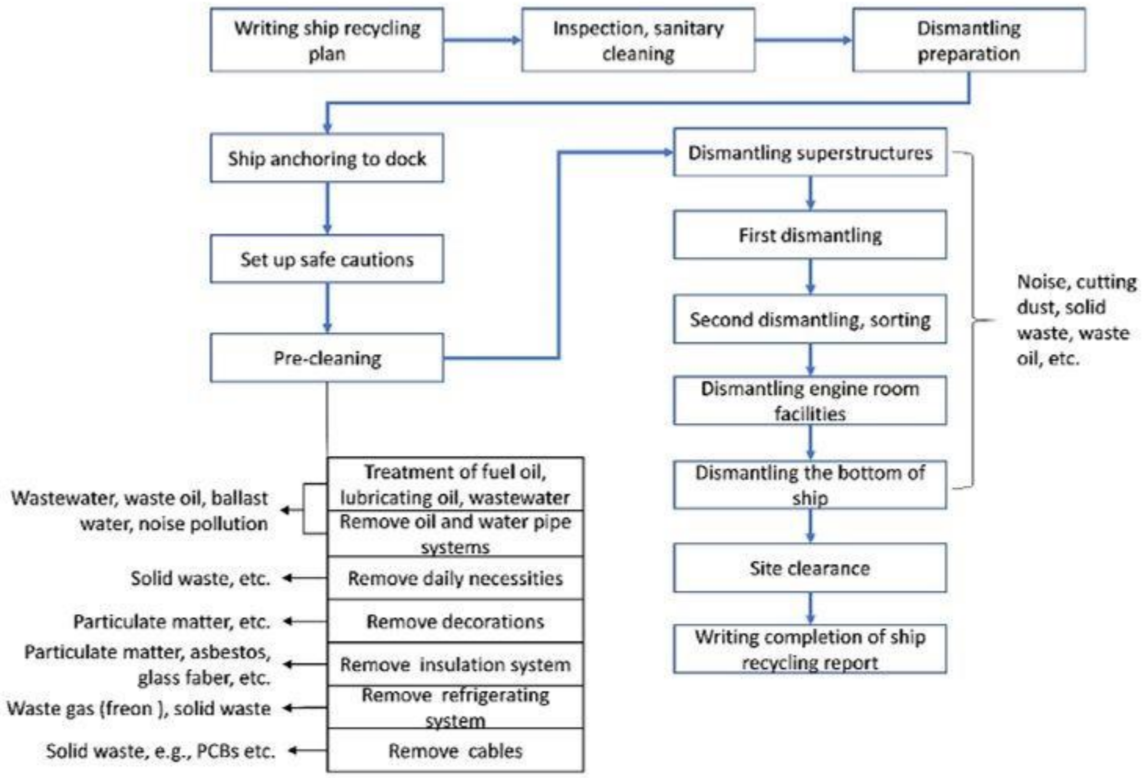

Figure 6. Procedure of ship dismantling (Zhou, 2021, p. 3).

2.3 Cutting technologies

Hot cutting which is the conventional cutting method implemented in ship breaking industry can lead to production of hazardous gases when it comes to paints, PCBs and solid foams in high temperatures. Therefore, waterjet could be considered as an alternative to the traditional methods of cutting. While waterjet can have several advantages for this application, its use can be tricky which is discussed here. High-pressure water is highly effective for drilling and transporting materials, and it can also propel abrasives to strike surfaces with great frequency and intensity. Waterjet can also be useful for dismantling asbestos containing materials as it can soak the asbestos and wash them away. Cutting cabins that contain asbestos is made possible with waterjet by applying negative pressure which also reduces the potential of asbestos fibres evading outside. The other advantage with water jet is that PCBs, solid foam, and fiberglass containing products can be cut without production of hazardous materials due to high temperatures and therefore reducing the chronical damage on people. More than that, with water jet, the ship could be cut systematically and cause little vibrations having less impact on the surroundings. However, it should be noted that utilizing water jet in this industry is not so straight-forward. The first reason is that the nozzle must be engineered to allow adjustments in speed, direction, and pressure, meaning the design must be tailored specifically to the needs of this industry. Additionally, with cuts made along welding lines, the waterjet needs to be adaptable to operate in confined spaces. (Yan, 2018, pp. 187-194.)

In one study (Gunbeyaz, 2022, pp. 564-576), how different technologies can affect the revenue and time taken is analysed. The technologies selected are oxyfuel cutting, plasma cutting, laser and water jet. However, laser is not an option as the mobility of a laser cutting system is very limited, its initial costs are exceptionally high, and laser cutting equipment requires specific measures for safety and health. In this study, only the cutting in the secondary zone has been simulated. The opted blocks have been accommodation block and double bottom block which are transported to secondary cutting zone. In Figure 7, and Figure 8, we can observe comparison of the total duration and cost of operation of different technologies. It should be noted that two different plasma cut technologies were tested and the effect of prior surface cleaning has been shown.

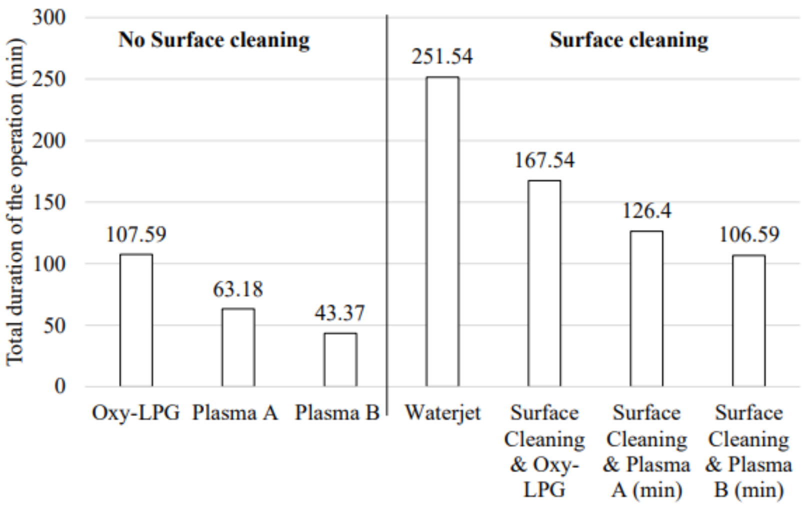

Figure 7. Comparison of the operation duration for different technologies during dismantling process (Gunbeyaz, 2022, p. 571).

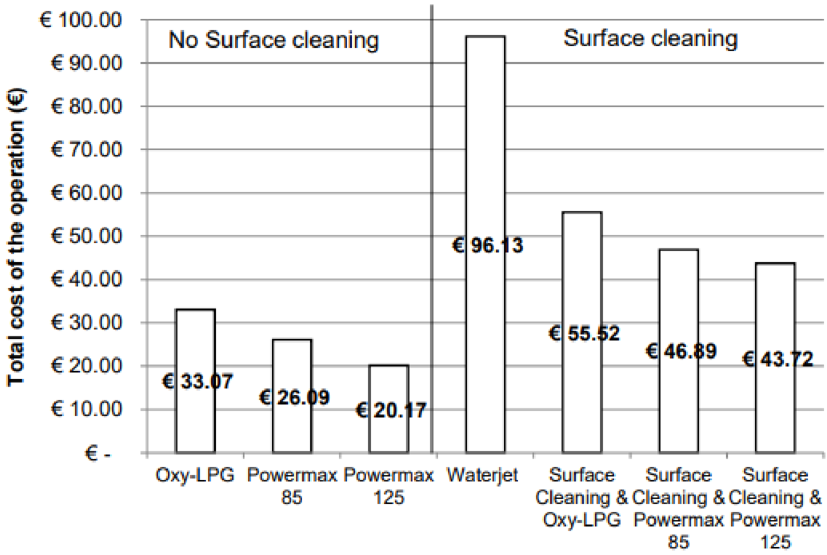

Figure 8. Comparison of the operation cost for different technologies during dismantling process (Gunbeyaz, 2022, p.572).

It can be understood from the simulation results that water jet technology implementation in this industry can be challenging due to high operation costs, slow cutting speed and the time required to set up. However, some ship recycling yards have already started emission-free dismantling of the ships in Kiel using ANT AG's waterjet technology and in Bremen (ANT AG, 2023). Overall, it can be concluded that for cutting a superstructure like a vessel, a combination of different technologies may be a viable, environmentally friendly, and economic choice. The reason is that with waterjet, we can respect environmental and safety aspects and with plasma technology, the plan can be more efficient.

2.4 Ship dismantling practice in Finland

As the World Steel Association has estimated the need for recycled steel will more than triple globally by 2050, the need for recycled steel in Finland and Sweden will largely grow. One great source of recycled steel could be from dismantled ships. In different parts of Finland such as Kemi port, Turku Repair Yard, Novia Vessel Recycling and Raahe, several studies have been conducted about ship recycling industry. In Raahe area, a ship dismantling yard is active which can produce the steel needed for nearby SSAB steel plant that supports green production of steel. This industry is regarded as fossil-free steel production. In Figure

9, dimensions of the dock in this region can be observed. In ship dismantling projects so far, ships recycled ranged in size from 220 to 240 meters and were dismantled mechanically either by flame cutting or by an excavator equipped with cutting tool. The method used for dismantling can be alongside or drydock. The steps taken for dismantling are very much similar to the general steps discussed previously. First, light interior structures are demolished, then hazardous materials, liquids, and reusable devices are removed. After that, machinery and superstructure are detached and finally the ship is cut into blocks using diamond wire cutting and then transferred by self-propelled modular transporters to demolition hall as in Figure 10. (Merisaari, 2024, pp. 1-80.)

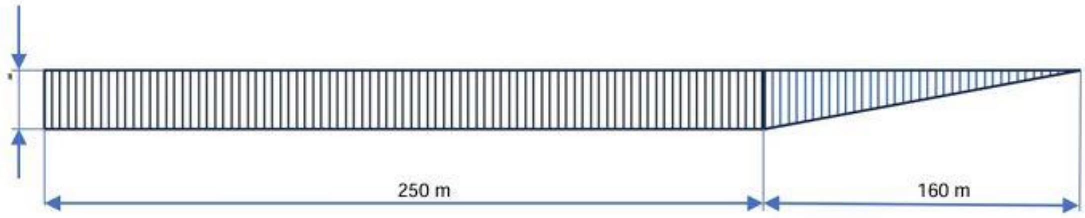

Figure 9. Dimensions of dock basin in Raahe (Merisaari, 2024, p.52).

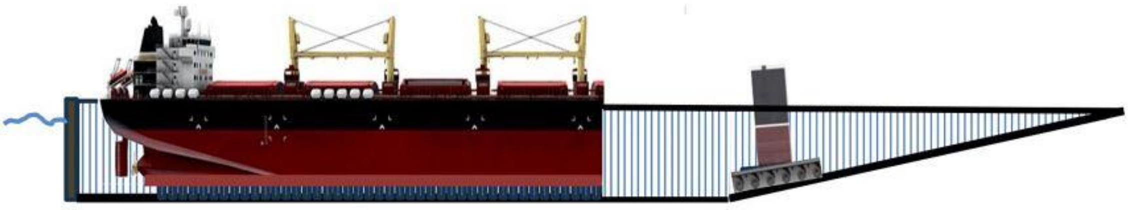

Figure 10. Conceptual image of the transfer of the cut-out block to the demolition hall (Merisaari, 2024, p.52).

A demolition hall, equipped with ventilation system to reduce harmful emissions, is used for further dismantling the brought blocks and further sorting of the steel. The lifting capacity in the demolition hall is 20 tons. (Merisaari, 2024, pp. 1-80.) In this project the idea of ship dismantling method originated from this method of cutting.

2.5 Ship's components break down

To easily do the dismantling process of a ship, it is preferable to have the information about ship's material which should be stored in lightweight distribution in ship's stability manual. An important step in environmentally safe recycling is knowing exactly what is going to be recycled. According to (Priya Jain, 2016, pp. 65-70), "ship's lightweight distribution provides useful information to quantify the materials available on ship, it contains a lot of ambiguous information which lacks details needed for development of ship recycling plan." The main reason "we need to know in detail what materials are present on a vessel is that a shipyard usually extracts certain types of scraps from an end-of-life ship instead of breaking down every ship component to the lowest possible chemical element." For instance, "ship's machinery may be reused as is instead of being cut to form ferrous scrap." Additionally, "ship's electrical and electronic equipment are not always dismantled on site as they are normally sold to companies responsible for downstream recycling." In Figure 11, different types of scraps that are generated during ship dismantling from materials and components can be observed. Overall, "a ship recycler mainly needs three types of ship-specific information which contains information on quantity and location of hazardous materials, weight of hull sections, and quantity of various types of scraps."

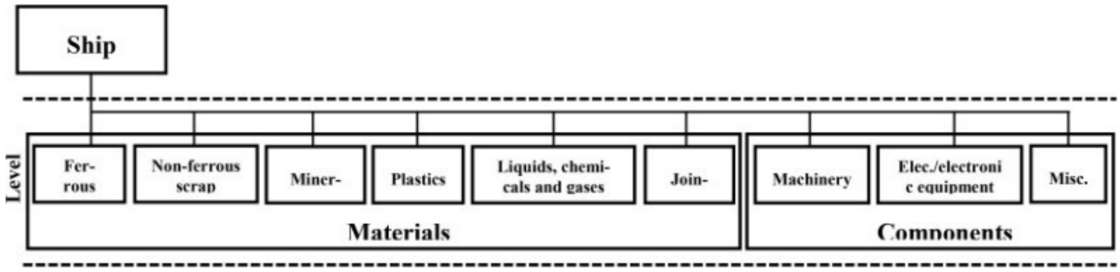

Figure 11. Types of scrap generated during ship recycling process (Priya Jain, 2016, p. 666).

The term "lightweight" typically encompasses details about the weight of the steel, outfitting, and machinery, providing clear information on the weight of hull sections and other steel components. This data is useful for planning steel cutting and section lifting operations, allowing for the determination of the necessary number of lifts based on the available lifting capacity. (Merisaari, 2024, 80 p.) However, specifications on some elements are missing with lightweight distribution as the exact type of scrap illustrated in Figure 12 cannot be determined. For instance, it is not clear what type of scrap machinery piping and electrical components produce. That means in lightweight distribution, two levels of ship's component break down is present. The first level describes the general groups which are machinery, outfitting, and steel components. The second level shows more detailed breakdown of each group. However, this level of breakdown is not sufficient for creation of ship recycling plan. That is why another level of component breakdown should be added as suggested in Figure 13. The purpose of adding another level of component breakdown is to realize an exact knowledge on the types of scrap each flow produces (Priya Jain, 2016, pp. 667-670).

Elements	Weight (T)	Gap analysis for ship recycling w.r.t. the type of scrap
MACHINERY COMPONENTS		
M01: Machinery piping	95.0	Not enough information
M02: Electrical	25.0	Not enough information
M03: Bridge equipment	6.0	Electrical and electronic scrap
M04: Tools and spares	15.0	Ferrous scrap
M05: Main engine	220.0	Machinery
M06: Shafts	28.0	Ferrous scrap
M07: Propeller	17.0	Non-ferrous scrap
M08: Auxiliary engines	38.0	Machinery
M09: Machinery comp	80.0	Not enough information
M10: Machinery equip	115.0	Not enough information
OUTFITTING COMPONENTS		
U01: Crane 1	57.0	Machinery
U02: Crane 2	57.0	Machinery
U03: Crane 3	57.0	Machinery
U04: Crane 4	57.0	Machinery
U05: Hatches	880.0	Ferrous scrap
U06: Outfit For	220.0	Not enough information
U07: Outfit Mid	200.0	Not enough information
U08: Outfit Aft	500.0	Not enough information
U09: Paint and Cathodes	130.0	Not enough information
STEEL COMPONENTS		
S01: Forepeak Fcle	320.0	Ferrous scrap
S02: Bhd CH1-CH2	182.0	Ferrous scrap
S03: Bhd CH2-CH3	198.0	Ferrous scrap
S04: Bhd CH3-CH4	198.0	Ferrous scrap
S05: Bhd CH4-CH5	132.0	Ferrous scrap
S06: Cargo section	5600.0	Ferrous scrap
S07: Machinery section	1070.0	Ferrous scrap
S08: Casing funnel	80.0	Ferrous scrap
S09: Accommodation	320.0	Ferrous scrap
S10: Hatch coaming	205.0	Ferrous scrap
S11: Crane pedestal 1	18.0	Ferrous scrap
S12: Crane pedestal 2	18.0	Ferrous scrap
S13: Crane pedestal 3	18.0	Ferrous scrap
S14: Crane pedestal 4	18.0	Ferrous scrap
S15: Deck house Fr. 72	12.0	Ferrous scrap
S16: Deck house Fr. 144	12.0	Ferrous scrap
CORRECTION FACTOR		
X01: Tol and Marg	−203.9	Ferrous scrap
Total	11044.1	

Figure 12. LDT distribution of ship given in stability manual with gap analysis for ship recycling (Priya Jain, 2016, p. 667).

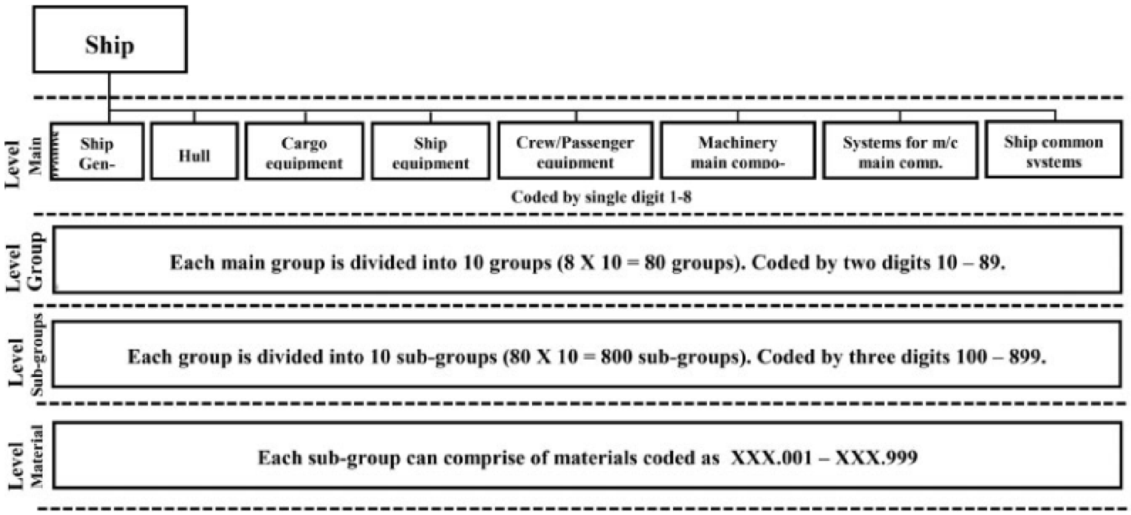

Figure 13. Concept of work breakdown structure of a ship (Priya Jain, 2016, p. 669).

A common work breakdown system utilized in the shipbuilding industry is the SFI Group System, which was created by the Ship Research Institute of Norway in 1972 and is now commercially offered by SpecTec (ShipResearchInstituteOfNorway, 1972). In case of traditional method of ship recycling plan generation, this component breakdown is a necessity as human expert needs to know what is available on the vessel to come up with the plan. However, in this project, as we are exploring innovative solutions for this industry, accessing a digital model of a ship can be translated as having a deep knowledge on all the components and details of the vessel without the need to use work breakdown system.

2.6 Aircraft dismantling

Having a look at the procedures with which other superstructures such as aircrafts are dismantled, can give us valuable information on constraints and objectives of our problem. As it can be observed in Figure 14, the general steps taken for decommissioning of aircrafts is similar to what we have seen in ship industry. Different types of aircrafts such as in-service, stored, abandoned, and accidental ones end up in repair or dismantling facilities. While some of the components are good enough for being back to aerospace industry either directly or after being repaired, the rest go through recycling stages. The remaining parts and components of the aircraft that are not decent for aerospace business, may be reused with/without changes in other industries or go to waste business. In waste business, materials can be recyclable or not (Scheelhaase, 2022, pp. 3-12).

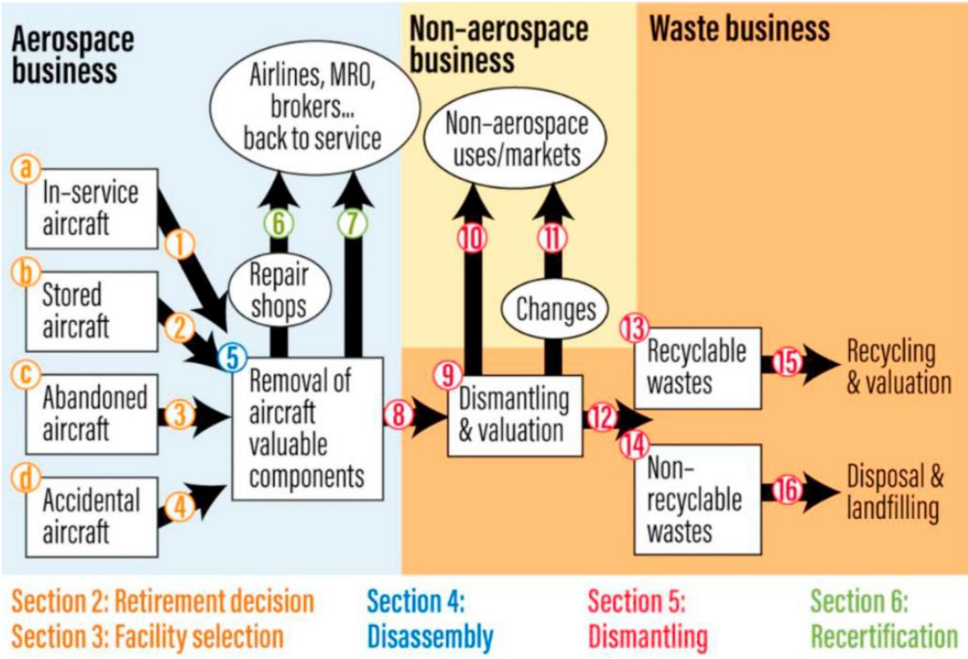

Figure 14. Process of aircraft decommissioning (Scheelhaase, 2022, p. 4).

The practice of dismantling aircrafts, similar to ships, can be destructive or non-destructive. By non-destructive method in case of large structures, taking out all fasteners is meant. This can hugely depend on which destination they are appropriate for. Non-destructive dismantling can increase homogeneity of the recovered material. Therefore, in case the recovered material ends up in aerospace business, it is relevant for it to be highly homogeneous as it is valuable. While if the stream ends up in waste business, non-destructive dismantling and more sorting of material for reaching homogeneity, may not be profitable as it increases the amount of effort needed for dismantling. Consequently, to preserve profitability in this industry, it is needed to implement a strategy in between, which utilizes both disassembly (non-destructive), and recycling (destructive) for superstructures. In Figure 15, we can observe that for high homogeneity of materials, the cost-benefit ratio for recycling decreases while for disassembly it is the opposite. The recovery process as a result, should be something in between. (Sabaghi, 2016, pp. 156-161.)

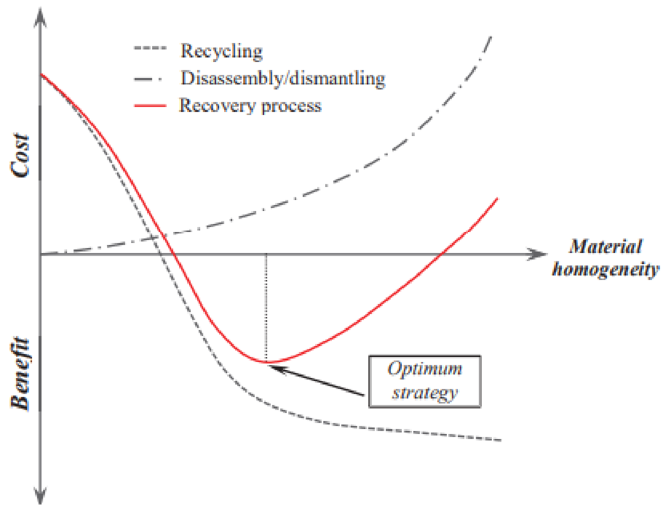

Figure 15. Schematic representation of cost-benefit associated to a recovery process (Sabaghi, 2016, p. 157).

Recycling practice of aircrafts highlights the importance of the value of the materials that are to be recycled and the destination they end up in.

2.7 Wind turbine dismantling

Like ship dismantling procedures, to recycle wind turbines, before cutting stage begins, some preparation works would be necessary. Recycling steps are de-energizing, removing liquids such as gas and lubrication oils and chemicals, and finally dismantling of components and backhauling to available port facilities nearby. (Hechler, 2019, 256 p.) The concept of dismantling can be considered as the reverse of commissioning process. Six different scenarios are feasible as in Figure 16.

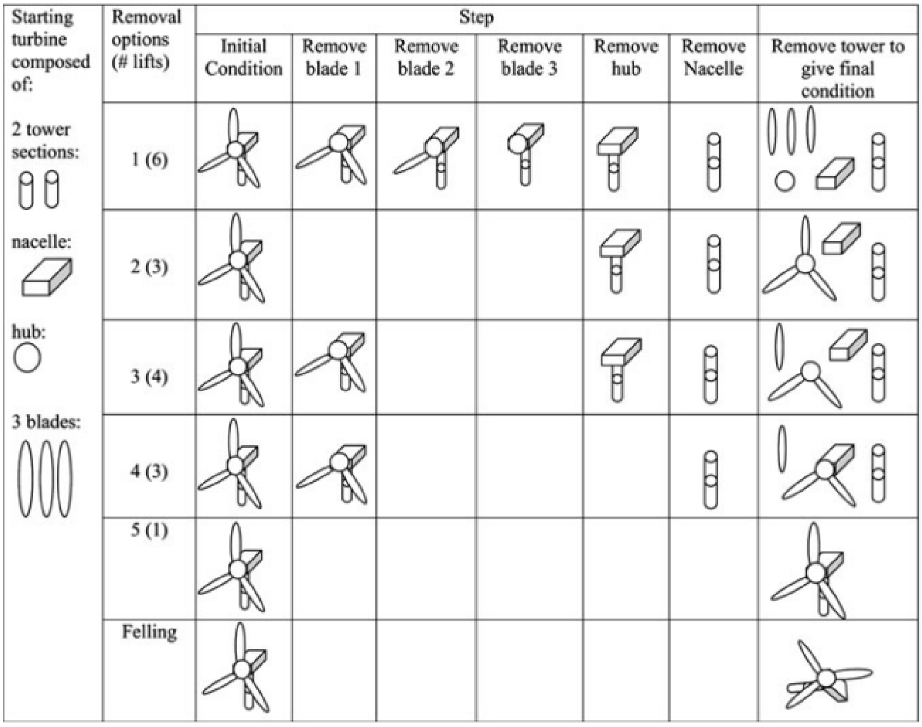

Figure 16. Wind turbine dismantling concepts (Hechler, 2019, p. 36).

In case no destructive mean of dismantling is deployed in recycling, the process can be considered reversible and reverse of assembling. While in ship recycling practice the cutting processes involved make it irreversible, still the assembly steps can give hints for dismantling procedures. Wind turbine decommissioning points out that dismantling procedure can mean separation of either one or several blocks of the superstructure which can be constrained by lifting and transportation capacities. These constraints are more serious in case of offshore wind turbines. That is why in this project, after deriving the needed data on the cross-sections of the ship hull, algorithms are allowed to choose cutting of one or several blocks at once.

3 Data extraction as input for optimization algorithms

To be able to produce an optimized plan of dismantling/disassembling, the product should be presented such that its data could be an input for an optimization approach based on the objective of optimization and the constraints present. As discussed in Figure 17, for generation of a ship recycling plan, the shipyard needs to breakdown all components so that the scrap stream they belong to is clear. That is why use of a digital twin or more simply a CAD model of the vessel can assist in generation of ship recycling plan without the need to access ship's manual or components breakdown. (Allagui, 2023, pp. 3-16.)

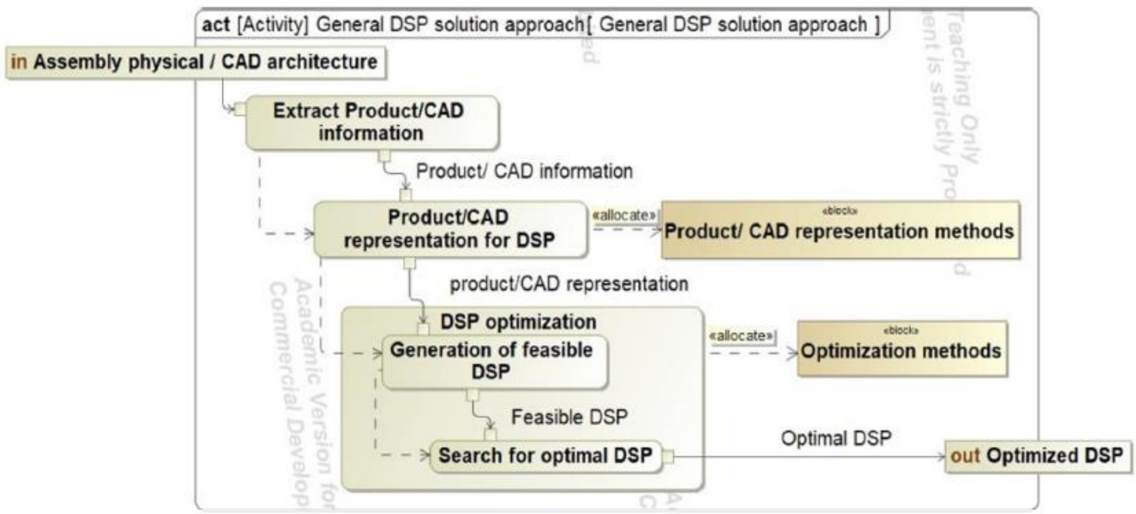

Figure 17. General disassembly sequence plan (DSP) solution approach (Allagui, 2023, p. 5).

As illustrated in Figure 17, to generate an optimized disassembly plan, starting from CAD model, the product information should be extracted. This information is used to represent the product. After that, all the possible sequences of disassembly should be generated, and an optimized one should be introduced. Therefore, for generation of the ship recycling plan, starting from the CAD model, based on the needed data for desirable optimization method, data should be derived which can represent the product.

3.1 Product representation method

The product can be represented with various methods, each of which has its own advantages and disadvantages. One traditional method is use of different types of graphs which can reveal all feasible sequences graphically. In this type of representation, all components in the product and their relation are illustrated. The drawback with this method is that they require manual definition of graphs or they would lack combinatorial explosion in case they are generated automatically. (S.K. Ong, 2021, pp. 3493-3508.) One method of graph representation of a product is Liaison diagram which shows geometric connection of parts of the product as in Figure 18. Also, precedence rules necessary for generation of a feasible plan are brought in Figure 18. Precedence rules point out the necessity of a specific disassembly task prior to the other one that mandate feasibility of a suggested sequence.

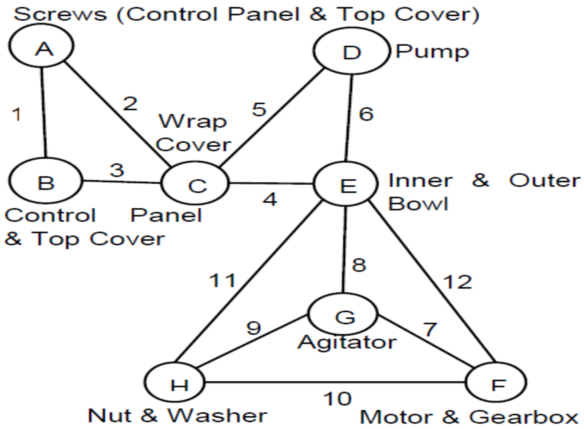

Figure 18. Liaison diagram for a washing machine (S.Kara, 2006, p. 39).

Liaison	Liaison's Prerequisites	Relationship
1		A-B
2	1	A-C
3	1,2	B-C
4	1,2,3,5	C-E
5		C-D
6	1,2,3,4,5	D-E
7		G-F
8	7	E-G
9	7,8	G-H
10	1,2,3,4,5,7,8,9	H-F
11	1,2,3,4,5,7,8,9,10	E-H
12	1,2,3,4,5,6,7,8,9,10,11	E-F

Figure 19. Precedence relationship for each Liaison (S.Kara, 2006, p. 39).

The other method of graphical representation of products is use of assembly drawings, connection diagrams, and disassembly trees.

In Figure 20b, connection diagram can illustrate the relationships between components of a product. For instance, in the given assembly, part A and B are in contact, while A and D have no direct connection. Finally, the disassembly tree is formed based on precedence rules that mandate first disassembly of A or/and D and after disassembly of D, separation of B and C becomes feasible (A.J.D.Lambert, 2003, pp. 3721-3759). The other method of graphical representation of a product is use of AND/OR graphs.

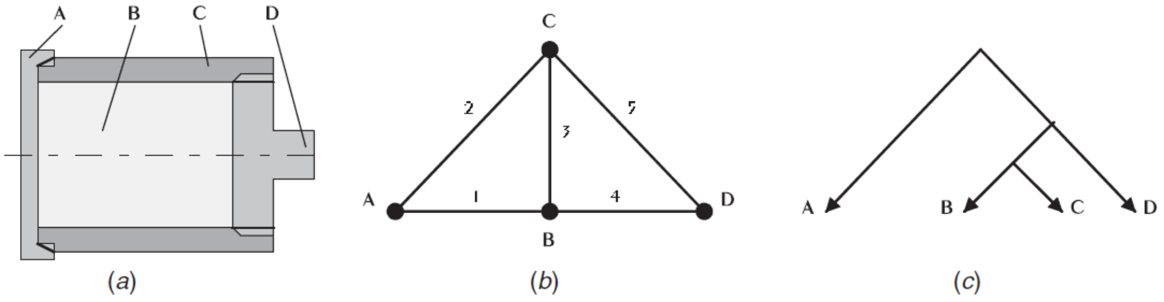

Figure 20. a) Assembly drawing, b) Connection diagram, c) Disassembly tree (A.J.D.Lambert, 2003, p. 3725).

And/or graphs as in Figure 21 and Figure 22 show all sets of sub-assemblies and parts in the product. However, some of these sub-assemblies are infeasible because of topological or geometric point of view. Overall, it can be understood that graphical representations are not suitable approaches when dealing with complex assemblies and structures like ships.

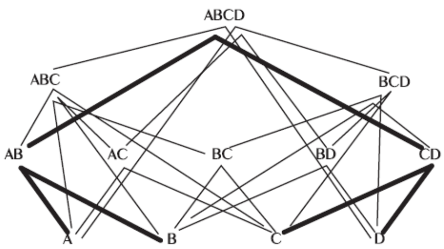

Figure 21. AND/OR graph for the assembly in figure 21 (A.J.D.Lambert, 2003, p. 3726).

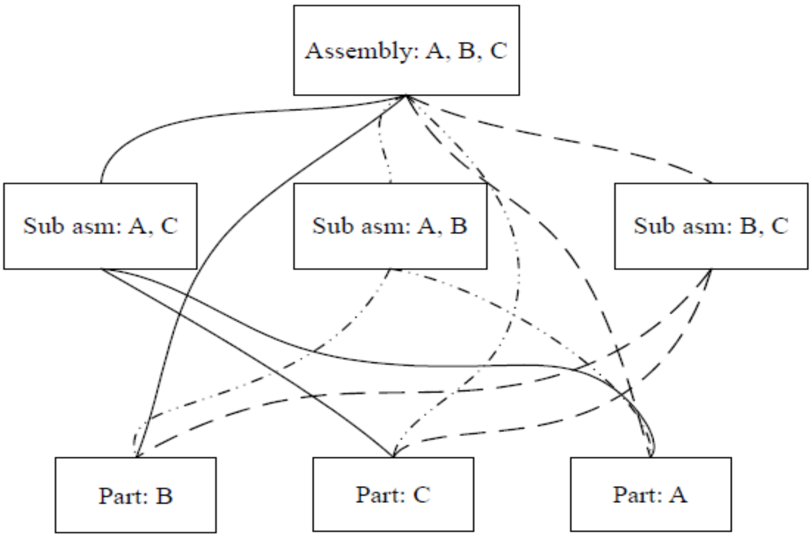

Figure 22. Using And/Or graph to represent all possible disassembly sequences (Hui Wang, 2013, p. 80).

The other group of approaches for product representation is matrix-based approaches that show all pairwise relationship for components with binary values forming square, sparse matrices. The advantage of this approach is that they are relatively easy to be processed by computer, and they can be automatically generated from the products' CAD model (S.K. Ong, 2021, pp. 3493-3508). One example of matrices that can help in generation of disassembly sequence generation is collision matrix which is a square matrix that would be null in diagonal and has ones in case of dynamic collision between parts as in Figure 23. The interoperability between CAD system and CAE applications can be realized using API (Application Programming Language). However, some applications like CADLab which is an extension to SolidWorks can also generate collision matrix automatically. To extract a feasible sequence in a specific direction, a row or a column depending on positive or negative direction of axis of disassembly respectively, should have a zero sum. After each step of disassembly, the collision matrix should be updated (Allagui, 2023, pp. 3-16).

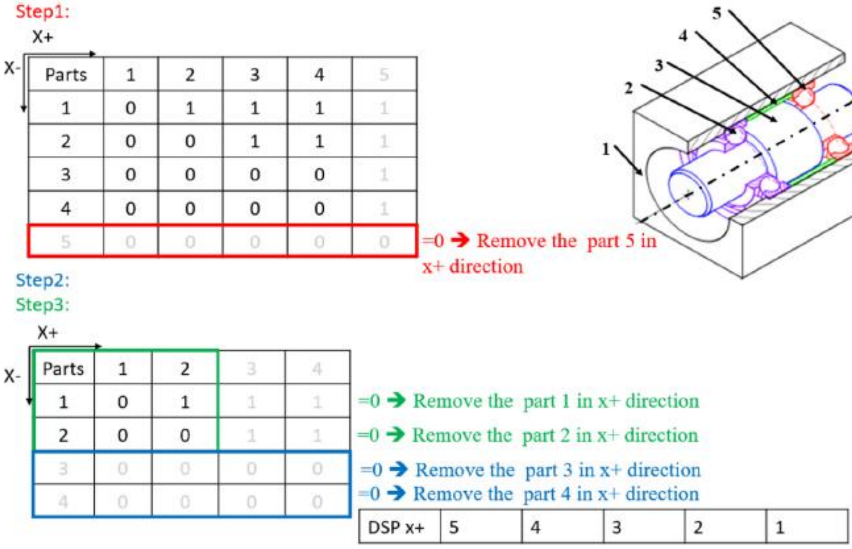

Figure 23. Description of disassembly sequence generation using the collision matrix (Allagui, 2023, p. 10).

3.2 Ship's digital twin

Digital twins are generally categorized into three main components: asset representation, behavioral models, and collected data. The collected data may include measurements from the asset itself as well as data from its operational environment. Asset representation often takes the form of a 3D model enriched with metadata, which provides details such as weight distribution, material properties, component specifications, and maintenance notes. Behavioural models instead enable the connection between the asset representation and physical reality. Physical reality is the measured data containing information on the operational performance (Fonseca, 2021, pp. 70-72).

As it could be observed in Figure 24, the behavioural model gives an insight which is used for monitoring, prediction and decision making for the operational condition of the vessel. This would be very useful as a vessel is still working. However, in the case of our project, an end-of-life vessel is going to be dismantled. This means that although an insight about the conditions of all components is obligatory for making an optimum recycling plan, not a detailed behavioural model would be needed. The reason why conditions of components can matter is that an objective of algorithms could be prioritizing disassembly of more healthy components instead of damaged ones. In case of this project though, preparation works like disassembly of loose items and separation of components is not intended. That is why we are going to use a CAD model of a ship which contains information about the geometry and materials of the components and not a fully defined digital twin.

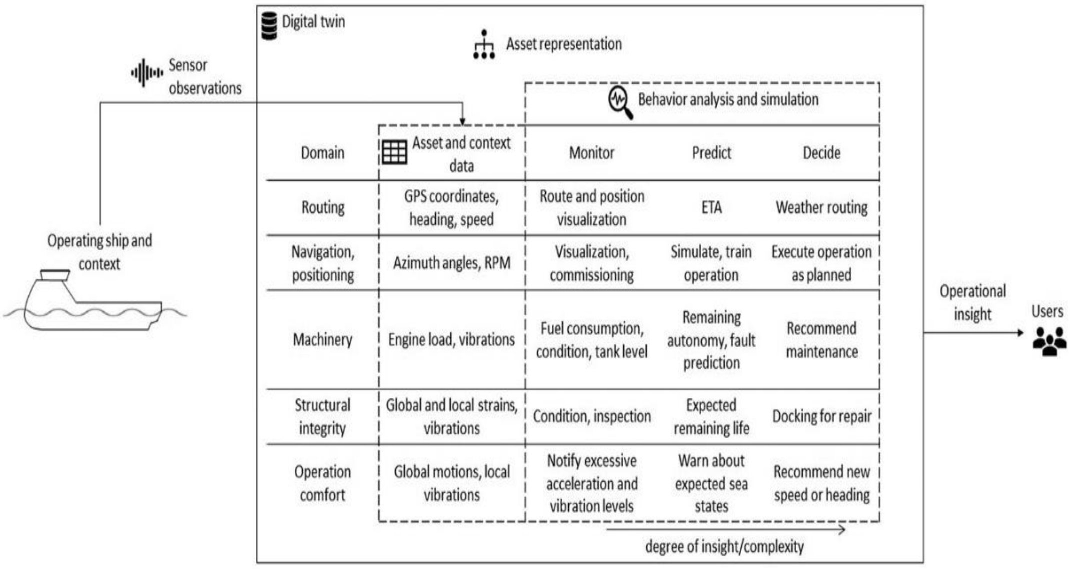

Figure 24. Digital twin elements and usage implementation of services in various domains (Fonseca, 2021, p. 73).

3.3 CAD model

In case of this project, as we are dealing with a complicated structure like ship, graphical methods can make the problem complicated. Other than that, as we are focusing on cutting the ship hull into large blocks resembling ship dismantling practice in Finland, matrix representation of relationships cannot be applied because the ship hull can be considered as a one-piece structure. Therefore, showing the product with collision matrix is not logical. That is why a CAD model (CAD from: (Kaushal, 2014)) of a ship is used which contains information needed for our optimization problem. That is true that a CAD model may not be a digital twin as it lacks behavioral models, but for generation of cutting plan, this would suffice.

3.3.1 Use of Fusion 360 programming interface

The CAD model used in Figure 25 belongs to a relatively small container ship with a length of nearly 40 meters. For larger ship hulls the same procedure that is going to be discussed can be applied which only requires more computational effort. As the aim of the project is to minimize the cutting area, we should have access to properties of cross sections spaced equally from each other. As a desirable space would be 10 mm, it is impossible to derive all that data interactively with Fusion. However, Application Programming Interface (API in short) is a set of functionalities exposed by an application that allows it to be controlled by a program. Therefore, repetitive operations can be automated resulting in better productivity. Fusion API is object oriented with which a nearly one-to-one correspondence with doable actions in user-interface exists. How the object-oriented characteristics affects the process is the way a specific object can be accessed. With user-interface, objects are accessed by clicking graphically, while with API, objects can be accessed using a hierarchical structure. Therefore, a parent-child relationship exists between objects (AutoDesk, 2024). Some of these relationships are shown in Figure 26.

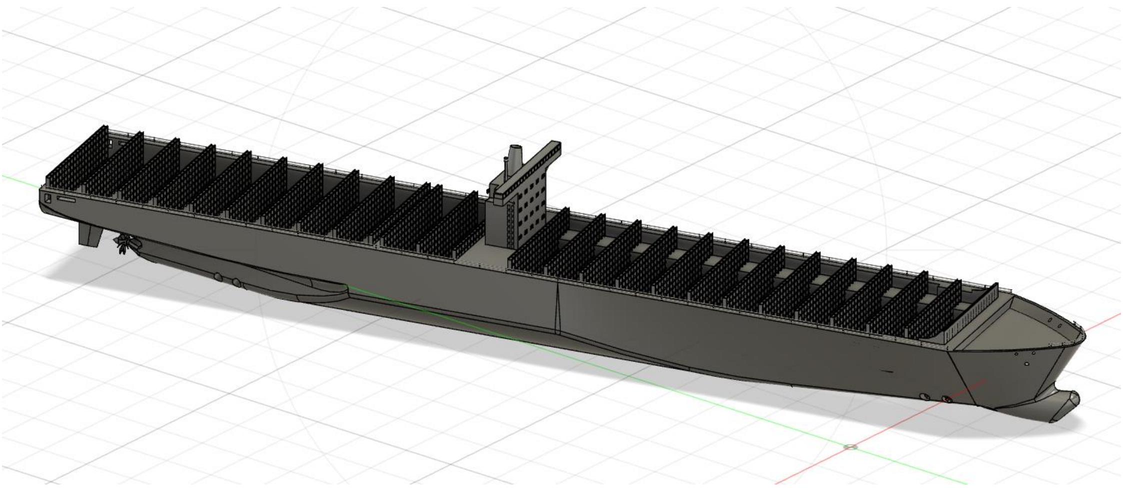

Figure 25. Ship CAD model in Fusion 360 environment.

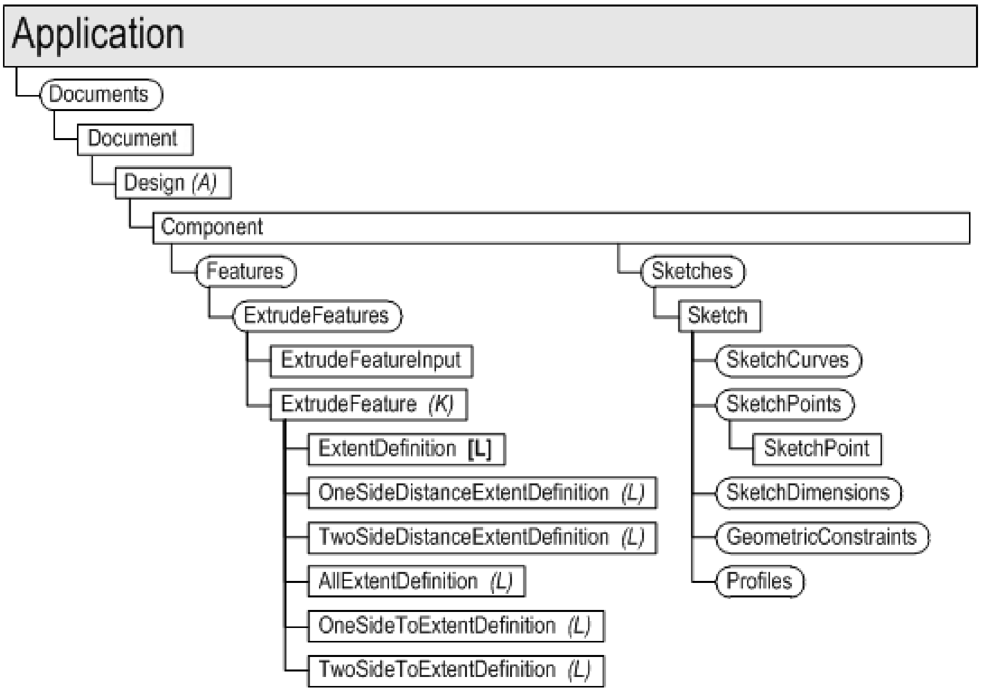

Figure 26. Hierarchical structure of objects in Fusion 360 API (AutoDesk, 2024).

For instance, in case sketches are to be accessed, we should start from the top-level object of application, then proceed to documents, document, design, component and finally sketches. Therefore, all the actions to be automated should first be thought of in the user interface, and then be done based on the hierarchy of objects and the commands available in Fusion 360 API manual.

All the described steps of data derivation is done using Python script. In this project, first the ship hull should be isolated as other components in the CAD model are not our concern. Then, planes that intersect with the cross section of the ship hull are located from the bow of the ship to its end at an equal distance of 10mm automatically as in Figure 27.

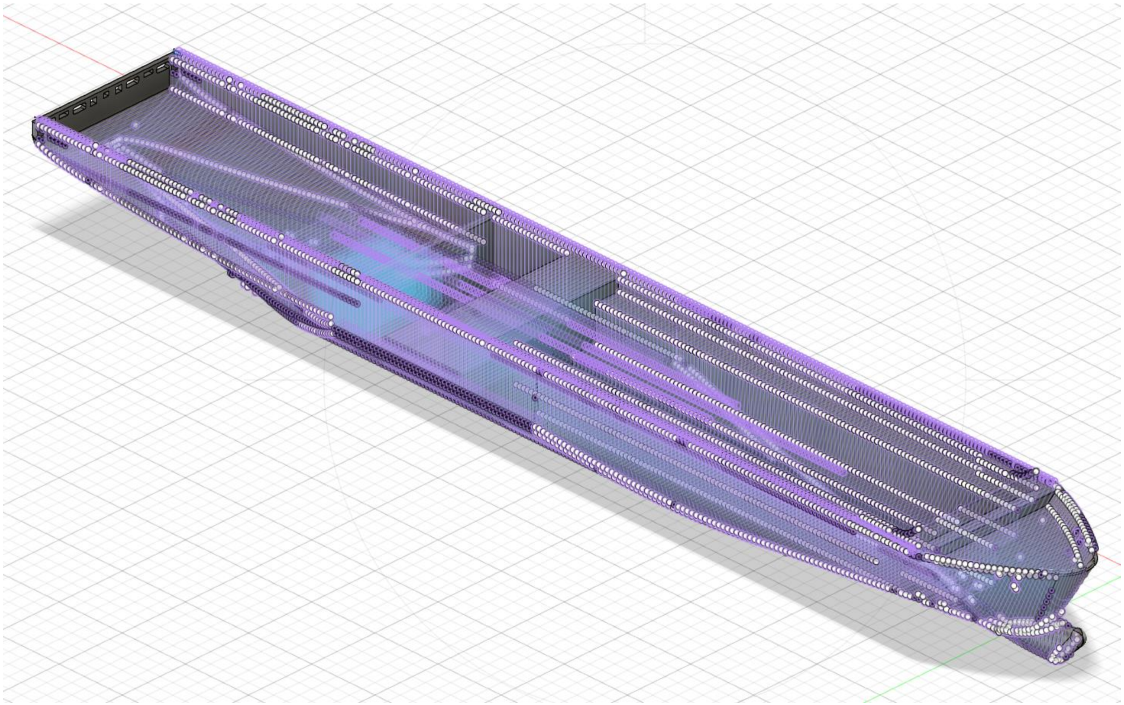

Figure 27. Ship hull CAD model with automatically generated planes spaced equally with Fusion 360 API.

When all the planes are intersected with the ship hull, it is possible to generate sketches that illustrate the shape of all cross sections and calculate their surface area. These sketches are saved as dxf files and have the position at which that cross section is positioned and the calculated surface area in their names such as cross_section_-325_Area_115027.18.dxf. The surface area is in cm^2. Also, it should be noted that for calculation of surface area of a sketch to be enabled in Fusion 360, we should have an enclosed shape as sketch. This means any small error in the CAD model which causes generation of open entity can cause problems. In this process, it was observed that even very small open gaps between the points of the generated sketch disable Fusion from area calculation. Therefore, those very small gaps that are only observable after several times of zooming, are modified by drawing lines between separate points. All the process of recognition of these points and modification of sketched is done automatically.

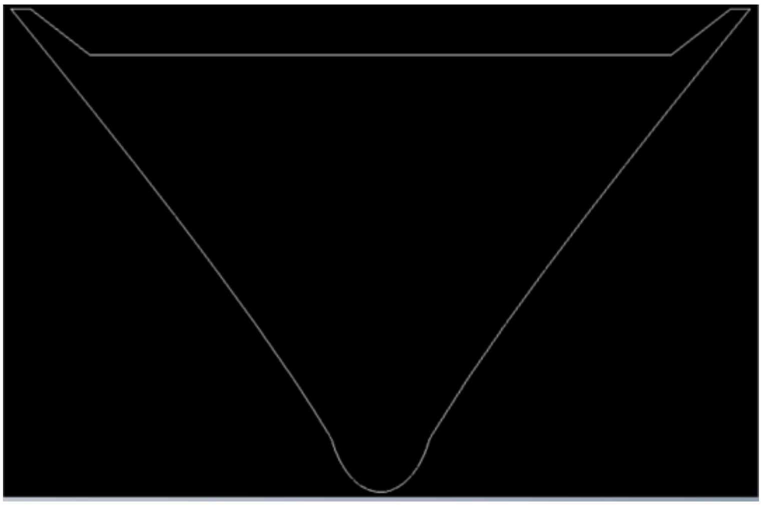

Figure 28. Cross section of the ship hull positioned near the bow with a surface area of 62520 cm^2.

More than the surface area of the cross sections that matter, other properties should be accessed using the API. In Fusion 360 is possible to derive data such as density, mass, volume, accuracy of the calculations of the data, centre of mass location, moments of inertia, and radius of gyration for all the bodies. Therefore, in our case, all the intersecting planes are used to generate a separate body. That is because the ship hull is only one body in this CAD while for the purpose of optimization, we need to know the mentioned data for all the generated objects between the planes. In general, the ship hull is a one-piece body. However, in some locations such as Figure 29, the intersection of planes with the ship hull can make multiple bodies instead of one. That is why after implementing 255 planes, 1068 bodies are generated.

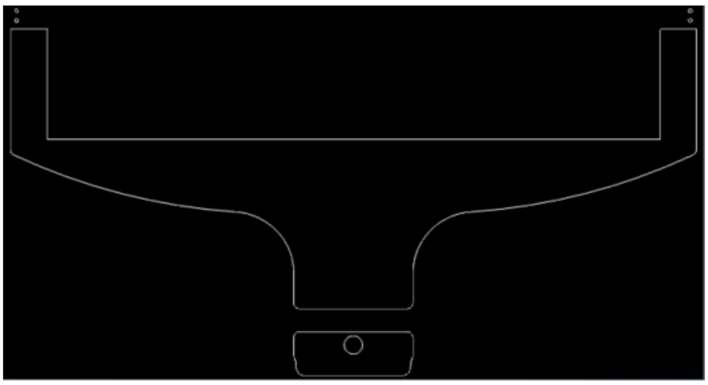

Figure 29. Cross section of the ship hull that has generated multiple bodies.

At last, all the mentioned data is automatically generated for the bodies and saved in a csv file. Before the use of artificial intelligence algorithms, based on the location of centre of masses of generated bodies, the equivalent mass, and centre of masses of entities between planes should be calculated so that instead of dealing with 1068 bodies, 255 entities are considered that exist between the intersecting planes. As shown in equation bellow, all the bodies located between the intersecting planes ranging from index k to n are considered for equivalent calculations. Therefore, the derived data needs to be refined to be considered as input for algorithms (Fooksa, 2023):

$$m_{\text{cross section}} = \sum_{i=k}^{n} m_i \text{ , } COM_{x,y,z} = \frac{\sum_{i=k}^{n} m_i . COM_{x,y,z}^{(i)}}{\sum_{i=k}^{n} m_i} \tag{1}$$

4 Optimization algorithms implementation

For the optimization problem to be defined, it is needed to know some details that are listed in Figure 30.

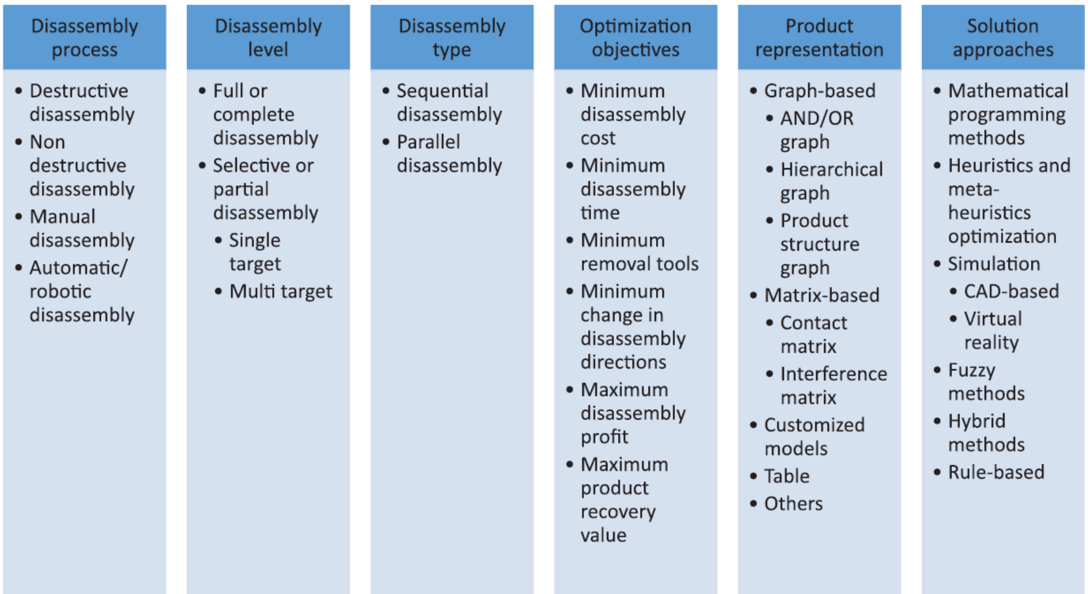

Figure 30. Disassembly problem details (S.K. Ong, 2021, p. 3495).

As it can be understood, more than the way the product is represented, other factors such as disassembly process, level, type, optimization objective and solution approach matter. Disassembly process can be either destructive or not. In this project, as we are going to plan for cutting the ship hull into large blocks, the process is considered destructive. In general, the disassembly can be a complete or selective one. Complete disassembly refers to a process in which all components are disassembled, while in selective one, only one or more components are disassembled. Also, the process can be done sequentially or in parallel. In this project, the cutting of the sections happens one after the other. However, in real practice, as the primary cutting is happening, secondary cutting is taking place in parallel in secondary zone. In fact, the secondary cutting zone is the primary constraint on the yard's production capacity, creating a bottleneck in the reverse production process. If cutting in the secondary zone is too slow, operations in the primary zone must also be halted. (Gunbeyaz, 2022, pp. 564-576.) The other imperative factor in optimization problem is the objective. It can be minimization of time, cost, removal tools, changes in direction of disassembly, or maximizing the profit and recovered value. More than this, some criteria which takes number of predecessors, part demand, hazardousness, state of material and fragility into account can be considered. (Gucdemir, 2023, pp. 1-6.) As discussed earlier, the method with which we represent the ship hull should be such that it suits the complexity of this product. Therefore, neither matrix nor graphic-based approaches are used. Instead, the necessary data is derived from the CAD model which are fed to the algorithms. It is clear that the search space for such problem is huge as we have more than 250 sections. Each of these sections are either going to be cut or not, therefore, the search space is as large as $2^{\#sections}$. The expanded search space can be managed using artificial intelligence methods like genetic algorithms and simulated annealing. However, these techniques have drawbacks, including the risk of suboptimal solutions, extended execution times, and limited transparency or understanding of the process (A.J.D.Lambert, 2003, pp. 3721-3759). The dismantling detail of this project is listed in Table 1.

Table 1. Ship hull dismantling optimization details.

Disassembly Process	Disassembly Level	Disassembly Type	Optimization Objective	Product Representation	Solution Approaches
Destructive disassembly	Complete disassembly of ship hull	Sequential disassembly	Minimization of disassembly time (area)	CAD model	meta-heuristic approaches

4.1 Genetic algorithm

The genetic algorithm is inspired by Darwin's theory of evolution and can be summarized as follows: it begins with a randomly chosen group of possible solutions, known as the population. All the members of the population are represented using artificial chromosomes that are combinations of numbers, alphabets, and/or other characters that allow for mapping of solution based on the information they contain. Based on the fitness function defined, the chromosomes are evaluated and scored. The new generation then is created iteratively hoping that new chromosome is better scored. At each step of creation, mutation and mating (or crossover) can happen. Fitter chromosomes are selected more as parents for creation of the next generation. The iteration keeps taking place until some stopping criteria is met. The stopping criteria could be a certain number of generations, convergence, sufficient fitness, or resource limit. (Kongar, 2006, pp. 497-506.)

4.1.1 Genetic algorithm example in disassembly

One example which inspired the use of genetic algorithm in this project is described here. As it could be observed in Figure 31, the assembly has 10 components that are named from 0 to 9. Each can be disassembled in ±x, ±y, and ±z directions. The components being unwanted, needed for reuse or recycling is shown with 0, 1, and 2 respectively. To use genetic algorithm, solutions and parameters are coded as chromosomes such that they contain information on key features of the problem so that desired characteristics can propagate to the next generation. (Kongar, 2006, pp. 497-506.)

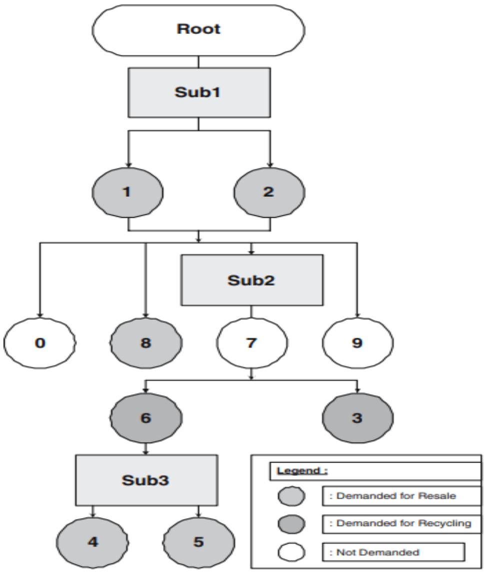

Figure 31. Original product structure of the end-of-life product (Kongar, 2006, p. 499).

An example of the chromosome can be as in Figure 32.

Sequence	Direction	Method	Demand	Material
2871063954,	$+x-z-x+x+y+y$ $+z-y-z-z$,	NNDNDD DDNN,	1101022011,	SPPSASS PPP

Figure 32. Example of a chromosome as a potential solution for disassembly problem (Kongar, 2006, p. 500).

The chromosome contains information on the sequence, direction and method of disassembly, and the demand and material of the parts. After that, we can come up with an initial population with a certain number of chromosomes. The next generation is formed by genetic operators of crossover which is exchange of information between two chromosomes and mutation which is mating between chromosomes. (Kongar, 2006, pp. 497-506.)

4.1.2 Genetic algorithm implementation in ship recycling plan generation

In this project, DEAP module in Python which is an evolutionary algorithm framework is used (deap, 2023). Chromosomes in a genetic algorithm implementation should be such that they can be interpreted based on characteristics of the problem. In this project, 255 cross sections of the ship hull and the equivalent mass and centre of mass of the entities between the planes are available. Therefore, the outcome of the algorithm should be which cross section to be cut or not. This means that the chromosomes are combinations of 0 and 1s, 1s showing that a cross section should be cut and 0s showing that it should not be cut. An example of a chromosome can be observed in Figure 33. Chromosomes are coded in this way so that fitness based on fulfilling the constraints and finding a specific total surface area, can propagate to the next generation.

```
Chromosome (0/1 representation): ['1', '0', '0', '1', '0', '0', '0', '1', '0', '0', '0', '0', '1', '0', '1', '0', '0', '1', '0', '1', '0', '0', '1', '0', '1',
'0', '1', '0', '1', '0', '1', '1', '0', '1', '0', '1', '1', '0', '1', '1', '1', '1', '1', '0', '1', '1', '0', '1', '0', '1', '1', '1', '1', '1', '0', '0', '1',
'0', '0', '0', '1', '0', '1', '0', '0', '1', '0', '0', '1', '0', '0', '1', '1', '0', '0', '1', '1', '0', '1', '1', '0', '1', '0', '1', '1', '1', '0', '0', '0',
'0', '1', '0', '0', '0', '0', '1', '0', '0', '0', '1', '0', '0', '0', '0', '1', '1', '1', '1', '1', '1', '1', '1', '1', '1', '1', '1', '1', '1', '1', '1', '0',
'1', '0', '1', '1', '0', '1', '0', '1', '1', '0', '1', '0', '1', '0', '1', '0', '1', '1', '0', '1', '0', '1', '1', '0', '1', '0', '1', '1', '0', '1', '0', '1',
'0', '1', '0', '1', '0', '1', '1', '0', '1', '0', '1', '0', '1', '0', '1', '0', '1', '0', '1', '0', '1', '1', '0', '1', '0', '0', '1', '0', '1', '0', '0', '1',
'0', '0', '1', '0', '0', '1', '0', '1', '0', '0', '0', '1', '0', '0', '0', '1', '0', '0', '1', '0', '0', '0', '0', '1', '0', '0', '0', '1', '0', '0', '1', '0',
'0', '0', '1', '1', '0', '0', '0', '1', '0', '0', '0', '1', '0', '1', '1', '1', '0', '1', '0', '1', '0', '1', '0', '1', '0', '0', '1', '0', '0', '1', '0', '0',
'0', '1', '0', '0', '0']
```

Figure 33. chromosome representation in Python.

After deciding about the representation of chromosomes, each individual in the initial population should be formed. One approach could be random generation of 0 and 1s for creation of initial individuals with 50% probability. The other approach could be weighted random generation of individuals which means that cross sections with heavier masses are more probable to be assigned a 1. The second approach can give the algorithm a better start while with unweighted random initialization of population, solution cannot be found. Therefore, the Equation bellow shows initialization of population in which x_{ij} is the j-th gene of the i-th individual, r is a random number between 0 and 1 (generated using the Mersenne Twister algorithm, with a uniform distribution) and p_j is the probability associated with the j-th gene calculated based on the mass of the cross sections. The multiplier considered for the probabilities offsets the values such that they are comparable with the random values generated.

$$P\left[p_j\right] = 250\times\frac{m_j}{\sum_1^n m_k} \rightarrow x_{ij} = \begin{cases} 1 & \text{if } r < 250\times p_j \\ 0 & \text{otherwise} \end{cases} \qquad (2)$$

As the next step, the selection operator should be determined so that the next generation can be produced. Selection operator should be chosen such that it suits the problem. For instance, two selection operators of selNSGA2 and selTournament were tested. The first one is a multi-objective optimization algorithm that keeps a diverse set of non-dominated solutions. This operator does not perform well in this case as in this problem we are not dealing with multi-objectives. With second one though, the best individual is chosen from a randomly selected group of individuals as a parent. As the objective of the algorithm is minimization of total cutting area, selTournament performs better. How this selection operator works can be observed in Figure 34. It should be noted that the mating pool is used to generate the next generation through mating and mutation operations.

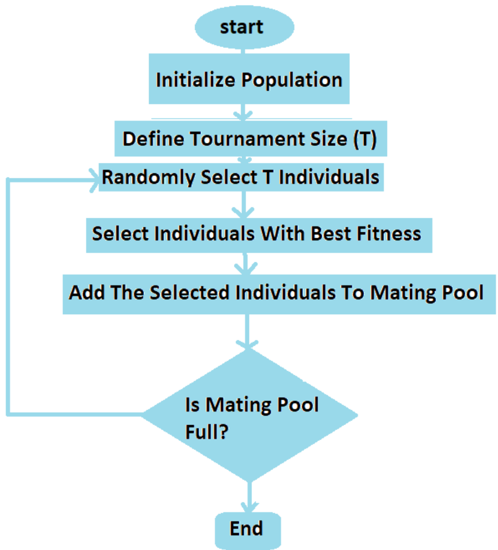

Figure 34. flowchart of selTournament operator in GA.

Then, a decision should be made about the operators of mating/crossover and mutation. For mating, cxTwoPoint is chosen which randomly swaps a portion of a randomly selected parent with that of another parent. This process produces two offsprings as in Equation bellow in which p1 and p2 are the parent individuals, child1 and child2 are the offsprings and l is the length of the chromosome (Kumar, 2012, pp. 98-101):

If $r<0.9$

perform crossover:select two crossover points c_1 and c_2 such that $0\leq c_1<c_2\leq l$

$$\text{For parent 1:child1}=[p1_1,p1_2,\ldots,p1_{c1},p2_{c1+1},\ldots,p2_{c2},p1_{c2+1},\ldots,p1_l] \quad (3)$$

$$\text{For parent 2:child2}=[p2_1,p2_2,\ldots,p2_{c1},p1_{c1+1},\ldots,p1_{c2},p2_{c2+1},\ldots,p2_l]$$

The mutation operator is mutFlipBit which flips the bits of an individual using a chosen probability. The mutation operator can be observed in the Equation bellow where x'_{ij} is the mutated gene and indpb is the mutation probability (deap, 2023):

$$x'_{ij}=\begin{cases} 1-x_{ij} \text{ if } r<\text{indpb} \\ x_{ij} \text{ otherwise} \end{cases} \tag{4}$$

$$\text{Total Area}= \sum_{i=1}^{n} x_i.\text{Area}_i\text{:to be minimized} \tag{5}$$

$$\text{Block Mass}= \sum_{j=\text{last cut}}^{i} m_j \text{ , if Block Mass>20tons, return } \infty \tag{6}$$

$$COM_{x,y,z}^{new}=\frac{COM_{x,y,z}^{old}.mass^{old}-\sum_j^i COMx,y,z[j]\times mass_j}{mass^{old}\text{-block mass}} \tag{7}$$

$$\text{if } |COM_{x,new}-COM_{x,old}|>50cm \text{ or } |COM_{y,new}-COM_{y,old}|> 50cm, |COM_{z,new}-COM_{z,old}|>50cm \text{ return } \infty$$

In evaluation function, total surface area based on the generated individual is calculated (5) and the mass constraint of blocks to be cut and displacement of centre of mass are imposed. The constraints are imposed such that in case of exceeding them, an infinite value is returned as the fitness value. Mass constraint is imposed to account for the lifting and transportation capacity in the shipyard as 20 tons (6), and the maximum displacement of the centre of mass in longitudinal direction of the ship hull between two consecutive cuts is 50cm (7) (Fooksa, 2023). That is because in case between two cuts centre of mass location in the remaining ship changes significantly, the stability of the ship may be lost. As illustrated with plots that would be discussed later in Result section, centre of mass location in transverse and vertical directions does not vary much and therefore for not making the computations heavier, they were not imposed in evaluation.

4.2 Particle swarm optimization

The particle swarm optimization (PSO) algorithm is an evolutionary method where particles navigate a multi-dimensional space, with their movement speed adjusted based on both individual learning and the collective knowledge of the group. In other words, the position and velocity are modified using the particle's own best performance and the best performance observed by the entire swarm, as shown in Figure 35. Based on the characteristics of the problem, the particles should be encoded to represent a solution. Therefore, particle position and velocity in D-dimension search space are defined as $X_i=[x_{i1},x_{i2},..,x_{iD}]$,$V_i=[v_{i1},v_{i2},..,v_{iD}]$ respectively. Using particle personal, and global best objective, acceleration coefficients, inertia weights (indicating how much of previous velocity should be retained), and introducing randomness, the velocity is updated. This process happens until a stopping criteria is met. (Tseng, 2011, pp. 1183-1197.)

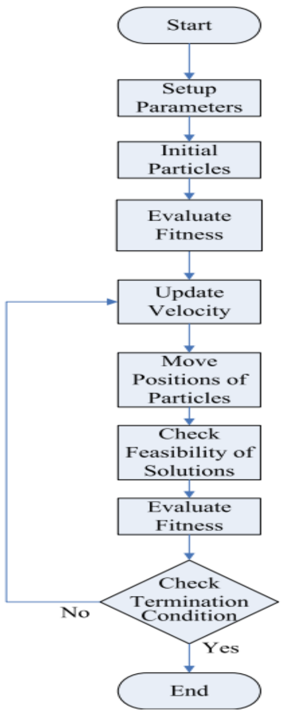

Figure 35. Flowchart of particle swarm optimization algorithm (Tseng, 2011, p. 1189).

4.2.1 Particle swarm optimization example in disassembly

In a disassembly problem, one constraint are precedence rules and the objective could be minimization of the disassembly process. As in this method, velocity calculations lead to formation of continuous values of position, a way of encoding the possible solution should be thought of in case of a discrete characterized problem such as disassembly sequence optimization. For instance, in case we have a set of positions calculated as [3.5 1.8 4.2 5.6 0.6 2.1], the ranked order values would be (4, 2, 5, 6, 1, 3) and therefore, for the set of component (C_1,C_2,C_3,C_4,C_5,C_6), the decoded sequence would be (C_5,C_2,C_6,C_1,C_3,C_4) in case we define our decoding approach as putting the component codes in an ascending order. When this order is formed, the precedence rules should be analyzed to check whether the generated sequence is feasible. Precedence rules can be checked using disassembly precedence matrix that has zeros if one component should not be disassembled prior to the other one (Tseng, 2011, pp. 1183-1197.) This matrix in Figure 37 looks like:

DPM =

	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
1	0	0	0	0	1	1	1	0	0	0	1	0	0	1	1	1	0	0	0	0	1	1	1	1	1
2	0	1	0	0	0	0	0	0	0	0	1	0	0	1	1	1	0	0	0	0	1	1	0	1	1
3	0	0	0	1	1	1	1	0	0	0	1	1	1	0	0	1	0	0	0	0	1	1	1	1	1
4	0	0	0	0	0	0	0	0	0	0	1	1	1	0	0	1	0	0	0	0	1	1	0	1	1
5	0	0	0	0	0	0	1	0	0	0	1	0	0	0	0	0	0	0	0	0	1	1	1	1	1
6	0	0	0	0	1	0	1	0	0	0	1	0	0	0	0	0	0	0	0	0	1	1	1	1	1
7	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	1	1	0	1	1
8	1	1	1	1	1	1	1	0	0	1	1	1	1	1	1	1	1	1	1	0	1	1	1	1	1
9	1	1	1	1	1	1	1	0	0	0	1	1	1	1	1	1	0	0	0	0	1	1	1	1	1
10	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	1	1	0	0	1	1	0	1	1
11	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	0	1	1
12	0	0	0	0	0	0	0	0	0	0	1	0	1	0	0	1	0	0	0	0	1	1	0	1	1
13	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	1	0	0	0	0	1	1	0	1	1
14	0	0	0	0	0	0	0	0	0	0	1	0	0	0	1	1	0	0	0	0	1	1	0	1	1
15	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	1	0	0	0	0	1	1	0	1	1
16	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	1	1	0	1	1
17	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	1	1	0	1	1
18	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	1	0	0	0	1	1	0	1	1
19	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	1	1	0	0	1	1	0	1	1
20	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0	1	1	1	1	1
21	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
22	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	0	0	0
23	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	1	1	0	1	1
24	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	0	0	0
25	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	0	0	0

Figure 36. Disassembly precedence matrix example (Tseng, 2011, p. 1189).

The cost function formed to represent fitness of the particles can reflect any objective as time, cost,… (Tseng, 2011, pp. 1183-1197).

4.2.2 Particle swarm optimization in ship recycling plan generation

In the case of our problem, each particle representing a solution has 255 dimensions. It would not be needed to form precedence rule matrix as ship hull dismantling is destructive and cutting the blocks is done one after the other. However, a method should be thought of that manages the continuous valued positions because of the effect of speed. Like the solution achieved by genetic algorithm, with PSO, a set of 0 and 1s is obtained at the end of optimization. Since 50% random generation of initial particles cannot lead to solutions that fulfil the constraints, particles are more likely to be assigned one in case they represent sections that have more mass. Therefore, the probabilities are created using the mass of each section divided by the total mass. Moreover, a bias factor which needs to be tuned is also considered that multiplies the probabilities so to offset the values of probabilities. This means by increasing this factor we can increase the probability of assigning 1 for a particular cross section. This process is similar to GA population initialization in (2).

$$v_i(t+1)=v_i(t)+\varphi_1.\text{random}().(x_{best}-x_i)+\varphi_2.\text{random}().(g_{best}-x_i) \tag{8}$$

$$x_i(t+1)=\begin{cases} 1 \text{ if } \text{rand}(0,1)<P_i=k\times\sigma(v_i), \text{where } \sigma(x)=\frac{1}{1+e^{-x}} \\ 0 \text{ otherwise} \end{cases} \tag{9}$$

The speed is initialized with random generation of a value between 0 and 1 ($v_i \sim U(s_{min},s_{max})$, U denotes uniform distribution, i is the index of particle). The reason why 0 and 1 are chosen as speed limits is to ease the update of position values by having comparable values to the random numbers generated. Random numbers generated in (8) have a uniform distribution. Then, the speed is updated by imposing the effect of individual (x), and swarm components positions(g) as brought in (8) (Thevenot, 2020). Individual and swarm effects are imposed with the so called “inertia weights” that are shown with φ_1 *and* φ_2 and need to be tuned. Since the generated velocity now has a continuous value, sigmoid function is used to convert it to a value between 0 and 1. Again, a sigmoid multiplier (k) is considered which needs to be tuned that shifts this function to more than 1 so that particles are more probable to get 1 as their position, which was found to find solutions that satisfy constraints more easily. The objective and constraints imposed in this algorithm are like that of GA.

4.3 Simulated annealing

In this section, integer linear programming and simulated annealing are introduced. The first method is discussed for generation of a suitable initial guess for simulated annealing rather than directly solving the problem.

4.3.1 Integer Linear Programming as initial state for simulated annealing

According to (Tseng, 2011, pp. 1183-1197), “Linear programming is a branch of mathematics developed in the twentieth century which can solve a system of simultaneous linear equations.” This method “can minimize or maximize a linear function while being subjected to equality or non-equality linear constraints.” Although “in real-world problems a linear model may not always be realistic, it can be a first approximate for understanding the problem.” An example of what this method can solve can be as follows (Tseng, 2011, pp. 1183-1197):

$$\begin{cases} \text{maximize:} z=x_1+x_2 \\ 2x_1+x_2\leq 13 \\ 0\leq x_1\leq 5 \\ 0\leq x_2\leq 5 \end{cases} \tag{10}$$

In our case, as we do not have the data on how many sections should be cut to both minimize the total cutting surface area and respect constraints of the problem, number of variables is not clear. While summation of the areas is a linear equation, for respecting the mass constraint, each block mass should be calculated by summing all the section masses that are decided not to be cut and the first section mass that is cut. This means that solving this problem directly with linear programming is impossible and the problem cannot be formulated like (10). However, based on the total mass of the ship and the lifting and transporting mass constraint of 20 tons, it is possible to know that at least about 90 cuts are needed. Disregarding the mass constraint on blocks and knowing the minimum number of cuts necessary, pulp library (pulp team, 2009) in Python can help us choose all the sections that have the minimized summation of area. What linear programming gives us is simply selection of as many sections as we determine as the minimum number of cut sections that have minimum summation of surface area. Although this is far from solving the problem, the result can lead to having a good initial guess for other algorithms such as simulated annealing.

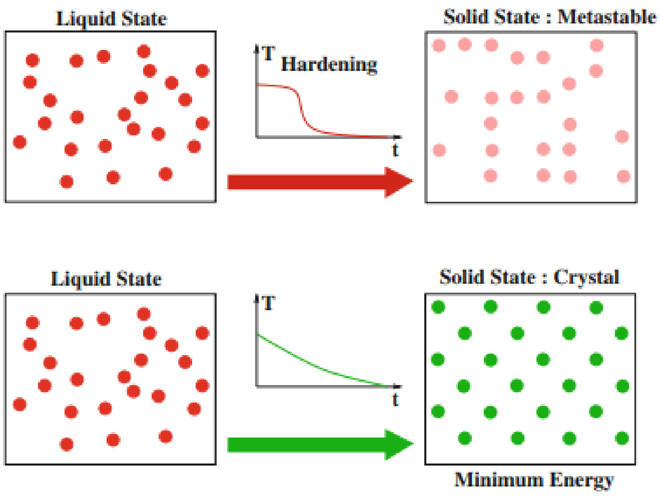

Figure 37. When the temperature is high the material is in liquid state. After hardening, the material reaches a state with non-minimal energy. With slow cooling however, a solid state with symmetrically organized atoms is achieved. (Gendreau, 2019, p. 4.)

Simulated annealing is inspired by slow cooling of metals which helps them form ideal, regularly configured crystals inside, with minimum energy state. Like this logic, gradually, the probability of accepting worse solutions reduces with lower temperatures. That is why the starting temperature in this algorithm is higher than the final temperature. The cooling schedule should be sufficiently slow to allow for a final configuration with superior structural integrity which means that the system has reached equilibrium. Simulated annealing, therefore, builds the similarity of search for global optimum for a discrete optimization problem and the described thermodynamic behaviour. (Henderson, 2006, pp. 287-319.) For each temperature, a certain number of loops are operated. In case that in each loop the solution is better than the current one, it is accepted while if it is not better, it is only accepted based on a certain probability just to enable the algorithm escape local optima. (Kizilay, 2022, pp. 1-10.) Accepting worse solutions which happens less frequently with decreased temperatures, is called hill-climbing moves.

Simulated annealing starts with an initial solution which could be generated either randomly or based on a pre-specified rule. The move from current solution to a candidate solution takes place by Metropolis acceptance criterion (Metropolis, 1953, pp. 1087-1092) so that the energy content is minimized (Henderson, 2006, pp. 287-319).

Therefore, in this algorithm, an initial set of solution, temperature change counter (alternatively called number of updates for each iteration), temperature cooling schedule, initial temperature, and repetition schedule (alternatively called number of iterations at each temperature) are chosen. These parameters need to be fine-tuned. The process has the following steps as in Figure 38.

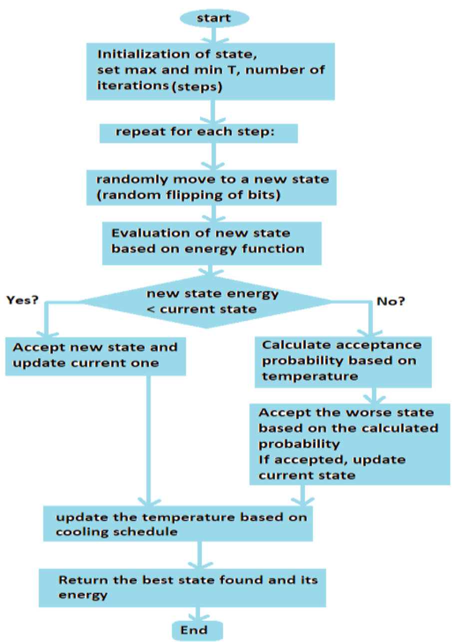

Figure 38. Flowchart of simulated annealing algorithm.

4.3.2 Simulated annealing implementation in ship recycling plan generation

For implementation of simulated annealing simanneal module in Python is used (Wagner, 2020). Initialization of problem is done both by setting 1 for all the sections and by the solution achieved by linear programming. The objective of the algorithm is to minimize the total cutting area and the constraints are associated with maximum allowed mass of cut blocks and changes in location of centre of mass after each cut.

$$E=\begin{cases} \infty, \text{ if } m_{block}>m_{max} \text{ for any block} \\ \infty, \text{ if } \left|COM_{y,i}-COM_{y,i-1}\right|>50\text{cm for any block} \\ A_{total}=\sum_{i=1}^{N} state[i].A_i \quad N\text{:number of cuts} \end{cases} \tag{11}$$

Here, the objective function is called energy which needs to be minimized to allow for best integrity of the structure during annealing process as in (11). Energy function returns infinite value if the constraints are not fulfilled in a certain solution. The potential solution in this algorithm has the same appearance as the previous two.

$$T_{k+1}=\alpha T_k, \ \alpha=\left(\frac{T_f}{T_0}\right)^{\frac{1}{N}} \tag{12}$$

The transition from one state to the other is $s^{'}$=move(s) which happens by random flipping of bits of state array. The cooling schedule is defined using cooling rate α that can be computed based on initial and final temperatures and number of iterations as in (12) (Delahaye, 2018, pp. 5-6).

$$P(E(s), E(s^{'}), T)=\exp\left(-\frac{E(s^{'})-E(s)}{T}\right) \tag{13}$$

To escape the local optima, an acceptance probability of states with higher energy is contemplated. As (13) (Delahaye, 2018, pp. 7-8) suggests, the probability of accepting worse solutions decreases with lower temperatures.

5 Results

In this section achieved solution, convergence and centre of mass evolution after each cut for different algorithms are analysed.

5.1 Genetic algorithm

As discussed previously, genetic algorithm can have several parameters that need to be tuned so that better results are obtained in shorter time. These parameters are population size (100, 500, 1000, 2000), mutation probability (0.01, 0.02, 0.05, 0.1), and cross over probability (0.5, 0.6, 0.7, 0.8, 0.9). Different combinations of these parameters are tested as presented in Figure 40.

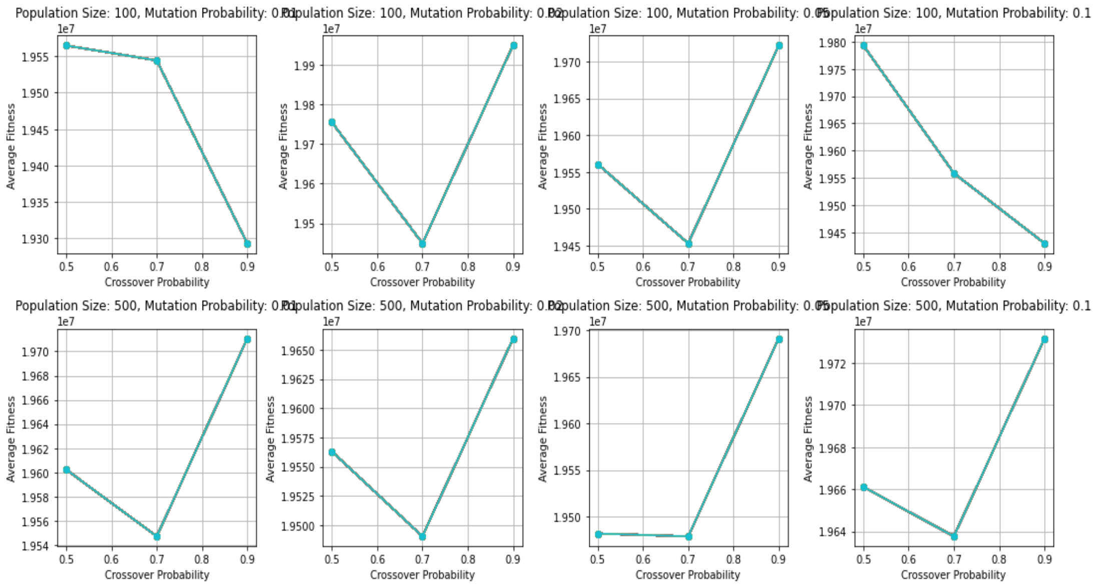

Figure 40. Genetic algorithm parameter tuning.

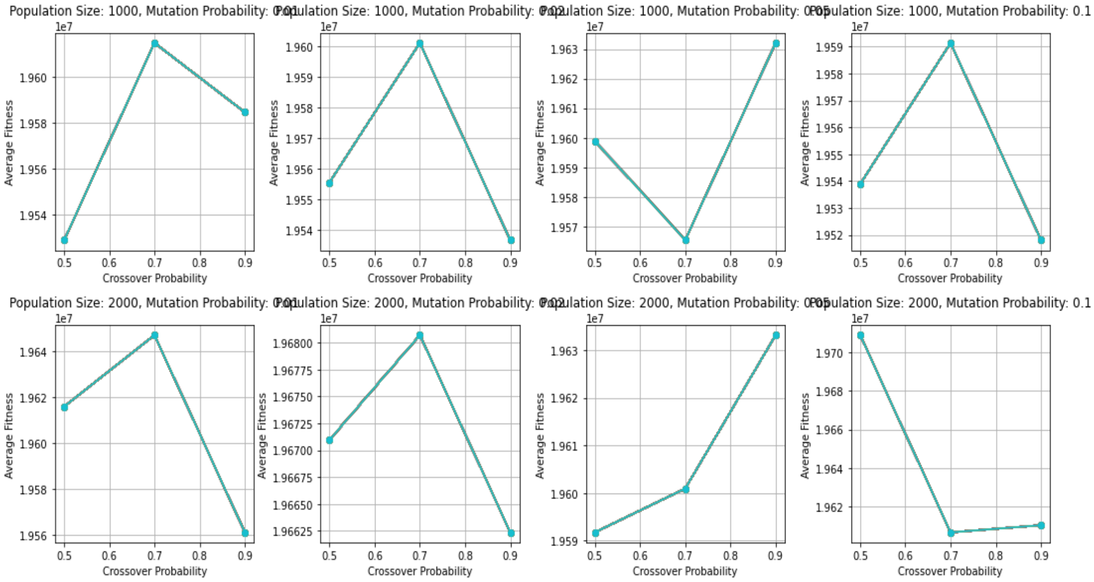

Figure 40 continues. Genetic algorithm parameter tuning.

The effect of different parameter combinations is shown on average fitness which means the average of fitness value over the last generation (100th). In each plot in Figure while keeping mutation probability and population size constant, the effect of crossover probability on average fitness value is analysed. After these plots are achieved, the parameters resulting in best fitness value in each plot are tested to see which set works the best. This means 16 runs are done to catch the best combination of parameters as population size of 2000, mutation probability of 0.02, and cross over probability of 0.9. With this set of tuned parameters, convergence should be analysed. The convergence is achieved if after a certain number of generations, the average fitness value does not change significantly having the value of 9165732.

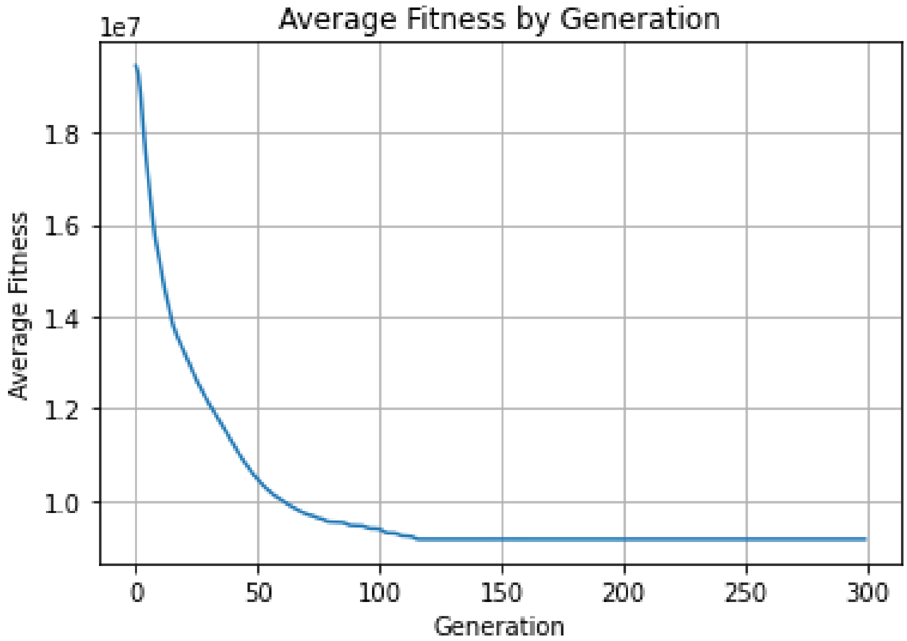

Figure 41. Convergence plot for genetic algorithm with population size of 2000, mutation probability of 0.02, and crossover probability of 0.9 (selection operator: selTournament).

Bellow, the best solution which represents the cross-sections that need to be cut with 1s is represented. This solution involves 117 cuts to be performed.

Chromosome (0/1 representation): ['1', '0', '0', '0', '1', '0', '0', '0', '0', '1', '0', '0', '0', '1', '0', '0', '0', '1', '0', '1', '0', '1', '0', '0', '1', '0', '1', '0', '1', '1', '0', '1', '0', '1', '0', '1', '0', '1', '0', '1', '0', '1', '0', '1', '1', '1', '0', '1', '0', '1', '1', '1', '1', '1', '0', '0', '1', '0', '0', '1', '0', '0', '1', '0', '0', '1', '0', '0', '1', '0', '0', '1', '1', '0', '0', '1', '0', '0', '1', '0', '1', '0', '1', '1', '1', '1', '0', '0', '1', '0', '0', '0', '0', '1', '0', '0', '1', '0', '0', '0', '1', '0', '0', '1', '0', '1', '1', '1', '1', '1', '1', '1', '1', '1', '1', '1', '1', '1', '1', '1', '0', '1', '0', '1', '0', '1', '0', '1', '1', '0', '1', '0', '1', '0', '1', '0', '1', '0', '1', '0', '1', '0', '1', '0', '1', '0', '1', '0', '1', '0', '1', '0', '1', '0', '1', '0', '1', '0', '1', '0', '1', '1', '0', '1', '0', '1', '0', '1', '0', '1', '1', '0', '1', '0', '1', '0', '1', '0', '0', '1', '0', '0', '1', '0', '1', '0', '0', '1', '0', '1', '0', '1', '0', '0', '1', '0', '0', '0', '1', '0', '0', '0', '1', '0', '0', '1', '0', '0', '1', '0', '0', '0', '0', '1', '0', '1', '0', '0', '1', '0', '0', '0', '1', '0', '0', '0', '1', '0', '0', '0', '1', '0', '1', '1', '0', '1', '1', '0', '1', '0', '1', '0', '1', '0', '0', '1', '0', '0', '1', '0', '0', '0', '1', '0', '0', '0']

The details of best-tuned operators and parameters are listed in Table 2.

Table 2. Genetic algorithm parameters and operators' details.

Population	Initiation: weighted random based on mass, Size: 2000
Mutation	Operator: mutFlipBit, Probability: 0.02
Crossover	Operator: cxTwoPoint, Probability: 0.9
Selection	Operator: selTournament, tourn size: 3

To illustrate the importance of the selection operator, with the same set of parameters, the selNSGA2 operator is tried in Figure 42. As it is clear, in case of wrong operator, convergence cannot be reached.

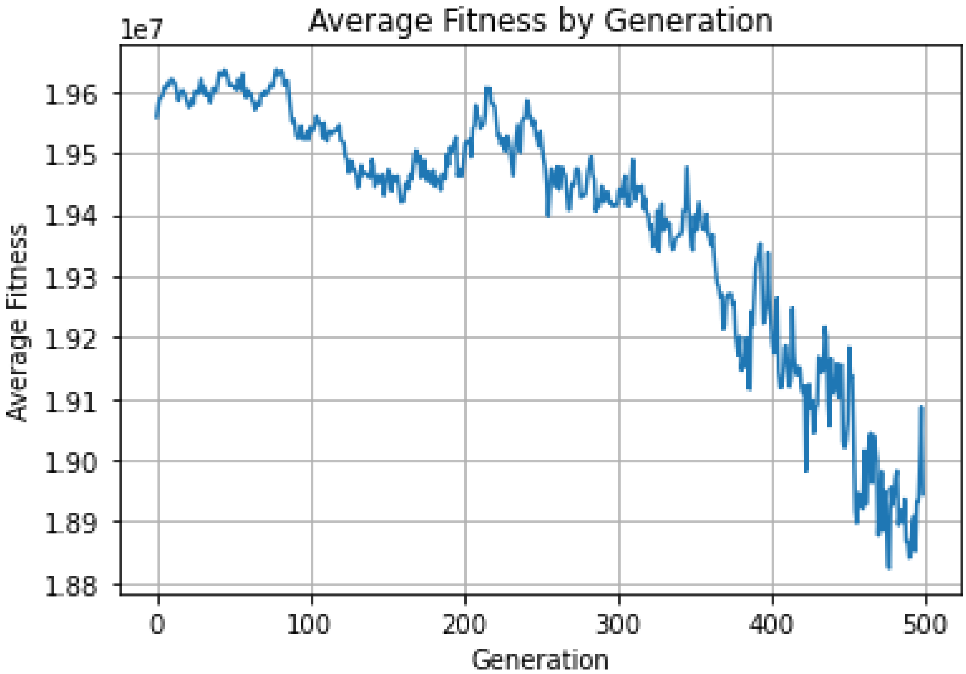

Figure 42. Convergence plot for genetic algorithm with population size of 2000, mutation probability of 0.02, and crossover probability of 0.9 (selection operator: selNSGA2).

Also, plots in Figure 43, and Figure 44 illustrate how the location of centre of mass changes after each cut for the best solution found by genetic algorithm. X, Y, and Z directions are transverse, vertical and longitudinal directions respectively. It could be observed that centre of mass in X and Z directions does not change significantly.

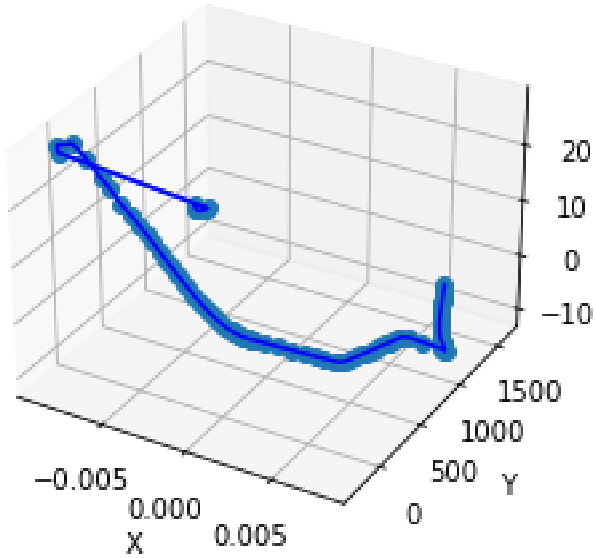

Figure 43. Centre of mass evolution after each cut for the best solution found by GA.

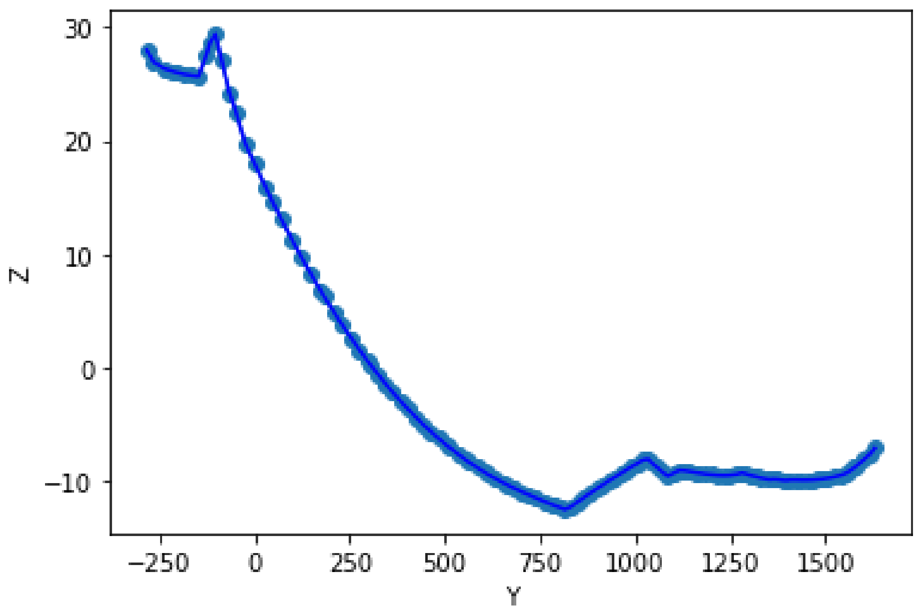

Figure 44. Centre of mass evolution in Z and Y direction after each cut for the best solution found by GA.

To have an idea about the complexity of ship recycling practice based on the optimized sequence generated, we can analyse minimum, average, maximum values of blocks and the displacements of the COM between two consecutive cuts as shown in Table 3.

Table 3. Statistical data on mass and displacement of COM of the found solution by GA (50cm constraint on COM).

Number of cuts	Average mass of blocks	Minimum mass of blocks	Maximum mass of blocks	Average displacement of COM between consecutive cuts	minimum displacement of COM between consecutive cuts	maximum displacement of COM between consecutive cuts
117	15.1 tons	4.2 tons	19.9tons	16.2 cm	4cm	30 cm

5.2 Particle swarm optimization

As discussed in 4.2.2 , inertia weights, probability bias factor, sigmoid multiplier and population size should be tuned such that best solutions are achieved like shown in Figure 45.

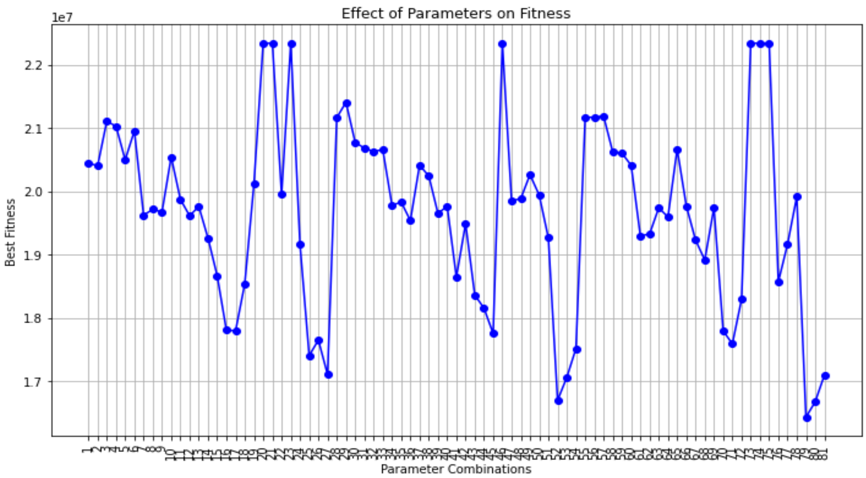

Figure 45. Effect of different parameters combination on the best fitness value by PSO.

The best set of parameters which are inertia weights, population size, sigmoid multiplier, and probability bias factor are found as (1, 1, 50000, 1.0, 10000). The best fitness value for this set is 16432500 cm^2. This value is nearly 60 percent more than that of genetic algorithm. That is why with this set, convergence is analysed to see if the solution is reliable.

Based on Figure 46, the algorithm has not converged, and it has only reached to a local optimum.

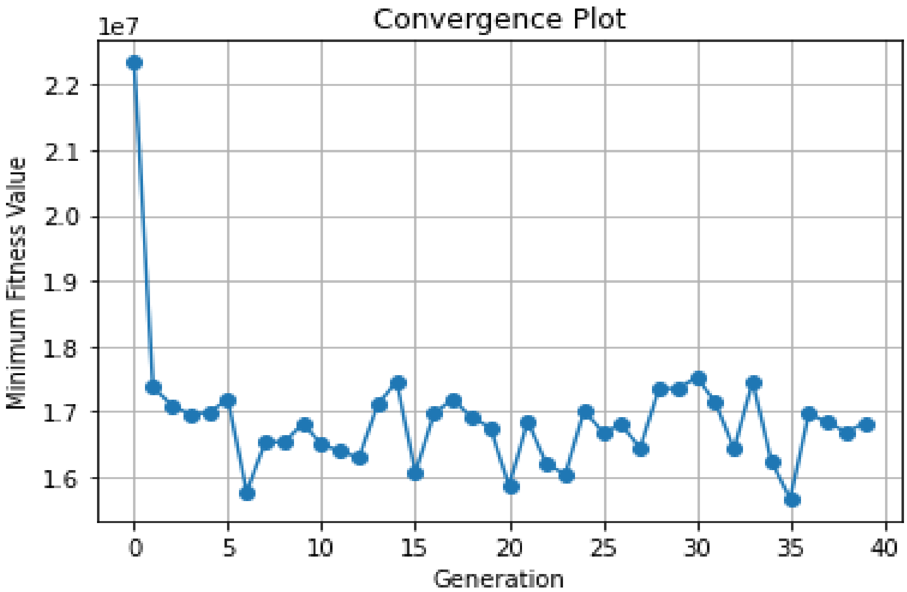

Figure 46. Convergence plot of PSO with the best set of parameters found after 40 generations.

5.3 Simulated annealing

As discussed in 55, an initial set of solution, number of updates, initial temperature, and number of iterations should be fine-tuned. This leads to generation of plots in Figure 47. While it is obvious that initial temperature should be chosen as 100000, effect of number of updates and iterations is vague. That is why another fine-tuning is needed that analyses the effect of the two mentioned parameters while keeping initial temperature 100000. Plots provided in Figure 48 illustrate that while number of iterations should be as high as 800000, number of updates does not affect the value of energy function and therefore for the sake of lowering computational effort, 1 is chosen for it. That is because number of updates is primarily used for monitoring the progress of optimization process rather than affecting the core of algorithm.

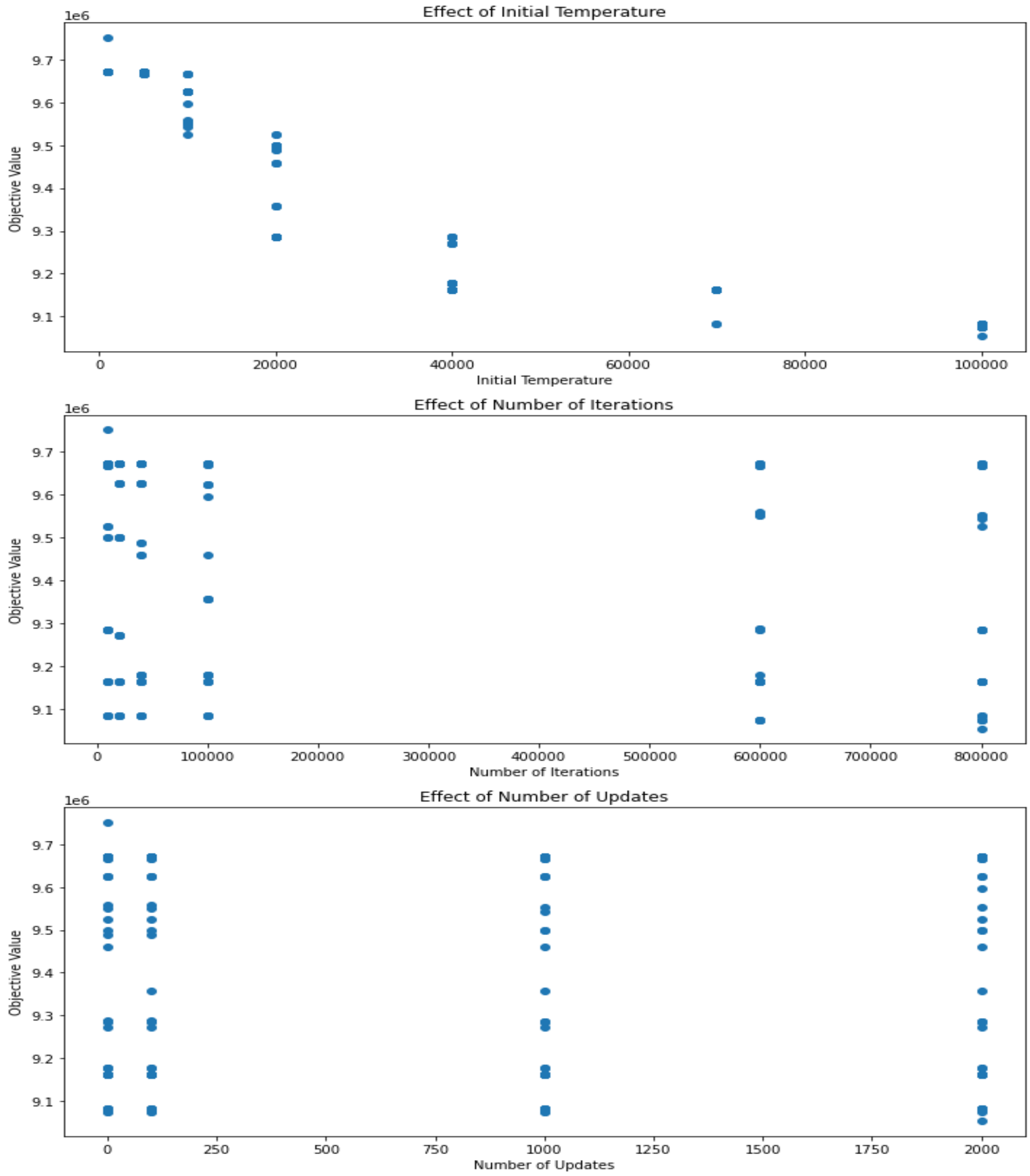

Figure 47. Effect of initial temperature, number of iterations and updates on energy function value.

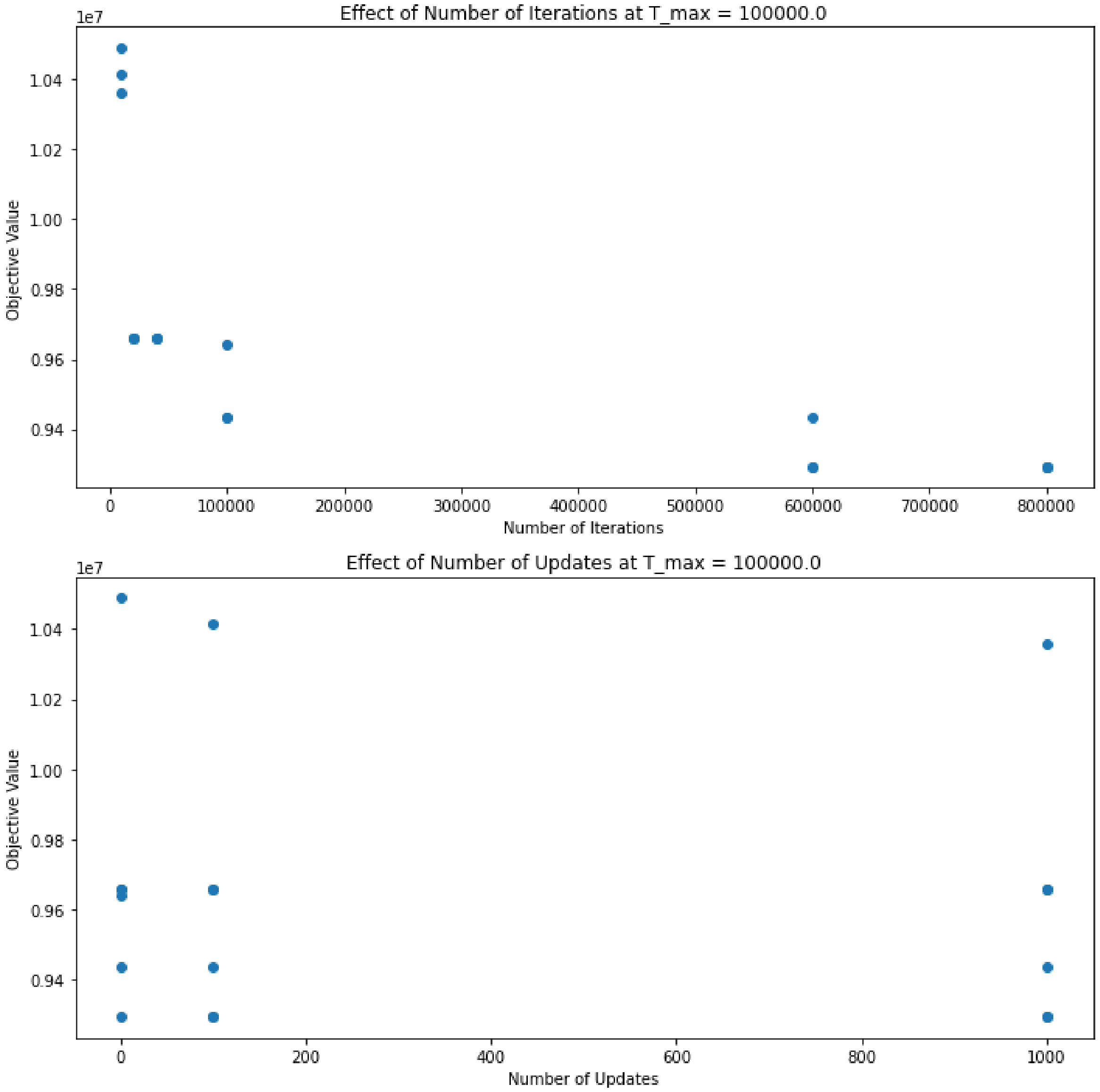

Figure 48. Effect of number of iterations and updates on energy function value while keeping initial temperature 100000.

With the set of fine-tuned parameters listed in Table 4, it is possible now to analyse stability.

Table 4. Simulated annealing parameters and details.

Initial temperature	100000
Initial state	All cross-sections to be cut
Final temperature	0.1
Number of iterations	800000
Number of updates	1
Temperature schedule	Exponential

In case of simulated annealing, convergence can have a slightly different meaning compared to genetic algorithm and particle swarm optimization. As suggested by simanneal documentation (Wagner, 2020), the state is examined after 20 different runs. If very similar results are obtained, the algorithm has converged to a nearly optimal answer as shown in Figure 49.

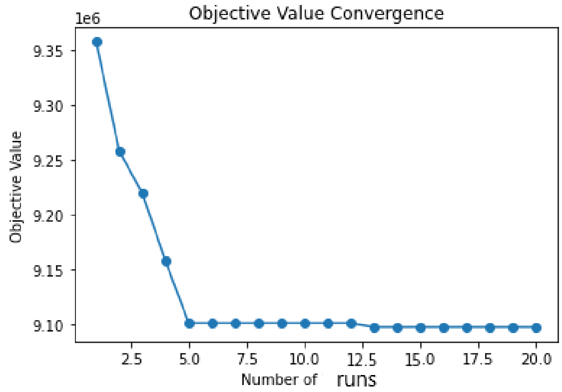

Figure 49. Convergence plot for simulated annealing algorithm.

Now, the evolution of location of centre of mass after each cut can be analysed. In Figure 50, evolution of centre of mass while the constraint on its displacement is 50cm is shown.

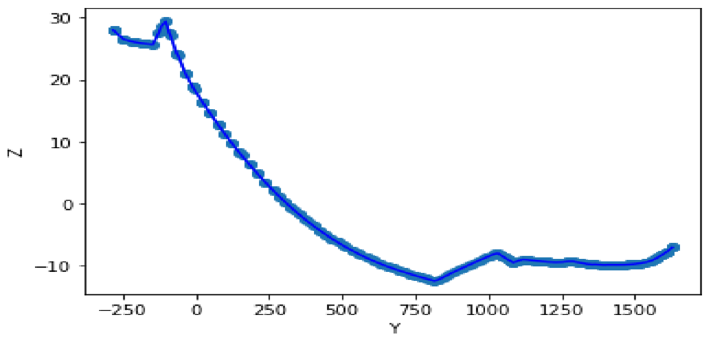

Figure 50. Centre of mass evolution in Z and Y direction after each cut for the best solution found by SA with an imposed constraint of allowed COM displacement of 50cm.

The algorithm can manage to find a solution even if we push this constraint to 25cm. As it could be seen in Figure 51, the plot looks denser than the plot in Figure 50 as more cross sections should be decided to be cut to fulfil the tighter constraint. Also, the value of the energy function which is representative of total cut area increases to 10189469cm^2. It should be noted that GA cannot reach convergence in case the centre of mass displacement constraint is pushed down to 25cm.

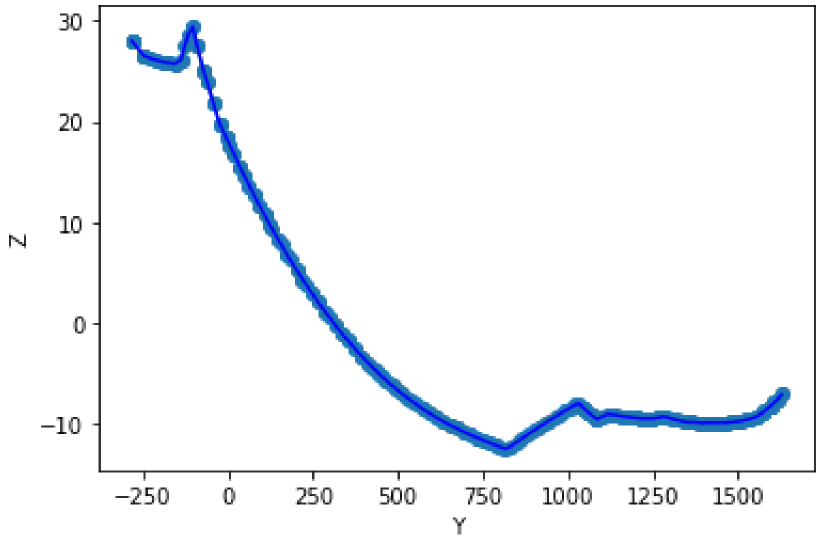

Figure 51. Centre of mass evolution in Z and Y direction after each cut for the best solution found by SA with an imposed constraint of allowed COM displacement of 25cm.

Result of analysis of minimum, average, maximum values of blocks and the displacements of the COM between two consecutive cuts for both 50cm and 25cm constraints are brought in Table 5 and Table 6 respectively.

Table 5. Statistical data on mass and displacement of COM of the found solution by SA (50cm constraint on COM).

#cuts	Average mass of blocks	Minimum mass of blocks	Maximum mass of blocks	Average displacement of COM between consecutive cuts	minimum displacement of COM between consecutive cuts	maximum displacement of COM between consecutive cuts
113	15.8 tons	3.8 tons	19.9tons	17.22 cm	4.2cm	43.5 cm

Table 6. Statistical data on mass and displacement of COM of the found solution by SA (25cm constraint on COM).

# cuts	Average mass of blocks	Minimum mass of blocks	Maximum mass of blocks	Average displacement of COM between consecutive cuts	minimum displacement of COM between consecutive cuts	maximum displacement of COM between consecutive cuts
118	14.6 tons	4.1 tons	19.9 tons	16.5 cm	4.2cm	24.3 cm

For trying the effect of the initial state given to the algorithm, time needed for computation was recorded. In case of initial state of all cross sections being assigned one, we will have:

Computational effort (elapsed time): 237.70 seconds

In case with linear programming minimum number of cut sections is imposed 110, the algorithm cannot find any solution with the previous set of parameters:

Objective value: inf

Computational effort (elapsed time): 70.24 seconds

The initial state produced by linear programming can lead to finding solution by the same set of parameters as before only if minimum number of cuts imposed in linear programming are 250 which basically is not much different from setting 1 for all cross sections. In this case, the elapsed time is very close to 237 seconds. The reason that despite expectation initial state produced by linear programming does not help but also troubles the algorithm is that it simply chooses the sections with minimum area and that means based on the geometry of the ship hull it can happen that several sections are decided not to be cut all one after the other. Therefore, mass and centre of mass constraints are not fulfilled initially, and the algorithm cannot find any solution as in SA, exploration happens around an already feasible solution. However, when the initial state is set as all cross sections to be cut, constraints are fulfilled and therefore by lowering the temperature, algorithm converges to a decent solution.

6 Discussion

In this section, first, characteristics of different algorithms are discussed to justify the reasons for the selection of their parameters and their functionality for this specific problem. After that, results obtained by different algorithms are compared.

6.1 Characteristics of algorithms

Genetic algorithm which has a population of individuals as the problem space, evolves the initial population to a high-quality set of individuals by operators like crossover, mutation and selection. Crossover which produces two offsprings from two parents can be based on single-point or two-point operations. In single-point cross over, always the first segment of the first parent is completed with the remaining string of the second parent or vice versa, while in two-point cross-over, intermediate segment of one parent is put into the middle of another parent (L. Haldurai, 2016). As it could be understood from the concept of crossover, two-point approach suits our application better as the structural characteristics of parent solutions are preserved better than one-point one. Therefore, producing feasible and closer to parent solutions is done more efficiently as in this problem mass and centre of mass displacement constraints can cause generation of infinite value of fitness function in case the chosen parents are significantly changed. Optimum value found for crossover was 0.9 which is a large value that is appropriate for preventing premature convergence to local optima and better exploration of search space. Mutation operator that produces offspring from a single parent by randomly flipping the bits, was found to be best when kept 0.02. This is because with large mutation values, the produced offspring is replaced by a randomly swapped chromosome which is more likely to have lost the fitness of the parent. In this problem with the constraint applied, it is the best practice to maintain good features of the parents while introducing explorations with decent amount of mutation and crossover. Finally, the selection operator was chosen as selTournament which selects a certain number of random individuals that are assessed based on their fitness for being chosen as parent (deap, 2023). The other selection operator that was tested was selNSGA2 that did not reach convergence as it is more appropriate for multi-objective problems. More than the operators, the number of individuals in the population was found to be best when 2000 which is quite large. This is explainable as the search space is large and with bigger population, more exploration is introduced which might take longer for computation but explores the search space better.

While with genetic algorithm, the quality of candidate solution improves iteratively by mechanisms such as crossover and mutation, particle swarm optimization method utilizes agents' plain behaviour and self-organizing interactions. Therefore, in PSO, each particle as a potential solution, flies through the space and combines some aspects of its own historical best location and current location and others to determine its next move (G.Gad, 2022). In this problem, each particle has had 255 dimensions. The problem with PSO is that with high-dimensional search space, it converges very slow towards the global optimum and most often with such problems it fails to find the global optimum. That is why even after tuning the parameters to get the best results, convergence was not achieved as it was having search instability around local optima. One possible solution to tackle local optima issue could be use of PSO variants that incorporate evolutionary algorithm capabilities. This method was not deployed in this project as genetic algorithm was already tested.

Despite PSO, simulated annealing is an extension of local search optimization algorithms which has an iterative process of starting from a feasible point and then exploring the neighbourhood of the current solution (Gendreau, 2019). In this project, best set of parameters in the algorithm were tuned such as initial temperature, number of updates and iterations. The initial temperature was found to be best when 100000, which is expressed with the same unit as the energy function that is optimised. The reason why this is relatively large is that based on the results from PSO, we know that the problem has many local optima and with higher initial temperature escaping them is easier and exploration of search space is better introduced. Moreover, higher temperatures increase the ability to accept transitions that degrade the energy function (Gendreau, 2019). The number of iterations was set to 800000 which is a fixed value and the number of updates was considered as 1. Therefore, the temperature decreases linearly from initial temperature to final one over the course of number of iterations. With larger number of iterations, the steps at which the temperature falls becomes smaller and therefore more thorough exploration of search space happens. The number of updates on the other hand was found not to significantly impact the optimization as this parameter is more utilized for monitoring the optimization process.

6.2 Comparison of results

Although a common problem with meta-heuristic approaches is being trapped around a local optimum, there are ways to ensure that a near-global optimum has been reached. That is why after deploying each algorithm, convergence plots were considered. However, convergence can have a different meaning when implemented for different algorithms. For instance, with GA, in case after a certain number of generations the solution does not change significantly, convergence is realized while with SA, no concept of generation exists. That is why the algorithm should run for several times to ensure convergence. Based on the characteristics of the algorithms and the problem itself, GA and SA (after 20 runs) reached convergence with the same value of objective function (Figure 41, Figure 49). However, high dimensionality of the problem disabled PSO to reach global optimum (Figure 46). The constraints play a crucial role on the obtained results as if we allow the maximum mass of blocks to be larger, less cross sections need to be cut. This is the same with the constraint on the allowed displacement of the centre of mass location in consecutive cuts. With 25cm displacement allowed, more cross sections should be cut to respect this constraint compared to 50cm. That is why Figure 1, looks denser than Figure 0. A comparison of results can be observed in Table 7.

Table 7. Comparison of results of deployed algorithms.

GA	• Convergence reached with weighted random initialization of population. • Total cutting area of around 9.1e6 cm^2 as the value of fitness function. • Block mass constraint of 20 tons. • Centre of mass displacement allowance of 50 cm.
PSO	• Convergence not reached even with weighted random initialization of particles and fine-tuned parameters. • Trapped in local optimum of about 1.7e7cm^2 as the value of fitness function.
SA	• Convergence reached with an initial state of all cut cross sections. • Initial state generated by ILP does not help. • Total cutting area of around 9.1e6 cm^2 as the value of fitness function. • Block mass constraint of 20 tons. • Centre of mass displacement allowance of 50 cm and 25cm.

7 Conclusions

The main aim of the project was to deploy innovative, AI methods for generation of cutting plan for a container ship hull. One important aspect of the problem was identification of the data needed as inputs of the algorithms. As cutting area determines the needed time for the cut and therefore the cost of operation, area of cross sections of the hull should have been accessed. More than that, the centre of masses of all the bodies and their masses should be available to reflect the constraints. That is why from digital model of the ship hull, using Fusion 360 programming interface and Python, the mentioned data was automatically extracted. Using AI algorithms enabled us to generate the cutting plan for the hull without the need of human expertise which can be both expensive and time-consuming. Imposing centre of mass displacement constraint increases social safety of workers. With this constraint, large changes of centre of mass in consecutive cuts is not allowed that is the main source of large block falls. More than that, the generated plan should be feasible by facility. That is why mass constraint of each cut block is considered. All that being done, the way for greener and safer recycling of ships is paved by reducing the costs of this industry. Implementation of AI algorithms has its own implications as each of them have their own characteristics making them suitable for a certain problem. In this work, GA, PSO, and SA were implemented such that they generate a solution that represents either a cross-section should be cut or not. The objective and constraints were also reflected in fitness/energy functions to guide the algorithms. As the size of problem is large, metaheuristic approaches can take long to reach a solution. For efficient performance of each algorithm consequently, fine tuning the parameters was done to ensure finding a solution that respects the constraints. The obtained solution by the set of fine-tuned parameters in all the utilized algorithms was verified by the analysis of convergence plots. PSO was not able to reach global optimum in this problem as it had 255 binary variables. Despite PSO, GA and SA successfully achieved convergence reaching nearly the same value for total cutting area while respecting the imposed constraints.

For the future work, more thorough consideration of capacities, equipment, and cutting stages can be done. The next step of ship recycling, which is the secondary cut can be optimized such that the recycling facility capacities and the recovered materials are thought of. In secondary cut, the large blocks provided by primary stage are further cut and sorted.

Therefore, based on the destinations that the recovered materials have and the place at which they are going to be treated, imposed constraints may vary. Furthermore, the cutting capabilities of shipyards can be implemented in the algorithms so that based on the equipment available, a feasible plan is generated. This can also produce an estimation of time needed for ship recycling. Other than the destructive stages of recycling that include performing cuts, ship recycling includes non-destructive disassembly steps as well like uninstallation of machineries. A wholesome ship recycling plan should contain information on those stages and preparation works too. Another problem that makes ship recycling procedures costly is the fact that the plan is ship specific. By utilizing other AI methods such as deep reinforcement learning when having access to data of large number of vessels, autonomous generation of cutting plan can be done more generally, making the process more affordable. This can be a method to generate a cutting plan which is not dependent on the type of vessel. Ultimately, dynamics of economy can be reflected in the algorithms which can provide plans that are adaptive to changes that the market experiences. By doing so, the components, cut parts, and recovered materials that are more demanded in the market, can be prioritized to be dismantled sooner by the algorithm.

References

A.J.D. Lambert, 2003. Disassembly sequencing: a survey. *International Journal of Production Research*, Volume 41, Pp. 3721-3759.

Allagui, B. P. H. P. A., 2023. Reinforcement learning for disassembly sequence planning optimization. *Computers in Industry*, Volume 151, Pp. 3-16.

ANT AG, 2023. Recycling Magazine. [Online] Available at: https://www.recycling-magazine.com/2023/09/04/waterjet-cutting-allows-for-environmentally-friendly-ship-recycling/ [Accessed 10 2 2024].

AutoDesk, 2024. Autodesk. [Online] Available at: https://help.autodesk.com/view/fusion360/ENU/?guid=GUID-A92A4B10-3781-4925-94C6-47DA85A4F65A [Accessed 20 2 2024].

deap, 2023. DEAP. [Online] Available at: https://deap.readthedocs.io/en/master/overview.html#operators [Accessed 25 3 2024].

Du, Z. Z. F. Y. D. W., 2018. Hazardous materials analysis and disposal procedures during ship recycling. *Resources, Conservation and Recycling*, Volume 131, Pp. 158-171.

European Commission, 2012. Regulation of the European parliament and of the council on ship recycling. [Online] Available at: https://eur-lex.europa.eu/LexUriServ/LexUriServ.do?uri=SWD:2012:0047:FIN:EN:PDF [Accessed 18 3 2024]. 150 p.

European Union, 2013. EU NO 1257/2013. [Online] Available at: https://eur-lex.europa.eu/LexUriServ/LexUriServ.do?uri=OJ:L:2013:330:0001:0020:EN:PDF [Accessed 25 4 2024]. 20 p.

Fonseca, G., 2021. Challenges when creating a cohesive digital twin ship: a data modelling perspective. *Ship Technology Research*, 68(2), Pp. 70-83.

Fooksa, 2023. *Study*. [Online] Available at: https://study.com/academy/lesson/calculating-center-of-mass-definition-equation-example.html [Accessed 17 9 2024].

G. Gad, A., 2022. Particle Swarm Optimization Algorithm and Its Applications: A systematic review. *Archives of Computational Methods in Engineering*, Volume 29, Pp. 2531-2561.

Gendreau, P., 2019. Simulated annealing: From basics to applications. In: *Handbook of Metaheuristics*. Montreal: Springer, Pp. 3-35.

GitHub, 2020. GitHub. [Online] Available at: https://github.com/perrygeo/simanneal [Accessed 15 3 2024].

Gourdon, 2019. Ship Recycling: An Overview. *Technology and Industry Policy Papers*, 49 p.

Gucdemir, I., 2023. A part grouping-based approach for disassembly sequencing. *Journal of Engineering Research*, 2(1), Pp. 1-6.

Gunbeyaz, E. K. T., 2022. Investigation of different cutting technologies in a ship recycling yard with simulation approach. *Ships and Offshore Structures*, 17(3), Pp. 564-576.

Hechler, K. J., 2019. Optimization of dismantling process of wind turbine blades from offshore wind farms during decommissioning, s.l.: Western Norway University of Applied Sciences, 256 p.

Henderson, H. J. W. J., 2006. The theory and practice of simulated annealing. s.l.:ResearchGate, Pp. 287-319.

IMO, 2011. IMO. [Online] Available at: https://wwwcdn.imo.org/localresources/en/OurWork/Environment/Documents/RESOLUTION%20MEPC.196(62).pdf [Accessed 13 9 2024]. 23 p.

K.P. Jain, J. P. J. H., 2017. Material flow analysis (MFA) as a tool to improve ship recycling. *Ocean Engineering*, Volume 130, Pp. 674-683.

Kaushal, A., 2014. GrabCAD. [Online] Available at: https://grabcad.com/library/container-ship-model-elly-maersk-1 [Accessed 1 3 2024].

Kizilay, D., 2022. A novel constraint programming and simulated annealing for disassembly line balancing problem with AND/OR precedence and sequence dependent set up times. *Computers and Operations Research*, Volume 146, Pp. 1-10.

Kongar, S. M. G., 2006. Disassembly sequencing using genetic algorithm. *The International Journal of Advanced Manufacturing Technology*, Volume 30, Pp. 497-506.

Kusumaningdyah, A. E. R. Y., 2012. Modelling trade-off in shipbreaking industry considering sustainability aspects: a system dynamics approach. Kyoto, *ScienceDirect*, Pp. 88-94.

L. Haldurai, T. M. R. R., 2016. A study on genetic algorithm and its applications. *International Journal of Computer Sciences and Engineering*, 4(10), Pp. 1-5.

Merisaari, P., 2024. Discharge yard business opportunities as part of fossil-free steel production, Raahe: s.n., 80 p.

Metropolis, W. R. N. R. H. T. T., 1953. Equation of state calculations by fast computing machines. *The Journal of Chemical Physics*, 21(6), Pp. 1087-1092.

M. Hiremath, S. K. P. S. R. A., 2016. Development of ship-specific recycling plan to improve health safety and environment in ship recycling yards. *Journal of Cleaner Production*, Volume 116, Pp. 279-298.

Priya Jain, P. H., 2016. Improving ship design process to enhance ship recycling. Lisbon, *ResearchGate*, P. 65-70.

pulp team, 2009. GitHub. [Online] Available at: https://coin-or.github.io/pulp/ [Accessed 15 4 2024].

Qyuen, P. T., 2019. An assessment of development opportunities of ship recycling facilities based on the shipbuilding yards' infrastructure, Malmö: Digital Repository of the World Maritime, 89 p.

S.K. Ong, M. A., 2021. Product disassembly sequence planning: state-of-the-art, challenges, opportunities and future directions. *International Journal of Production Research*, 59(11), Pp. 3493-3508.

S. Kara, P. H., 2006. Selective disassembly sequencing: A methodology for the disassembly of end-of-life products. *CIRP Annals*, 55(1), Pp. 37-40.

Sabaghi, C. M. B., 2016. Towards a sustainable disassembly/dismantling in aerospace industry. *Procedia CIRP*, Volume 40, Pp. 156-161.

Scheelhaase, M. E. G., 2022. Economic and environmental aspects of aircraft recycling. *Transportation Research Procedia*, Volume 65, Pp. 3-12.

Shipbreaking, N., 2024. NGO Shipbreaking Platform. [Online] Available at: https://shipbreakingplatform.org/our-work/glossary/#:~:text=Light%20Displacement%20Tonnage%20(LDT),used%20to%20operate%20steam%20machinery [Accessed 15 4 2024].

ShipResearchInstituteOfNorway, 1972. SpecTec. [Online] Available at: https://spectec.net/sfi-technical-coding-solution/ [Accessed 15 9 2024].

Solakivi, K. K. O., 2021. The European ship recycling regulation and its market implications: ship recycling capacity and market potential. *Journal of Cleaner Production*, Volume 294, Pp. 1-4.

T.C. Hu, A. B., 2016. *Linear and integer programming made easy*. California: Springer, 310 p.

Tseng, Y.-J. Y. F.-Y. H. F.-Y., 2011. A green assembly sequence planning model with a closed-loop assembly and disassembly sequence planning with particle swarm optimization method. *International Journal of Advanced Manufacturing Technology*, Volume 57, Pp. 1183-1197.

Wagner, R. J., 2020. GitHub. [Online] Available at: https://github.com/perrygeo/simanneal/tree/master/simanneal [Accessed 12 3 2024].

Wang, X. R. Z., 2013. Intelligent disassembly planning: a review on its fundamental methodology. *Assembly Automation*, February, 33(1), Pp. 78-85.

Yan, W. Y., 2018. The environmental impact analysis of hazardous materials and the development of green technology in the shipbreaking process. *Ocean Engineering*, Volume 161, Pp. 187-194.

Zakaria, M. T. A., 2012. Underlying problems of ship recycling industries in Bangladesh and way forward. *Journal of Naval Architecture and Marine Engineering*, 9(2), Pp. 98-100.

Zhou, D. L. L. J., 2021. Factors influencing green ship recycling: a conceptual framework and modelling. *Journal of Cleaner Production*, Volume 322, Pp. 2-5.