D.T1.4.1 - Berth allocation algorithm design report

Version n. 1.00

Subtitle **12/2023**

Summary

LIST OF TABLES

LIST OF FIGURES

LIST OF ACRONYMS

ADRIREP - Mandatory ships reporting system in the Adriatic Sea

AIS – Automatic Identification System

AMSPM - Administration for Maritime Safety and Port Management of Montenegro

ASL - Above Sea Level

ASTERIX - All-Purpose Structured Eurocontrol Surveillance Information Exchange

ATA - Actual Time of Arrival

AtoN - Aids to Navigation

BAP – Berth Allocation Problem

BC - Beneficiary Country

BoQ - Bill of Quantity

BS - Base Station

CA - Contracting Authority

CAMP - Coastal Area Management Programme

CBC – Cross border cooperation

CS - Coastal Station

CCTV - Closed Circuit TV

DB – Database

DE - Differential Evolution

DF - Direction Finding

DGNSS – Differential Global Navigation Satellite System

DGPS - Differential Global Positioning System

EA - Evolutionary Algorithms

EC – European Commission

ECDIS - Electronic Charts Display and Information System

EEZ - Exclusive Economic Zone

EMSA – European Maritime Safety Agency

ETA - Estimated Time of Arrival

ETD - Estimated Time of Departure

ENI - European Neighbourhood Instrument

EU – European Union

FAL - Convention on Facilitation of International Maritime Traffic

GMDSS - Global Maritime Distress and Safety System

GIS - Geographic Information System

GHG - Greenhouse gas

GPS - Global Positioning System

HAZMAT - Dangerous and Polluting Goods

HM - Harbour Master

IALA - International Association of Marine Aids to Navigation and Lighthouse Authorities

ICG - Italian Coast Guard

IMDG - International Maritime Dangerous Goods

IMO - International Maritime Organization

IMS - Integrated Maritime Services

IP - Integer Programming

IPA II - Instrument for Pre-Accession II

ISPS - International Code for the Security of Ships and of Port Facilities

ITOPF - The International Tanker Owners Pollution Federation Limited

IVEF - Inter VTS Exchange Format

LRIT - Long Range Information and Tracking system

MAREΣ – Mediterranean Regional AIS server

MARPOL - International Convention for the Prevention of Pollution from Ships

MCT - Maritime Container Terminal

MEPC - Marine Environment Protection Committee

MILP - Mixed-Integer Linear Programming

MMSI – Maritime Mobile Service Identities

MPA – Marine Protected Areas

MRCC - Maritime Rescue Coordination Centre

MTTR - Mean time to repair

N.A. - Not Applicable

NAS - Navigational Assistance Service

NAIS - National Agency for Information Society

NCA – National Competent Authority

NM - Nautical Miles

OPRC - International Convention on Oil Pollution Preparedness, Response and Cooperation

OSD - Oil Spill Detection

PCS - Port Community System

PFSO - Port Facility Security Officer

PMC - Port Monitoring Centre

PSO - Particle Swarm Optimization

PSSA - Particularly Sensitive Sea Area

PS - Port State

PSC - Port State Control

RF - Radio Frequency

SafeSeaNet - Vessel traffic monitoring in EU waters

SAR - Search and Rescue

SOLAS - Safety of Life at Sea SP State Police

SAR - Synthetic Aperture Radar or Search and Rescue

SLA – Service Level Agreement

SSL - Secure Sockets Layer

TBC - To Be Confirmed

UPS - Uninterruptible Power Supply

VHF - Very High Frequency

VoIP - Voice over Internet Protocol

VPN - Virtual Private Network

VTMIS - Vessel Traffic Monitoring and Information Services

VTS - Vessel Traffic Services

WAN - Wide Area Network

WMS - Web Mapping Services

XML - eXtensible Markup Language

1. INTRODUCTION

The management of ports involves a many complexities, and challenges are amplified when transportation of hazardous materials are involved. Effective berth allocation is crucial in any port management system, but when hazardous materials are in transit, the stakes are significantly higher. This document aims to introduce the design considerations and frameworks underlying a specialized berth allocation algorithm tailored specifically for the transportation of hazardous materials.

Typical operational and service level indicators, such as berth allocation waiting time, are very important for port performance intensity of port asset utilization. The waiting time between arrival and the allocation of berth is decreasing constantly. The world's largest ports, like Antwerp and Hamburg, recorded a reduction in the port-to berth time. Less positive performances were recorded elsewhere, while in some ports port-to-berth waiting times have increased like in India and some African countries [1].

Traditional berth allocation focuses on various operational objectives such as minimizing wait times, optimizing resource usage, and maximizing throughput. However, these objectives, although critical, are not sufficient when hazardous materials are involved. Factors such as safety regulations, environmental risks, proximity to populated areas, and the potential for catastrophic events demand a more nuanced and specialized approach to berth allocation. In the past there have been many catastrophic events during manipulation of dangerous goods in ports.

Proposed algorithm is designed to integrate these multiple layers of complexity into a cohesive system that aligns with both operational goals and safety protocols. Leveraging a combination of exact and heuristic methods, this algorithm aims to provide not just an optimized but also a safe berth allocation solution.

The scope of this introduction serves to set the stage for the detailed discussions that follow, encompassing problem formulation, mathematical modelling, algorithmic design, and testing and validation phases. By the end of this report, the goal is to present a robust, safety-first berth allocation algorithm that efficiently manages the heightened risks associated with transporting hazardous materials through port facilities.

In summary, the overarching objective is to deliver a berth allocation solution that maintains the delicate balance between operational efficiency and the stringent safety requirements that the transportation of hazardous materials necessitates.

1.1 General Background

Ports serve as pivotal nodes in global trade networks, facilitating the exchange of goods and services across international borders. Over the years, port operations have become increasingly complex due to growing trade volumes, diverse types of cargo, and the advancement in shipping technologies. Among the types of cargo handled, hazardous materials present a unique set of challenges that require specialized attention.

Hazardous materials, also known as HazMat, include substances that are flammable, toxic, reactive, or corrosive. The transportation of these materials through ports involves heightened risks, including the potential for accidents that could result in fires, explosions, or environmental contamination. The complexities and dangers associated with hazardous materials make traditional berth allocation algorithms insufficient.

Transporting hazardous materials is governed by an intricate web of regulations at both national and international levels. Agencies such as the International Maritime Organization (IMO) and national agencies have guidelines and requirements that specifically address the safe handling and storage of hazardous materials. Failure to adhere to these guidelines can result in severe legal penalties and reputational damage. In the past there have been many catastrophic events during manipulation of dangerous goods in ports because of failure to adhere to these guidelines. One of the largest non-nuclear explosions in history damaged the port and damaged over half the Beirut city. The explosion of the cargo of ammonium nitrate had entered Beirut's port, in November 2013[1]. There have been noted another similar cases with ammonium nitrate cargo in the past but with less damage like in USA, Winston-Salem, North Carolina in 2022 (0 casualties), China Port of Tianjin in 2015 (173 casualties), USA, Vest, Texas in 2013 (15 casualties) etc.

Regarding Programming area of Interreg Albania-Italy-Montenegro it is worth mentioned the recent case of transportation of ammonium nitrate in Port of Bar. The Montenegrin public discovered in Jully 2023 that a ship with 30,000 tons of bulk ammonium nitrate had sailed from the Russian Federation to the Port of Bar, from where it should be transported to Serbia. As the transit of such goods is considered dangerous, especially if stored inadequately, port authorities has adopted a safety plan following the transhipment process. Also railway company adopted a safety plan following the transportation process. The entire process is supervised by a team of qualified personnel who have decades of experience in working with nitrogen fertilizers[2]. Anyway, the citizens of Bar were very upset. The unloading of ammonium nitrate, in bulk from the ship started in middle of August 2023. The transfer of the ship to the anchorage was carried out in accordance with all the safety procedures that we are obliged to follow when dealing with this type of cargo[3].

Traditional berth allocation algorithms focus on optimizing key performance indicators like minimizing ship turnaround time, maximizing berth utilization, and reducing operational costs. While these algorithms work well for general cargo, they often lack the specialized features needed for hazardous material handling, such as risk assessment models and emergency response strategies.

Given the regulatory landscape and the elevated risks, there is an imperative need for an algorithm that can handle the complexities of hazardous material transportation. A specialized berth allocation algorithm for hazardous materials must not only aim for operational efficiency but also give paramount importance to safety and compliance with regulations. Against this background, the objective is to design a berth allocation algorithm that incorporates the multi-faceted complexities associated with hazardous material transportation, providing a solution that is both efficient and exceptionally safe.

[1] https://www.hrw.org/report/2021/08/03/they-killed-us-inside/investigation-august-4-beirut-blast

[2] https://www.cdm.me/english/hazardous-cargo-awaiting-transit-from-port-of-bar/

[3] https://www.youtube.com/watch?v=RBssgyUlbtA

This forms the foundational context within which the algorithm is to be developed, striking a balance between efficiency, safety, and compliance, to cater to the specific challenges posed by hazardous material transportation through ports.

Regarding berth allocation problem, the goal of CRISIS project is to optimally assign and schedule ships to berthing areas along a quay. The objective is the minimization of the total (weighted) service time for all ships, defined as the time elapsed between the arrival in the port and the completion of handling the minimization activity includes the estimate of the downtime due to wave and wind action at a certain berth. This analysis will be punctual regarding the ports of Albania, Italy and Montenegro. When the transportation of hazardous materials is involved, one must also consider the level of risk associated to the transported goods. To this purpose, the risk measures identified in Activity A.T1.2 will be used. In addition, the models will account for the level of exposure of the port areas with respect to wave agitation and/or overtopping.

2 OBJECTIVES, BENEFICIARIES, DESCRIPTION OF ASSIGNMENT AND OUTPUTS

This chapter will describe objectives, beneficiaries, and descriptions of assignments and outputs.

2.1 General Background

The Program Area of Interreg - IPA CBC Italy - Albania – Montenegro[4] is particularly exposed to risks arising from natural and human disasters: desertification, fires, and pollution, are just some examples, to which it must be added the aggression deriving from the processes of economic development that afflict the territory.

The strategic partnership that links Italy to Albania and Montenegro has led, over the years, to the signing of a series of treaties that have created a favourable environment for investments aimed at promoting the stabilization and pacification of the Balkan region, through the development cooperation and territorial promotion, favoured by important trilateral trade and cultural relations in various sectors: energy, manufacturing industries, urban planning, water resources management, environmental reclamation, etc.

So, it is in this perspective that the action of this project is inserted, aimed at mitigating the effects deriving from the disasters caused by the sea multimodal transport of hazardous materials. The most important challenge, therefore, is to develop common policies capable of constantly monitoring the transport of these materials, through the development of systemic cooperation schemes that involve, at various levels, the stakeholders of the participating countries [2].

The main objective of this project is to improve the transportation activities in the programme area, emphasizing the transportation of hazardous materials. In particular, this project will contribute to the specific objective "4.1 Transport" by studying the peculiar risks in the program area and developing novel decision support modules aiming to assist cross-border management of hazardous materials[5].

2.1.1 Specific Objectives

The CRISIS project will contribute to allocating ships carrying hazardous materials to berths based on real-time numerical simulations of weather (wave and wind) conditions. The main outputs of the project will be the identification of specific risk measures capturing the main aspects of hazardous material transportation in the programme area, the design and development of a multimodal safest routing algorithm for dangerous

[4] https://www.italy-albania-montenegro.eu/index.php/programme/south-adriatic-2021-27/south-adriatic-docs

[5] https://crisis.italy-albania-montenegro.eu/

material transportation in the programme area, and the design and development of a berth allocation algorithm for hazardous material transportation in the programme area.

The specific objective of the CRISIS project is to improve the programme area's transportation activities, emphasising the transport of hazardous materials. The project will study the peculiar risks in the programme area, aiming to develop novel decision support modules aiming to assist cross-border management of hazardous materials [2].

2.2 Beneficiaries

The main beneficiaries are listed below:

- Città di Molfetta (IT)[6], Lead partner
- FLAG Molise Costiero[7] (IT), project partner and
- Municipality of Ulcinj[8] (ME), project partner and
- National Environment Agency (AL), associated partner.

However, the benefit from the project will have the whole society in the programming area, where the action is taking place.

2.3 Description of the assignment and tasks

In order to ensure the smooth i implementation of the project and tasks, in line with the approved application form, CRISIS project partners have engaged external experts to support the spread of project activities, results, and outputs to the Programme area and beyond.

According to ToR following objectives must be achieved: data collection and analysis of the problems of routing hazardous materials inside the ports, and the surrounding areas, monitoring and supporting passing ships and allocating ships carrying dangerous materials to berths according to the approved Application Form of the project CRISIS „Cross-border RISk management of hazardous material transportation“.

The requested services are divided into four activities and presented below. This deliverable covers the tasks under activity A.T1.4 “Berth allocation algorithm design”.

[6] https://www.comune.molfetta.ba.it/

[7] www.Flagmolise.it

[8] www.ul-gov.me

2.3.1 Activity A.T1.1 - Data collection and analysis

This activity aims to analyse the problems of routing hazardous materials inside the ports and surrounding areas, monitoring and supporting passing ships and allocating ships carrying dangerous materials to berths [2]. The goal is to identify the peculiar problems and to collect data related to the different ports and areas where the proposed methodologies could be implemented.

This activity performs maritime traffic analysis in the programming area and data related to maritime dangerous cargo transportation in Albania, Italy and Montenegro.

2.3.2 Activity A.T1.2 - Definition of specific risk measures

This activity will define specific risk measures to consider when designing the models and algorithms.

In the frame of this activity, data on previous incidents while handling dangerous cargo in the programming area and Montenegro will be performed. Based on historical data, specific risk measures will be proposed.

2.3.3 Activity A.T1.3 - Multimodal safest path algorithm design

The aim of this activity is to develop models and algorithms to route shipments in the transportation network in such a way that, not only travel cost is reduced, but also transportation risk is minimized. In fact, in order to carry some hazardous goods from an origin to a destination, the path with the minimum travel cost may not always correspond to the minimum-risk route (i.e., the safest path). The models should include explicitly real-time information about the weather and sea conditions.

2.3.4 Activity A.T1.4 - Berth allocation algorithm design

The berth allocation problem aims to optimally assign and schedule ships to berthing areas along a quay. The objective is the depreciation of the total (weighted) service time for all ships, defined as the time elapsed between the arrival in the port and the completion of handling the minimisation activity. It includes the estimate of the downtime due to wave and wind action at a particular berth.

2.4 Required output and deliverables

In the frame of T1 following four deliverables will be prepared and listed and shortly explained in the following subchapters. This document is actually the deliverable D.T1.1.3 described in subchapter 2.4.3.

2.4.1 Deliverable D.T1.1.1 - Data analysis report

A report with a preliminary analysis aimed at making sense of the data collected in order to highlight the peculiarities and critical aspects of hazardous transportation in the programme area.

The desk research is conducted, and data collection is performed on the maritime transport and transport of dangerous cargo in the program area.

2.4.2 Deliverable D.T1.2.1 - Risk measures report

A report on specific risk measures capturing the main aspects of hazardous material transportation in the programme area.

The desk research and data collection will be performed on previous incidents and potential risks during the maritime transport of dangerous cargo in the program area.

2.4.3 Deliverable D.T1.3.1 - Multimodal safest path algorithm design report

A report on designing the multimodal safest routing algorithm for hazardous material transportation in the programme area.

2.4.4 Deliverable D.T1.4.1 - Berth allocation algorithm design report

A report on the design of the berth allocation algorithm for hazardous material transportation in the programme area. The results will be presented in this deliverable.

3 LITERATURE REVIEW OF BERTH ALLOCATION PROBLEM (BAP)

The efficient utilization of port resources is a nowadays a challenge for maritime logistics and port management in congested ports. Among the various challenges faced by modern port terminals, the Berth Allocation Problem (BAP) emerges as a critical issue affecting the operational efficiency of a port and, consequently, the entire supply chain. Berth allocation is the act of assigning incoming ships to specific berths for cargo operations over a planned time horizon. The problem is complex, encompassing several considerations such as time windows, various ship sizes, types of cargo, and resource constraints. This literature review aims to provide a comprehensive overview of the Berth Allocation Problem, discussing market and social needs for BAP, BAP in context of environmental safety, np-completeness of BAP, BAP classification, continuous vs discrete berthing layout, static vs dynamic vessel arrival and generic problem definition and formulation.

The BAP has been a subject of academic interest for several decades. Early research in the field, primarily in the 1970s and 1980s, focused on static models that aimed at optimizing a single objective such as minimizing total service time or waiting time. However, the field has seen significant evolution over the years, leading to increasingly complex models that consider multiple objectives and constraints, including environmental factors.

Studies on BAP can be categorized based on various factors like problem environment (static vs. dynamic), number of objectives (single vs. multi-objective), and type of berth layout (continuous vs. discrete). Each category brings its own set of complexities and requires different solution methodologies.

Linear programming, integer programming, and mixed-integer programming are some of the popular mathematical techniques employed to model the BAP. More recently, stochastic and robust optimization models have been introduced to account for uncertainties in arrival times, loading/unloading rates, and other parameters.

Solution methods for the BAP range from exact algorithms like branch-and-bound to heuristics and metaheuristics such as Genetic Algorithms, Simulated Annealing, and Particle Swarm Optimization. Hybrid methods that combine the strengths of various algorithms have also been proposed.

The Berth Allocation Problem does not exist in isolation but is closely integrated with other port operations like quay crane scheduling, yard allocation, and ship routing. Studies that examine BAP in the context of these other problems offer a more holistic view of port operations optimization.

Understanding the intricacies of the Berth Allocation Problem is essential for both researchers and practitioners in maritime logistics and port management. This literature review serves as a starting point for anyone interested in gaining a deeper insight into the subject, providing a comprehensive discussion of its various aspects and the solution techniques that have been proposed over the years.

In the subsequent sections, each of these topics will be explored in greater detail to offer a well-rounded understanding of the state-of-the-art in Berth Allocation Problem research.

3.1 Market and Social Needs for Berth Allocation

The Berth Allocation Problem (BAP) is a crucial challenge in port management with wide-ranging implications beyond operational concerns. Efficient berth allocation is key to boosting a port's economic competitiveness, as it reduces ship turnaround times and attracts more business. Environmentally, optimizing BAP can mitigate issues like air pollution by reducing ship idling. In terms of operational resilience, effective berth allocation enables ports to recover swiftly from disruptions, maintaining stability in supply chains and market operations. Considerable traffic loads with increasing waiting and handling times can lead to reduced productivity of port and can lead to serious local environmental problems such as noise and harmful emissions [3].

Furthermore, it has social benefits by creating job opportunities and improving community relations through reduced negative externalities like noise and air pollution. Lastly, efficient berth allocation aids in meeting regulatory compliance, positioning ports favourably for sustainability incentives. Therefore, tackling BAP is essential not only for improving port operations but also for addressing broader market and social needs.

As an example we can mention Maritime Container Terminal (MCT) that serves as an important node in the shipping industry to deal with increasing sea trade. A report presented by Barbosa et al. [4] stated that worldwide ports handled almost 701 million twenty-foot equivalent units (TEUs) of containers in 2016. At the same time, the throughput of container ports is also continuously increasing, and the management of MCTs' operations is becoming a challenging task. MCT operations can be categorized into three major operational areas, namely seaside, land-side, and yard-side operations. In the ideal scenario, as soon as a vessel arrives at the MCT, it should be moored at its preferred berthing position. If the MCT cannot serve the vessel at the time of arrival, the vessel must be towed to the waiting area of the terminal. As a result of the increased number of ships in the waiting area, congestion and navigational challenges are created at the seaside of the terminal.

Based on information from the UNCTAD Report of Maritime Transport [1], container berth productivity has several constraints among which the most important is the growing volume of containers exchanged in vessel calls during peak hours. In this publication, it is indicated that the deployment of larger vessels and company alliances have direct impacts on the quantity of the containers exchanged per ship call, which causes additional pressure on ports' handling capacities. In fact, the need to handle more containers at the same time exerts pressure on berth and yard operations, and this is the reason why so many research efforts are put into solving the problem of adequate allocation and assignment of terminal facilities and assets.

Facing these challenges, the Bert Allocation Problem (BAP) can be defined as a mathematical approach to finding the optimal solution for the time and place to berth a vessel that needs the available containers onboard to discharge, handle, store, and allocate on the container yard. In fact, the BAP focuses on assigning the adequate berth position to the vessel based on the characteristics of the berths (e.g., length, depth) and vessels (e.g., dimensions, draft) [5]. For this purpose, the berth allocation of ships according to their arrival and departure time, size of the ship, dimensions, and technical features are the most important factors in the optimization of BAP. The factors represent the technical constraints in the form of variables for mathematical modelling using advanced algorithms in the search for an optimal solution and allocation of berths and cranes [6]. Apart from BAP, for the seaside operations, there are two additional well-known operational problems, i.e., quay crane assignment problem (QCAP), and quay crane scheduling problem (QCSP).

It is obvious that such a complex problem like BAP should be solved in the most effective and efficient way and therefore this has significant implications for market and social needs for optimal berthing. The market needs dimension is reflected through several aspects that comprise mainly the criteria of efficiency as well as adequate utilization of available resources and assets. This would enable optimal berthing time for vessels that are calling the port and the best berthing position for each vessel that is coming to the container terminal. In that sense, the market needs of container shipping companies are directed towards optimization of all services and times for processing the container units, because any delay in delivery of goods from containers, due to a plethora of reasons, could be a significant cost for shippers and companies. Therefore, the concept of "just in time" (JIT) is of utmost importance to all stakeholders in the supply chain. Also, the improvement of container terminal operations and management efficiency, under size and resource constraints is a key to enhancing the economic performance and core competitiveness of container terminals. The results of the good berth allocation strategy are the rise of economic efficiency of port scheduling and increased customer satisfaction [7].

The social needs are fully correlated and dependent on the above-mentioned market needs. Indeed, optimal allocation of berths and management of goods transfer impact the stability of transport flows enabling positive social effects. So, if markets are supplied by on-time deliveries from ports and intermodal terminals, the level of supply and demand for transported goods will be in balance and the opposite, if the market is not enough covered with goods, the demand will move to areas, cities, and hubs where the supply is regular, making the impact on social dynamics.

To match all these requirements, the BAP is formulated in the sense that the berthing time is equal to the arrival time for each vessel, and in solving this model, a berthing position is found that minimizes the maximum quay length required to serve vessels in accordance with the schedule, as proposed by Lim (1998) [8].

3.2 Berth Allocation in context of environmental safety

Efficient berth allocation is not just an operational necessity for ports but also a critical factor in promoting environmental safety. Poorly managed berth allocation can lead to extended ship idling and congestion, contributing to increased emissions of pollutants such as sulphur dioxide, nitrogen oxides, and particulate matter. These emissions pose environmental risks, impacting both local air quality and contributing to climate change. By optimizing the Berth Allocation Problem (BAP), ports can significantly reduce ship idling times and, consequently, minimize emissions. This not only aligns port operations with broader goals of environmental sustainability but also helps ports to comply with environmental regulations and standards. Therefore, solving BAP effectively plays a pivotal role in enhancing environmental safety in and around port areas.

One of the most recent advanced concepts for connecting all key assets and components of the maritime supply chain in an innovative way is the Internet of Ships (IoS). It is widely known the concept of the Internet of Things (IoT) for the interconnection of a huge number of sensors and data sources, and the Physical Internet (PI) for logistics. Building on similar concepts such as e-navigation and advancement of various IoT technologies, the IoS in an intelligent way interconnects the maritime physical device or infrastructure associated with a ship, a port, or the transportation itself, including cranes, containers, the bridge navigation system, the ship engine, buoys, or even smartphones carried by key personnel, as summarized by Aslam et al. (2020) in [9]. This concept comprehends three key areas such as smart ships, smart ports, and smart transportation, but in this section, the focus is on the automatic berthing as part of smart port terminals. The maritime IoS comprises several layers in its architecture dedicated to sensing, heterogeneous network establishing, data computation, service, and application as well as exhibition for data visualization and sharing. Following this approach, automatic berthing is an advanced step within autonomous shipping, but it should be more developed in the future. The automatic berthing is based on an Artificial Neural Network (ANN) with uses of non-linear programming for optimal steering when a berthing process begins. This approach also included the possibility of an IoS system to find vacant positions on the shore and to send information to ships about available locations for berthing. This is done by using sensing layers in IoS and afterward the data computation layers for location and finally the application layer using the Android application named “Smart-Ship-Berthing”, as described by Kamolov and Park (2018) [10] . Due to its comprehensiveness and automation, all these approaches significantly contribute to increasing the environmental safety and in general safety of navigation in the port as well as berthing on seaside.

3.3 NP-Completeness of Berth Allocation

The Berth Allocation Problem (BAP) is often categorized as an NP-complete problem, indicating its computational complexity and the challenge it poses for finding optimal solutions in polynomial time [11]. The BAP is an important maritime problem in port logistics , and a well-known as NP-hard problem whose solution has challenged researchers worldwide [12].

In computational complexity theory, a problem is NP-complete when fulfils several criteria. Firstly, when it is a decision problem, meaning that for any input to the problem, the output is either "yes" or "no". Secondly when the answer is "yes", this can be demonstrated through the existence of a short (polynomial length) solution. Also the correctness of each solution can be verified quickly and a brute-force search algorithm can find a solution by trying all possible solutions. Lastly the problem can be used to simulate every other problem for which we can verify quickly that a solution is correct. It means that NP-complete problems are the hardest of the problems to which solutions can be verified quickly[9].

The NP-completeness of BAP implies that as the problem size grows—considering factors such as the number of berths, ships, time windows, and other constraints—the computational effort required to find an optimal solution grows exponentially. This makes it impractical to solve large instances of the problem using exact algorithms within a reasonable time frame. The NP-completeness of BAP is not just a theoretical concern but also has practical implications for real-world port operations where timely and efficient solutions are critical. This complexity underscores the importance of developing efficient heuristics, metaheuristics, or approximation algorithms capable of producing near-optimal solutions quickly, especially in dynamic and uncertain port environments.

As evidenced by relevant literature, the Berth allocation is the nondeterministic polynomial-time (NP)-hard problem and it is related to the set of partitioning problems together with single machine scheduling Problems and two-dimensional cutting stock problems. Also, together with BAP, the closest problem related to port terminal management is the Quay Crane Assignment and Scheduling Problem (QCAP and QCSP), which represent the NP-hard problem in the strong sense, because it considers situations with more than

[9] https://en.wikipedia.org/wiki/NP-completeness

two cranes on the seaside and non-uniform processing times given for ships [13]. To summarize the main components for both optimization problems, Figure 1 comprising all these inputs is given below. In the literature overview, two different versions of the problem called the discrete (BAP-D) and the continuous (BAP-C) cases, can be abstracted and both of them are classified as NP-hard problems.

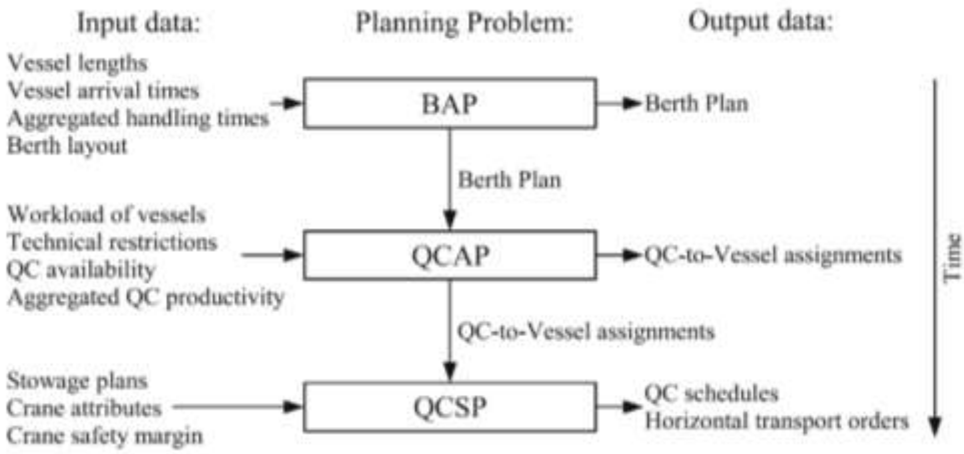

Figure 1 Sequential planning of seaside operations

(Source: [13])

To solve the three problems together, a three-stage procedure is proposed in the paper of Hsu, Wang et al., (2017) [14], which proposed an approach for modelling and solving the seaside operational problems (BAP, QCAP, QCSP) by using Object-Oriented and Timed Predicate/ Transition Net (OOTPr/Tr). In the beginning stage, a vessel is allocated to the berth with some constraints. In the next stage, quay cranes are assigned to the berths. In the third stage, the beginning time of operation/process and its ending time are estimated for each ship and task with respect to the constraints for this phase. This approach is shown in the following Figure 2, as representation of a graphical tool method that has been employed in this research, and termed an OOTPr/Tr net, to model and solve three seaside problems at the same time.

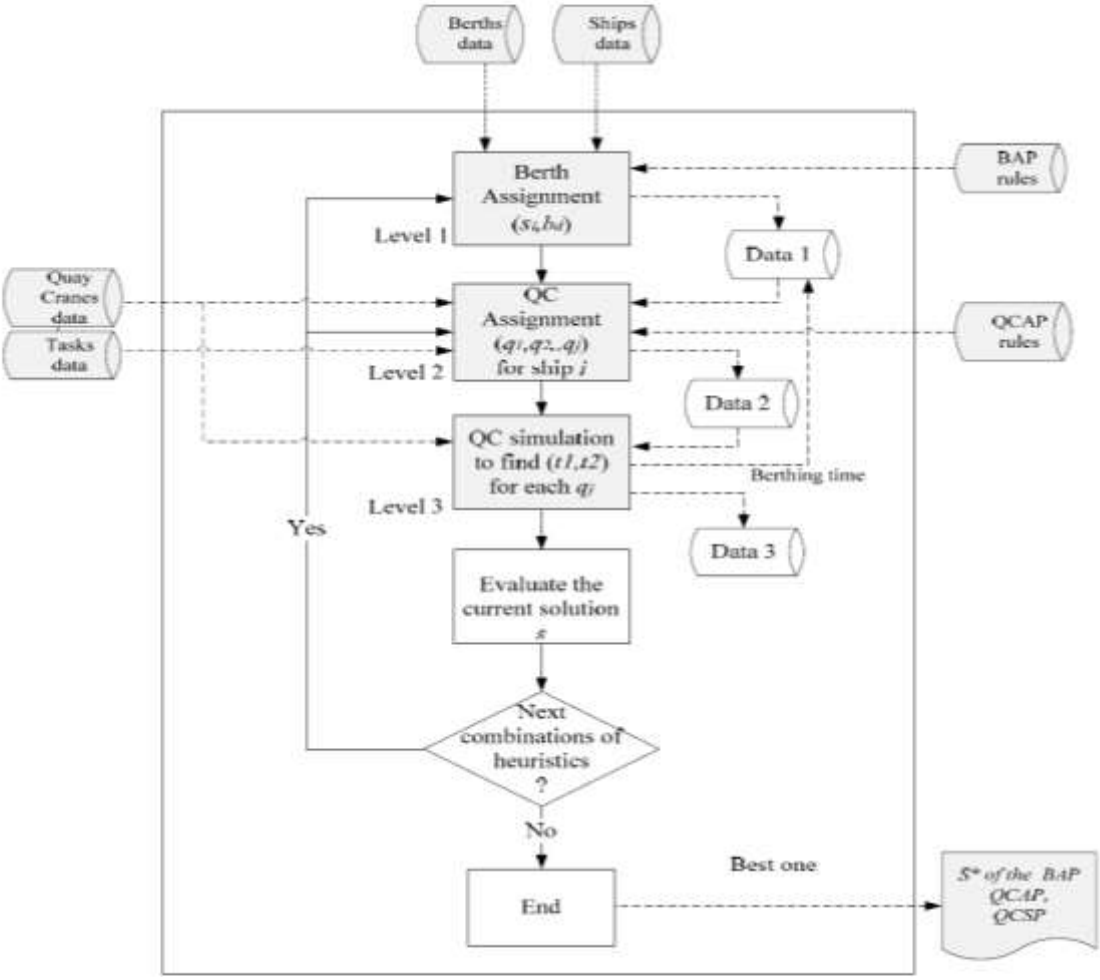

Figure 2 The input and output of the three-level framework of heuristics for simulation (Source [14])

3.4 Berth Allocation classification

The Berth Allocation Problem (BAP) can be classified along multiple dimensions that capture its inherent complexities and constraints. There are many articles related to BAP in the literature. In order to acquire a better understanding of these papers it is necessary to have general information about different types of BAPs [15].

One common way to categorize BAP is based on the problem environment, distinguishing between static and dynamic scenarios. In a static BAP, all information such as ship arrivals and service times is known in advance, whereas in a dynamic BAP, these variables are subject to change and uncertainty.

Another important classification is based on the number of objectives being considered: single-objective versus multi-objective BAP. While single-objective problems focus on optimizing a specific metric, such as minimizing total turnaround time, multi-objective problems aim to balance various goals like cost, time, and environmental impact.

The type of berth layout also offers another categorization, typically bifurcated into continuous and discrete models. Continuous models allow for any point along the quay to be a potential berth position, while discrete models work with predefined berthing positions. Both discrete and continuous BAP has been studied in the literature. The overall classification is illustrated in Figure 3.

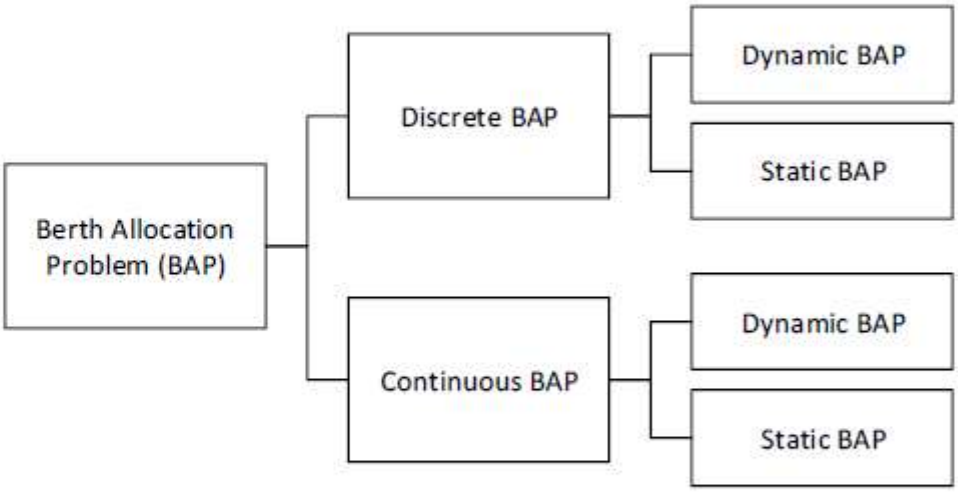

Figure 3 - Berth Allocation Problem Classification

(source [15])

Authors Carlo et al., (2015) in [5] made some modifications to Bierwirth and Meisel model presented in papers [13] and completed the BAP classification scheme presented in Table 1 BAP Classification scheme modified from Bierwirth and Mesisel (Source) as given below.

Table 1 BAP Classification scheme modified from Bierwirth and Mesisel (Source [5])

Value	Description
Spatial Attribute	
disc	Discrete berths (1 vessel per berth)
cont	Continuous berth
hybr	Hybrid berth
draft	Berth limited by vessel draft
Temporal Attribute	
stat	Static – all vessels currently available to berth
dyn	Dynamic – vessels have estimated arrival time
due	Vessels must depart before a due date
Handling Times Attribute	
fix	Fixed – handling time only depends on the number of containers
pos	Position – handling time depends on berth assigned
stoch	Handling time is stochastic
QCAP	Handling time depends on quay cranes' assignment
QCSP	Handling time depends on quay cranes' schedule
TVSP	Handling time depends on transfer vehicles' schedule
YCSP	Handling time depends on yard cranes' schedule
Performance Measure Attribute (to Minimize)	
wait	Waiting time of the vessel
hand	Handling time of a vessel
compl	Completion time of vessel
speed	Necessary speedup of vessel to meet expected arrival time
tard	Tardiness of vessel with respect to due date
order	Deviation between vessel arrival order and service order
rej	Rejection of a vessel
res	Terminals' resource utilization
pos	Deviation between actual and desired berthing position
yard	Travel distance between assigned berth and assigned yard blocks
misc	Any other

These classifications are crucial for determining the appropriate mathematical models and solution approaches suitable for tackling various instances of the BAP and will be further elaborated in next subchapters.

3.4.1 Continuous vs Discrete Berthing layout

The berthing layout in the Berth Allocation Problem (BAP) is commonly classified into two types: continuous and discrete. In some literature we have also Hybrid Layout which will be elaborated here [13]. In order to better understand classification of BAP, general information about different types is needed. In one aspect the BAPs can be divided into two main classes; the continuous and the discrete BAP. In the discrete BAP, a dock has limited number of berths which can accept only one ship. In the continuous type of problem a ship can choose its position of the dock if its length is less than the length of unused section of the berth. It means that using a berth in a continuous form would lead to a better utilization, comparing with the discrete allocation [15].

In a continuous berthing layout, ships can be allocated to any point along the quay, providing a flexible but computationally complex scenario. This approach often requires solving optimization problems that can take into account variable positioning and spacing between ships, leading to potentially more efficient use of space but at the cost of increased computational effort. For this layout, there is no partitioning of the seaside for berthing the vessel and it is possible to allocate all arrived ships with no limitations on the length dimensions they have, since there is no dedicated berth for a specific category of the vessel and vessels can be moored within the boundaries of the quays. Authors Bierwirth and Meisel argue in [13] and [16] that management and planning on this kind of terminal is more complex than for the discrete layout of the container terminal. According to this layout, vessels can moor anywhere in the quay space, but spatial restrictions must be considered, as for example the size of the ship. Several authors provided some different approaches for solving this problem, among them are: mixed integer-programming model (MIP) solved using Simulated Annealing (SA), heuristic procedure for BAPC, mixed integer non-linear programming, greedy randomized adaptive search procedure, stochastic beam search method, an Immune Algorithm (IA), a neighbourhood search heuristic and a particle swarm optimization algorithm, as summarized by Sahin et al., (2016) in [17]. Apart from mentioned approaches, the cited authors propose a new method called Differential Evolution Approach (DE) which is successfully employed on continuous space problems, with aim to investigate the performance of DE method on Dynamic BAP Continuous layout.

On the other hand, in a discrete berthing layout, the quay is divided into predefined sections or berths, and ships must be allocated to one of these fixed positions. While this simplifies the allocation problem and often makes it quicker to solve, it might not fully optimize the use of available quay space and could result in suboptimal solutions. For this layout, the quay length is divided into several parts called berths and each part is dedicated to some category of ship length so that a vessel can be served at each single berth at the time. In fact, all berthing positions are predefined so that exactly one vessel can be assigned to each berth, regardless of its size. In solving the BAP for discrete layout, many authors propose different methods. For example, this problem is solved by using the following techniques: Tabu Search Heuristics, genetic algorithm-based solution algorithm for BAPD in a multi-user container terminal, Lagrange Relaxation-based algorithm, heuristic based on *k* -best algorithm and clustering search based simulated annealing, as well as lambda-optimal based heuristic [17].

Hybrid Layout combines the features of the previous layouts. It has dedicated berths like a discrete layout but the berthing is adapted to the current situation in the anchorage, e.g. if there is one large ship, her length can take more than a berth per one ship, and two smaller ships can share the position of one wider berth. In order to show the time and space relation for the berthing vessels and cranes assigned to them, the following Figure 4. Space-time representation of a berth plan (a), assignment of cranes to vessels (b) gives the plan for mooring the vessels on berths upon their arrival, processing, and departure time.

One of the most used methods for BAP is the heuristic solution model which solves a discrete BAP first and then improves the obtained solution by shifting vessels along the quay as allowed in the continuous BAP, being extended by incorporating the vessel draft in the berth allocation decision. The hybrid BAP is also analysed by several researchers with berthing areas defined at the tactical level tending to achieve robust berthing plans respecting the stochastic features of vessel arrivals.

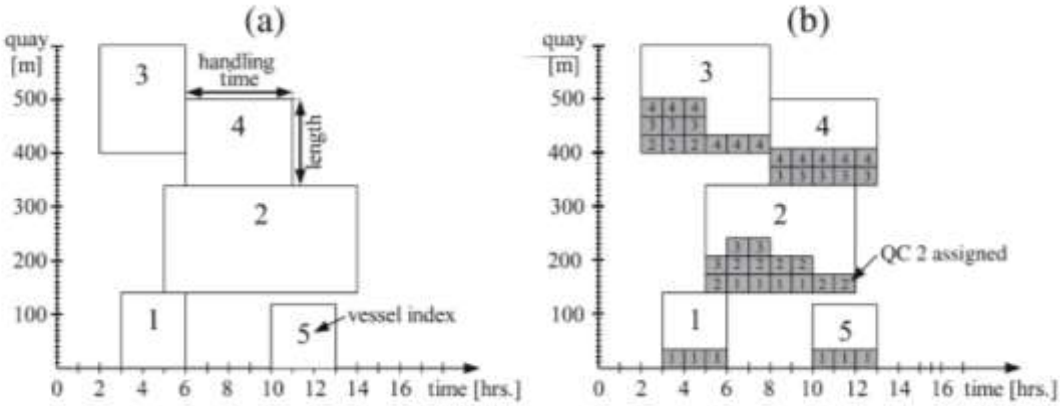

Figure 4. Space-time representation of a berth plan (a), assignment of cranes to vessels (b)

(Source: [13])

Specifically, authors Ernst et al., (2017) in [18], propose a berth allocation problem (BAP) when the berth is considered as a continuous resource in an export Dry Bulk Terminal with tidal constraints defined as BAP_DBT. This approach considers the continual layout with limited length and set of vessels calling the port, but with different times of arrival and length of each vessel. A distinctive constraint in this model is the formulation of the existence of tides criterium which implies the dependence of vessel servicing upon the tidal low level, since the vessel can be loaded on low tide but to leave the port they need high tide. The objective of this approach is to minimize the sum of vessel completion times, or equivalently to minimize the total flow time over all vessels.

The choice between layouts has significant implications for both the mathematical modelling and the solution techniques applicable for solving BAP. Continuous layouts often demand more sophisticated algorithms and models to capture their complexity, while discrete layouts may allow for simpler, yet less flexible, solution approaches.

3.4.2 Static vs Dynamic Vessel Arrival

In the context of the Berth Allocation Problem (BAP), temporal constraints are important for the optimal berthing of the vessels in container ports, so vessel arrivals can be categorized as either static or dynamic [13] [16], each presenting unique challenges and considerations for port operations. In a static scenario, all vessel arrival times, as well as their service requirements, are known in advance. This allows for the formulation of optimization models that aim for a single, optimal allocation of berths.

In Static vessel arrivals there are no specific arrival times given to vessels but they are already in the port, at the time of the planning, and assume that all vessels have arrived at the port and wait for being served. While computationally more straightforward, static models may lack the flexibility to adapt to real-world uncertainties such as delays and varying service times. In the static arrival problem all the vessels to be served are already in the port at the time scheduling begins. In the dynamic arrival scenario not all the vessels have arrived, but ETA is known. The majority of the scientific papers in BAP considers the latter case [19].

In static vessel arrival, vessel handling time is considered as an input [20], [21]. In the dynamic vessel arrival, vessel handling is a variable and typically a function of the quay equipment operating on the vessel and the distance of the vessel's berthing position from a location in the yard [22] [23].

Dynamic vessel arrival involves uncertain or variable arrival times and possibly changing service requirements. This demands a more adaptive and robust approach to berth allocation. Dynamic models need to be capable of re-optimizing the berthing schedule in real-time as new information becomes available. While providing greater adaptability, the computational complexity for dynamic scenarios is often higher, requiring more advanced optimization techniques or heuristics. Vessels come to the port at individual times imposing the constraint for the berth allocation. Other authors define the 'dynamic' berth allocation problem to recognize that the service time of a vessel when berthed may differ depending on the berth on the quayside at which it is serviced.

Furthermore, the dynamic ship berth allocation problem is considered by De et al. (2020) in [24] for vessel waiting time at the anchorage using the developed mixed integer linear programming model (MINLP). Also, compared to Block-Based Genetic Algorithm (BBGA), Genetic Algorithm (GA), and Particle Swarm Optimization (PSO), a Chemical Reaction Optimization Algorithm (CRO) is developed to solve the stated problem for dynamic BAP large-scale realistic environment.

The model for BAP, developed by Simrin and Diabat (2015) in [25], considers the dynamic arrival of vessels which allows vessels to arrive before or after the berthing plan is determined. The model, therefore, takes into consideration the constraint that a vessel cannot be serviced before its arrival. Moreover, all vessels in the presented problem must be completely serviced at one berth only without interruption from other vessels. The objective of the model is to minimize the total time of the whole service process for all vessels, which is the total duration of time vessels spend at a terminal between their arrival to the terminal and their departure. In order to maintain the solution's feasibility, the model must satisfy the following constraints:

1. Each vessel must be serviced exactly once and without interruption from other vessels.

2. A vessel must be serviced at one berth only.

3. A berth cannot handle more than one vessel at a time.

4. A vessel cannot be berthed before its arrival.

Here is applied the Genetic Algorithm (GA) which first generates a population of solutions, which is usually feasible and generated by the programmer. Then the evaluation of all solutions is done by calculating the so-called fitness value of every solution in the generation, which reflects the level of goodness of the solution. The full GA process is given in Figure X.

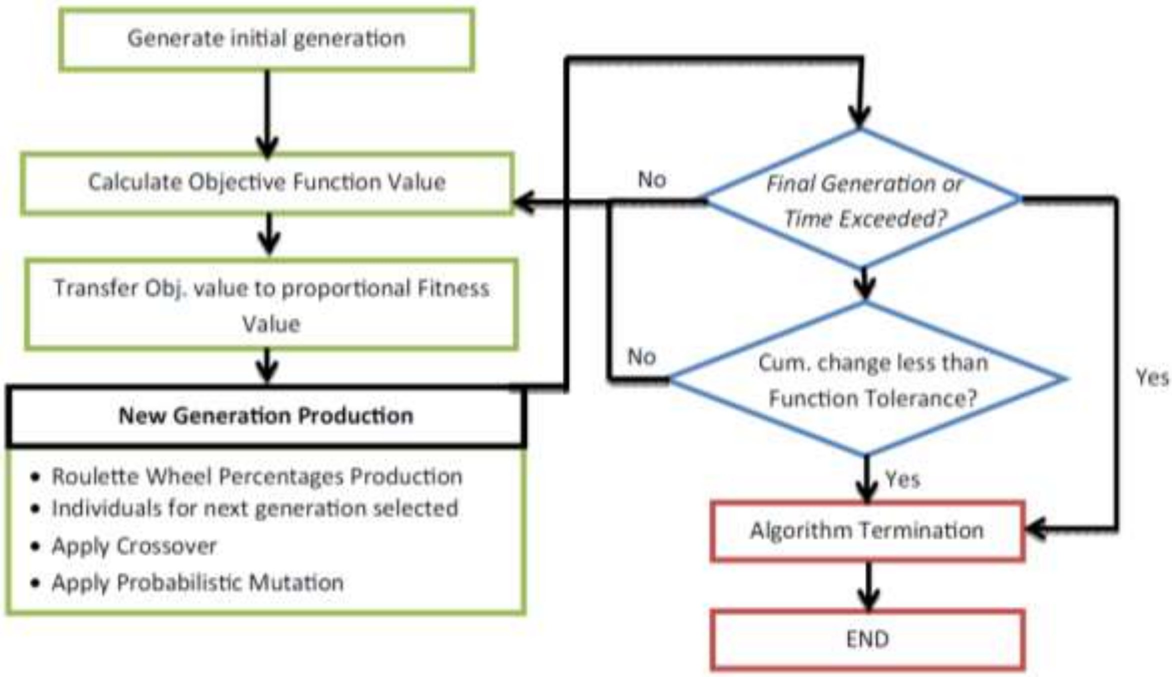

Figure 5 Genetic Algorithms process

(Source [25])

In cited research, for each solution, it was important to decide the values of the decision variables xijk. If that is known, then is possible to calculate the total handling and waiting time of all vessels of that solution. In order to calculate that by coding, it is taken into consideration the time berths become ready for service, the arrival times of vessels, as well as the handling times of vessels on different berths.

As the conclusion, the distinction between static and dynamic vessel arrivals significantly influences the choice of mathematical models and solution methods employed for solving BAP, as well as the operational flexibility and efficiency level that can be achieved.

3.5 Generic problem definition and formulation

In optimization problems, including the Berth Allocation Problem (BAP), the generic problem definition and formulation provide the framework for understanding and solving the challenge at hand. The problem definition usually specifies the objective function to be optimized, whether it is to minimize costs, time, or other metrics. This is coupled with a set of constraints that outline the optimisation's limitations, such as resource availability, physical restrictions, or regulatory requirements.

Formulation, on the other hand, translates this conceptual definition into a mathematical model. This often involves using techniques such as linear programming, integer programming, or mixed-integer programming, among others. The formulation captures the objective function mathematically and also encapsulates the constraints in algebraic form. It serves as the basis for applying various solution methods, whether they are exact algorithms, heuristics, or metaheuristics. An example of analysis of the continuous berth allocation problem in container ports using a genetic algorithm is given in [26].

The generic problem definition and formulation serve as the cornerstone for any optimization problem, providing the structure necessary for subsequent analysis, solution approaches, and interpretation of results. They help to clarify what "optimal" means in the given context and set the stage for the computational techniques that can be used to find the best possible solution within the specified constraints.

4 GENERAL BAP SOLVING METHODOLOGIES AND ALGORITHMS

Solving the Berth Allocation Problem (BAP) involves various methodologies and algorithms, each suited to different types of BAP classifications like static vs. dynamic or continuous vs. discrete layouts. Broadly, these methodologies can be categorized into exact algorithms, heuristics, and metaheuristics.

Exact Algorithms are typically employed for smaller instances of BAP where an optimal solution can be feasibly computed. Methods like Integer Programming and Branch-and-Bound are common in this category. They guarantee an optimal solution but often at the cost of high computational time, especially for larger and more complex problems.

Heuristic Methods are rule-based methods designed to find a good solution quickly but without the guarantee of optimality. Common heuristics include First-Come-First-Serve (FCFS) or Nearest-Neighbour techniques. They are generally easier to implement and quicker to execute but may result in suboptimal solutions.

Metaheuristic Algorithms are higher-level procedures that guide other heuristics towards better solutions. Methods like Genetic Algorithms, Simulated Annealing, and Tabu Search fall under this category. Metaheuristics are useful for tackling larger and more complex BAP instances where exact methods are impractical.

The choice of methodology often depends on the specific requirements of the BAP instance at hand, including the size of the problem, the level of accuracy needed, and the computational resources available. Each approach has its advantages and drawbacks, and in many cases, a hybrid approach that combines elements of different methodologies may offer the most effective solution.

4.1 Exact solution literature algorithms

The literature on exact solution algorithms for the Berth Allocation Problem (BAP) primarily focuses on providing optimal solutions through mathematical formulations. These exact algorithms are particularly useful for smaller problem instances or scenarios where a guaranteed optimal solution is essential. Common techniques include Integer Programming (IP), Mixed-Integer Linear Programming (MILP), and Branch-and-Bound algorithms.

Integer Programming and Mixed-Integer Linear Programming often define the objective function—such as minimizing turnaround time or costs—along with a set of constraints that cover various operational limitations. IPs and MILPs are well-suited for BAP instances that can be linearized and provide a global optimum, but they often struggle with computational efficiency for large problem sizes.

Branch-and-Bound Algorithms are designed to explore the solution space systematically, eliminating sub-optimal solutions through bounding techniques. They are particularly useful when the problem involves multiple objectives or constraints that cannot be easily linearized.

The exact algorithms are highly reliable for finding the best possible solutions but come with the trade-off of computational intensity, making them less suitable for larger, more complex, or dynamic instances of BAP. Nevertheless, they set a benchmark for performance, against which heuristic and metaheuristic solutions can be compared.

4.1.1 Mixed Integer Linear Programming

Mixed-Integer Linear Programming (MILP) has emerged as a prominent tool in solving Berth Allocation Problems (BAP). The technique offers a framework for creating precise mathematical models that define the BAP objectives—such as minimizing docking time or operational costs—and the constraints that ports must operate under, like limited berthing space or specific safety measures.

Among the exact solution algorithms, the distinguished place takes Mixed Integer Linear Programming as a very suitable method for optimizing the BAP. Following this approach, the authors Alsoufi et al., (2016) in [6] developed a Mixed Integer Programming model for BAP using the Genetic Algorithms (GA) simulated in MATLAB and calculations done in IBM ILOG CPLEX Optimization Studio (CPLEX), with the novelty that this model considers the solutions for robust berth plan, providing optimum berthing time, berthing position and, the enough time between the berthing times of vessels. They took into consideration the following assumptions in order to set up the model [6]:

1. Every segment of the continuous wharf can handle only one vessel at a time;
2. Safety distance between nearby vessels;
3. Once the processing of the vessel starts the vessel leaves only after its processing has finished;
4. A vessel can be handled anywhere in the wharf depending on its arrival time and the availability of wharf space.

Many parameters and some binary variables have been defined, including the length of the wharf, estimated arrival time for a vessel, requested departure time for a vessel, estimated operation/processing time to handle the vessel, length of the vessel, the desired berthing position of a vessel (determined by the position of yard storage areas allocated to that vessel), tardiness cost of vessel and Distance cost of a vessel for mooring, instability in arrival time of a vessel, etc.

In the computational experiments, 20 instances of the mathematical model of Robust BAP with different numbers of vessels have been solved using B&C in CPLEX and GA. The test results of these computations were the average objective function and standard deviation of GA, which became closer to optimum solutions. These numerical results indicate that the hybrid met-heuristic method of combining the B&C (CPLEX) together with GA is superior to both of these particular methods and it contributes to finding solutions to all problems in acceptable time and accuracy for berthing activities.

For dealing with BAP on an operational level, the authors Frojan et al. (2015) in [27], developed an integer linear model and then a genetic algorithm that works on sequences of vessels that are decoded by a constructive algorithm. To find the optimal solutions made by the genetic algorithm, they used the local search procedure. After extensive computational experiments, the optimal solutions in berthing the ships on both single and multiple quays were found together with the development of a random instance generator for the problem with multiple quays, for the study of the factors affecting such a complex problem.

Among other important applications Genetic algorithm are used for non-linear mixed integer programming problems and its applications [28]. Genetic Algorithms are largely used to solve the BAP and QCAP problems individually or simultaneously. As a novel approach, authors Hsu, Chiang, Wang et al. (2019) in [29] have proposed the three hybrid GAs (HGAs), which deal with the dynamic and discrete BAP (DDBAP) and the dynamic QCAP (DQCAP) simultaneously. The HGA firstly creates the solution for BAP an QCAP. This solution, which is time-invariant later becomes the variable and further processed towards optimized final solution. After investigations and experiments, the HGA showed superiority over traditional GA in term of fitness function. To better explain the functions of this approach, the following scheme in Figure 6 The procedure of hybrid genetic algorithms (HGAs) shows the procedure of related algorithms, where the DDBAP stands for Dynamic and Discrete BAP and DQCAP for Dynamic QCAP.

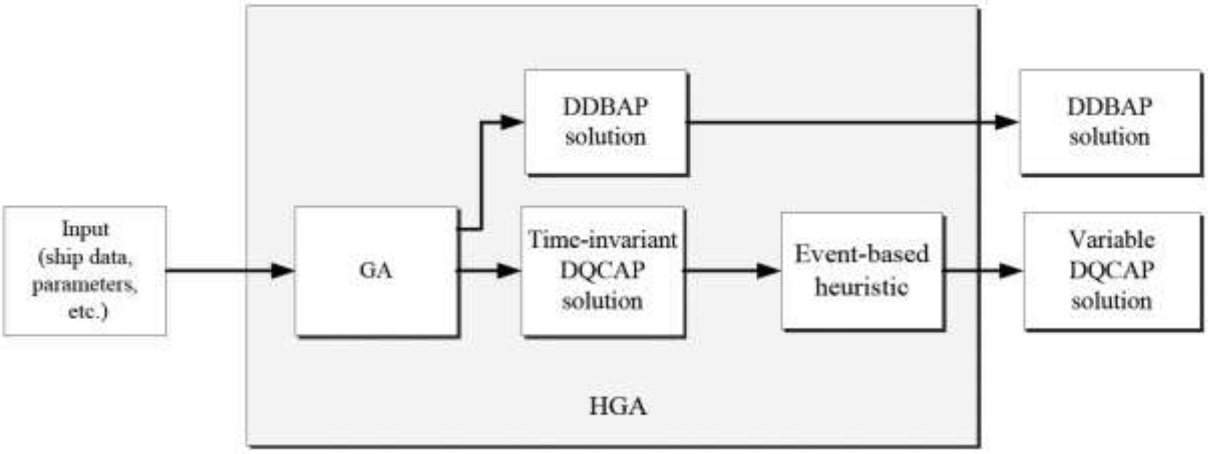

Figure 6 The procedure of hybrid genetic algorithms (HGAs)

(Source [29])

An important approach for reducing the costs of vessel berthing is proposed by Jos et al.(2019) in [30] focusing on the minimum cost berth allocation problem (MCBAP) at a container terminal where the maritime vessels arrive dynamically. This approach is classified under mixed integer linear programming (MILP) models. On the considered berth, vessels are berthed with an objective function that consists of optimized values for waiting for a time penalty, tardiness penalty, handling cost, and benefit of early service completion of vessels. Compared to other models, MCBAP performs its functions the best and with increasing the number of vessels and berths, it becomes robust and enables huge savings in computational cost.

Below are most important features of MILP for BAP:

- Optimization Goals: MILP excels in optimizing complex objective functions. In the case of BAP, these can range from minimizing the total berthing time to maximizing port throughput.
- Constraints Handling: One of the key strengths of MILP is its ability to manage a wide array of constraints, making it especially useful for problems like BAP where spatial limitations, time windows, and safety protocols must be accounted for.

- Global Optimum: MILP guarantees the identification of global optimum solutions for smaller problem instances, making it a reliable method for generating the most efficient berthing schedules.
- Computational Intensity: The downside of MILP is its computational burden, particularly for larger instances of BAP. However, it often serves as a benchmark for comparing other heuristic or metaheuristic methods.
- Flexibility: MILP models can be adapted to accommodate various types of BAP, including those involving hazardous materials, multiple objectives, or dynamic arrivals of vessels.

In summary, MILP provides a rigorous, adaptable, and comprehensive approach for solving BAP but may be computationally intensive for larger or more complex scenarios. Nonetheless, it sets a gold standard against which other methodologies and algorithms can be measured.

4.1.2 Others solution

While Mixed-Integer Linear Programming (MILP) has been a go-to approach for solving Berth Allocation Problems (BAP), various other methodologies and algorithms have gained traction, especially for large-scale or dynamic problems where MILP becomes computationally expensive. We will mention some of them:

- Heuristic Methods: Algorithms like Greedy Search and Local Search offer quicker, albeit sub-optimal, solutions to BAP. They are particularly useful for real-time decision-making where rapid answers are needed.
- Metaheuristic Approaches: Methods like Genetic Algorithms, Simulated Annealing, and Particle Swarm Optimization can navigate large and complex solution spaces effectively. They provide good-quality solutions in relatively short computational times and can handle multiple objectives and constraints.
- Dynamic Programming: Particularly useful for problems with staged decisions, dynamic programming can provide good solutions to BAPs, especially those that have temporal dimensions like time-windows and variable arrival rates.
- Machine Learning Methods: Data-driven approaches, like Reinforcement Learning, can learn from historical data to make predictive berth allocations. These methods are growing in popularity due to their adaptability to changing conditions.
- Hybrid Algorithms: Combining features from different methodologies can often yield algorithms that are both fast and accurate. For example, an initial solution may be generated using a heuristic and then refined using metaheuristic methods.

- Decomposition Techniques: For large-scale problems, decomposition methods like column generation or Lagrangian relaxation can be useful. These techniques break down the BAP into smaller, more manageable sub-problems.
- Simulation-based Approaches: Monte Carlo simulations and other stochastic models can be employed to handle uncertainties in ship arrivals, durations, and other random factors.

One of the other solutions that significantly contributed to BAP is the non-linear mixed integer programming model together with the stochastic beam search algorithm, proposed by Wang and Lim (2017) in [31] with the aim to minimize the costs of delay and reallocation of the assets on the terminal. This approach was tested in the case of Port of Singapore where more than 400 vessels in one hour were involved in simulation and evaluation. Given results of this approach, showed the superiority of the proposed method in comparison to the traditional beam search algorithm in terms of solution quality and the simulated annealing [5].

An efficient terminal management requires the reducing time of ships spent in the port on the loading/unloading and other services, and therefore, the Port Collaborative Decision Making (PortCDM) concept is introduced by Lind, Michaelides et al (2019) in . The main contribution of this concept is the intelligent system that will improve port call data sharing and enable high-precision calculations of ships Estimated Time of Arrival (ETA) and Expected Time of Departure (ETD), which is of great significance for berthing operations and reducing the ship time in port in waiting queues at anchorage, as well as other bottlenecks related to berthing/unberthing and servicing on the docks. Port CDM enhances the planning of port calls and performs the coordination of standardized data sharing for spatial and temporal component optimization.

Together with this approach, the same authors Michaelides, Lind et al.(2019) in [32], analysed the port to port communication enhancing short sea shipping performance related to the berthing/ unberthing processes for cruise and other ships including the case study of the Port of Limassol at Cyprus and general in Eastern Mediterranean. They found that efficient planning leads to higher use of port resources, which is an ecological gain, based on port to port communication that can be used to improve their performance with respect to the principles of PortCDM.

An interesting approach was made by Xi et al. (2017) in [33], conceptualizing the bi-objective robust berth allocation model (BRBAM), that aims to determine where and when vessels should be moored to minimize the total cost of berthing allocation and maximize customer satisfaction. Its focus is on economic performance and customer satisfaction, aiming to optimize the robustness of the berth allocation policy. For this purpose, an adaptive grey wolf optimizer (AGWO) algorithm is developed to solve the proposed model. The GWO is a simple algorithm with few parameters but is competitive with other meta-heuristic algorithms, such as genetic algorithm (GA) and differential evolution, and is mostly used to optimize the continuous berth layout and environment. Finally, the proposed method for BAP optimization is applicable to realistic environments that include unforeseen events and uncertain factors (i.e., deviation in arrival time and operation time).

In summary, there is a growing arsenal of alternative methodologies and algorithms that offer a range of trade-offs between computational speed and solution quality for solving BAP. These alternatives are often more suited for specific scenarios where MILP might not be the most efficient or feasible choice.

4.2 Evolutionary Algorithms

Evolutionary Algorithms (EAs) have gained notable attention as a viable approach for solving the complex Berth Allocation Problems. These algorithms draw inspiration from the mechanisms of natural evolution, such as selection, crossover (recombination), and mutation, to explore the solution space and optimize berth allocation strategies.

De et al., (2020) in [24] propose the Chemical reaction optimization (CRO) algorithm that is inspired by the thermodynamic laws of molecular reactions. This approach is a meta-heuristic algorithm, which is, in fact, the variable population-based evolutionary algorithm. This algorithm requires the initial solution with values of decision variables for various elements of the process of berthing including the number of quay cranes, container groups, handling time, specific vessel, and arrival and departure time, which will be later improved and optimized through the process when the values and fed into the “molecules” of the CRO algorithm. The flowchart representing this algorithm's steps is given in Figure 7. The following steps of the CRO algorithm are:

1. The values of the objective function and constraints of the mathematical formulation is considered,
2. Assigning initial values to parameters,
3. Complex computation according to the objective function of a mathematical model,
4. Stopping criteria if maximum achieved and termination of algorithm, otherwise, it proceeds with execution of additional steps by setting conditions to population extent and performing search and comparison among obtained results,
5. The obtained best solution of the iteration is compared with the global best solution.

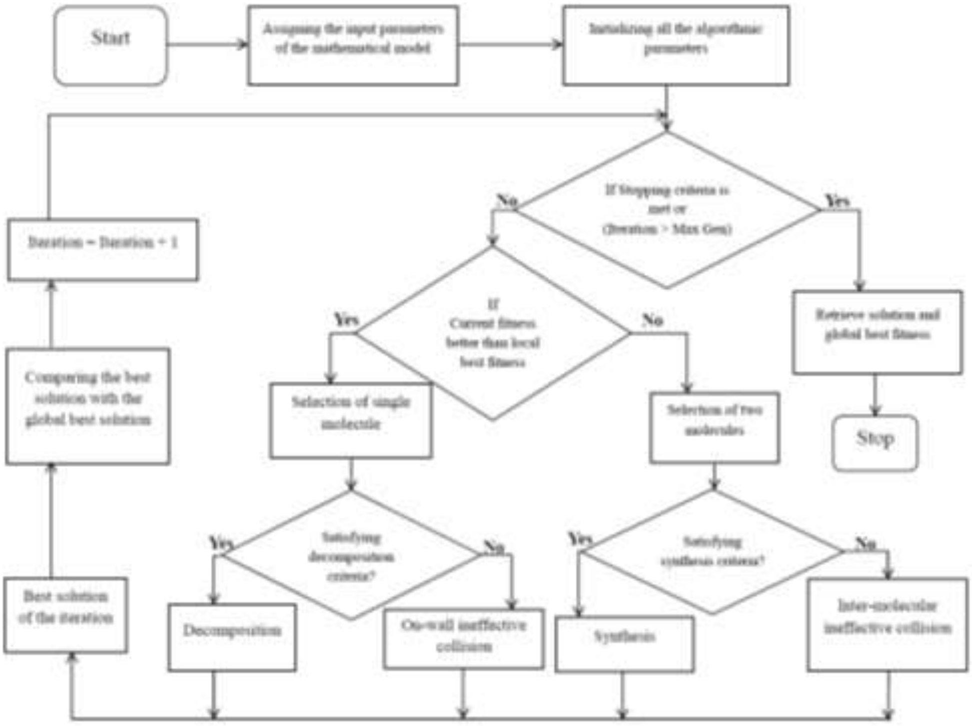

Figure 7 Flowchart of chemical reaction optimization algorithm

(Source [24])

A novel Evolutionary Algorithm is proposed by Dulebenets (2017) in [34] , whose purpose is to assist with berth scheduling at container terminals. The objective of this approach is to minimize the total weighted vessel service cost. The evolutionary algorithm applies a constant mutation rate value, determined from the parameter tuning analysis, and this characteristic is used as a parameter to evaluate its efficiency in a set of numerical experiments conducted evaluate the performance of the developed algorithm. It is proved that using this algorithm can significantly optimize the vessel service cost, large-size problem instances, and computational time.

EA has following features:

- Adaptability: One of the strongest features of EAs is their adaptability to different types of BAPs. Whether the issue involves multiple objectives, time-windows, or dynamic changes in vessel arrivals, EAs can be tailored to fit specific requirements.
- Quality of Solutions: Although not guaranteeing global optimality like some exact methods, EAs often yield high-quality, near-optimal solutions, which are generally sufficient for most practical applications.

- Handling Complex Constraints: EAs are particularly proficient at managing multiple constraints that often arise in BAP, such as spatial limitations, safety protocols, and resource availabilities. The algorithms naturally evolve solutions that adhere to these constraints.
- Computational Efficiency: Compared to methods like MILP, which can become computationally prohibitive for large-scale problems, EAs can provide quicker results. This is especially important in real-world scenarios where timely decisions are critical.
- Robustness: Evolutionary Algorithms can handle uncertainties and dynamic changes effectively, making them robust solutions for a range of BAP scenarios.
- Tuning and Customization: While EAs are flexible and adaptive, they also require careful tuning of parameters like mutation rates, crossover rates, and population sizes to ensure effective optimization.
- Multi-objective Optimization: Evolutionary algorithms like the Pareto-based Multi-Objective Genetic Algorithm (MOGA) can simultaneously optimize multiple conflicting objectives, offering a range of solution alternatives for decision-makers to consider.

In summary, Evolutionary Algorithms offer a highly adaptable, efficient, and robust approach for solving Berth Allocation Problems. They excel in scenarios that involve complex constraints and multiple objectives, providing quality solutions within a reasonable computational timeframe.

4.3 Particle Swarm Optimization

Particle Swarm Optimization (PSO) has become increasingly popular as a methodology for solving Berth Allocation Problems (BAP). Originating from the simulated social behaviour of birds, fishes, and even human crowds, PSO uses a swarm of particles to explore the solution space and converge toward optimal or near-optimal solutions.

The swarm intelligence optimization algorithm is successfully applied to solve some optimization problems related to transport and logistics needs. Therefore, the authors Li, Xiao, Lei, Zhang, and Tian (2020) in [35], propose the combination of this algorithm with other methods to make a new Cuckoo Search (CS) extension with Q-Learning step size and genetic operator, namely a dynamic step size cuckoo search algorithm (DMQL-CS). Compared with various CS algorithms and variants of DE, the results demonstrate that the DMQL-CS algorithm is a competitive to swarm algorithm. In addition, the DMQL-CS algorithm was applied to solve the problem of logistics distribution center location. The experimental results compared with those of other approaches demonstrated the superiority of the proposed strategy. A series of simulation experiments showed that DMQL-CS is more accurate and efficient than other evolutionary methods in terms of the quality and convergence rate.

PSO has following features:

- Ease of Implementation: PSO is relatively easy to implement compared to some complex mathematical methods like Mixed-Integer Linear Programming (MILP). This ease has contributed to its rising popularity for solving BAPs.
- Quick Convergence: PSO is known for its quick convergence to good-quality solutions, making it suitable for scenarios where timely decisions are crucial.
- Handling Constraints: PSO can be adapted to manage various constraints present in berth allocation, such as limited space, time windows, and safety regulations, by penalizing solutions that violate these constraints.
- Scalability: PSO algorithms are highly scalable, capable of handling BAPs for larger ports with multiple berths, various types of ships, and complex conditions.
- Global Search Capability: Unlike some heuristic methods that may get stuck in local minima, PSO has the ability to explore the solution space more fully, providing a better chance at finding global or near-global optimal solutions.
- Parameter Sensitivity: One challenge of using PSO is the sensitivity to the choice of parameters like swarm size, cognitive and social coefficients. Incorrect parameter selection can lead to suboptimal solutions or slow convergence.
- Dynamic Adaptability: PSO can be adapted for dynamic BAP scenarios where conditions change over time, such as unpredictable ship arrivals or varying unloading times.
- Multi-objective Optimization: Like other metaheuristic algorithms, PSO can be adapted to tackle multi-objective problems, offering a balance between conflicting objectives like minimizing time and maximizing throughput.

In summary, Particle Swarm Optimization offers an efficient, scalable, and adaptable approach to solving Berth Allocation Problems. While it may require careful tuning of parameters, its benefits in terms of speed and quality of solutions make it an attractive choice for tackling complex and dynamic BAP scenarios.

4.4 Differential Evolution

Differential Evolution (DE) has emerged as a potent algorithmic approach for tackling the complexities associated with Berth Allocation Problems (BAP). Originating from the family of evolutionary algorithms, DE is particularly effective at global optimization and has certain advantages over other metaheuristic and exact methods.

Within the algorithms for solving BAP, the evolutionary algorithm proposed by Sahin and Kuvvetli (2016) in [17], which is called the differential evolution algorithm, is adapted to solve the dynamic continuous berth allocation problem. This approach used ANOVA technique for analysis of test results, finding that crossover and F factors affect the fitness function significantly. This method is very useful because it enables calculations even when the number of ships is growing, having the methodology deviation from the optimal solution slightly and calculation time is still within a reasonable time frame. Since it is concluded that Differential Evolutionary Algorithm is very effective in generating optimal solutions for DBAPC, this approach can be employed for the simultaneous scheduling of other components of terminals.

DE has following features:

- Simplicity and Ease of Use: Differential Evolution is known for its straightforward implementation. This makes it an appealing choice for BAP scenarios where developing a complex mathematical model may not be feasible.
- High-Quality Solutions: DE is effective in exploring the solution landscape and often yields high-quality, near-optimal solutions for BAP. While it may not guarantee an absolute optimum like some exact methods, it usually provides solutions that are practically useful.
- Constraint Handling: DE can be adapted to manage the multifaceted constraints that are inherent to BAP, such as berth length limitations, time-windows, and safety considerations for hazardous materials.
- Speed and Efficiency: Compared to more computationally intensive methods like Mixed-Integer Linear Programming (MILP), DE is often faster, especially for large-scale and complex berth allocation problems.
- Global Search Capability: DE is known for its robust global search capabilities. This helps in avoiding local minima and makes the algorithm effective for complex and highly constrained problems.
- Parameter Tuning: Like other evolutionary algorithms, DE does require some parameter tuning (e.g., mutation factor, crossover rate), but it is generally less sensitive to parameter settings compared to some other methods like Particle Swarm Optimization (PSO).
- Adaptability: The algorithm can be easily adapted for various forms of BAP, whether it's static or dynamic, single-objective or multi-objective.
- Stochastic Nature: Due to its stochastic nature, DE can also be useful in scenarios where there is uncertainty in vessel arrival times, loading/unloading durations, and other variable factors.

In summary, Differential Evolution offers a robust, efficient, and adaptable method for solving Berth Allocation Problems. Its simplicity, speed, and ability to deliver high-quality solutions make it a strong candidate for addressing the complexities and constraints inherent in BAP scenarios.

4.5 Other heuristic or metaheuristic solutions

Beyond popular metaheuristics like Particle Swarm Optimization and Differential Evolution, a variety of other heuristic and metaheuristic approaches are available for solving Berth Allocation Problems. These alternative methods offer unique advantages and challenges, catering to different requirements of BAP scenarios.

Tabu Search as iterative method excels at escaping local optima by prohibiting certain solutions temporarily. It can be useful in solving highly constrained BAP scenarios, where typical heuristics might get stuck. It keeps a record (tabu list) of previous solutions to avoid revisiting them. Models of Tabu Search heuristics for the BAP are presented in [36].

Ant Colony Optimization is inspired by the foraging behaviour of ants. this algorithm is good at finding optimal paths and thus is suitable for BAPs that involve sequencing and scheduling of berths along a quay. In [11] BAP is formulated as a permutation-based combinatorial optimization problem and the paper suggests an improved Ant Colony algorithm to solve it.

Multi-objective genetic algorithm (moGA) is based on NSGA-II algorithm for the maximization of operational efficiency and minimization of cost. It is developed for solving the bi-objective model by using a two-part representation scheme. The algorithm is developed by Hu in 2015 [37] and considers the sensitivities of the algorithmic parameters and trade-offs between daytime preference and delayed workloads. The daytime preference indicates that berth allocation schedule should be mostly conducted during the day and just I few as possible cases at night, in order to save working comfort, safety, and energy consumption as well as to increase operational efficiency.

Simulated Annealing is inspired by the annealing process in metallurgy. Simulated Annealing is a probabilistic technique that explores the solution space by occasionally accepting worse solutions to escape local minima. It is known for its versatility, and offers a balance between exploration and exploitation of the solution space, making it a solid choice for various types of BAP. In [38] two efficient and effective simulated annealing (SA) algorithms are proposed to allocate vessels along the quay. SA algorithm is also used to minimize the vessel waiting time and berthing positions between pairs of vessels [13].

Greedy Algorithms provide heuristics quickly generate solutions by making the best local choice at each step. They are computationally efficient but might not always provide optimal solutions. Solving BAP for 10000 vessels by a simple greedy algorithm can take only 4 seconds. Attentions should be paid to avoid possible bias of one greedy algorithm and use also other algorithms [39].

Hill Climbing is a straightforward local search algorithm that is quick and simple but might get stuck in local optima. It's often used as a part of more complex algorithms to refine solutions. A probabilistic hill-climbing algorithm could be used to address also other single-source transportation problems [40]. In some scenarios to obtain the solution Late Acceptance Hill Climbing [41], is applied which only accepts a solution if it is not worse than the solution evaluated iterations ago [42].

Random Search is suitable for problems with a large or poorly understood solution space. These methods can be computationally intensive but offer a wide-ranging search. In [43] a computationally efficient approximate solution method based on random search is proposed.

Adaptive Large Neighbourhood Search (ALNS) is proposed by Mauri et al. (2016) in [44] as heuristic approach for both discrete and continuous models. After many experiments and computation processes, it can be concluded that this method provides high-quality solutions and outperforms competing algorithms for the same problem, with statistically significant improvements in all examined cases. The algorithm ALNS functions with the procedure that, at each iteration, the particular component of the algorithm destroys part of the current solution s and repairs it in a different way, generating a new and better solution s', which is accepted according to a criterion defined by a search paradigm applied at the master level. Related to BAP-

C, ALNS implementation provided the identification of 10 new best solutions in the first phase and the best solutions for all instances of the third set.

Universal island-based metaheuristic algorithm (UIMA) is proposed by authors Kavoosi, Mikijeljević et al. (2019) [45], for the spatially constrained berth scheduling problem to be optimally solved. In this study, the emphasis is put on the exact optimization and metaheuristic algorithms that can be used to solve the Berth Scheduling Problem (BSP). Also, the UIMA refers to a method in which the population is divided into four sub-populations (which are also referred to as "islands"). To search the islands, the four metaheuristics are assumed for this action, and they involve:

(1) evolutionary algorithm (EA);

(2) particle swarm optimization (PSO);

(3) estimation of distribution algorithm (EDA); and

(4) differential evolution (DE).

The key steps of UIMA are illustrated in Figure 8. CPLEX and all the candidate metaheuristic algorithms were executed for all the developed small-size problem instances. The numerical experiments, conducted as a part of this study, demonstrate clearly the superiority of the developed UIMA algorithm over the population-based and single-solution-based metaheuristic algorithms.

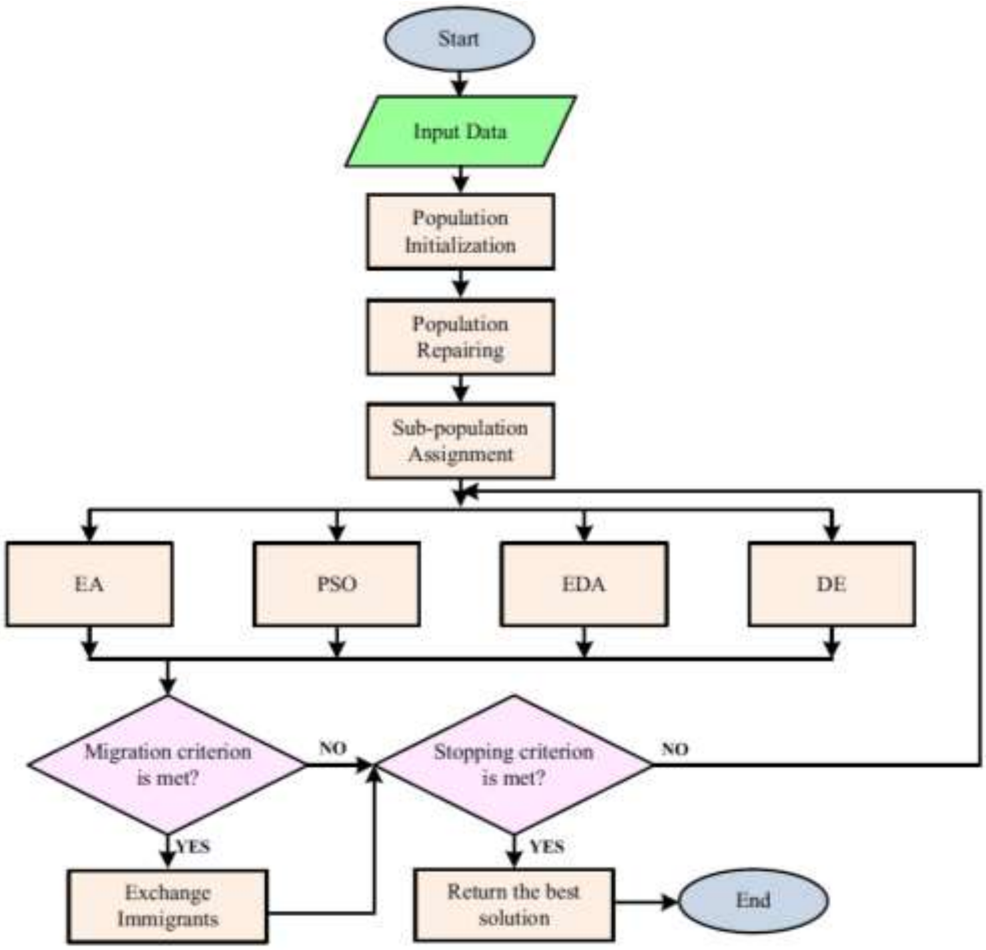

Figure 8. The basic UIMA steps

(Source [45])

Hybrid Approaches combine different algorithms, which can often yield a method that leverages the strengths of each component. For example, a Genetic Algorithm can be combined with a local search method to enhance solution quality. Combining heuristics or metaheuristics with exact methods like MILP can result in algorithms that offer both speed and optimality. Work done in [46] presented a new hybrid column generation technique to solve the BAP.

In summary, a wide array of other heuristic and metaheuristic methods exists, each with its own set of advantages and limitations. The choice of method should be dictated by the specific requirements of the BAP at hand, such as the size of the problem, constraints, objectives, and available computational resources.

5 DYNAMIC-ARRIVALS HYBRID BERTHING LAYOUT SAFE BERTH ALLOCATION PROBLEM (DH-SBAP)

5.1 Specific Mathematical Formulation

This work is primarily focused on the hybrid berthing layout with dynamic vessel arrivals, hence it will be referred as DH-BAP, which is more complex with respect to the scenario with static arrivals. The choice of hybrid berthing layout is taken due to the need of assigning a safety score to pre-determined berthing point in the whole quay which is difficult if applied with a high level of granularity. Hence, the hybrid layout comes from the division of the dock in a fixed number of berthing points, even if long ships are allowed to occupy more than one, if necessary.

For formulation simplicity, the Maritime Container Terminal (MCT) is considered possessing one berthing layout with known length to accommodate vessels arriving at various time points dynamically. The set of all potential berthing positions on the wharf is denoted as $B = \{1, 2, \dots, M\}$. This simple case is extendable for each berth, even with wharfs with particular berthing configuration, with no or low effort.

Typically, the BAP is tailored to a specific time frame for vessel arrivals, in this specific case a focus was put on the upcoming 24 hours (next day). This period is hence divided into a set of 30-minute time intervals denoted as $T = \{1, 2, \dots, K\}$. Each interval is accompanied by a weather assessment, detailing both wind and sea conditions expected during that specific time segment.

The set $S = \{1, 2, \dots, N\}$ encompasses all ships scheduled to arrive at the terminal on the following day. For each ship, crucial information is available beforehand, including the estimated time of arrival (ETA), preferred berthing position (PBP), ship's length, estimated (or requested) time of departure (ETD), and a cargo risk estimation based on the pollution risk posed by the transported products and their potential impact on marine life species. Moreover, estimated handling times for each ship were considered known in advance, being dependent on previous agreements between the MCT and the incoming ships, such as the number of quay cranes rented by the ship or number of containers to be loaded/unloaded during the handling period.

In an ideal scenario (free wharf and good weather condition), as soon a ship arrives it would be allocated at the safest spot in the quay, immediately served and dismissed, respecting the handling times. If more ships arrive in the same interval, priority must be given to ships with higher cargo risk, reserving them the safest spots in wharf. Other ships are then allocated in less safe spots (if available) or have to wait for a safe spot to be available, based on both weather conditions, wharf availability and cargo risk assessment. In the end, in case of severe weather conditions, the algorithm should be able to trade-off handling speed and safety by delaying unsafe operations.

Total risk cost for a ship arriving at the MCT is split in three different terms, two of which have the most impact:

- **Waiting Costs (WC)** influenced by the total time a ship has to wait before being served (Waiting Time or WT), the average wave risk assessment for the WT and the ship’s cargo risk level. For waiting costs only wave risk is considered due to waiting areas often exposed to higher marine currents. Equation for waiting costs, expressed as [risk/hour] is the following:

$$WC = W_w * [(CRS_s + 1)^2 * W_{WAS}] * WT_s$$

Where:

- W_w is the waiting weight, expressed as cost per unit time, indicating how waiting is considered high on cost impacts on the overall cost
- CRS_s is the Cargo Risk Score of ship s
- W_{WAS} is the average *Waiting WAve Score* for that wharf in the waiting times
- $WT_s = BT_s - ETA_s$; BT_s is the berthing time for the ship.

- **Handling Costs (HC)** are influenced by the time necessary for a ship to be served once docked (Handling Time, HT), the average wind risk assessment for the whole period in which the ship is served, the ship's cargo risk level and the berthing point safety assessment score. Since wharfs are usually protected from strong marine currents, only wind scores are considered for handling costs, being quay cranes operations riskier under severe wind conditions. Equation for handling costs is the following:

$$HC = H_w * \left[(CRS_s + 1)^{H_{WIS}/BSS}\right] * HT_s$$

Where:

- H_w is the handling weight, expressed as cost per unit time, the index on how handling costs impact on total cost
- H_{WIS} is the average *Handling WInd Score* for that wharf during the whole handling period of the ship
- BSS is the Berth Safety Score, assigned to a berthing point based on its positioning on wharf and its exposure to sea and winds

- **Late Departure Costs (LDC)** are influenced only by the time a ship exceeds its expected departure time. This difference is computable as: $LDT = ETD - (ETA + WT + HT)$ and it can assume also negative values, resulting in an incentive towards fast ship handling. Equation is the following one:

$$LDC = LD_w * LDT_s$$

Where LD_w is the late departure weight expressed as cost per unit time indicating how early or late departure impacts on the total cost.

Hence, the overall cost equation for a single ship can be expressed as following, considering a ship s, berthed at time BT_s and in berthing position BP_s, waiting under average wave conditions W_{WAS} and being served under average wind conditions H_{WIS}:

$$Cost(s, BP_s, BT_s, W_{WAS}, H_{WIS}) = WC + HC + LDC$$

The goal of the berth allocation problem is to find the optimal berthing position and times for all ships coming at the planning horizon such as the overall cost is minimized:

$$minimize \sum_{s \in S} \sum_{b \in B} \sum_{t \in T} x_{sbt} * Cost(s, BP_s, BT_s, W_{WAS}, H_{WIS})$$

subject to [47]**:**

$$[C1]\; x_{sbt} \in \mathbf{0}, \mathbf{1} \qquad \forall \boldsymbol{s} \in \boldsymbol{S}, \boldsymbol{b} \in \boldsymbol{B}, \boldsymbol{t} \in \boldsymbol{T}$$

$$[C2]\sum_{b\in B}\sum_{t\in T} \boldsymbol{x\_\{sbt\}} \;=\; \mathbf{1} \qquad \forall \boldsymbol{s} \in \boldsymbol{S}$$

$$[C3]\; \boldsymbol{BT_s} \geq \boldsymbol{ETA_s} \qquad \forall \boldsymbol{s} \in \boldsymbol{S}$$

$$[C4]\; |\boldsymbol{BT_s} - \boldsymbol{BT_{s'}}| \geq \boldsymbol{SET} \qquad \forall \boldsymbol{s}, \boldsymbol{s'} \in \boldsymbol{S}$$

$$[C5]\; BP_s + L_s \leq W \qquad \forall s \in S$$

$$[C6] \sum_{s\prime \neq s\, \in S} \;\sum_{b=BP_s - Ls'+1}^{BP_s+L_s} \;\sum_{t=BT_s-HT_{s'}+1}^{BT_s+HT_s} x_{s'bt} \;=\; 0 \qquad \forall s \in S$$

[1] x_{sbt} is a binary variable which takes value 1 if a ship s is assigned to berthing position b at berthing time t, 0 otherwise.
[2] This constraint ensures that any ship is berthed only once during the planning horizon.
[3] Third constraint ensures that ships cannot be served before their arrival.
[4] Safety Entrance Time (SET) constraint ensures that two ships cannot be berthed simultaneously. Safety Entrance Time is included in the problem formulation and implementation since most ports welcome one ship at a time due to physical constraints at their entrance.
[5] Length constraint is applied on the whole wharf, ensuring that all ships are allocated inside the physical dimension of the quay.
[6] The last constraint ensures that, during planning, two ships cannot even partially overlap in either space and time: two ships cannot coexist in the same berthing point if they share the same handling time slots.

5.2 Chosen algorithm: Cuckoo Search

The Cuckoo Search Algorithm (CSA) is a powerful nature-inspired optimization technique that derives its inspiration from the unique reproductive behaviour of cuckoo birds. The inspiration for CSA comes from the brood parasitism strategy employed by certain species of cuckoo birds. These birds lay their eggs in the nests of other bird species, shifting the responsibility of incubating and caring for their offspring onto unwitting host birds. To survive, the cuckoo chicks must outcompete the host birds' own chicks for food and care. This concept of laying eggs in other birds' nests, combined with the need for cuckoo chicks to thrive in a competitive environment, served as the foundation for the Cuckoo Search Algorithm. In optimization terms, the "eggs" represent potential solutions to a problem, while the "nests" are the solution spaces. The objective is to find the best-fit solution by continually improving and replacing eggs in suitable nests.

Introduced by Xin-She Yang and Suash Deb in 2009, CSA has gained widespread recognition and adoption in the field of optimization. Its appeal lies in its ability to effectively address complex optimization problems, particularly those characterized by multi-modal and non-linear search spaces. CSA operates as a population-based optimization algorithm. It starts by initializing a population of "nests" or potential solutions to the optimization problem. Each nest represents a potential solution, and the quality of these solutions is evaluated based on an objective function. The algorithm then proceeds through a series of iterations, where cuckoos (representing new potential solutions) are introduced into the population. These cuckoos lay eggs (representing potential solutions) in nests, with the quality of the eggs determined by their fitness. If an egg is of higher quality than the nest it is placed in, it replaces the previous content of that nest. CSA also incorporates mechanisms to maintain diversity in the population. It identifies the "worst" nests and either replaces them with new random nests or abandons them altogether. Simultaneously, the "best" nests are retained to ensure that the algorithm does not lose promising solutions. The process continues for a predefined number of iterations or until a termination condition is met. Throughout these iterations, CSA explores the solution space, gradually improving the quality of solutions, and eventually converging to an optimal or near-optimal solution.

The time complexity of the Cuckoo Search Algorithm is a topic of interest, as it influences its practical applicability. CSA's time complexity depends on various factors, including problem size, the choice of parameters, and the complexity of the objective function. In general, CSA exhibits a moderate time complexity, often comparable to other metaheuristic optimization algorithms such as genetic algorithms and particle swarm optimization. The primary computational burden arises from the evaluation of the objective function for each nest (potential solution) and cuckoo (new potential solution). The algorithm's performance can vary significantly based on the problem's characteristics. In cases where the objective function is computationally expensive, CSA may require more time to converge. Additionally, the number of iterations and the size of the population influence the overall runtime. Efforts have been made to enhance CSA's efficiency, such as parallel implementations and hybridization with other optimization techniques. These adaptations aim to reduce the time complexity and accelerate convergence, especially for large-scale and computationally intensive problems.

CSA offers several notable advantages that make it a valuable tool in the realm of optimization:

- **Global Search Capability**: CSA's ability to explore extensive search spaces and locate global optima is one of its primary strengths. It excels in scenarios where the optimization landscape is complex and multi-modal, ensuring that it doesn't get trapped in local optima.
- **Simple Implementation:** The algorithm's simplicity is a significant advantage. CSA's minimal parameter requirements and straightforward structure make it accessible to both researchers and practitioners. It can be readily implemented and customized to address a wide range of optimization problems.
- **Diversity Maintenance:** CSA incorporates mechanisms for maintaining diversity within the population. By identifying and replacing the worst nests while preserving the best ones, the algorithm strikes a balance between exploration and exploitation. This feature reduces the risk of premature convergence and promotes the discovery of high-quality solutions.
- **Parallelization Potential:** CSA's population-based approach lends itself well to parallelization. This means that it can harness the computational power of modern hardware, making it suitable for addressing computationally intensive optimization problems efficiently.

While CSA offers several advantages, it is essential to consider its limitations:

- **Parameter Sensitivity:** CSA's performance is highly sensitive to the choice of parameters, including the population size, the termination criteria and parameters related to random generation of new solutions or deletion of less important ones. Tuning these parameters to achieve optimal results can be a non-trivial task and may require extensive experimentation.
- **Limited Scalability:** CSA may encounter challenges when applied to very large-scale optimization problems. The population-based nature of the algorithm implies that it needs to maintain and update a considerable number of nests, which can be computationally demanding and resource-intensive for massive problem instances.
- **Convergence Rate:** CSA, while effective at global exploration, may exhibit a slower convergence rate compared to some other optimization algorithms for certain problem instances. Achieving convergence to an optimal solution might require more iterations, making it less suitable for time-sensitive applications.

```
Objective function f(X), X = (f(x1, x2, ..., xd))^T
Generate initial population of n host nests Xi (i=1, 2, …, n)
While t < Max_itertions do
      Get a cuckoo randomly by Levy flights
      Evaluate its quality/ fitness Fi
      Choose a nest among n (say, j) randomly
      If Fi > Fj then
           replace j by the new solution;
      End If
      A fraction (Pa) of worse nests are abandoned and
      new ones are built;
      Keep the best solutions
      Rank the solutions and find the current best
End While
Postprocess results and visualization
```

Figure 9: Example of pseudocode for Cuckoo Search Algorithm [48]

Cuckoo Search Algorithm proved to be a more effective algorithm compared to Mixed Integer Linear Programming (MILP) or Genetic Algorithms (GAs) in [47], giving both faster responses and converging to optimal solutions better with respect to other metaheuristic algorithms. CSA implements a series of mechanisms to improve exploration, such as the use of random walks or replacements of a portion of worst nests with the aim of generating new solutions. While random walks (levy flights) helps improving the solutions in the neighbourhood of previous ones, while nest replacement abandon worst solutions to explore new ones in the solution space.

Cuckoo Search proved its effectiveness in searching an acceptable local optima, often near the global one, even with multi-objective functions, such as the one formulated to include cargo loading/unloading risks and a highly-constrained search space like the one imposed by the berth allocation problem.

5.3 Design and implementation details

Cuckoo Search Algorithm was implemented using **python 3.10.4** and deployed as an independent module with respect to the backend. It act as a service on calls, accepting an input and returning the planning. The code was organized in classes, modelling both the inputs and the solution. While implementing cuckoo search, several aspects were taken in account, such as:

- **Egg and Nest definitions:** it was important to define, pragmatically speaking, the characteristic of an egg, meaning the shape of the solution. In the algorithm an egg was strictly related to a single ship, meaning that a nest is composed by **N** eggs, where **N** is the number of vessels taken in account in an execution. For each ship, both berthing time BT_s and berthing position BP_s were taken in account, as depicted by the cost function defined in Section 5.1. Hence, an egg is represented by a berthing point depending on the wharf and a time slot from those defined in the problem formulation. This adaption to the specific *discrete* use case, led to an egg structure similar to a hash map, basing the search space on the integer indexes of both the berthing points and the time slots.
- **Constraints definition:** two major types of constraints were identified while developing the solution, namely *egg-domain constraints* and *nest-domain constraints.* The former are related to the placing of a single ship in the wharf, so constraints C1, C2, C3 and C5; constraints C4 and C6, instead, involve more than one ship in a solution. Defining constraints types was useful to control operations while executing the planning algorithm, avoiding unfeasible solutions.
- **Starting conditions:** starting conditions are necessary for every evolutionary algorithm and adopting strategies allows them to converge as soon as possible. In the design of the cuckoo search algorithm, it was impossible to set a fixed starting conditions due to the variable nature of weather, ship arrivals and port structures. However, to avoid unfeasibility, starting population was forced to respect both nest and egg constraints.
- **Evolutionary strategy:** as depicted in [47], using levy flights led to a fast-convergence algorithm. The same strategy was adopted here, further details will be provided later in this chapter.
- **Replacement strategy:** two replacement strategy for cuckoo search were designed for the algorithm execution. The first one consisted in simply replacing the worst nests with new randomly generated

ones. The second replacement strategy implements a *crossing over* mechanisms where the resulting new nests are bred from two random nests in the whole solution space.

- **Hyperparameters tuning:** once set the problem definition, one of the most important part for cuckoo search algorithm execution is defining its working mechanisms by setting algorithm hyperparameters. CSA convergence speed is highly influenced by its settings and finding an optimal configuration is often a trial and error workflow. The following list is a comprehensive set of hyperparameters already tuned to provide a high convergence speed:
  - **N_nest = 100:** size of the solution space, namely the total number of nests generated as population sample. Higher the number of nests, higher the chances to find an optimal solution but also the execution times.
  - **N_iterations = 100:** max number of iterations of the algorithm. Higher the iterations, higher the execution times but generally lower the global fitness score reached. To avoid reaching the maximum number of iterations with no improvement, an early stopping mechanism was designed to stop the algorithm if it does not improve overall fitness after 10 iterations.
  - **pa = 0.65:** fraction of worst nests to be deleted. Usually, in cuckoo search, this number is fixes at 0.25. Higher the fraction, higher the chances to find an optimal solution and the execution times. A too high value, however, can lead to convergence problems depending on the strategy used to replace abandoned nests. The value was set so high due to the trade-off between execution times and constraint compliance.
  - **max_tries = 2:** maximum number tries for iteration to avoid generation operations to stuck in endless loops. This could happen if the nest is not able to produce a new solution due to constrains and number of ships.
  - **levy_beta = 1.5, sigma_u = 0.6966, sigma_v = 1, c_multiplier = 1:** set of hyperparameters for the levy flight operations from literature. Noteworthy the c_multiplier parameter which decides how much the levy flight step influences the new solution, usually set to a fraction, but being set to 1 in this use case due to the particular solution structure.

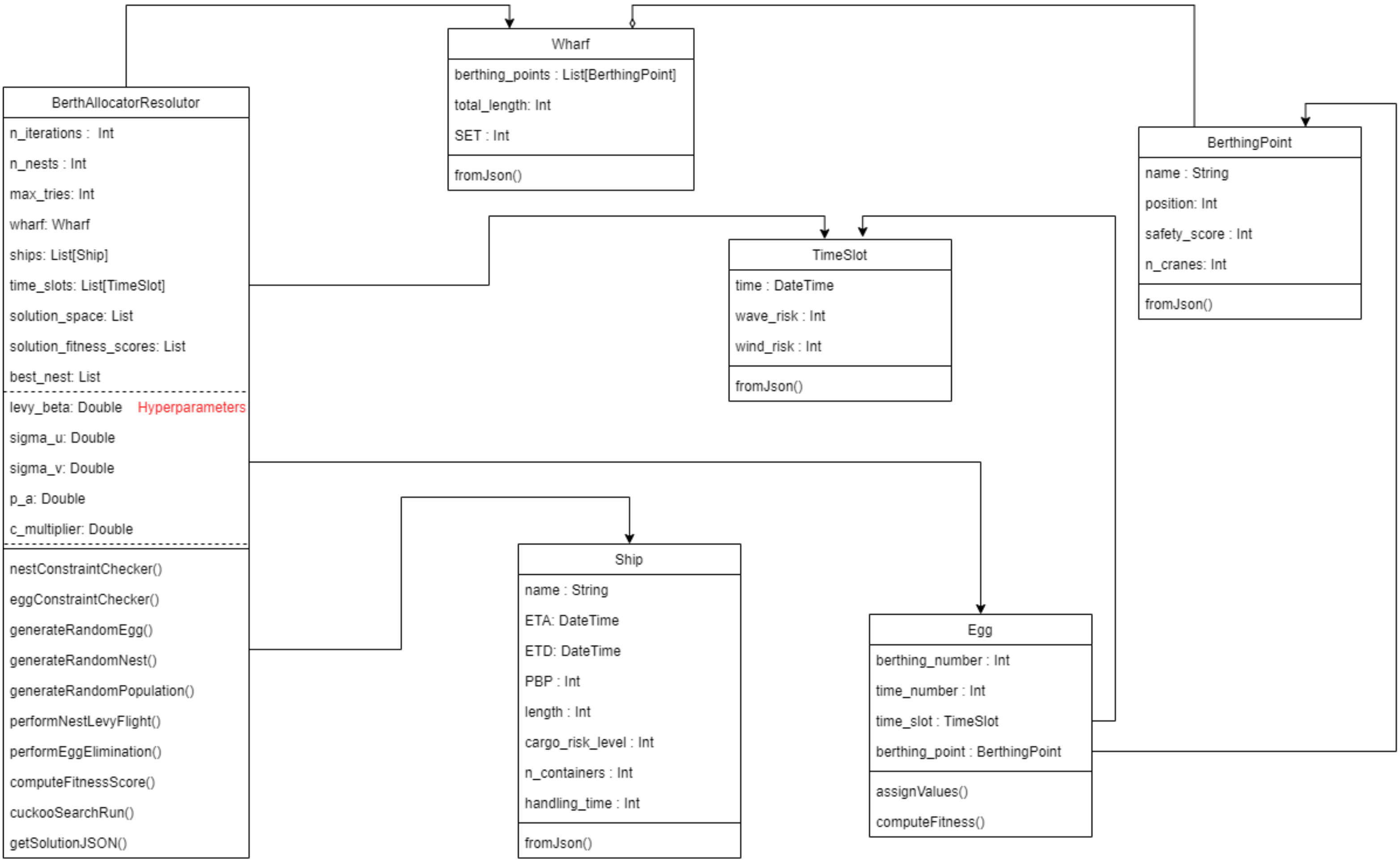

Figure 10: Berth Allocation Algorithm with Cuckoo Search UML class diagram.
***Note:** in this diagram, hyperparameters refers to the ones related to the levy flight and egg replacement operations.*

Here, the following pseudo-code to document the most important modifications apported to cuckoo search algorithm for solving the DH-SBAP. Operation on eggs were mainly performed on two-sized arrays, containing the indexes of berthing points and time slot of the current solution. When the egg indices are modified by the algorithm, the resulting object field for berthing point and time slot are also filled. Each egg has the responsibility to compute its fitness score, based on the BAP environment (weather variables included in the time slots list). Nests fitness and all constraints, instead, are in charge of the berth allocation solver.

Start

Given the following objective function:
$min \sum_{s \in S} \sum_{b \in B} \sum_{t \in T} x_{sbt} * Cost\,(s, BP_s, BT_s, W_{WAS}, H_{WIS})$
Generate Random Population
While t $< n_{iterations}$ **do**:
    Get Best Nest
    for each nest **do**:
        Perform Nest Levy Flight (nest, bestnest)
    Sort Nests by Fitness
    for each nest **do**:
        Perform Egg Elimination(nest)
    Reduce current $c_{multiplier}$ by $\frac{1}{100}$ its current value
End

Figure 11: Cuckoo Search Algorithm, CRISIS version

Start

$levy_\beta = 1.5$
$\sigma_u = 0.6966$
$\sigma_v = 1$
Get current nest fitness score
while n < max tries **do**:
    for each egg in nest **do**:
        Get the same ship egg in the best nest
        Compute levy flight step toward a better solution using indices:
            u = array of 2 values normally distributed with mean 0 and std σ_u
            u = array of 2 values normally distributed with mean 0 and std σ_v
            $s = \frac{u}{|v^{\frac{1}{levy_\beta}}|}$
            new egg $= c_{multiplier} * s * (egg - bestegg)$
        if new egg respects egg-contraints **then:**
            Compute new egg fitness score
            if new egg is better than the previous one **then:**
                Swap eggs
    if new nest respects nest-contraints **then:**
        return new nest
End

Figure 12: CRISIS Cuckoo Search's modified levy flight step

Start

Get the p_a fraction of worst nests
for each nest in worst nest list **do**:
  while t < max tries **do**:
    Generate two different random number between 0 and $n_{nests} - 1$
    Pick $nests_1, nest_2$ in solution space using these two numbers
    for each egg in current selected nest **do**:
      select egg_1, egg_2 from $nest_1, nest_2$ using the related egg indices
      new egg = egg + N[0, 1) * $(egg_1 - egg_2)$
      if new egg respects egg-contraints **then:**
        Compute new egg fitness score
        if new egg is better than the previous one **then:**
          Swap new egg with old egg
    if new nest **do not** respects nest-contraints **then** repeat attempt
Swap worst nests with new nests
End

Figure 13: CRISIS Mixing Replacement Strategy. Egg operations should be treated as vector element-wise operations

Start

Get the p_a fraction of worst nests
for each nest in worst nest list **do**:
  while t < max tries **do**:
    for each egg in current selected nest **do**:
      Generate random egg
      if new egg respects egg-contraints **then:**
        Compute new egg fitness score
        if new egg is better than the previous one **then:**
          Swap new egg with old egg
    if new nest **do not** respects nest-contraints **then** repeat attempt
Swap worst nests with new nests
End

Figure 14 Cuckoo Search Replacement Strategy

Among the two above-mentioned replacement strategy, the first one was kept, since it resulted in a better convergence rate and slightly lower execution times. Each time a new egg is generated or evolved from other ones, its fitness is evaluated against the whole nest: if the nest with the new egg has an overall fitness score lower than the previous one, the new egg is kept. The use of more nests ensures the algorithm to check for different optima in the solution space, trying different combinations.

computeFitness(egg, ship)
Start

Get the ship related to the current egg
Get all time slots included in waiting time period of the related ship
Compute **mean wave risk score** for the selected waiting time slots
Get all time slots included in handling time period of the related ship
Compute **mean wind risk score** for the selected handling time slots
Compute waiting times, handling times and late departure times in seconds
Compute waiting costs using the average wave risk
Compute handling costs based on the average wind risk
Compute late departure costs
Sum all costs
End

Figure 15: Egg fitness score computing pseudocode, based on the fitness function formula above

BIBLIOGRAPHY

[1] UNCTAD, "REVIEW OF MARITIME TRANSPORT 2018," UNCTAD, 2018. [Online]. Available: https://unctad.org/system/files/official-document/rmt2018ch4_en.pdf. [Accessed 31 August 2023].

[2] CRISIS project Consortium, "CRISIS Application Form," INTERREG IPA CBC ITALY–ALBANIA–MONTENEGRO PROGRAMME, 2ND CALL FOR PROJECTS IPA II CBC ITALY-ALBANIA-MONTENEGRO - TARGETED, Bari, Italy, 2022.

[3] Jahn, Carlos (Ed.); Kersten, Wolfgang (Ed.); Ringle, Christian M. (Ed.), "Digital Transformation in Maritime and City Logistics: Smart Solutions for Logistics," Proceedings of the Hamburg International Conference of Logistics (HICL), No. 28, [Online]. Available: https://www.econstor.eu/bitstream/10419/209197/1/hicl-vol-28.pdf. [Accessed 1 Spetember 2023].

[4] Barbosa F, Rampazzo PCB, Yamakami A, Camanho AS, "The use of frontier techniques to identify efficient solutions for the berth allocation problem solved with a hybrid evolutionary algorithm," in *Comput Oper Res. 2019;107:43–60.*.

[5] Carlo HJ, Vis IF, Roodbergen KJ., "Seaside operations in container terminals: literature overview, trends, and research directions," vol. Flex Serv Manuf J. 2015;27(2 3):224–62..

[6] Alsoufi G, Yang X, Salhi A. , "Robust berth allocation using a hybrid approach combining branch-and-cut and the genetic algorithm.," *International Workshop on hybrid metaheuristics, (Springer). 2016; p. 187–201.*.

[7] Xiang Xi, Liu C, Miao L. , "A bi-objective robust model for berth allocation scheduling under uncertainty.," *Transp Res Part E Logist Transp Rev. 2017;106:294–319.*.

[8] A. Lim, "The berth planning problem," *J. Operations Research Letters. vol. 22, No. 2, pp. 105-110. Elsevier, (1998).*.

[9] Aslam S, Michaelides MP, Herodotou H. , "Internet of ships: a survey on architectures, emerging applications, and challenges," *IEEE Internet of Things J. 2020;7:9714–27.*

[10] A. Kamolov and S. H. Park,, "An IoT Based Smart Berthing (Parking) System for Vessels and Ports," in *in Proceedings of the International Conference on Mobile and Wireless Technology. Springer, 2018, pp. 129–139.*.

[11] R. Wang et al., "An Adaptive Ant Colony System Based on Variable Range Receding Horizon Control for Berth Allocation Problem," *IEEE Transactions on Intelligent Transportation Systems, vol. 23, no. 11, pp. 21675-21686, Nov. 2022, doi: 10.1109/TITS.2022.3172719.*.

[12] Boris Pérez-Cañedo, José Luis Verdegay, Alejandro Rosete, Eduardo René Concepción-Morales,, "A multi-objective berth allocation problem in fuzzy environment," *Neurocomputing,* Vols. 500, ISSN 0925-2312,, no. https://doi.org/10.1016/j.neucom.2021.08.161, pp. 341-350, 2022.

[13] Bierwirth C, Meisel F. , "A survey of berth allocation and quay crane scheduling problems in container terminals.," *Eur J Oper Res. 2010;202(3):615–27..*

[14] Hsu H-P, Wang C-N, Chou C-C, Lee Y, Wen Y-F. , "Modeling and solving the three seaside operational problems using an object-oriented and timed predicate/transition net.," *Appl Sci. 2017;7(3):218.,* no. https://doi.org/10.3390/app7030218.

[15] H. Eskandari, M. A. Rahaee, E. Hasannayebi, M. Memarpour and S. A. Malek,, "Evaluation of different berthing scenarios in Shahid Rajaee container terminal using discrete-event simulation," in *2013 Winter Simulations Conference (WSC)*, Washington, DC, USA, 2013.

[16] Bierwirth C, Meisel F. , "A follow-up survey of berth allocation and quay crane scheduling problems in container terminals.," *Eur J Oper Res. 2015;244(3):675–89..*

[17] Şahin C, Kuvvetli Y. , "Differential evolution based meta-heuristic algorithm for dynamic continuous berth allocation problem," *Appl. Math Model. 2016;40(23–24):10679–88..*

[18] Ernst AT, Oğuz C, Singh G, Taherkhani G. , "Mathematical models for the berth allocation problem in dry bulk terminals," *J Sched. 2017;20(5):459–73..*

[19] G. K. D. Saharidis & M. M. Golias & M. Boile & S. Theofanis & M. G. Ierapetritou, "The berth scheduling problem with customer differentiation: a new methodological approach based on hierarchical optimization," *Int J Adv Manuf Technol (2010) 46:377–393,* no. DOI 10.1007/s00170-009-2068-x.

[20] Hansen P, Oguz C, Mladenovic N (2008) , "Variable neighborhood search for minimum cost berth allocation.," *Eur J Oper Res 191 (3):636–649. doi:10.1016/j.ejor.2006.12.057.*

[21] Imai A, Nishimura E, Papadimitriou S , "Berth allocation with service priority.," *Transp Res Part B 37:437–457. doi:10.1016/S0191-2615(02)00023-1,* 2003.

[22] Imai A, Chen HC, Nishimura E, Papadimitriou S, "The simultaneous berth and quay crane allocation problem," *Transp Res Part E 44(5):900–920. doi:10.1016/j.tre.2007.03.003,* 2008.

[23] Park MY, Kim HK, "A scheduling method for berth and quay cranes," *Oper Res Spectr 25(1):1–23. doi:10.1007/s00291-002-0109-z Springer,* 2003.

[24] De A, Pratap S, Kumar A, Tiwari M., "A hybrid dynamic berth allocation planning problem with fuel costs considerations for container terminal port using chemical reaction optimization approach," *Ann Oper Res. 2020;290(1):783–811..*

[25] Simrin A, Diabat A. , "The dynamic berth allocation problem: a linearized formulation," *RAIRO-Oper Res. 2015;49(3):473–94..*

[26] S. R. Seyedalizadeh Ganji, A. Babazadeh & N. Arabshahi , "Analysis of the continuous berth allocation problem in container ports using a genetic algorithm," *Journal of Marine Science and Technology volume 15, pages408–416 (2010),* no. DOI: 10.1007/s00773-010-0095-9.

[27] Frojan P, Correcher JF, Alvarez-Valdes R, Koulouris G, Tamarit JM. , "The continuous berth allocation problem in a container terminal with multiple quays.," *Expert Syst Appl. 2015;42(21):7356–66..*

[28] Takao Yokota, Mitsuo Gen, Yin-Xiu Li, "Genetic algorithm for non-linear mixed integer programming problems and its applications," *Computers & Industrial Engineering,* no. https://doi.org/10.1016/0360-8352(96)00041-1, pp. Volume 30, Issue 4, September 1996, Pages 905-917.

[29] Hsu H-P, Chiang T-L, Wang C-N, Fu H-P, Chou C-C. , "A hybrid GA with variable quay crane assignment for solving berth allocation problem and quay crane assignment problem simultaneously.," *Sustainability. 2019;11(7):2018–38..*

[30] Jos BC, Harimanikandan M, Rajendran C, Ziegler H. , "Minimum cost berth allocation problem in maritime logistics: new mixed integer programming models.," *Sādhanā. 2019;44(6):149..*

[31] Wang, F., Lim, A.: , "A stochastic beam search for the berth allocation problem. J. Decision Support," *Systems. Vol. 42, No. 4, pp. 2186{2196. Elsevier, (2007).*

[32] Lind M, Michaelides M, Ward R, Herodotou H, Watson R., " Boosting data-sharing to improve short sea shipping performance: evidence from Limassol port calls analysis.," *Tech. Rep. 35, UNCTAD Transport and Trade Facilitation Newsletter No. 82-Second Quarter 2019.*

[33] Xiang Xi, Liu C, Miao L. , "A bi-objective robust model for berth allocation scheduling under uncertainty.," *Transp Res Part E Logist Transp Rev. 2017;106:294–319..*

[34] Dulebenets MA. , "Application of evolutionary computation for berth scheduling at marine container terminals: Parameter tuning versus parameter control.," *IEEE Trans Intell Transp Syst. 2017;19(1):25–37..*

[35] J. Li, D. Xiao, H. Lei, T. Zhang, T. Tian, "Using Cuckoo Search Algorithm with Q-Learning and Genetic Operation to Solve the Problem of Logistics Distribution Center Location," *Mathematics Vol. 8, No. 149, 2020, doi:10.3390/math8020149.*

[36] Jean-François Cordeau, Gilbert Laporte, Pasquale Legato and Luigi Moccia, "Models and Tabu Search Heuristics for the Berth-Allocation Problem," *Transportation Science,* vol. Published By: INFORMS, no. https://www.jstor.org/stable/25769273, pp. Vol. 39, No. 4 (November 2005), pp. 526-538 (13 pages).

[37] Hu Z-H. , "Multi-objective genetic algorithm for berth allocation problem considering daytime preference," *Comput Ind Eng. 2015;89:2–14..*

[38] Shih-Wei Lin, Ching-Jung Ting & Kun-Chih Wu , "Simulated annealing with different vessel assignment strategies for the continuous berth allocation problem," *Flexible Services and Manufacturing Journal volume 30, pages740–763 (2018),* no. https://doi.org/10.1007/s10696-017-9298-2.

[39] Jakub Wawrzyniak a, Maciej Drozdowski a, Éric Sanlaville b, "Selecting algorithms for large berth allocation problems," *European Journal of Operational Research,* Vols. Volume 283, Issue 3, 16 June 2020, Pages 844-862, no. https://doi.org/10.1016/j.ejor.2019.11.055.

[40] Pisut Pongchairerks, "A Probabilistic Hill-Climbing Algorithm for the Single-Source Transportation Problem," *Sustainability 2023, 15(5), 4289; https://doi.org/10.3390/su15054289.*

[41] Burke, E. K. and Bykov, Y. , "The late acceptance hill-climbing heuristic.," *European Journal of Operational Research, 258(1):70 { 78.,* 2017.

[42] "The berth allocation problem in terminals with irregular layouts," *European Journal of Operational Research,* Vols. Volume 272, Issue 3, 1 February 2019, Pages 1096-1108, no. https://doi.org/10.1016/j.ejor.2018.07.019.

[43] Cristiano Cervellera, Mauro Gaggero, Danilo Macci, "A Receding Horizon Approach for Berth Allocation Based on Random Search Optimization," in *ODS 2019 - Optimisation and Decision Science* , Genova - Italy, 2019.

[44] Mauri GR, Ribeiro GM, Lorena LAN, Laporte G. , "An adaptive large neighborhood search for the discrete and continuous berth allocation problem," *Comput Oper Res. 2016;70:140–54..*

[45] Kavoosi M, et al. , "Berth scheduling at marine container terminals.," *Marit Bus Rev. 2019;5(1):30–66..*

[46] Geraldo R. Mauri, Alexandre C. M. Oliveira & Luiz Antonio Nogueira Lorena, "A Hybrid Column Generation Approach for the Berth Allocation Problem," in *Evolutionary Computation in Combinatorial Optimization. EvoCOP 2008. Lecture Notes in Computer Science, vol 4972. Springer, Berlin, Heidelberg.*.

[47] S. Aslam, M. P. Michaelides and H. Herodotou, "Enhanced Berth Allocation using the cuckoo search algorithm," *SN Computer Science, 3(4),* no. doi:10.1007/s42979-022-01211-z, 2022.

[48] S. Mohammad, T. K. Ahmad and M. Laouchedi, "A hybrid method based on Cuckoo search algorithm for global optimization problems," *Journal of Information and Communication Technology,* vol. 17, 2018.

Contacts

LP Municipality of Molfetta
antonella.fatone@comune.molfetta.ba.it

PP2 FLAG Molise Costiero
info@flagmolise.it

PP3 Municipality of Ulcinj
kabinet@ul-gov.me

This project is co-financed by the European Union under the instrument for Pre-Accession Assistance (IPA II)

This document has been produced with the financial assistance of the Interreg IPA CBC Italy-Albania-Montenegro Programme. The contents of this document are the sole responsibility of Municipality of Molfetta, FLAG Molise Costiero and Municipality of Ulcinj and can under no circumstances be regarded as reflecting the position of the European Union and of the Interreg IPA CBC Italy-Albania-Montenegro Programme Authorities.