Nature-Inspired Metaheuristics for Solving Complex Optimization Problems in the Maritime Industry

Matej Šuper [1], Marko Gulić [1,2], Lovro Maglić [1], Ana Perić Hadžić [1]

[1] *University of Rijeka, Faculty of Maritime Studies, Studentska 2, Rijeka, Croatia*
[2] *University of Rijeka, Center for Artificial Intelligence and Cybersecurity, Rijeka, Croatia*

***Abstract* – The maritime industry is crucial for global trade and the promotion of economic development. However, it faces major challenges, especially in tackling complex NP-hard problems that require effective decision support. To overcome these challenges, nature-inspired metaheuristic algorithms have proven to be powerful tools for optimization processes in the maritime sector. This paper provides a systematic overview of the application of these algorithms to various maritime problems, including collision avoidance, ship routing, tugboat scheduling, evacuation planning, container stowage, berth allocation, quay crane allocation, transport optimisation, search and rescue operations, hydrant location optimization and the damage stability problem. In addition, new optimisation algorithms are constantly being presented in the literature to further improve performance in various applications. As shown in this paper, recent algorithms such as The Pelican Optimization Algorithm, The Squirrel Search Optimization Algorithm, The Snow Leopard Optimization Algorithm and The Deer Hunting Optimization Algorithm have outperformed traditional metaheuristics in optimising known test functions, suggesting that they may offer promising improvements for solving complex maritime optimization problems.**

***Keywords* – Algorithm comparison, maritime industry, nature-inspired metaheuristics, optimization.**

DOI: 10.18421/TEM153-24
https://doi.org/10.18421/TEM153-24

Corresponding author: Matej Šuper,
University of Rijeka, Faculty of Maritime Studies, Studentska 2, Rijeka, Croatia
Email: matej.super@pfri.uniri.hr

Received: 28 August 2025.
Revised: 10 January 2026.
Accepted: 17 January 2026.
Published: 27 August 2026.

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1. Introduction

An efficient maritime industry is essential for the economic growth of countries and regions of the world. Conversely, major disruptions in the industry can have a serious impact on global trade and economy [1], [2]. An example of a major disruption is the stranding of the container ship "Ever Given" in 2021 in the Suez Canal, Egypt which caused a blockage that lasted 6 days [3]. The delay, according to Allianz Insurance report, caused additional costs in global trade from a range of 6 to 10 billion dollars as well as delays in the delivery of the goods. The indirect effects included short-term increases in shipping costs and the rise in oil prices [4].

To avoid unpredictable negative events or mitigate the consequences of those that cannot be avoided, it is essential to make the best possible decisions at that moment for each stakeholder in a particular process. The use of computational tools, such as optimization algorithms, can assist in improving problem-solving and decision-making processes. Optimization, i.e. the search for an optimal solution to a problem, is directly and indirectly beneficial. Because of the limitations of resources (mainly time and money), optimization is widely used in most industries with complex processes: in engineering (shipbuilding), healthcare (E.R. waiting rooms), finance (maximizing net profit), transportation, business planning and in the maritime industry (route optimization, collision avoidance, container stowage, etc.) [5]. The optimization algorithms can be divided into two types: deterministic and stochastic. Deterministic algorithms follow strict procedures, and the path and values of the variables and the functions are repeatable (particular input will give the same output) while stochastic algorithms always include randomness. Deterministic algorithms produce precise solutions, but their substantial time consumption makes them impractical for solving nondeterministic polynomial time hard problems (NP-hard problems) in the maritime industry.

The stochastic algorithms are used in hard optimization problems for a quality solution (in a reasonable time frame), but cannot guarantee that the solution is optimal. There are two types of stochastic algorithms: heuristic (search for the optimal solution by trial and error) and metaheuristic (incorporates intelligence in the trial-and-error process) [5]. The nature-inspired metaheuristic algorithms are a part of stochastic metaheuristic algorithms, which have proven to be highly effective in solving a wide range of NP-hard problems.

Some of the most recognised metaheuristic algorithms used to solve optimization problems in the maritime industry are the Genetic Algorithm (GA) [6], Ant Colony Optimization (ACO) [7], Evolutionary Algorithms (EA) [8] and the Particle Swarm Optimization Algorithm (PSO) [9]. There is a significant number of studies that use metaheuristic algorithms to solve complex optimization problems in the maritime industry, showing how effective they are in handling these challenges.

Hence the first contribution of this paper is a review of a large number of NP-hard problems in the maritime industry and an analysis of current proposed solutions in research literature, which are utilizing nature-inspired metaheuristic algorithms. The optimization problems in the maritime industry include: collision avoidance, ship routing, tugboat scheduling, evacuation planning, container stowage, berth allocation, quay crane allocation, transportation optimization, SAR operation, fire hydrant location optimization and damage stability problem.

To address optimization problems in the maritime industry, multiple metaheuristic algorithms may be used, since a single algorithm that works well for one problem may not necessarily provide optimal results for others. This idea is captured by the No Free Lunch Theorem (NFL), as described in [10]. Because of the NFL theorem and the no-size-fits-all nature of these algorithms, new metaheuristics continue to emerge to offer potentially better solutions to various optimization problems.

As a second contribution to this paper, several newer algorithms that have not yet been researched for their potential use in the maritime industry are presented. These algorithms have demonstrated excellent performance in optimization processes on well-known test functions surpassing the effectiveness of the algorithms most widely applied in the maritime industry; the GA and PSO. Among the new algorithms is the Pelican Optimization Algorithm [11], the Squirrel Search Algorithm [12], the Snow Leopard Optimization Algorithm [13] and the Deer Hunting Optimization Algorithm [14].

These newer algorithms are expected to enhance the solutions to the optimization problems in the maritime industry.

Given their enhanced performance, these algorithms present promising alternatives for addressing complex optimization challenges in this domain. Moreover, their success in test environments indicates strong potential for real-world applications, positioning them as valuable tools for advancing optimization practices within the maritime sector.

As a third contribution of this work, an evaluation and comparative analysis between all four algorithms have been conducted, based on the optimization results obtained for well-known test functions in [11], [12], [13], [14].

The following sections will explore the optimization challenges within the maritime industry and introduce new approaches to address these challenges.

2. Optimization Problems in the Maritime Industry

The maritime industry encompasses a variety of operational and logistical challenges, many of which are characterized by complex optimization problems. Numerous problems in this area are classified as NP-hard, meaning that they are computationally intensive and cannot be solved efficiently using conventional algorithms. Tackling these problems requires sophisticated optimization techniques and innovative methods. This section deals with eleven important optimization problems in the maritime industry that have been optimized by applying metaheuristic algorithms. These problems include collision avoidance, ship routing, tugboat scheduling, evacuation planning, container stowage, berth allocation, quay crane allocation, transportation optimization, search and rescue (SAR) operations, fire hydrant location optimization and damage stability. Each of these topics presents unique challenges and requires tailored optimization strategies to improve operational efficiency and effectiveness.

2.1. Collision Avoidance

With regard to the safe navigation of a ship, avoiding collisions is one of the main tasks of a navigational officer of the watch. Due to different regulations in different countries, the shipping industry has started to regulate collision avoidance. Today, the Convention on the International Regulations for Preventing Collisions at Sea, 1972 (COLREG) is in force. The convention establishes rules to ensure safe navigation and prevent collisions at sea [15].

The COLREGs include 41 rules divided into six sections. According to COLREGS, collision avoidance situations can be categorized into three types [16]: Head-on situation, Crossing situation and Overtaking situation.

Avoiding ship collisions involves intricate decision-making processes to ensure safe navigation. These processes include [17]: Collecting data about the voyage, Data pre-processing, Vessel encounter classification, Collision risk level calculation, Collision avoidance method selection and Collision avoidance optimization.

Due to all these processes, it is difficult to create a precise mathematical model to describe ship collisions. For this reason, in recent years academics started to implement metaheuristic algorithms such as the GA, ACO, PSO, etc. in the field of collision avoidance.

Authors in [18] used GA to optimize the direction and speed of unmanned surface ships. Equally important, a decision support tool based on GA is developed that can recommend the shortest route for collision avoidance, taking into account both safety and economic factors [19]. Next, an optimization method based on a GA is applied to find optimal ship trajectories considering various navigation constraints on inland waterways [20]. Trajectory planning for collision avoidance is performed using several GA and the linear expansion algorithm [21]. Additionally [22] considers collision risk, economic factors, COLREGS and collision avoidance time for unmanned surface vehicle. Also, an automatic control system for manoeuvring vessels in collision situations was developed using improved GA that incorporates COLREGs and a stochastic predictor to identify obstacles and predict collision hazards [23]. Furthermore, an improved GA for path planning of unmanned surface vehicles for lake patrol is proposed, which can generate shorter and safer paths compared to the traditional GA [24]. The ship speed is incorporated into the cost function of the GA and modified based on the navigation environment and the cost function value to ensure safe navigation in busy areas in [25]. Moreover, two methods, the branch-and-bound method and the GA, are presented in [26] for identifying the best safe route for a ship during a potential collision situation using fuzzy set theory. Authors [27] proposed hybrid GA which generates optimal trajectories that meet the safety and distance requirements.

The EA used in [28], [29] considers the boundaries of the manoeuvring area, navigation obstacles, and other moving vessels, and reduces the problem of collision avoidance at sea to a dynamic optimization task with static and dynamic constraints. Study [30] proposed a collision avoidance system for unmanned surface based on the COLREGs and an improved differential EA.

An EA for trajectory planning of multiple vessels is presented by [31], that finds near-optimal safe trajectories in real time. Subsequently an EA models ship trajectories to avoid collisions in dynamic environments [32]. An EA method, for planning safe ship trajectories within traffic separation schemes is presented, that combines course alterations and speed reduction manoeuvres [33]. A method called “evolutionary sets of safe trajectories” is presented [34], which uses EA and game theoretic principles to obtain a close-to-optimal set of safe trajectories for all participating vessels involved in a multi-vessel situation. An improved multi-objective EA utilized [35] to optimize the ship collision avoidance strategies by balancing safety and economy, using the avoidance angle, time to action point, and fuzzy ship domain to assess the risk of collision. A multi-objective EA is used [36] to search for the optimal collision avoidance strategy for vessels, considering both safety and economic factors.

A new approach to path planning for ships in dynamic environments using ACO that can be applied in decision support systems on board ships or in obstacle detection and avoidance systems for unmanned surface vehicles [37]. Collision avoidance model based on ACO is presented [38], which integrates navigation practices, maritime regulations, and real-time AIS data to plan safe and economical collision avoidance paths for ships.

A PSO is implemented by authors [39] to plan ship paths and reduce the risk of collisions between ships navigating in open water. The paper [40] presents a method for preventing ship collisions by formulating it as a multi-objective constrained optimization problem based on ship manoeuvring equations and motion data, and solving it using a PSO algorithm to determine the best collision avoidance path and ship control actions.

Finally, Artificial Fish Swarm Algorithm (AFS) is integrated with ECDIS and can provide decision support to the officer on watch [41].

2.2. Ship Routing Problem

Passage planning is a critical process for all vessels, ensuring safe navigation from one port to another. The most important stages consist of [42]: Appraisal, Planning, Execution and Monitoring. Appraisal includes the collection of relevant information for the planned passage, identification of all critical areas and risk assessment using charts, pilot books, weather routes and local/international rules and regulations. Planning is the actual development of the passage plan, based on the appraisal, it includes the entire voyage plan from berth to berth, taking into account potential hazards, favourable routes, etc. (in the planning phase electronic or paper charts are used for route development).

Execution is the stage that includes following the passage plan (while underway) and prioritizing safe and efficient navigation. Monitoring is keeping track of the ship's progress, ensuring that the plan is adhered to and updating the plan with any new safety-related information (e.g., navigational warnings, etc.).

When planning multicriteria ship routes, the following factors are essential [43]:

1. Reducing navigation time - efficient routes should minimize the time spent at sea.
2. Lowering fuel consumption - optimal routes help reduce fuel usage.
3. Avoiding severe sea conditions - routes should steer clear of areas with challenging weather conditions to enhance ship and cargo safety.

The authors [44] have developed GA for optimizing ship routes in dynamic weather conditions, with the aim of determining the minimum voyage time. Next, GA is used for the development of a weather routing method to determine the optimal route [45]. The study [46] developed and solved a capacitated vehicle routing problem involving pickups, drop-offs and strict time windows using GA to determine optimal routes for a container ship fleet supplying the islands of the Aegean archipelago. Paper [47] deals with the planning of container liner shipping service networks while also considering the movement and allocation of empty containers. A quadratic optimization GA for ship route planning is proposed [48], which takes into account ship manoeuvrability constraints and is validated by experiments on a test fireboat.

The GA in [49] included several innovative techniques, such as a fitness assignment method, a hybrid mutation operator, and population diversity strategies, to improve the search for the optimal solution. Additionally, [50] authors provide a new application and extension of the Vehicle Routing Problem with time windows (VRPTW) for offshore logistics. Also, a new modified GA for solving a ship routing problem with container handling is presented [51]. The fisheries survey problem, which is a voyage routing problem, with multiple ports and visiting locations is solved with the use of GA [52].

A project to develop a new solution for ship weather routing, using the EA is described [53], which improves handling of uncertainties by improving predictions of a ship's performance and its behavior under different sea conditions through the use of ensemble forecasting and real-time data assimilation.

An improved ACO algorithm for solving the ship weather routing problem is introduced [54]. The aim of the algorithm is to find the most efficient transoceanic route for ships in a fast, accurate and cost-effective manner.

The authors in [55] present an ACO approach to optimize ship routing for transoceanic voyages with the goal of reducing fuel consumption and environmental impact while considering navigational safety. An enhanced method built upon an improved ACO is introduced [56] to address the ship weather-routing optimization problem, taking into account navigational safety, fuel use, and voyage duration.

Equally important, [43], [57] a hybrid heuristic algorithm combining GA and PSO is introduced to improve the accuracy and robustness of shipping route planning in restricted maritime traffic networks.

SA algorithm is used to determine the optimal ship routing by minimizing cost function [58].

2.3. Tugboat Scheduling

With the rapid growth of international maritime trade, the auxiliary operations in the port, which include ship arrival and departure, loading and discharging, etc., are becoming more and more complex from year to year [59]. Tugs play a critical role in manoeuvring operations, and without tugboats, large vessels are at greater risk of grounding and/or collision. Tugs provide pushing or towing assistance to ensure that the ship sails in a wanted direction [60], [61]. To avoid delays, maximize the profit of the port service and reduce fuel consumption, a tugboat scheduling problem (optimization problem) must be solved using scientific methods. Among others, metaheuristic algorithms inspired by nature are proposed to solve the tugboat scheduling problem.

Firstly, in [62] the authors start from the route design (taking the shortest route for the goal) and propose the use of GA to optimize the tugboat route. Next, [63] an optimization model is proposed with aim of reducing the wait time of the ship and the operating cost of the tug using GA. Paper [64] proposes an optimization model using GA for tugboat scheduling in multi-terminal seaports to minimize the idle distance while considering uncertainties. A GA-based optimization model for scheduling tugboats in a port to reduce the waiting time of ships and the operating costs of tugboats is presented [65].

The EA in [66] is proposed with the aim of reducing overall completion time. Additionally, EA is used to optimize a model [67], [68]. The algorithm considers the characteristics of a large number of vessels entering and leaving the port and calculates the fuel consumption of the tugs.

A hybrid ACO algorithm with the goal of reducing the overall total operating time of all tugboats in port is proposed [69]. ACO is also applied [70] to find the best scheduling plan. GA and ACO are combined [71] to solve the tugboat scheduling problem in container terminals.

PSO is utilized in, [72] for the container terminal tugboat scheduling problem and for the resource allocation problem. In [59], a relatively new Grey Wolf algorithm is proposed for the tugboat scheduling problem that considers multiple berths, time windows, and operational uncertainties with the objective of minimizing the total cost of fuel and delays.

2.4. Evacuation Planning

In 2022 20.4 million passengers travelled onboard cruise ships to various destinations. This number is expected to double by the year 2027 [73]. Both the current and projected number of passengers increase the number of potential fatalities. In a period of 7 years, from 2011 to 2018, at least 2526 fatalities were reported on passenger ships [74].

For this reason, an efficient evacuation plan must be implemented. A ship evacuation consists of three parts: 1. Response, 2. Evacuation, 3. Embarkation and launching period [75]. Part 2, the evacuation and the evacuation time are the central part of the ship evacuation process. The response period begins after the initial announcement and lasts until the decision has been made to proceed to a mustering point.

Once the decision has been made, the evacuation starts (from the starting point to the assembly point), after which the launching period begins. Ship evacuation is a complex problem in which various aspects such as the environment (in which the ship is sailing), the layout of a ship, the behavior of passengers and crew and personal characteristics (age, gender, physical condition) must be taken into account [74].

GA is used to optimize the layout of evacuation routes on passenger ships to minimize the evacuation time [76]. EA is used in [77] with the objectives of optimal path finding and optimal safe area selection. An improved ACO algorithm is presented for multi-path crowd evacuation planning (considering the speed and density of a crowd) [78]. PSO [79] is used to simulate the evacuation behavior on ships.

2.5. Container Stowage

Maritime transportation is an important part of global transportation, with container traffic accounting for more than 15% [1]. A container terminal is a crucial link in the container transportation process as it facilitates the transfer of containers between land transportation (trucks, trains) and sea transportation (ships).

Efficient operation of container terminals depends on optimizing the stowage, loading, and unloading of containers.

Terminals face several challenges (berth allocation, container stacking, and transport optimization) that must be addressed to reduce waiting times for ships, trains and trucks, thereby increasing throughput [80].

Container stowage optimization, i.e. the creation of a stowage plan with the aim of minimizing unnecessary container shifts and thereby reducing loading and unloading times, is an important factor in efficient terminal operation. Terminal operators review and refine the stowage plan, with the aim of minimizing container relocations and optimizing the stacking distances between the berth and storage areas in order to increase efficiency. In addition to optimizing container stowage, the strength and stability of the ship must also be taken into account.

All processes between the ship and terminal are interlinked, so that the optimization of one side (ship) cannot work without the optimization of the other side (terminal). Since stowage planning is considered an NP-hard problem various metaheuristic solutions are proposed [81].

GA model is presented [80] to reduce the number of container relocations within a single bay. Also, GA is utilized with the aim of minimizing the number of container movements required [82]. The authors in [83] use GA for a planning method, which comprises two steps: selecting the containers for relocation, building a relocation plan for the selected containers. Additionally, a GA is used [84] to integrate container-transfer and container-location models to determine the optimal storage locations and handling schedule. Next, GA is presented to solve an extended version of the storage space allocation problem in a container terminal, which involves allocating different types of containers to storage blocks to balance workload and minimize storage/retrieval times [85]. GA with the aim of minimizing the turnaround time of container ships is utilized [86]. Paper , [87] use GA to solve the container relocation problem with the aim of minimizing the number of additional container relocations required. GA is suggested [88] for the problem which also incorporates ship stability constraints. A new problem called the “block relocation problem with weights (BRP-W)” is presented [89] and describes the development of a “global retrieval heuristic (GRH)” algorithm embedded within a GA optimization method to solve this problem. Study [90] presents a simulation-optimization method that combines a GA with the goal of reducing the total number of container movements. The 3D container ship loading planning problem is formulated [91] and propose a new representation called “Representation by Rules” to efficiently solve it using GA.

A multi-objective evolutionary algorithm (EA) is used to solve the problem in [92], [93], with objectives including ship stability optimization and the minimization of container shifts.

ACO with the objective of minimizing crane operation time is utilized in [94].

A Simulated annealing algorithm (SA) is advocated in [95], seeking to minimize the relocations of containers that block access to the one scheduled for retrieval.

Finally, a Coronavirus algorithm (CA) in [96] is applied for optimization of stowage for dangerous goods.

2.6. Berth Allocation Problem

As already mentioned before, one of the challenges facing terminals is the berth allocation (scheduling) problem. The berth scheduling problem is a decision-making problem, in which the arriving ships need to be assigned to the available berth, and the order of the service for the vessel needs to be determined for each berth on the terminal [97]. The planning process can be divided into three levels [98]: Monthly planning, Weekly planning and Daily planning

A comparative analysis of three metaheuristic algorithms, GA, ACO, and SA, is presented [99] to solve the bulk port problem, aiming to minimise the total penalty cost associated with violating the time windows specified in the chartering contracts. Next, [100], [101] address the problem using GA for optimizing multi-user container terminal with indented berths for handling mega-containerships and feeder ships. Additionally, multi-objective GA is developed [102] to address the trade-off between operational efficiency/cost and daytime preference in berth allocation scheduling. GA to solve the berth allocation and quay crane assignment problem, aiming to minimize the total service time while maximizing buffer times to absorb potential disruptions is used in [103]. Three hybrid GA's were utilised [104] to solve the berth allocation problem and quay crane assignment problem simultaneously.

EA formulates the coupling problem between berth allocation and quay crane assignment [105], taking into account the interactions between these two aspects. Also, a new solution method based on the differential EA to solve the problem is proposed [106]. A study [107] proposes a decision model, using an EA that aims to minimize the costs associated with the berth allocation schedule, including delay costs and costs related to non-optimal berthing locations, based on the concept of service level. A novel, self-adaptive EA to solve the problem at container terminals and compare its performance against other evolutionary algorithms with different parameter control strategies is suggested [108].

Mathematical model and hybrid EA for the problem, with the objective of minimizing both the total service cost and carbon dioxide emissions (due to container handling) is presented in [109].

Multi-objective ACO is showcased [110], [111], [112]. to solve the problem in container ports, with the objectives of ship schedule optimization to minimize service time and departure delays.

Finally, [113] proposes a PSO approach that assigns ships to berths and minimizes waiting and handling times.

2.7. Quay Crane Allocation

The quay crane split is the allocation of available cranes to specific ships alongside the terminal. The crane allocation problem is important to solve because if an insufficient number of cranes are allocated to a ship, the loading/unloading process slows down (which increases costs and makes berth allocation more difficult). The objective of quay crane optimization is to allocate the optimal number of cranes to a ship (minimizing vessel time in port while maximizing economic utilization) [114]. The Quay crane allocation is also proven to be an NP-hard problem and the use of different metaheuristic algorithms has been proposed [115].

GA, which simultaneously considers two interdependent problems: quay crane scheduling and quay crane assignment is utilised [116]. Studies [117], [118] describe the development of a GA approach to efficiently schedule two quay cranes with non-interference constraints at the Narvik container terminal. In [119] GA is proposed and the effectiveness of the model and algorithm is demonstrated through several methods: comparing scheduling results with those found in the literature for a single ship, comparing scheduling results between multiple ships and a single ship, and simulating dynamic quay crane scheduling across multiple ships. Paper [120] proposes GA for assigning quay cranes based on a vessel priority list and the bay area partition. Study [121] proposes a multi-objective hybrid GA approach to solve the problem and obtain the best solution.

Equally important, [122] suggests an improved discrete PSO algorithm to solve the problem, with the objective of minimizing the turnaround time of ships.

2.8. Transportation Optimization

The transportation of containers at the container terminal can be divided into horizontal and vertical transport (stacking cranes). Horizontal transport can be divided into quayside which links the stacking area to the vessel and landside transport, which connect the stacking area to trucks or trains.

The vehicles used for horizontal transportation are trucks, straddle carriers, automated guided vehicles, etc.

The transportation optimization of container transfer considers synchronization with the quay and stacking cranes. The objective of transportation optimization is to increase the productivity of vehicles that operate between vessel and stacking area, and stacking area and train/truck by defining the optimal work schedule for each vehicle (to minimize transfer time and empty running distance). Crane wait time has to be reduced as much as possible as well.

An adaptive GA approach is shown [123] for the synchronised scheduling of parts and automated guided vehicles (AGVs) in a flexible manufacturing system environment, to minimize penalty cost and machine idle time. A general scheduling model for container terminal logistics problems is introduced [124], demonstrating its application to various real-world scheduling scenarios and evaluating GA approaches for solving the model. The GA-based approach was implemented [125] for the terminal scheduling system and tested, demonstrating that it could reduce the overall time-related cost of container transfers.

The EA is used [126] with the primary objective of shortening vessel port time by maximizing gantry crane productivity and minimizing the delay times of container transport.

2.9. SAR Operation

The purpose of the Search and Rescue (SAR) operation is to determine the position of people in distress as quickly as possible. The longer the person is in the water, the lower the chance of survival [15].

An appropriately designed route helps shorten the SAR time and increase the efficiency of the operation. There are many voyage planning algorithms that are based on ideal environmental conditions and do not consider wind, waves, currents and other conditions specific to a SAR operation, so there is a need for an algorithm that considers both static and dynamic obstacles. Two research papers [127], [128] use nature-inspired ACO algorithm for the optimization of path planning in the SAR operation.

2.10. Fire Hydrant Location Optimization

The positioning of a fire hydrant on a ship is an important part of ship design. The optimal positioning of hydrants requires a detailed analysis of potential fire hazards.

Designers must consider various factors including applicable regulations, technical specifications and hazard assessments. Applicable regulations include SOLAS (International Convention for the Safety of Life at Sea, 1974) with its FFS Code (International Code for Fire Safety Systems) and classification society rules. Based on the aforementioned regulations, designers start by designing a layout of the hydrants for the ship which includes the minimum number and location of hydrants to maximize the effectiveness of the system (effectiveness also depends on the type of hydrant, water pressure and accessibility). The hydrant locations can be determined by manual calculation, empirically, or by the use of optimization algorithms. A computer-aided design system for the optimal positioning of fire hydrants, using the PSO algorithm is suggested [129].

2.11. Damage Stability

Damage stability calculations assess a ship's ability to resist capsizing and return to equilibrium in both calm water and waves, ensuring it retains adequate buoyancy and stability even after one or more compartments have been breached [130]. The IMO (International Maritime Organization) has been updating and enhancing rules related to damage stability throughout the years. Along with IMO, academic researchers have been developing ways to calculate and enhance damage stability [131], [132]. Research is divided into a probabilistic and a deterministic approach and metaheuristic algorithms can be used to optimize the damage stability of ships. Firstly, in [131], a collaborative optimization algorithm combining reinforcement learning and PSO improves ship damage stability design. Secondly, [132] proposes a framework for optimization of the damage stability characteristics of a Ro-Ro passenger ship using probabilistic damage stability analysis and PSO to improve the safety of the ship design.

2.12. Overview of NP-Hard Problems in the Maritime Industry

To improve the understanding of the use of metaheuristics in the maritime industry, Table 1 presents an overview of all the problems listed in Sections 2.1 through 2.11, along with the relevant papers in which specific metaheuristic algorithms are used to address these optimization problems.

This table aims to provide a summary of the use of metaheuristic algorithms across various optimization challenges within the maritime industry.

Table 1. Nature inspired metaheuristics in maritime industry

Problem/Algorithm	GA	EA	ACO	PSO	AFS	SA	Hybrid	GWO	CA
Collision avoidance	[18], [19], [20], [21], [22], [23], [24], [25], [26], [27]	[28], [29], [30], [31], [32], [33], [34], [35], [36]	[37], [38]	[39], [40]	[41]	N / A	N / A	N / A	N / A
Ship routing	[44], [45], [46], [47], [48], [49], [50], [51], [52]	[53]	[54], [55], [56]	N / A	N / A	[58]	PSO,GA [43], [57]	N / A	N / A
Tugboat scheduling	[62], [63] [64], [65]	[66], [67], [68]	[70]	[72],	N / A	N / A	SA. ACO [69] GA, ACO [71]	[59]	N / A
Evacuation planning	[76]	[77]	[78]	[79]	N / A	N / A	N / A	N / A	N / A
Container stowage	[80], [82], [83], [84], [85], [86], [87], [88] [89], [90], [91]	[92], [93]	[94]	N / A	N / A	[95]	N / A	N / A	[96]
Berth allocation	[99] [100], [101], [102], [103], [104]	[105], [106], [107], [108], [109],	[110], [111], [112]	[113]	N / A	[99]	N / A	N / A	N / A
Quay crane allocation	[116], [117], [118], [119], [120]	N / A	N / A	[122]	N / A	N / A	N / A	N / A	N / A
Transportation optimization	[123], [124], [125]	[126]	N / A	N / A	N / A	N / A	N / A	N / A	N / A
SAR operation	N / A	N / A	[127], [128]	N / A	N / A	N / A	N / A	N / A	N / A
Fire hydrant location	N / A	N / A	N / A	[129]	N / A	N / A	N / A	N / A	N / A
Damage stability	N / A	N / A	N / A	[131] [132]	N / A	N / A	N / A	N / A	N / A

The analysis of Table 1 shows that the metaheuristic algorithms most frequently used to solve optimization problems in the research for maritime industry are the GA (51 papers), the EA (22 papers) and the PSO algorithm (12 papers).

Since GA and PSO are among the most commonly used optimization algorithms, they were used in Section 4 to assess and compare the effectiveness of novel state-of-the-art algorithms through the use of benchmark test functions.

These newer algorithms have shown better test function performance compared to the GA and PSO in [11], [12], [13], [14]. The evaluation suggests that these algorithms could achieve optimal results in solving optimization problems in the maritime industry. Accordingly, algorithms and their pseudocodes are presented in Section 3.

3. State of the Art Algorithms for Maritime Industry Optimization Problems

The four state-of-the-art algorithms to which the GA and PSO will be compared are the Pelican Optimization algorithm (POA), the Squirrel search algorithm (SSA), Snow Leopard Optimization algorithm (SLOA) and the Deer Hunting Optimization Algorithm (DHOA). In the following section, a comprehensive description of each algorithm is provided, detailing the underlying principles that guide their design and implementation. Additionally, the pseudocode for each algorithm is presented, offering a clear and structured overview of their fundamental operations. This serves to highlight the distinctive features of these algorithms, facilitating a comparison with GA and PSO in subsequent sections.

3.1. Pelican Optimization Algorithm

POA is a novel metaheuristic inspired by the hunting behavior of pelicans. Pelicans typically hunt in groups, coordinating their efforts. When they spot prey, they dive from heights of around 15 meters. As they descend, they extend their wings to skim the water's surface, driving fish towards shallower waters for easier capture. During the catch, pelicans scoop up a significant amount of water along with their prey, necessitating a forward thrust of the head to drain the excess water before swallowing [133]. Figure 1 presents the pseudocode for the algorithm described and provides a clear and structured overview of its basic operations. This pseudocode serves as a blueprint that describes the main steps and procedures that the algorithm performs to solve optimization problems.

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Procedure POA
Data:
  N – the size of population X
  T – number of iterations
Result:
  X – the best solution within the population X
Initialize the positions of pelicans in population X (Equation 52)
Calculate the objective function for each pelican
for t = 1 to T do
    Generate the position of the prey at random
    for i = 1 to N do
        Phase 1: Moving towards prey (exploration phase)
        for j = 1 to m do
            Calculate new status of the j-th dimension using Equation 4
        end for
        Update the i-th population member using Equation 5
        Phase 2: Winging on the water surface (exploitation phase)
        for j = 1 to m do
            Calculate new status of the j-th dimension using Equation 6
        end for
        Update the i-th population member using Equation 7
    end for
    Update best candidate solution
end for
Return X, the best candidate solution obtained by POA
```

Figure 1. POA algorithm pseudocode [11]

3.2. Squirrel Search Algorithm

SSA is modeled after the foraging behavior of flying squirrels. In favorable weather, these squirrels glide from tree to tree in search of food [12]. They eat acorns when available and continue searching for higher-quality food sources, such as hickory nuts, to cache for the winter. During winter time, flying squirrels are less active but they do not hibernate, therefore facing a higher risk of predation due to the lack of cover. This foraging cycle is repeated throughout their lives and is the foundation of SSA. A distinctive feature of this algorithm is the use of the Lévy distribution, a powerful mathematical tool that improves global exploration in this and other metaheuristic algorithms [134], [135]. Figure 2 provides the pseudocode for the algorithm described and gives a concise and organized overview of its core functions.

```
Procedure squirrelSearchAlgorithm
Data:
  N – the size of population P;
Result:
  X – the best solution within the population P
1. Generate the initial random population P on N flying squirrels
using Equation 2;
2. Evaluate fitness of each flying squirrel's location (solution);
3. Sort the locations of flying squirrels in ascending order depending
upon their fitness value;
4. Declare the flying squirrels on hickory nut tree, acorn nuts trees,
and normal trees;
5. Randomly select some flying squirrels which are on normal trees to
move towards hickory nut tree and the remaining will move towards
acorn nuts trees;
6. while (the stopping criterion is not satisfied) do
7.    for t = 1 to n1 (n1 = total flying squirrels which are on acorn
trees and moving towards hickory nut tree) do
8.       if (R1 ≥ Pdp) then
9.          resolve Equation 4. a);
10.      else
11.         resolve Equation 4. b);
12.   end for
13.   for t = 1 to n2 (n2 = total flying squirrels which are on normal
trees and moving towards acorn trees) do
14.      if (R2 ≥ Pdp) then
15.         resolve Equation 5. a);
16.      else
17.         resolve Equation 5. b);
18.   end for
19.   for t = 1 to n3 (n3 = total flying squirrels which are on normal
trees and moving towards hickory nut tree) do
20.      if (R3 ≥ Pdp) then
21.         resolve Equation 6. a);
22.      else
23.         resolve Equation 6. b);
24.   end for
25.   Calculate seasonal constant (Sc) using Equation 12;
26.   if (Seasonal monitoring condition is satisfied) then
27.      Randomly relocate flying squirrels using Equation 14;
28.   Update the minimum value of seasonal constant (Smin) using
Equation 13;
29. end while
30. X ← The location of squirrel on hickory nut tree is the final
optimal solution
```

Figure 2. SSA algorithm pseudocode [133]

3.3. Snow Leopard Optimization Algorithm

The SLOA metaheuristic is inspired by the natural behavior of snow leopards. Snow leopards mark their territory with scent and move in a zigzag pattern to communicate their location and track each other. They hunt by using rocky cliffs for cover, which allows them to approach their prey stealthily. Once they are close enough, they slowly creep forward before making a sudden dash to catch and kill the prey by biting its neck. This behavior of leopards is made up of four components: migration routes, prey searching (as mentioned), reproduction, and mortality [13]. In Figure 3 the pseudocode for the described algorithm, presents a streamlined and well-structured summary of its main functions.

```
Procedure SLOA
Data:
  N – the number of snow leopards
  T – number of iterations
  variables – problem variables
  objective_function – objective function to be optimized
  constraints – problem constraints
Result:
  best_solution – the best quasi-optimal solution obtained with the
SLOA
1. Initialize population matrix X randomly
2. Evaluate the objective function for each snow leopard in X
3. for t = 1 to T do
4.    Phase 1: Travel routes and movement
5.    for I = 1 to N do
6.       for d = 1 to m do
7.          Calculate x_i,d_P1 using Equation (3) and Equation (5)
8.       end for
9.       Update X_i using Equation (4)
10.   end for
11.   Phase 2: Hunting
12.   for I = 1 to N do
13.      for d = 1 to m do
14.         Calculate location of prey p_i,d using Equation (6)
15.         Calculate x_i,d_P2 using Equation (7)
16.      end for
17.      Update X_i using Equation (8)
18.   end for
19.   Phase 3: Reproduction
20.   for l = 1 to 0.5 × N do
21.      Generate cub C_l using Equation (9)
22.   end for
23.   Phase 4: Mortality
24.   Adjust the number of snow leopards to N due to mortality based
on criterion of the objective function
25.   Save the best quasi-optimal solution obtained so far
26. end for
27. Output the best quasi-optimal solution obtained
Return best_solution
End Procedure
```

Figure 3. SLOA algorithm pseudocode [13]

3.4. Deer Hunting Optimization Algorithm

The DHOA is the algorithm modelled on the hunting strategies of deer hunters. In this method, two hunters move in a coordinated manner towards the optimal position until they successfully reach the target deer. In addition, deer have strong sense of alertness and can detect danger with a sense of smell that is 60 times more sensitive than that of humans. They warn others with aggressive kicks and loud sniff. Deer can also perceive UH (Ultra High) frequency sounds which exceed human hearing. For this reason, the algorithm must consider not only the movements of the hunters, but also the behavior characteristics of a deer. The aim of the proposed metaheuristic is to identify the optimal human hunting position by analysing the deer’s behaviour and characteristics. A deer possess vision roughly five times sharper than that of humans, have a peripheral field of view ranging from 250 to 270 degrees, and can detect even the slightest movements [14].

Figure 4 presents the pseudocode for the described algorithm, providing a concise and organized summary of its primary functions.

```
Procedure DHOA
Data:
   N – the size of population Y
   MAX – maximum number of iterations
Result:
   X – the best solution within the population Y

Generate the initial random population Y on N solutions
for t = 1 to MAX do
   for i = 1 to N do
      Compute the fitness of solution i
      Update a, d, A, p, X, L and b
      if (p < 1) then
         if (|L| ≥ 1) then
            Update the position of the individual using equation 4
         else
            Update the position of the individual using equation 12
         end if
      else
         Update the position of the individual using equation 11
      end if
      Compute the fitness of each solution
      Update Y_lead and Y_successor
   end for
end for
X ← select the best solution (Y_lead)

Return X, the best solution obtained by DHOA
End Procedure
```

Figure 4. DHOA pseudocode [133]

4. State of the Art Algorithms for Maritime Industry Optimization Problems

In this section, a comparative analysis of three algorithms is presented, focusing on their performance on a set of standardized test functions. These test functions, used in [11], [12], [13], [14] served as a benchmark for evaluating the efficiency of each algorithm. In this paper, four new algorithms are compared with the well-established GA and PSO to gain a broader perspective on their performance.

The core of the analysis consists of a ranking system that assigns first, second and third place, based on the performance of each algorithm compared to the others on test functions from [11], [12], [13], [14] .

The use of previously validated test functions ensures that the comparative analysis is based on reliable and well-established benchmarks, enhancing the validity of the findings. The insights derived from this ranking system are intended to guide future research and development efforts, helping to identify the most effective algorithms for various optimization challenges. This chapter aims to contribute to the continuous development of optimization techniques by providing a detailed comparison of multiple algorithms across a diverse set of test functions.

4.1. POA-GA-PSO Evaluation

The comparison between test function results of POA, GA and the PSO is shown in Figure 5. For the evaluation, results of twenty-three objective test functions from [11] have been used. When an algorithm is placed first, it means that it had a better result (closest to optimal) than the others on a single particular test function. Second place, on the other hand, indicates a middle-tier performance. Third place indicates the lowest performance among the three and highlights relative inefficiency of the algorithm on that particular test function. By aggregating these rankings across multiple test functions, the figures in this chapter provide an assessment of each algorithm. The frequency with which an algorithm places first, second or third serves as a quantitative measure of its overall effectiveness.

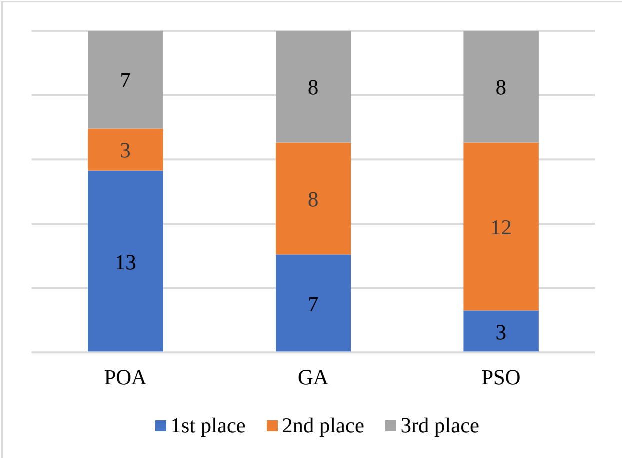

Figure 5. Performance rankings of POA, GA and PSO across test functions: frequency of 1st, 2nd and 3rd place results [11]

The POA emerged as the most robust algorithm, achieving the first place in thirteen out of the twenty-three test functions, demonstrating its superiority over GA and PSO in most cases. POA ranked second in three functions and third in seven. In comparison, the GA exhibited competitive performance, securing first place in seven test functions. However, it displayed variability in its effectiveness, ranking second in eight test functions and third in another eight, suggesting a more fluctuating performance relative to POA. The PSO, while often regarded as a strong algorithm, achieved first place in only three of the test functions. Despite this, it consistently performed at a mid-tier level, ranking second in 12 test functions. However, it also recorded the highest number of last-place finishes, ranking third in eight test functions. These results provide a clear ranking of the algorithms, with the POA demonstrating the best overall performance, followed by GA, and PSO, which although highly competitive in mid-tier rankings, showed the least effectiveness in securing first place results.

Table 2. Head-to-head comparison of POA, GA and PSO

Algorithm Comparison	
POA-GA	13:10
POA-PSO	15:8
GA-PSO	12:11

Table 2 presents a head-to-head comparison between the algorithms with the number of “wins” and “losses” between algorithm pairs on optimization results of 23 test functions, highlighting the relative performance of POA, GA, and PSO. While the POA demonstrates superior overall results, with 13 “wins” over GA and 15 “wins” over PSO there are some test functions where it underperforms compared to the other algorithms. This result is consistent with the No Free Lunch (NFL) theorem, which posits that an algorithm excelling on one set of problems may not necessarily outperform others on different problem sets. Given the POA’s strong performance on the majority of test functions, it is reasonable to presume that it may also offer advantages in solving optimization challenges within the maritime industry.

4.2. SSA, GA and PSO Evaluation

The comparison of optimization results among SSA, GA, and PSO is illustrated in Figure 6. Results of twenty-six objective test functions from [12] were used for the evaluation, and the rankings for all three algorithms for these functions are shown.

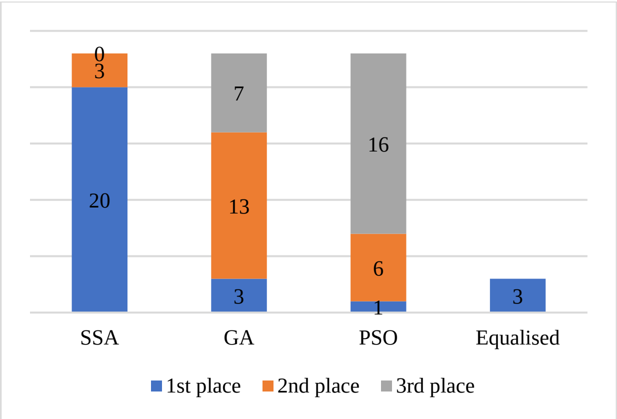

Figure 6. Performance rankings of SSA, GA and PSO across test functions: frequency of 1st, 2nd and 3rd place results [12]

The SSA demonstrates the strongest overall performance when compared to GA and PSO. Out of the results of 26 test functions, SSA achieved the highest rank in 20, significantly outperforming the other two algorithms. In contrast, GA secured the best result in only three functions, while PSO led in just one, which it shared with SSA. Additionally, three functions resulted in equal scores for all three algorithms.

The SSA ranked second in three test functions and did not place third in any of the 26 functions. GA, while competitive, ranked second in 13 functions but fell to last place in seven. PSO, although occasionally achieving mid-tier performance with six second-place rankings, ranked last in 16 functions, indicating a relative weakness in comparison to SSA and GA. These results underscore SSA’s dominance across the test functions, with GA performing moderately and PSO showing the least effectiveness.

Table 3. Head-to-head comparison of SSA, GA and PSO

Algorithm comparison	
SSA-GA	20:3
SSA-PSO	22:0
GA-PSO	16:7

Table 3 presents a pairwise comparison of the algorithms, with SSA demonstrating the strongest overall performance with 20 “wins” over GA and 22 “wins” over PSO. However, as with the previous case involving POA, the No Free Lunch (NFL) theorem remains applicable. While SSA excels in many instances, it does not guarantee superior performance across all problem sets, underscoring that no single algorithm performs optimally across all optimization problems. Given SSA’s performance across the majority of test functions, it is reasonable to infer that it may also provide significant advantages in addressing optimization challenges within the maritime industry.

4.3. SLOA-GA-PSO Evaluation

The optimization results of the SLOA, GA, and PSO are compared in Figure 7. A total of twenty-three objective test functions results from [13] were used for the evaluation, and the results for all three algorithms on these functions are presented.

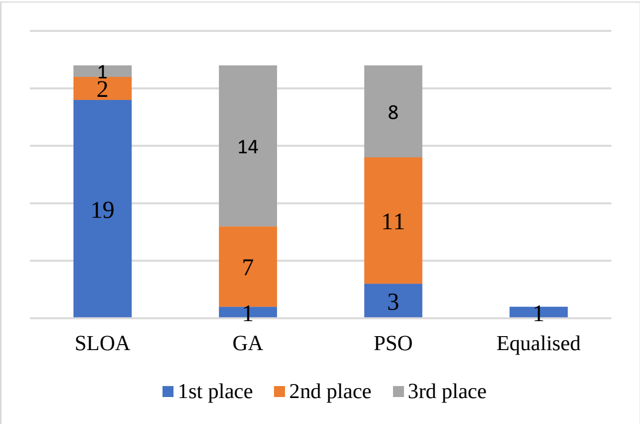

Figure 7. Performance rankings of SLOA, GA and PSO across test functions: frequency of 1st, 2nd and 3rd place results [13]

The SLOA achieved the best overall performance in comparison to GA and PSO. Out of the results of 23 test functions, SLOA ranked highest in 19, significantly outperforming both GA and PSO. In contrast, GA secured the top position in only one function, while PSO ranked first in three functions, one of which was shared with SLOA. Additionally, one of the 23 functions resulted in equal scores across all three algorithms. SLOA ranked second in two test functions and placed last in only one. GA, while competitive in certain cases, ranked second in seven functions and finished third in 14, indicating greater variability in its performance. PSO, despite showing some mid-tier success with 11 second-place rankings, ranked last in eight functions, revealing a relative weakness compared to SLOA and GA. These results highlight SLOA's dominance across the test functions, with PSO showing moderate effectiveness and GA performing least effectively.

Table 4. Head-to-head comparison of SLOA, GA and PSO

Algorithm comparison	
SLOA-GA	22:1
SLOA-PSO	18:3
GA-PSO	8:14

Table 4 presents a comparison between pairs of algorithms with SLOA demonstrating the strongest performance on the test functions with 22 "wins" against GA and 18 "wins" against PSO. However, as with the previous cases, the No Free Lunch (NFL) theorem remains relevant. While SLOA excels in many functions, this does not guarantee its superiority across all problem sets, emphasizing that no single algorithm is universally optimal for every optimization challenge. Similarly, based on SLOA's consistently superior results, it is plausible to presume that this algorithm could offer considerable benefits for solving various optimization problems in the maritime sector as well.

4.4. DHOA-GA-PSO Evaluation

The optimization results of the DHOA, GA, and PSO are shown in Figure 8. The evaluation was conducted using the results of thirty-three objective test functions from [14], and the outcomes for all three algorithms on these functions are displayed.

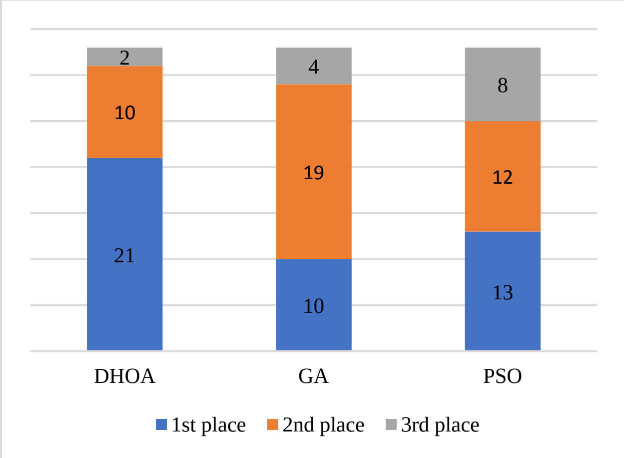

Figure 8. Performance rankings of DHOA, GA and PSO across test functions: frequency of 1st, 2nd and 3rd place results [14]

The DHOA demonstrated the strongest overall performance compared to GA and PSO, having the most optimal result in 21 out of 33 test functions. In contrast, GA ranked first in 10 functions, while PSO secured the top position in 13 functions, with 11 of these being shared with DHOA. DHOA consistently performed well, achieving second place in 10 functions and placing last in only two, underscoring its robustness across the majority of test cases. GA, while competitive, ranked second in 19 functions and placed third in four, suggesting a more variable performance. PSO, despite showing strength with 12 second-place finishes, ranked worst in eight test functions, indicating a relative weakness compared to DHOA and GA. These results emphasize DHOA's dominance across the test functions, with GA showing moderate effectiveness and PSO performing the least effective overall.

Table 5. Head-to-head comparison of DHOA, GA and PSO

Algorithm comparison	
DHOA-GA	22:11
DHOA-PSO	19:2
GA-PSO	14:19

Table 5 presents a comparison between pairs of algorithms, with DHOA exhibiting the strongest performance across, with 22 "wins" against GA and 19 "wins" against PSO. However, as in previous cases, the No Free Lunch (NFL) theorem applies. While DHOA performs exceptionally well on many test functions, this does not ensure its superiority across all problem sets. Given DHOA's consistently superior performance, it is reasonable to presume that this algorithm may provide significant advantages in addressing a range of optimization problems within the maritime sector.

4.5. DHOA-SSA-POA-SLOA Evaluation

For the evaluation between the DHOA, SSA, POA and SLOA, the test results from the authors in [133] are used in this section. Figure 9 illustrates the comparative performance of the algorithms, with each bar representing the percentage of instances in which one algorithm outperformed another across the test functions. In the figure, blue bars denote the performance of Algorithm 1, while orange bars represent Algorithm 2.

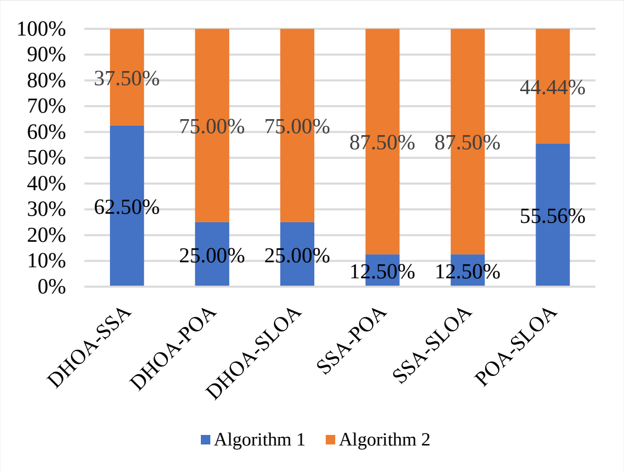

Figure 9. DHOA-SSA-POA-SLOA comparison

The data reveals that DHOA outperformed SSA, demonstrating its relative strength in comparison. POA generally exceeded the performance of both DHOA and SSA, indicating its superior efficacy in most test scenarios. SLOA, while also outperforming DHOA and SSA, showed a level of performance that was comparable to POA, suggesting that it is competitive with POA but not superior. These observations highlight that no single algorithm consistently outperforms all others across all test functions. This variability reinforces the No Free Lunch (NFL) theorem.

5. Conclusion

In summary, optimization remains a critical component for enhancing efficiency in the maritime industry. This paper presents eleven optimization problems in the maritime industry which include: Collision avoidance, Ship routing, Tugboat scheduling, Evacuation planning, Container stowage, Berth allocation, Quay crane allocation, Transportation optimization, SAR operation, Fire hydrant location optimization and Damage stability. In research literature, these problems have been addressed using well-known nature-inspired metaheuristic algorithms, such as Genetic Algorithms, Ant Colony Optimization, and Particle Swarm Optimization.

Recent developments have introduced newer metaheuristic algorithms, such as the Pelican Optimization Algorithm, Squirrel Search Algorithm, Snow Leopard Optimization Algorithm, and Deer Hunting Optimization Algorithm.

In this paper, the results from test functions are used to compare the performance of the newer algorithms against the older, well-known ones. According to these results, newer algorithms outperform traditional algorithms, which suggest their promising potential for solving complex optimization problems more effectively in the maritime sector. These results can serve as a baseline for future research and utilization of nature-inspired metaheuristics in the maritime industry.

However, the disadvantage of using the results of a test function is that the optimization algorithms are not compared with a problem but with a result of a test function. For future research, the newer algorithms could be compared to older ones, for a specific optimization problem in the maritime industry. This could give a better insight into the effectiveness of the algorithm for a specific problem.

It is also important to understand the No Free Lunch Theorem (NFL) which states that no single algorithm is superior for all.

Overall, while new emerging metaheuristic algorithms could provide better results, the choice of an algorithm must be matched to the specific nature of the problem. Continued research with both well-known and newer algorithms is important for achieving optimal results in the maritime industry.

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