Meta-heuristic Approach for control of the mobility of ships

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ABSTRACT-

In the context of maritime transport, the main objective of controlling the mobility of ships is to achieve a compromise between the safety navigation and the operation economy. The planning process and the appropriate optimization method need to consider this compromise. Therefore, in addition to economic efficiency, transportation management must also include environmental protection to prevent pollution as well as the avoidance of obstacles to prevent accidents and collisions between ships. Geographic Information Systems (GIS) are key systems for maritime navigation. The ship route planning is usually based on three items. The first item is to get the reliable weather forecasts. The second item is the ship performance under different weather conditions. The last item is to use an appropriate optimization algorithm. In this paper we used the Ant Colony Algorithm (ACA) to create initial population and the Genetic Algorithm to have more and better results.

KEY WORD: *Meta-heuristic; Multi-objective optimization; Geographic Information Systems; maritime navigation*

1. INTRODUCTION

The explosion of trade flows, mainly maritime, is one of the main manifestations of globalization: more than ninety percent (90%) of world trade is transported on sea [1]. According to statistics, the volume of goods transported by sea has had negative effects on the environment, and is becoming an important and growing source of air pollutants [2]. Decreasing fuel consumption during navigation time can minimize the current degree of air pollution.
Selecting the optimal route, maintaining speed and avoiding obstacles can at the same time minimize fuel consumption, and also improve security of navigation. A compromise between safety of navigation and economic efficiency must be found [3] because determining the optimal route is a non-linear multi-criteria problem and contains many constraints. In other words, the planning process must take into account the assessment of security risks in the event of deviation during navigation, and also avoid an increase in the total cost due to diversion measures.
The problem of ship route planning is to minimize the travel time and distances crossed by a ship from a current point to a final point. Various meteorological constraints can be considered: wind strength and wave characteristics. We are interested in the problem of maritime navigation. It is known in the literature as NP-Hard [4]. To solve large instances, a solution is to first use combinatorial optimization methods such as metaheuristics.

Wang and Jing [5] developed a solution that integrates a heuristic search with an enhanced Ant Colony Optimization (ACO) algorithm to improve the safety and efficiency of obstacle avoidance in maritime traffic.
Tsou and Cheng [6] utilized a hybrid approach combining the Ant Colony Algorithm (ACA) and the Genetic Algorithm (GA) to optimize maritime route planning on the Electronic Chart Display and Information System (ECDIS) platform. The primary objective was to determine optimal routes for transoceanic crossings.

Adhi et al. [7] introduced a Modified Hybrid Particle Swarm Optimization (MHPSO) algorithm for the Maritime Inventory Routing Problem (MIRP), a method that integrates Particle Swarm Optimization (PSO) with the Nahwaz-Enscore-Ham (NEH) and 3-Opt heuristics, reporting a 0.64% improvement over existing methods.
Wang and Li [8] presented an enhanced Ant Colony Algorithm for providing an automated system that can generate the most efficient routes, even in complex environments with numerous obstacles.
Han et al. [9] Kumari et al. [10] developed an innovative framework that integrates a seakeeping model with optimal control to generate weather-sensitive routes that reduce fuel consumption and improve trajectory performance.
More recent studies have focused on multi-objective and complex system optimization. Yang et al. [11] developed an improved multi-objective ACA that comprehensively accounts for both navigation risk and fuel consumption under complex sea conditions, providing a practical solution for shipping companies.
Guo et al. [12] introduced a hierarchical, three-layer framework called the Global–Local-Formation Module (GLFM) for the intelligent route planning of transport ship formations. While simulation results showed the potential of this algorithm, its practical performance requires future validation through sea trials.
Lazarowska's research [13] focused on developing and validating novel heuristic and deterministic algorithms for path planning and collision avoidance. This research is a significant contribution to the field of autonomous ship navigation, fostering safer and more efficient maritime operations.
Alhamad et al. [14] presented the Ship Routing and Scheduling Problem with a metaheuristic algorithm designed to minimize total operational cost while adhering to all constraints.
Lazarowska [15] presented a new approach utilizing a multi-criteria Ant Colony Optimization-based algorithm in order to solve a safe path planning problem for ships in the environment containing both static and dynamic obstacles, method presented can be applicable in modern Navigation and Control (GNC) system.
Sardar et al. [16] proposed an approach combined, artificial intelligence (AI) and Ant Colony Optimization (ACO) to optimize complex operational tasks, with the explicit goal of minimizing human error through automated, standardized instructions.
Li et al. [17] proposed an optimization study method used to optimize based on a multi-objective optimization algorithm NSGA-II to create reasonable and safe ship collision avoidance strategies.
Sobecka et al. [18] presented a multi-objective method based on an evolutionary multi-objective (EMO) algorithm, with objective functions that minimize total passage time, the sum of course alterations, and the average heel angle.
Abdalsalam and Szłapczyńska [19] discussed the possibilities of High Performance Computing (HPC) integration with multi-objective optimization method for ship weather routing, with the aim to illustrate how HPC can enhance the performance and practical applicability of weather routing systems.
Li et al [20] specifically applied an ACO algorithm to the weather routing problem for transoceanic ships, showing that it can find shorter, safer, and faster routes, efficiently avoiding dangerous areas.
Zhang et al. [21] presented a sophisticated and efficient approach utilizing an enhanced ant colony optimization (ACO) algorithm to address the multi-objective ship weather routing optimization problem, taking into account navigation safety, fuel economy, and travel duration.
Zhou et al. [22] proposed a study using a path planning algorithm for maritime navigation systems that combines global trajectory extraction with local dynamic collision avoidance using the dynamic window approach (DWA) enhancing both safety and navigational efficiency.

In this paper, we will study the problem of optimal ship routing by modeling the displacement and releasing a solution based on an optimization algorithm that will optimize the movements made by ships and which will take into account both the security and the economy. To accomplish and implement this optimization, we proposed to adapt the Ant Colony Algorithm (ACA) with the incorporation of the concepts of the Genetic Algorithm (GA). We will also study the dynamic aspect of the problem of integrating a collision avoidance mechanism between moving ships and not just fixed obstacles. The calculation and search of geographic information is provided by the Geographical Information System (GIS) developed.

2. NAVIGATION MARITIME

Navigation refers to all the techniques and methods that allow the ship to determine its position and to calculate the route to get to its destination safely [23].

A. *Ship route*

There is no data today on the routes actually followed by ships traveling the world's seas. On the other hand, there are ports of departure and destination for most commercial voyages, occasional information on the position of certain ships near the coast, as well as data on the main routes generally crossed by ships.

Currently, in evaluating the optimal shipping routes, the important factor, in addition to security, is generally given to navigation times rather than distance. Considering the criteria of security and energy consumption, the shortest distance between a current point and a final point is not necessarily an optimal route. The route that records the shortest time ensuring ship's security is the optimal route.

B. *Calculation of optimal ship route*

The solution to an optimal ship route problem is to reach the route with the least cost between all candidate routes, considering the weather data. The total cost is not restricted to distance only, but must take into account fuel consumption, navigation time. The primary decision variables that influence this cost are the ship's heading angle and its speed maneuvers. The cumulative cost (K) is formally evaluated as the aggregate of costs for each individual segment of the planned route (s). It consists of many parameters:

- Position of ship (P),
- Heading and speed of ship (H),
- Time cost (t).

The following formula can be used to define the problem of ship routing:

$$K = \int_S f\big(P(s), H(s), t(s)\big)ds \tag{1}$$

With:

- f (P, H, t): travel cost function for a given position, speed of ship and time t; $P \in R$, $H \in H_A$.
- R: navigation area.
- H_A: variable control of heading and maintaining speed of ship.
- ds is estimated by fuel consumption and level of ship's security on navigation.

C. *Path modeling*

In the context of maritime navigation, major progress has been made in modeling moving objects (ships). Geographic information systems (GIS) which, for their part, support the management and manipulation of these data.

Yvan Bédard's team at Laval University in Quebec has developed a general method that allows any graphic modeling formalism to be extended for geographic design. This method is an extension of UML class diagrams for the definition of spatio-temporal data. Several notations have been taken from the Modul-R Entity-Relationship method [24].

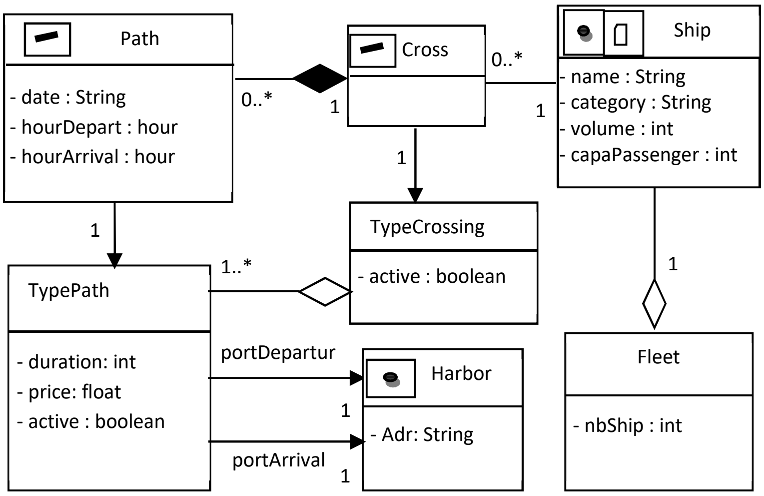

Figure 1: conceptual data model GEO-UML

3. ANT COLONY ALGORITHM AND SHIP ROUTING

The principle is inspired by the mass behavior of ant colonies. In the natural world, in the search for food by ants, they initially traverse different possible paths from their nest to a food source. This search is a collaborative process where the paths are marked by pheromones. Over time, the majority of ants converge on the shortest path, as it is reinforced by a higher concentration of pheromones. This collective, self-organizing behavior serves as the basis for the algorithm's capability to find optimal solutions.

A. *The algorithm principle*

A set of artificial agents (ships), analogous to ants, are used to explore potential routes based on a predefined set of search rules. The objective of the ship routing problem is to discover the global optimal path that minimizes cost while ensuring safety and most economical shipping path based on weather conditions and the rules of avoidance of oil rigs attached to the seabed between the points of departure and destination as well as collision avoidance mechanism between moving ships.

B. *Matrix of the navigation area*

In the grid-based approaches, the navigation area to be controlled is divided into cells to create a spatial grid system [25], and the navigation routes consists of waypoints. The procedure to make a matrix of the navigation area is as follows:

- Initially, create an orthodromic route between the departure port (P1, μ1) and the final port (P2, μ2).
- Then define a distance D, and define segment points along the navigation area (Pd, μd) in intervals of D.
- Then join the segmentation points to make a matrix of the navigation area.
- Finally create the matrix with coordinates of waypoints, and the route planning will be determined in this matrix of the navigation area.

C. *The implementation*

- The first step is to create a spatial grid system and define its node matrix of the sailing zone.
- To form the initial matrix of nodes, give each node with the appropriate initial value.
- Make all the artificial ants on the departure position to permit them to move forward in the same time in the way of the target area, and to reach the final point.

At each step, an ant selects its next node using a probabilistic state transition rule. Once every ant has completed a full route, the value of the objective function is computed for each generated path. The pheromone on each arc is then updated based on the quality of the path taken, reinforcing successful routes. This pheromone update mechanism incorporates both a deposition component (from the ants) and an evaporation component. This cycle of exploration, evaluation, and pheromone update is repeated until the algorithm identifies the optimal route. The detailed process is further explained below [26]:

1) Adjusting the amount of pheromone

The number of artificial ants is supposed equal to *n*. And, each ant selects its next path based on a probability proportional to the amount of pheromone on the corresponding trajectory, while avoiding previously visited routes. Upon completing its path, each ant deposits a new concentration of pheromone according to the total length of the route. The pheromone concentration on each traversed arc is then updated.

The pheromone concentration on arc (x, y) at time t is denoted by $\tau_{xy}(t)$. The updated concentration at time t+1 is calculated as follows:

$$\tau_{xy}(t+1) = \rho.\tau_{xy}(t) + \sum_{k=1}^{n} \Delta\tau_{xy}^{k} \tag{2}$$

With:

ρ: An indicator of the pheromone quantity parameter, its value is in [0, 1], and (1 - ρ) stands for the evaporation coefficient of pheromone.

$\Delta\tau_{xy}^{k}$: Indicates the amount of pheromone added on the arc (x, y) by the artificial ant k between time t and t +1.

$$\Delta\tau_{xy}^{k} = \begin{cases} \frac{Q}{d_{xy}} & \text{If the kth ant passes through (x, y)} \\ 0 & \text{Else} \end{cases} \tag{3}$$

Q: A parameter that represents the total amount of pheromone deposited by each artificial ant; d_{xy} equals to the distance from node *x* to node *y*.

Eq. (3) shows that the increase in pheromone concentration depends to the cost of the selected route.

2) Crossing points (Waypoints) selection principle

The transition rule is to orient the search direction of each artificial ant towards the potential solution. For the ant *k* located at node *x*, the probability of choosing the next arc (x, y) at time t is determined by:

$$P_{xy}^{k}(t) = \begin{cases} \dfrac{\tau_{xy}^{\alpha}(t).\,\eta_{xy}^{\beta}}{\sum_{y\in S_{k(x)}} \tau_{xy}^{\alpha}(t).\eta_{xy}^{\beta}}, & \text{if } y \in S_{k(x)} \\ 0 & \text{else} \end{cases} \tag{4}$$

With:

$S_{k(x)}$: the selection of nodes that can be crossed by the ant *k* at the point *x*.
H_{xy}: heuristic value, called visibility, defined by the inverse of the cost on the arc (x, y); $\eta_{xy} = 1/d_{xy}$.
α, β: The two main parameters, which control the relative importance of the intensity and visibility of an arc.
T_{xy} (t): Quantity of pheromones on the arc (x, y) at time t.

This transition rule provides the probability of choosing the following node to be selected based on the local heuristic value and the amount of pheromones. Parameters α and β determine the relative importance of these two components. When α equals zero, the ants select the node that has the highest heuristic value. On the other hand, when β equals to zero, the quantity of pheromones becomes the only factor that determines the probability of the selection. The pheromone is reinforced immediately when an artificial ant completes a route. The quantity of pheromones added varies based on the quality of the traversed route.

3) Procedure of computation

The Ant Colony Algorithm (ACA) finds the optimal route through a series of iterative steps:
1. An initial pheromone matrix is created by assigning a uniform amount of pheromone to all nodes in the navigation area.
2. A total of m artificial ants are placed at the departure point A, ready to begin their search.
3. Each ant, using the state transition rule from Equation (4), moves from node to node to generate a possible route toward the destination.
4. The objective function value for each ant's route is computed using the cost formula from Equation (1). The best route found so far is stored as the current optimal route.
5. Based on the objective function values and the pheromone update rule from Equation (2), the amount of pheromone on each node is adjusted.
6. The algorithm checks if the termination conditions such as reaching a predetermined number of iterations or finding a minimum objective function value are met. If not, the process returns to step 2, and the cycle is repeated until a satisfactory solution is found.

4) Estimation of the shipping cost

Environmental factors, dangerous maritime navigation areas and the hydrodynamic performance of ships must all be considered when computing of navigation shipping costs.

a) Hydrodynamic performance of the ship: In maritime navigation, especially in areas like the Mediterranean Sea, a ship's hydrodynamic performance is significantly affected by environmental factors, particularly wind and waves. The ship's actual speed in waves is necessarily lower than its speed in calm water. This factor is crucial in maritime route calculation, as it profoundly impacts a ship's positioning accuracy [27]. This effect is of particular importance as it directly influences the accuracy of a ship's position and its navigational precision.

Speed degradation can be calculated using a specific formula to generate performance curves (see Figure 2), and its effect varies depending on the wave direction relative to the ship's orientation if it is in front or back, as shown in Figure 3.

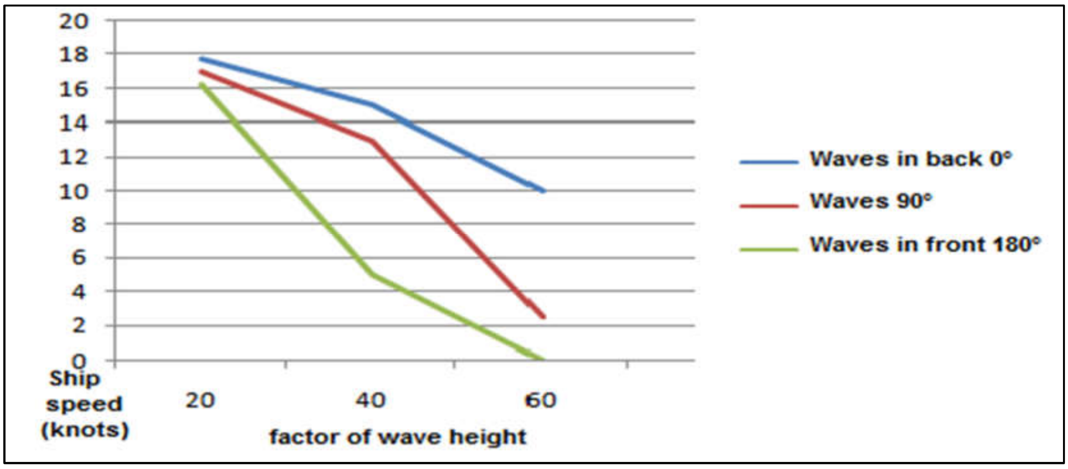

Figure 2: Performance curves of the ship

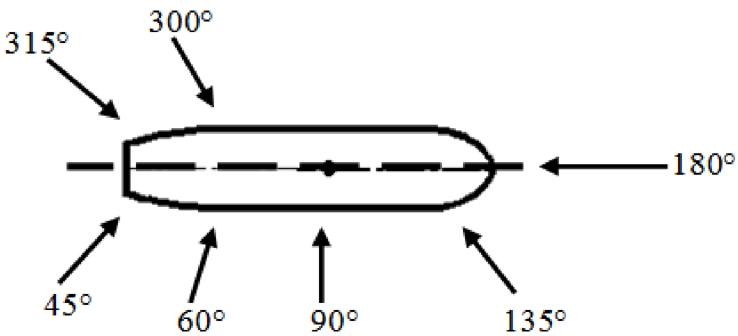

Figure 3: Direction of the waves and ship's Orientation

The main factors affecting the speed of the ship are the waves and the wind, where the height of the waves is depended to the speed of the wind. For the reasons of simplicity, the follow formula for calculating the slowing speed of the ship has been chosen. The main factors included are wave height, wave direction, and ship's coefficient of performance. It is formulated as follows:

$$S = S_0 - (0.745h - 0.257g*h) * (1.0 - 1.35*10^{-6}*L*S_0) \tag{5}$$

With:

S: the ship's real speed.
S_0: the ship's speed in the calm Sea.
h: the wave's height.
g: the angle between the direction of the waves and the ship's heading.
L: the ship's total weight.

b) Geographical and meteorological data: Environmental data includes geographic, navigation, and meteorological forecast. Various cost data can be obtained by aggregating computations, navigation distance measurements and environmental data. The computation process is:

Geographical data: sea boundaries and land boundaries and hazardous areas (eg. oil rigs or sea areas with little depth) are recorded and initialized in the GIS with the zero value, while the other nodes are initialized by a constant value. And this to make ants pass just in the sea area in safety and avoid collision with the oil rigs.

Meteorological data: meteorological data are made by collecting quantitative data about the current state of the wind and the waves (significant wave height of wind and swell, mean wave direction, the speed of the wind …). Using GRIB data (General Regularly-distributed Information in Binary form) allow us to convert this data in GIS format for calculation process. The GRIB data is designed and is developed by the W.M.O (World Meteorological Organization), and this format is used by different stations around the world to broadcast meteorological data. These data can be downloaded from internet and updated, often every six hours.

c) Calculation method: The proposed route cost calculation methodology involves several steps. First, environmental data, specifically wave height and wave direction, are extracted from GRIB files. This data is then converted into grid-based data layers within a Geographic Information System (GIS) to facilitate spatial analysis. Next, GIS spatial analysis functions are employed to calculate the distance of each candidate route and to query the corresponding wave data for every cell along the path. By applying a specialized ship speed deceleration formula, the reduction in speed due to wave effects is quantified. This information allows for the final calculation of the route's cost, which can be expressed in terms of either total navigation time or fuel consumption. When navigation time is the primary cost metric, the calculation is performed using the following formula:

$$t_j = \frac{d_i}{s-w_i} \tag{6}$$

$$T_c = \sum_{i\in I}(t_i + d_i \times F_i) \tag{7}$$

With:

t_i: the necessary time for the candidate path to traverse the i^{th} cell.
d_i: the distance for candidate path to traverse the i^{h} cell.
s: usual speed with normal weather conditions.
w_i: the reduction in speed caused by waves in the i^{th} cell.
T_c: total navigation cost.
F_i: supplementary distance parameter in the i^{th} cell.

5) Contribution to improving computing performance

a) Restrictions of deviation angle and limit length of path segment: given the large number of nodes, many computing abilities will be lost. The advantage of limiting maximum direction deviation and limiting the maximum length of route segment is to avoid many unnecessary calculations. We have limited the deviation angle to ± 45 ° from the initial direction and the length of the path segment is restricted to a maximum that corresponds to the distance navigable in six hours with the actual speed.

b) Determination of the critical speed: During route optimization, a crucial safety parameter is the ship's critical speed. It must be factored in to account for different weather conditions. This critical speed serves as a ceiling for the ship's velocity, ensuring that the resulting route prioritizes safety. Its value is fundamentally dependent on the height and direction of the waves. To impose these necessary speed limitations for safe navigation, the following formula [29] is applied.

$$V_{Limit} = e^{0.13[\mu(q)-h]^{1.6}} + r(q) \tag{8}$$

With:

$\mu(q) = 12.0 + 1.4*10^{-4}*q^{2.3}$
$r(q) = 7.0 + 4.0*10^{-4}*q^{2.3}$
q: represents the direction of the waves.
h: represents the height of the waves.

c) The integration of crossover mechanism for the algorithm: To improve the exploration of the solution space and avoid premature convergence, a crossover mechanism is incorporated into the search process. This operator is applied probabilistically at each iteration. The condition for crossover is the intersection of two distinct ant paths at a common node (except the node of departure and the node of destination). Once this condition is met, the genetic crossover is performed by swapping path segments between the two routes, thereby generating two new solutions. These newly created paths are then evaluated against the existing optimal solution, and an update is made if a better path is found. The introduction of this operation not only increases the algorithm's potential to discover higher-quality solutions but also effectively diversifies the search process.

d) The addition of mutation operation: To improve the algorithm's ability to explore a wider range of solutions and to counter the issues of premature convergence and solution homogeneity, a mutation operation was introduced. This process involves the random selection of a node on the current optimal path, which is then mutated by being replaced with a randomly chosen node from the set of unvisited grid points. The resulting new route is then assessed. If this new route yields a lower cost, it is adopted as the new optimal solution, thus ensuring that the search for a global optimum remains active.

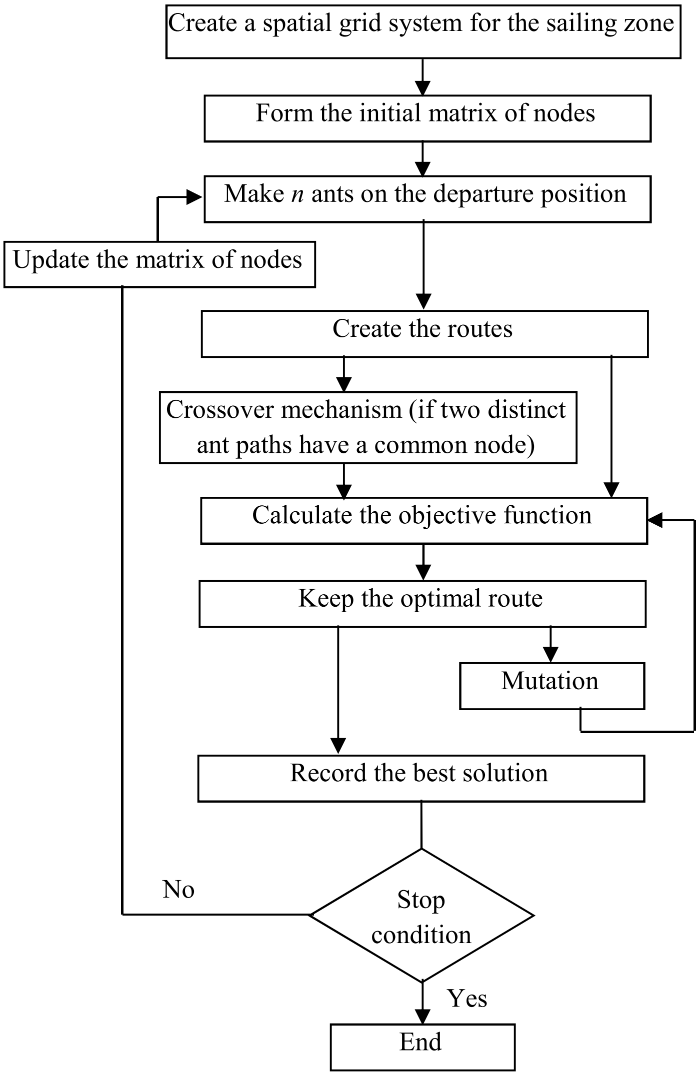

Figure 4: Flowchart of the approach

4. Results

Simulation experiments on shipping routes were realized from Oran-Algeria to Bizerte-Tunisia, with (35 ° 42 '54' 'N, 0 ° 37' 50 '' W) as departure port location, and (37 ° 16 '34' 'N, 9 ° 50' 44 '' E) as arrival port location. GRIB data were used for the Mediterranean in 21/03/2025. The speed of navigation is 18 knots in calm sea. The route was produced by ACA research; it was produced by joining the waypoints.

The simulated results, illustrated in Figure 4, compare the great circle route (in black) with the optimal route generated by the algorithm (in red) and the exploratory paths (in yellow).

Our analysis, based on minimizing total navigation time, revealed that the algorithm's performance is directly dependent on the choice to its parameters.

The results obtained for Alpha equal to zero are not affected by neglecting of this parameter. This behavior of the algorithm explains that the Alpha parameter is a factor of emergence and not of exploration of the search space and efficiency. By repeating the same experimental conditions of the algorithm, the neglect of the importance factor of the heuristic Beta demeaned the performance of the solution.

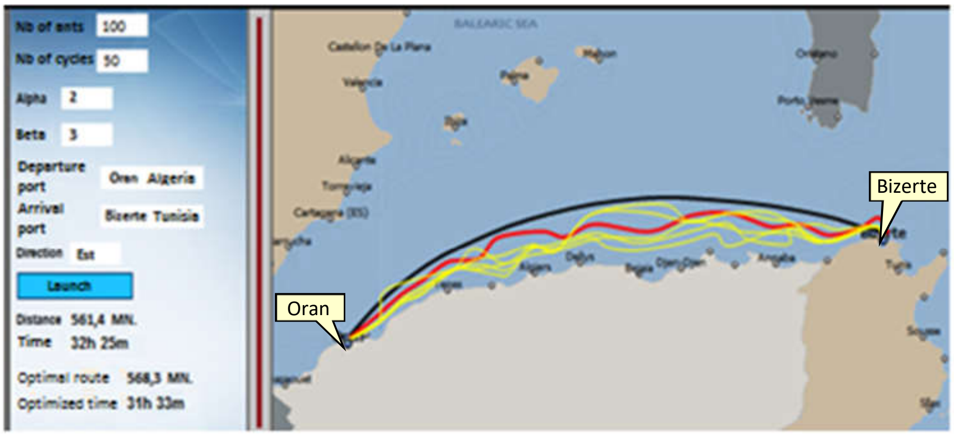

Figure 4: Simulation of routes generated by the algorithm

The execution of the algorithm, depending on the variations of the Alpha and Beta parameters, gave the following observations:

The results are similar for Alpha values equal to 0 or equal to 2, with the same importance given to the heuristic.
This behavior of the algorithm with respect to both Alpha and Beta parameters shows that heuristics or visibility are the essential element in terms of improving results, and that the pheromone is a way of emergence and learning to accelerate the achievement of the solution and to avoid the trapping situation.

When the number of artificial ants is low, the algorithm does not indicate evident signs of convergence, and the optimal solution is difficult to attain. This is also true when the number of artificial ants is bigger (10) and the parameters α and β are of small value (≤ 3). Increasing the values of α and β to ≥ 4 improved convergence, but it also increased the required number of iterations. The best convergence was observed with a relatively large number of ants ≥ 30 with α and $\beta > 4$, though this configuration frequently resulted in local optima.

The most favorable results, in terms of both convergence and solution quality, were obtained with a large population of artificial ants and a specific parameter relationship where $\alpha < \beta$ (e.g., $\alpha = 2$, $\beta = 3$). This setting consistently produced near-optimal solutions. Consequently, the final parameters for this study were defined as:
$\alpha = 2$, $\beta = 3$, $\rho = 0.5$, n (ant no.) = 100 and C (cycle no.) = 50.

An empirical validation on an eastbound voyage confirmed the algorithm's effectiveness. The great circle route, spanning 522.9 nautical miles, took 32 hours and 25 minutes to complete (average speed: 16.13 knots). In contrast, the optimal route identified by the algorithm, at 528.3 nautical miles, reduced the travel time to 31 hours and 33 minutes (average speed: 16.74 knots). This outcome represents a net time savings of 52 minutes and demonstrates a substantial gain in fuel efficiency over the traditional great circle route. In the case of sailing in the West-direction, the meteorological conditions were advantageous and better. The distance generated by the algorithm was 531.4 NM and the sailing time was 31h 10m with the average speed was 17.05 knots.

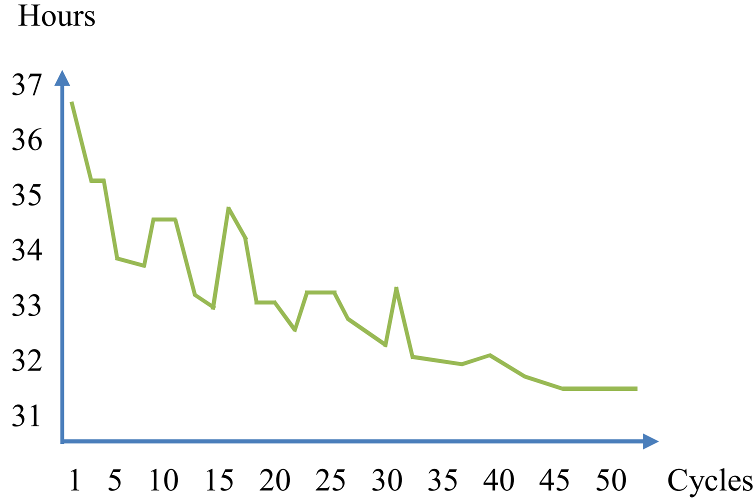

Figure 5: Optimal navigation time in East-direction

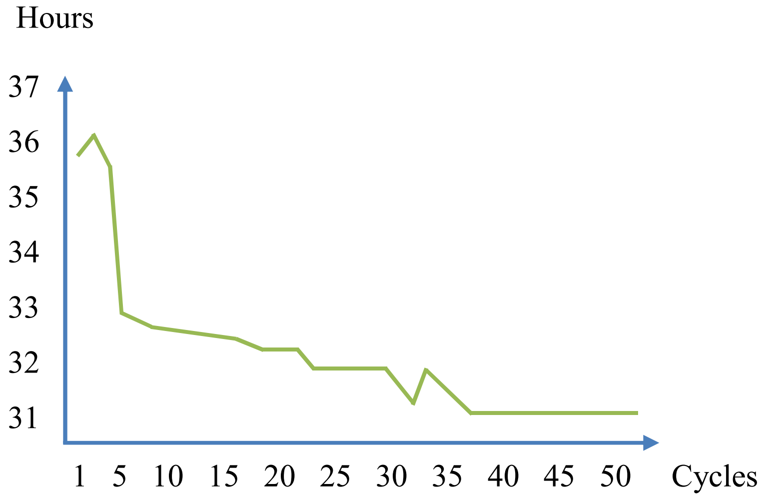

Figure 6: Optimal navigation time in West-direction

The following table shows the results of numerical simulations:

	Distance (NM)	Average speed (knots)	Time (Hours)	Direction
Great circle route	522.9	16.13	32.42	East
Optimal route produced by the algorithm	528.3	16.74	31.56	East
Great circle route	522.9	16.42	31.84	West
Optimal route produced by the algorithm	531.4	17.05	31.17	West

Table 1: Results of numerical simulations

Figure 7.a: The ship to be controlled is at the departure port

Figure 7.b: Positioning of ships after 9 hours of navigation

Figure 7.c: Positioning of the ships after 20 hours of navigation

By applying collision avoidance rules [29] and [30], Figures 7 (a), (b), (c) show us the optimal route produced by the algorithm by avoiding collision with three moving ships.

5. CONCLUSION

In this paper, we have studied the problem of optimal ship routing by modeling displacement and releasing a solution based on an optimization algorithm that optimizes the movements made by ships and that takes into account both safety and the economy. For this, we have proposed to use the Ant Colony Algorithm (ACA) with the incorporation of the concepts of the Genetic Algorithm (GA). The Geographic Information System (GIS) allowed for the computation and facilitated the exploration of geographic information.

We have also integrated a collision avoidance mechanism between ships and not just fixed obstacles (oil rigs) to improve the safety of navigation.

In future research, and with emerging technologies such as artificial intelligence (AI), a new algorithm can be developed for intelligent ships featuring an autonomous navigation system (self-optimizing route) to identify optimal routes, capable of adapting to actual conditions in real-time.

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