A multi-stage multi-criteria dynamic decision-making framework for fishing route planning and optimization

Tiantian Zhu, Masoud Naseri, Sushmit Dhar

Department of technology and safety, UiT-The Arctic University of Norway, Tromsø, Norway
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Abstract

Fishing is one of the main activities in the Arctic waters. Improving fishing vessel's trip planning presents a viable avenue for enhancing fishing catch efficiency, profitability, and sustainability. Simultaneously, it offers the opportunity to mitigate accident risks stemming from adverse weather conditions and lessen environmental footprint through reduced fuel consumption. Today, fishing trip planning and route optimization rely on the experiences and know-how of individual skippers. Determining where and when to go for fishing is a challenge. This paper presents a conceptual framework and an exemplified algorithm for multi-stage, multi-criteria dynamic route planning and optimization for pelagic fishing in the Arctic. Such an algorithm aims to allow using available data in decision-making for more efficient fishing. The proposed route planning and optimization framework uses graph theory, Pareto optimality, and genetic algorithms to find a set of optimal routes which contains a set of sequential fishing grounds to visit and a fishing factory to deliver the catch, a sequence of speed to sail between locations and a sequence of durations to stop at each location. A robustness-based principle is used to determine the next action (i.e., choosing the next location to fish, the average speed to reach there, and the duration to stay at the next location) from the set of optimal routes. A dynamic routing process is proposed for the optimization of a complete trip, which means that only the next action is chosen from optimal routes, while further actions are still open to future opportunities and information updates. Dynamic routing provides an alternative to that of determining the whole trip from one optimization with information available at the beginning of the trip. By using the proposed fishing route planning and optimization framework, users can customize their objectives such as cost, catch, safety and fuel consumption, including the objective functions. At the same time, the algorithm can be tuned and improved through daily application and feedback to form a rich body of knowledge. The rich empiric knowledge of skippers can be saved and transferred to new generations in the form of algorithms.
Keywords: Route planning and optimization, fishing vessels, multi-stage multi-criteria decision-making, dynamic routing, Arctic fishing

1. Introduction

1.1. Background

Fishing is one of the most dangerous occupations in the world. Fishing accounted for 26% of the total-loss accidents among the total-loss marine accidents of ships of 100 gross tonnage or above between 1998-2018, according to the data from Lloyd's List Intelligence Casualty Statistics (Chen, Bian et al. 2020). Small fishing vessels with less than 100 gross tonnage are even more prone to capsizing accidents (Davis, Colbourne et al. 2019). In Norway, fishing is one of the major industries, and its death rate remains high even though accident prevention, survival training, and search and rescue services offered are among the best in the world. The high death rate is partly due to the fishing fleet operating in areas with rapidly changing natural conditions where strong winds, frigid waters, darkness and ice constitute a considerable risk of loss of lives (McGuinness, Aasjord et al. 2013a, McGuinness, Aasjord et al. 2013b).

In the Arctic waters, fishing vessel operation is one of the main activities (Silber and Adams 2019). There is a polar-ward movement of fishery because receding sea ice opens the way to widespread fishing (Stocker, Renner et al. 2020; Fauchald, Arneberg et al. 2021). The Arctic environment is fragile and needs more careful planning for future fishing. Better trip planning is of interest to skippers and ship owners for their profits and business sustainability (Granholm, Auran et al. 2017). There is a need for more efficient, safer and ecologically sustainable fishing in the Arctic. Optimizing fishing routes is a feasible way to achieve safer, more sustainable and environmental-friendly fishing (Luo and Shin 2019), which forms the rationale of this work. Even though route planning and optimization or weather routing is a popular topic in the maritime sector, it is less considered for fishing vessels. Optimizing fishing routes is a challenging task due to their complexity, uncertainties, and dynamic conditions regarding the location and size of fish schools, multiple objectives, and constraints, such as legislation, that need to be considered (Granado, Hernando et al. 2021). Currently, experienced skippers take the role of route optimization, which is a very knowledge and experience-demanding job.

1.2. Existing research

Fishing route optimization is a multi-disciplinary topic which involves research in several directions, as shown in Fig. 1. Route optimization serves the overall goal of fishing optimization. It also belongs to the direction of weather routing because weather routing is about finding optimal routes for ships. The further goal of routing is to achieve deeper needs such as cost saving, safety, reduced fuel consumption, and sustainability. To achieve such goals, finding optimal routes requires proper operational formulations between those goals and route characteristics. Objective function modelling or cost (function) modelling plays the role here. The state-of-the-art in the relevant directions are provided in the following Sections 1.2.1-1.2.5.

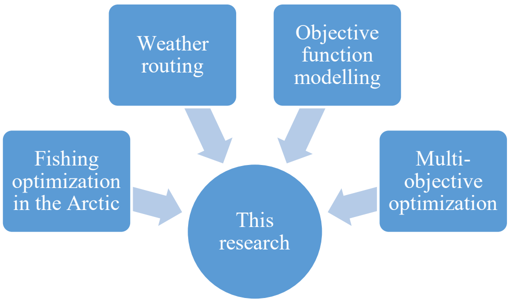

Fig. 1. Research discipline

1.2.1. Fishing route optimization

In practice, commercial catch per unit effort, among all factors to be considered, is used by ship owners and skippers for route planning (Salthaug and Aanes 2003). Fishing vessels increase their profit and long-term business sustainability by reducing fuel consumption, catching high-value species, reducing time at sea, or catching larger-size fish whilst dealing with constraints, such as emissions, bycatch limitations, or catch quotas. A few research studies have been carried out on fishing route optimization. Vettor, Tadros et al. (2016) used a weather routing system to optimize the route for a pelagic fishing vessel to transit from a port in Portugal to Norway. A ship response model is included in the algorithm to estimate fuel consumption. In addressing the multi-objective nature of the fishing routing problem, three key objectives are prioritized for the route optimization: minimizing fuel consumption, mitigating risk, and ensuring timely arrival at the destination. Strength Pareto Evolutionary Algorithm SPEA2 (Zitzler, Laumanns et al. 2001) was used to find a set of optimal routes. Prior single objective optimization was used to choose the most favorable route among the set of optimal routes; a rank of routes was obtained according to the importance rank of objectives to make sure the chosen route satisfies the most important objective (Vettor, Tadros et al. 2016). Granado, Hernando et al. (2024) proposed a dynamic routing algorithm, called GA-TDA*, for the planning of a single fishing trip for a tuna purse seiner that follows a set of exclusive drifting fishing aggregation devices (dFAD). The GA-TDA* algorithm couples a genetic algorithm (GA) with a time-dependent A* algorithm. The dynamic fishing routing problem (DFRP) of a tuna purse seiner is formulated on two levels. The first level problem, which is to find the set of dFADs to visit, is formalized as the dynamic k-travelling salesperson problem with moving targets and time windows, whereas the second level problem, which is to find an optimal path between two dFADs, is formulated as the time-dependent shortest path problem. Two objectives, minimizing fuel consumption and maximizing the probability of high catches, are compromised to determine the optimum.

1.2.2. Weather routing

Weather routing and metrological path planning are the most widely applied terms for ships' route planning and optimization, even though these are not targeted at fishing vessels per se. Weather routing (Zis, Psaraftis et al. 2020) is the use of real-time weather data to find the optimal route for a ship's voyage to enhance navigation safety and reduce navigation costs in terms of emissions, energy, and time under multiple constraints. Thus, weather routing is often modelled as single-objective or multi-objective optimization problems. Various methods have been employed to ship weather routing optimization problems, ranging from Dijkstra's algorithm (Dijkstra 1959), dynamic programming and optimal control methods to isochrone methods or iterative approaches such as genetic algorithms for solving nonlinear optimization problems (Walther, Rizvanolli et al. 2016, Charalambopoulos, Xidias et al. 2023). The determination regarding whether an approach is suitable and produces sufficient results strongly depends on the specific requirements concerning optimization objectives, control variables and constraints, as well as the implementation. To seek the best route, one usually considers several types of factors, including weather forecasts, ship characteristics, and voyage mission requirements. For ship navigation in the Arctic, research about route optimization for transit in sea ice-covered areas has been carried out (Kotovirta, Jalonen et al. 2009; Lee, Roh et al. 2021). Even though the technology for weather routing can be adapted to the route optimization for fishing vessels, the available algorithms and objective functions still need to be improved to meet the needs of different types of fishing vessels and other particularities (Granado, Hernando et al. 2021).

1.2.3. Route risk modelling

Another motive for fishing route optimization is to enhance safety. Fishing vessels in the Arctic are subject to many types of threats, such as storms, polar lows, icing (Dhar, Samuelsen et al. 2022), improper loading, and heavy winch or crane operation, etc. (Davis, Colbourne et al. 2019). The aforementioned threaten the stability of fishing vessels (Davis, Colbourne et al. 2019) and potentially lead to capsizing (Míguez González and Bulian 2018, Manderbacka, Themelis et al. 2019). To take safety into account in route optimization, a working route risk model is vital. Recent developments, elaborated in the following, can contribute to risk modelling of fishing vessels and route optimization based on both weather conditions and operational conditions of vessels. For example, ship icing risk can be modelled as a relation with ship characteristics (Dehghani, Naterer et al. 2018), sailing velocity, and weather conditions (Samuelsen and Graversen 2019). AIS data can potentially be used to assess the collision risk of a fishing vessel (Du, Goerlandt et al. 2020). The capsizing or stability loss risk model should include factors like maintenance conditions, loading conditions (Mantari, Silva et al. 2011), harsh weather conditions, vessel modifications that reduce vessel stability, port availability, compromised watertight integrity conditions, poor design, and the crew's competences (Davis, Colbourne et al. 2019). The stability guidance system proposed by Santiago Caamaño, Míguez González et al. (2018), which calculates the metacentric height by estimating the natural roll frequency in operation, can measure the real-time stability of fishing vessels. Kim and Yeo (2020) proposed methods for the estimation of drafts and metacentric heights of small fishing vessels according to loading conditions. Im and Choe (2021) proposed an index approach for the assessment of intact stability. These methods can be used in risk modelling for stability loss of fishing routes.

1.2.4. Route fuel consumption modelling

With fuel consumption accounting for up to 30% of the operational cost for some fishing vessels (according to personal talks with ship owners), reducing fuel consumption is one of the primary focuses of route planning and optimization. The fuel consumption of fishing vessels is impacted by vessel size and design, engine conditions and use patterns, fishing gears, fishing trip and route patterns, and targeted species and their migration routes (Basurko, Gabiña et al. 2013). In the maritime sector, various fuel consumption models have been proposed for ship fuel consumption estimation with a primary motivation to optimize energy efficiency (Yu, Fang et al. 2021, Fan, Yang et al. 2022). It is common to use a ship response model to predict route fuel consumption in order to assist routing because such a model calculates the added resistance from environmental forces according to the forecasted sea states (Rusu and Guedes Soares 2014). Cepowski and Drozd (2023) used measurements from a 4800 TEU container carrier that was in operation for 1,187 days data after hull cleaning to develop a possible mathematical relationship between fuel consumption and operation parameters, such as rotational speed, draught, trim, hull fouling time, wind speed, wave height, and seawater temperature. Basurko, Gabiña et al. (2022) investigated the energy efficiency of tropical tuna purse seiners fleet by comparing the two fishing strategies employed by the fleet: fish aggregating device (FAD) and free-swimming school (FSC) fishing. Furthermore, they studied the activity and energy consumption patterns of a tuna purse seiner operating in the Indian Ocean and identified the vessel and engine performance variables that can be used to classify the different vessel activities. A modular weather routing system developed by Vettor and Guedes Soares (2016) includes a ship model to control speed for fuel consumption optimization. The results from these research works can be used to establish an objective function of fuel consumption for fishing routing.

1.2.5. Multi-objective optimization

Multi-objective optimization is about decision-making in the presence of multiple objectives, generally conflicting objectives. Because objectives are conflicting, it is not possible to find a solution that achieves the optimization of all objectives. For multi-objective optimization, several types of methods have been developed, such as the weighted sum method (Marler and Arora 2010, Yang 2014), lexicographic optimization (Isermann 1982), Ɛ-constraint multi-objective optimization method (Thunuguntla and Injeti 2020), and Pareto optimization (Deb, Pratap et al. 2002). The weighted sum method is a classical optimization method that suggests converting a multi-objective optimization to a single-objective optimization problem by giving weight to different objectives. Thus, a single solution that gives the best objective value is obtained. The lexicographic optimization method ranks the importance of objectives and finds the optimal solution which provides maximum achievement for the most important objectives. An Ɛ-constraint multi-objective optimization method reformulates the optimization problem by taking one of the objectives as an objective function and converting other objectives into constraints (by setting specific limits for them). Pareto optimization methods try to find a set of optimal solutions that are as diverse as possible to balance the relative importance of different objectives. Several multi-objective evolutionary algorithms (MOEAs) have been proposed to find the Pareto optima set, such as Elitist Non-dominated Sorting generic algorithms (NSGA) that use non-dominated sorting and sharing (Deb, Pratap et al. 2002).

1.3. Research gaps and objective

Route optimization for fishing vessels is relatively less addressed compared to other types of vessels. Plausibly, a reason for this might be that the types of fishing activities and information about fish stock distribution are relatively dominant among other factors. We are aware of the lack of studies on fishing route optimization for fishing activities, specifically in the Arctic. There is also a lack of research in route risk modelling for fishing vessels, which needs to consider the particularities of fishing vessels, fishing patterns, weather conditions and hazard differences among different geographical regions.

The objective of this research is to provide a multi-stage, multi-criteria dynamic routing solution for route planning and optimization for fishing vessels in the Arctic. The optimized fishing route can provide references and guidance for route selection and optimization for fishing vessel captains or skippers.

1.4. Paper structure

The rest of the paper is structured as follows: Section 2 describes the multi-stage multi-criteria dynamic routing framework. Section 3 describe the corresponding problem formulation. Section 4 presents the proposed mathematical solution. Section 5 discusses the results of the paper and section 6 concludes the research.

2. Multi-stage multi-criteria dynamic routing framework

Error! Reference source not found. illustrates the multi-stage multi-criteria decision-making framework for fishing route planning and optimization according to typical common fishing practices. Decisions made at "Level 1: Tactical Decisions" determine the targeted fish species, regions and seasons. Such decisions are usually made for long-term fishing plans, including what quota to purchase and fishing gears to be equipped. Level 1 decisions do not relate to specific fishing trips but determine some key parameters for "Level 2: Route Decisions", where the

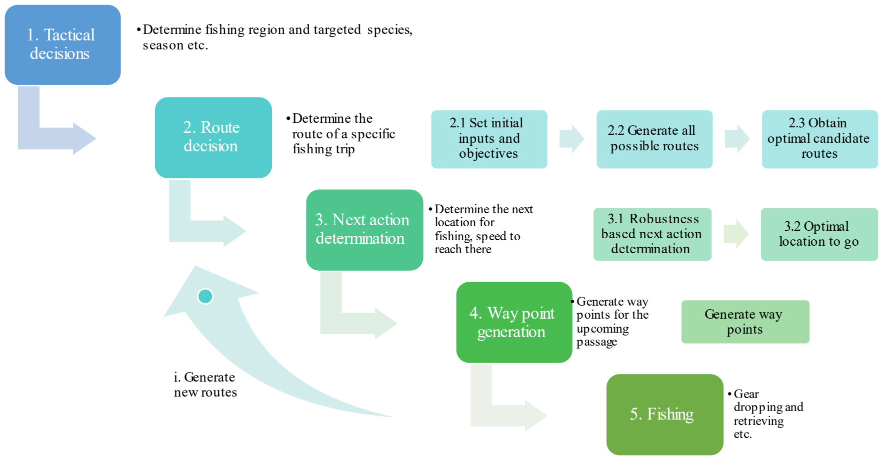

Fig. 2. Overarching framework of the proposed multi-stage multi-criteria dynamic routing

route for a specific fishing trip is proposed. A route consists of both spatial and temporal dimensions. The spatial dimension is expressed by a sequence of passages and locations (including the home port, fishing grounds, factories for delivering the catch, and the destination port), which will be visited during a fishing trip. Meanwhile, the temporal dimension is expressed by a sequence of speed in each passage and a sequence of stop duration at each location. To this aim, a set of initial inputs and objectives are determined, all possible routes are identified, and given the problem objectives and constraints, a set of optimal candidate routes is proposed.

At "Level 3: Next Action Determination", the decision is to determine the next location to sail and the average sailing speed through the corresponding passage to approach that location. For this purpose, determining only the next action instead of the whole route keeps options open for future optimization with new information, where re-optimization can be conducted again to determine the next action based on new information. Due to the existence of multiple optimal routes, the next actions may not be the same among them. It is also necessary to determine which action to choose. If there is only one optimal route, the next action is the first one in the optimal route. "Level 4: Waypoint Generation" is about generating more specific waypoints for the chosen passage from the current location to the next location. Level 5 decisions are dropping and/or retrieving fishing gear.

The proposed framework operates on the assumption that solving a problem involves addressing all its constituent subproblems. Global optimal can be achieved if all subproblems' optima are achieved. Recognizing the interdependency and interconnectedness among various decision-making levels and statuses, as well as the dynamic nature of fishing trips and the inherent uncertainties associated with weather forecasts, fish stock distribution, and catch, the level-by-level decision-making approach aims to approximate a degree of optimum.

3. Mathematical problem formulation of route decisions

When it comes to fishing route planning, Level 2 and 3 decisions are included in the scope for problem formulation. Assuming there are several fishing grounds at different locations, with a variety of fish stock and fish factories to deliver the catch, the problem is how to arrange the fishing routes so that the fishing vessel can achieve its objectives within a range of constraints. A directed graph can be used as a graphical representation of fishing routes, as illustrated by Fig. 3. Here, a route is defined as a sequence of geographical locations that the vessel could proceed through to complete the fishing trip. The locations can be ports (where stops are made for refueling, quick repairs, removing the ice, and avoiding extreme weather), fishing grounds, the vessel's home port, and the destination port (which may be the same as the home port), and the waypoints where a ship passes by on its route.

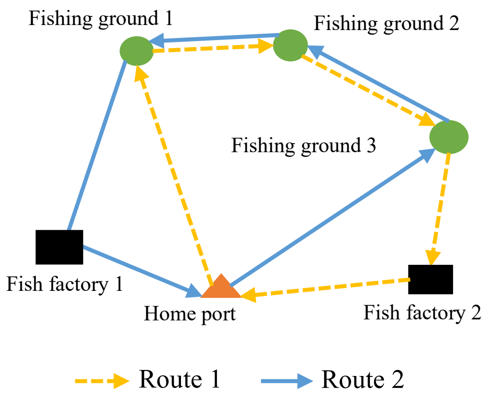

Fig. 3. An example of fishing routes presented by a directed graph, showing two possible routes

A route r can be mathematically expressed as a sequence of passage, location, time tuples,

$$r = \left\{\left(r_{home,grd_i;s_i}, grd_{1;d_{grd_1}}\right), \left(r_{grd_1,grd_2;s_2}, grd_{2;d_{grd_2}}\right), \dots, \left(r_{grd_{n-1},grd_n;s_n}, grd_{n;d_{grd_n}}\right), \left(r_{grd_n,fac;s_{fac}}, fac_{d_{fac}}\right), \left(r_{fac,home;s_{fac}}, home_{d_{home}}\right)\right\}$$

where $grd_{n;d_{grd_n}}$ is fishing ground n, taking place at the nth fishing ground with a fishing duration d_{grd_n} and $r_{grd_{n-1},grd_n;s_{grd_n}}$ is the passage to the nth fishing ground grd_n from the previous fishing ground at an average sailing speed s_{grd_n}; fac is the fish factory where fish will be delivered to with a stop duration d_{fac}; $r_{grd_n,fac,s_{fac}}$ is the passage from the last fishing ground to the fish factory, fac, with sailing speed s_{fac} and $r_{fac,home;s_{home}}$ denotes the passage for returning from the fish factory fac to $home$ port with sailing speed s_{home}. Other ports may also be defined and added to the route, where a fishing vessel may stop for the removal of ice or to avoid extreme weather. The length of each passage and the average sailing speed determine the sailing time spent for each passage. The sailing time of all previous passages and the stop duration at previous locations determine the arrival time and departure time for each location.

A sequence of places that a fishing vessel stops can be expressed as:

$$Loc = (home\ port \quad grd_1 \quad grd_2 \ \cdots \ fac \quad destination\ port)$$

A sequence of passages between two places that a ship pass can be expressed as:

$$Pas = ((home\ port \quad grd_1) \quad (grd_2 \quad grd_3) \cdots (grd_n \quad fac) \quad (fac \quad destination\ port))$$

The speed sequence of all passages of a route can be expressed as:

$$S = (\ s_1 \quad s_2 \quad s_3 \cdots s_f \quad s_h)$$

The stop duration sequence of all places of a route can be expressed as:

$$D = (\ d_1 \quad d_2 \quad d_3 \ \cdots\cdots d_f)$$

The route planning and optimization problem can be expressed as a multi-objective optimization problem whose aim is to find a set of feasible routes (at least one) that could satisfy the set of objectives and constraints. The general multi-criteria route optimization form can be formulated as follows:

Minimize/maximize	$O_i(r)$	$i = 1, 2, \dots I;$
Subject to constraints	$g_j(r) \geq 0$	$j = 1, 2, \dots J;$
	$h_k(r) = 0$	$k = 1, 2, \dots K;$
	$r_m{}^{(L)} \leq r_m \leq r_m{}^{(U)}$	$m = 1, 2, \dots M;$

where $O_i(r)$ is the ith objective, which can represent the cost, reward, and risk of route r, $g_j(r) \geq 0$ is jth inequality constraint, $h_k(r) = 0$, is the kth equality constraint and r_m is the control variable bounded by a lower bound $r_m{}^{(L)}$ and an upper bound $r_m{}^{(U)}$.

4. Mathematical solution

Table 1 provides an overview of the algorithms used to solve the formulated dynamic routing problem. To operationalize the algorithms, Python, as a high-level, general-purpose programming language, is used, where ship parameters, weather maps, fish distribution maps, targeted fish types, bathymetric maps and problem constraints and objectives are used as inputs. Graph theory is used to represent the locations as nodes and passages as edges. Optimization methods such as non-dominated sorting algorithm for Pareto optimality, genetic algorithm, and objective modelling to connect routes to optimization objectives and constraints are required to solve the multi-objective routing problem. To implement the algorithms for a specific case, users need to specify a ship with its parameter values, targeted fish type, coordinates of the home harbor, potential fish grounds and fish factories, constraints, and objectives to be optimized.

Table 1. Architecture of the algorithms to implement the proposed solution.

Algorithm	Note
Result from tactical decisions	
Establish initial objectives, constraints, cost function, route network.	
While a fishing trip is not finished:	Starting or while in a fishing trip
Update information regarding ship parameters, fish grounds, fish stock, weather forecast, inventory, objectives.	If no new information is available, then follow the predetermined optimal route.
Calculate pareto optimal routes.	
Use a genetic algorithm to generate a defined number of pareto optimal sets of speed and duration of stay, separately for all the possible routes from the current location to the end.	Please see section 3.3.2 for pareto optimality and section 3.3.3 for the genetic algorithm
Apply pareto optimality again to select a defined number of optimal routes with speed and duration combinations.	Please see section 3.3.2 for pareto optimality.
Determine the next stop, average speed to reach the next location and duration of stay at the next location:	
Determine the next location to visit from the selected pareto optimal routes by applying the most popular principle.	Please see section 3.3.4 for next action determination.
Determine the sailing speed from the filtered routes.	
Determine the duration to stay at the next location.	

4.1. Modelling of objective functions

In order to find the optimal routes, proper formulation of cost/reward functions for objectives and constraints is crucial. For each objective i, the accumulated cost of a route can be expressed by:

$$O_i(r) = o_{i,r_{home,grd_1},s_{grd_1}} + o_{i,\,grd_1,d_{grd_1}} + \sum_{k=2}^{k=K}\left(o_{i,r_{grd_{k-1},grd_k},s_{grd_k}} + o_{i,\,grd_k,d_{grd_k}}\right) + o_{i,\,r_{grd_K,fac},s_{fac}} + o_{i,\mathrm{fac},d_f} + o_{i,r_{fac,home},s_{fac}}$$

For any objective $i,\ i = 1, 2, \ldots n$, the accumulated cost can be divided into two types of costs, the cost incurred by staying at a location, denoted by $o_{i,loc,d_{loc}}$, where $loc \in \{fac, grd_k\}, k = 1, \ldots K$, and the cost incurred by sailing along a passage, denoted by $o_{i,r_{loc_a,loc_b},s_{loc_b}}$, where $loc_a, loc_b \in \{home, grd_k, fac\}, k = 1, \ldots K$, and s_{loc_k} is the average sailing speed to loc_b. For example, $o_{i,grd_k,d_{grd_k}}$ is the total cost of fishing at a fishing ground grd_k for a duration of d_{grd_k}, and $o_{i,r_{grd_{k-1},grd_k},s_{grd_k}}$ is the cost of passing along the passage r_{grd_{k-1},grd_k} toward a fishing ground grd_k with an average sailing speed of s_{grd_k}. These two types of costs can be modelled as a function of time, weather conditions, distances, conditions of fishing grounds, ship conditions and parameters, etc. In particular, one may express these as:

$$o_{i,loc;d_{loc}} = f_{loc}(W(t, loc), g(p_1, p_2, \ldots, p_m), loc, d_{loc}, prediction\ accuracy)$$

$$o_{i,r_{loc_a,loc_b};s_{loc_b}} = f_r\big(W\big(t, r_{loc_a,loc_b}\big), g(p_1, p_2, \ldots, p_m), r_{loc_a,loc_b}, \mathrm{s}_{loc_b}, prediction\ accuracy\big)$$

Where $W(t, loc)$ is a function of weather and sea conditions at time t and location loc, $g(p_1, p_2, \ldots, p_n)$ is a function of ship parameters. Users can define their customized cost functions (i.e., $f_{loc}(\cdot)$ and $f_r(\cdot)$) for their objectives and constraints of interests. The common objectives for a fishing vessel can be to maximize catch and minimize accident risk and operational cost. Furthermore, the cost function of risk can be composed of capsizing risk, potential damage to fishing equipment, and risk of certain meteorological phenomena such as spray icing and sea ice. Operational costs usually include personnel costs, fuel costs, degradation of fishing equipment and other administrative costs, etc.

4.2. Pareto Optimality

Pareto optimality is a state in which the value of one objective function cannot be improved without impairing the value of another. Therefore, Pareto optimality is achieved when it is not possible to optimize one objective further without sacrificing any other objectives. The solutions that fulfil Pareto optimality is called the Pareto optimal solutions. The concept of dominance is instrumental in comparing solutions and identifying Pareto optimal solutions. Pareto dominance enables one to compare solutions without requiring preference information in the problem definition. A solution $r^{(1)}$ is said to dominate the other solution $r^{(2)}$ if both the following conditions are true (Emmerich and Deutz 2018):

1) The solution $r^{(1)}$ is no worse than $r^{(2)}$ in all objectives.
2) The solution $r^{(1)}$ is strictly better than $r^{(2)}$ in at least one objective.

When a solution is Pareto optimal, no other solution exists that can dominate it. Solutions in the same Pareto front, such as the true Pareto front labelled in Fig. 4, are equivalent because they cannot dominate each other. As illustrated in Fig. 4, finding Pareto-optimal solutions is to find the set of feasible solutions that are 1) as close as possible to the Pareto-optimal front (convergence) and 2) as diverse as possible (diversity) so that they represent the entire Pareto-Optimal front. In this study, the non-dominated sorting algorithm proposed by Deb, Pratap et al. (2002) is used to obtain a set of Pareto-optimal routes.

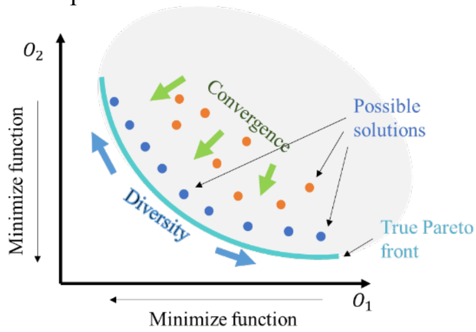

Fig. 4. Pareto Optimality

4.3. Genetic algorithms for speed and stop duration optimization of a path

For each path, to obtain a set of optimal combinations of sailing speed sequence and stop duration at sequence, a genetic algorithm (Mitchell 1998, Deb, Pratap et al. 2002) is used. The genetic algorithm repeatedly modifies a population of individual solutions. At each step, it selects individuals from the current population to be parents and uses them to produce the children for the next generation. Over successive generations, the population "evolves" toward an optimal solution. The genetic algorithm uses three main types of operations at each step to create the next generation from the current population:

- Selection: Select a predefined number of individuals, called parents, that contribute to the population of the next generation. The top individuals, sorted according to Pareto optimality, are selected.
- Crossover: Combine two parents into a pair and randomly select a cutting point to perform crossover on the two parents.
- Mutation: Apply random changes to parents after crossover operation to form children.

To initiate the evolution, a set of solutions are generated randomly from predefined gene spaces. Gene spaces are collections of feasible values of speed and stop duration for solution generation. To make sure that speed and stop duration fulfil certain constraints, the gene space for sampling speed and stop duration for each passage and node should be constrained. After each generation, a set of optimal solutions is selected using non-dominated sorting algorithms to achieve the Pareto optimal front. Following such an evolutionary process, solutions converge to a local or global optimal after many generations.

4.4. Robustness-based next action determination for dynamic routing

A fishing trip is a sequential activity with uncertainty about weather conditions and fish stock distribution. After obtaining the set of optimal routes, instead of randomly choosing a route among the set of obtained Pareto optimal routes, the strategy is only to decide the next action (a tuple of the next location to go, average speed to reach the next location and duration to stay at the next location) instead of determining the whole route following the obtained Pareto optimal routes. Algorithms for this are presented in Table 2. The next location to go is the location with the highest vote among the Pareto optimal routes. For example, among the obtained 9 Pareto optimal routes, 5 routes have chosen to go to the fishing ground grd_1 to start the fishing trip, 3 routes have chosen to go to the fishing ground grd_2, location 2, whereas only 1 route has chosen to go to location 3. Therefore, location 1 will be the next place to visit because it receives the highest vote (5 out of 9) compared to the other 2 locations. Speed and duration are determined in the same way. Choosing the action with the highest votes can keep the highest chance that the chosen action is the next step of an optimal route despite uncertainties and changes. Doing so not only keeps the route optimal but also maintains a high level of robustness in route selection. In case there is no solution that has a majority of votes, a prior objective importance ranking and/or uncertainty ranking will be used to determine which solution to choose or a random choice between the ones with the highest votes will be made.

Table 2 Algorithm of robustness-based next action determination

Algorithm steps

Assuming n optimal routes are found using Pareto optimality and genetic algorithms:

$$Optimal\ routes = \{r_1, \dots, r_n\}$$

Find the next location to go from all optimal routes by:

$$All\ possible\ next\ locations = \{loc_1 \quad \cdots \quad loc_n\}$$

$$Next\ Location = mode(All\ possible\ next\ locations)$$

Considering the $Next\ Location$, obtain the set of reduced optimal routes:

$Reduced\ optimal\ routes = \{r_i | i = 1, \dots, n$ and $Next\ Location$ is the next immediate location to be visited in route $r_i\}$

Find the optimal speed to reach the $Next\ Location$ from the reduced collection of optimal routes:

$$Speed\ collection\ to\ reach\ the\ next\ location = \{s_i | i = 1, \dots, |Reduced\ optimal\ routes|^{1}\}$$

$$Speed = mode(Speed\ collection\ to\ reach\ next\ location)$$

In the same way, the optimal duration of stay at the next location can be determined.

Note: $mode$ is the operator to find the element with the highest number of appearances in a collection.

5. Discussion

The proposed multi-stage multi-criteria dynamic routing framework can be used as a decision support tool by skippers for their fishing trip planning and optimization. The algorithms proposed for routing possess high possibility and flexibility of customization. Ship owners and skippers can modify their objective functions based on their preferences and ship characteristics and customize their objectives for route optimization. The computation speed is acceptable for onboard applications. In addition to onboard decision support, the algorithms can also be used for scenario simulation when making tactical decisions and training future skippers. The proposed algorithms can be further developed into a platform for fishing routing combined with other data sources such as weather prediction data, historical metocean data, hazard database, historical AIS data of fishing vessels, fishing stock/grounds prediction, etc. Potentially, data-driven cost functions can be obtained from historical data as well.

Still, there are some issues that should be noted. Genetic algorithms cannot guarantee that the absolute optimum all the time. The calculation time for the evolutionary algorithm is dependent on the complexity of the functions used to calculate the values of objectives, sizes of gene spaces, No. of generations, required No. of optimal solutions, No. of pairs required for child generation creation. In order to speed up the computation of the optimal route, dynamic gene spaces can be implemented to reduce the sampling size for the genetic algorithm, as seen by Pan, Zhang et al. (2021), to find the optimal speed and durations.

To make the algorithms meaningful, the goodness of objective functions is the driver that guides the search for an optimal route. Therefore, detailed objective function development is necessary regarding factors such as fuel, operational cost, and the risks associated with passages and fishing activities. Fishing school behavior is dynamic, not static. The prediction of fishing ground locations and fish stocks is demanding and has a big impact on routing. It would be useful to take into the prediction accuracy into account in the objective function. However, the prediction accuracy is not easy to know. A ship response model can be included in the optimization algorithm to estimate fuel consumption, etc., of a route for route planning and optimization.

Another thing to bear in mind is that Pareto optimality treats all objectives equally important, which is useful for objectives that cannot be traded with each other or converted into others. However, it can be true that some objectives are more important than others, and thus, it might be beneficial to try the weight sum method for multi-objective optimization or to combine Pareto optimality and lexicographic optimization. For dynamic routing, it is important to keep consistency in objectives because changing objectives will change the optimal route in a dynamic routing process. What was optimal in the past will not be optimal in the future, even though there will be no change in information and the environment. However, changing objectives can actually happen in reality; optimizing routes to handle inconsistent objectives is another problem to resolve.

The purpose of route optimization is to achieve a global optimal, which is challenging due to the dynamics of the problem, uncertainty, and prediction inaccuracy. To address this challenge, the overall routing problem is divided into subproblems, which are solved sequentially and based on knowledge of a new state and the availability of new information. A question is how many subproblems should be created or how to know whether there are too many or too few decisions. A topic for further discussion is how to divide the global optimization problems into subproblems. In the present study, the division is done by dividing the whole trip spectrum into segments in a time sequence, which is logical because the framing of subsequent subproblems is dependent on the results of earlier

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[1] | x | implies the number of elements in the set x.

subproblems and newly arrived information. However, we did not try to prove that this is the optimal way of discomposing such a type of problem.

6. Conclusion

This work proposes a multi-stage multi-criteria dynamic routing framework and algorithm for fishing vessels. A combination of a genetic algorithm, Pareto optimality, and graph theory is proposed to find a set of optimal location, speed and duration combinations to achieve multi-objective optimization for fishing vessels. A robustness-based concept is used to determine the next step from the obtained optimal routes in the previous step. This approach reduces the impact of uncertainty and keeps more options available for the future in case of changes in the environment where the predicted optimal will not be optimal anymore. The proposed framework can be further developed into a standardized platform combined with other data sources to make fishing activities more sustainable, safer, more environmental-friendly, and more efficient, as well as to achieve a secure seafood supply. Further research will focus on objective (such as route safety) function modelling and case studies that apply the proposed algorithms to demonstrate and validate their applicability and feasibility for real-life applications.

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